Taking Over the Size Effect: Asset Pricing Implications of Merger Activity*

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Abstract

We show that merger announcement returns account for virtually all of the measured size premium. An empirical proxy for ex ante takeover exposure positively and robustly relates to cross-sectional expected returns. The relation between size and expected returns becomes positive or insignificant, rather than negative, conditional on this takeover characteristic. Asset pricing models that include a factor based on the takeover characteristic outperform otherwise similar models that include the conventional size factor. We conclude that the takeover factor should replace the conventional size factor in benchmark asset pricing models.

Keywords: Takeovers, mergers, acquisitions, return premia, factor models, expected returns

JEL Codes: G34, G12, G14

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1 Introduction

The size effect refers to a negative relationship between average stock returns and market capitalization that is not explained by market risk exposure (Banz (1981)). Scores of studies document the size effect, and the most influential multi-factor asset pricing models include a factor based on firm size (Fama and French (1993, 2015)). Such is the perceived importance of size that it is common to construct other characteristics-based asset pricing factors via a double sorting procedure that sorts firms both with respect to size as well as with respect to the characteristic of interest. From this perspective, it can be argued that firm size is the preeminent characteristic in asset pricing.

Despite its prominence, a degree of controversy surrounds the size effect and the associated pricing factor. Recent studies challenge the relevance of the traditional size factor of Fama and French (1993).[1] For example, Alquist et al. (2018) argue that the size premium is small relative to other factors, varies over time, is concentrated among micro-cap stocks, and is less robust internationally than other prominent factors. However, Asness et al. (2018) find robust evidence for the size premium upon controlling for measures of firm quality, suggesting continued relevance for the size factor in asset pricing models.

In this paper, we establish a deep connection between merger activity and the size effect. Specifically, we show that positive average returns associated with size-based hedge portfolios are primarily driven by merger and acquisition (M&A) news. In fact, acquisition news explains virtually all of the size premium in U.S. data. Motivated by these return decomposition results, we construct an ex ante takeover likelihood characteristic and associated 'takeover factor' in the spirit of Cremers et al. (2009). The returns on this factor correlate relatively highly with SMB returns, and the two factor premia exhibit similar cyclical behavior. However, the size premium falls over recent decades and becomes insignificantly different from zero, whereas the premium associated with the takeover factor remains robust.

[1] The *theoretical* basis for a size premium is also debated in the literature. Potential explanations include the effects of time-varying risk or risk premia, the role of growth options, limits to arbitrage and associated mispricing, and liquidity effects. See, e.g., associated discussion and citations in Asness et al. (2019).

In a series of asset pricing tests, we show that the takeover factor dominates the size factor, in the sense that models including the size factor are unable to price the takeover factor, but models including the takeover factor price the size factor. We conclude that researchers and practitioners would be well-advised to replace the conventional size factor with a takeover factor in benchmark asset pricing models.

The first portion of our study decomposes ex post average returns for the size factor and other anomaly portfolios into a component associated with realized M&A news and a residual. We measure the M&A component of returns using standard event study methods. Specifically, the M&A component of a stock's daily return equals the abnormal return on each day that the firm is within the defined event window around an acquisition announcement involving the firm, either as target or acquirer. Outside of this window, the M&A component equals zero. Using the resulting panel dataset of firm-level decomposed returns, we compute the daily M&A component of returns for size-based hedge portfolios and other anomaly long-short portfolios.

Takeover announcements are relatively rare events driving large valuation effects for only a handful of firms at most times.[2] It might seem, therefore, that M&A news should have little impact on the performance of diversified hedge portfolios that take positions in hundreds of firms. However, our evidence is not consistent with this hypothesis and we find that the size premium is entirely driven by the M&A component of returns. For example, the annualized average return for a long-short portfolio based on size quintiles is approximately 1% over our sample period. We show that around 1.6% of this premium – over 100% of the premium – is attributable to the realized M&A component of returns. The 'residual' size premium is negative, such that small firms earn *lower* average returns relative to large firms after removing the M&A return component.

Several features of size-based hedge portfolios jointly contribute to generate the significant M&A component that we document. First, targets are more likely to be small firms and

[2]There are approximately 6 deal announcements per trading day involving a publicly listed US target and/or acquirer in our 30-year sample obtained from SDCs U.S. Mergers and Acquisitions Database.

therefore predominantly appear within the long leg of the portfolio. The average abnormal target return is positive and economically large. In addition, average abnormal target returns are roughly twice as large for small cap targets relative to large cap targets. Moreover, because the long leg of the portfolio mechanically consists of *other firms with small market capitalization*, announcement returns for small-cap targets are 'granular' (Gabaix (2011)) and materially impact the return for the long leg of the portfolio despite the fact that this portfolio is diversified in the sense of taking positions in a large number of firms. Consistent with this intuition, we show that the majority of the M&A component of average returns accrues to targets. However, it is also the case that average abnormal returns for small-cap acquirers significantly exceed those for large-cap acquirers (Moeller et al. (2004)). The greater average abnormal acquirer return for small acquirers also contributes materially to the M&A component of the size premium.

The second portion of our paper shifts to an ex ante perspective. Theoretically, cross-sectional differences in takeover exposure potentially reflect differences in exposure to state variables determining asset prices, and therefore relate to cross-sectional differences in expected returns (Cremers et al. (2009)). We measure differences in exposure to takeover activity via the estimated likelihood that a firm will become a target in the following year based on a logistic regression model. The model-based takeover characteristic is a relatively rich function of underlying firm variables, in the sense that the takeover characteristic does not correlate overly strongly with any single input variable (e.g., firm size or profitability).

The takeover characteristic positively and significantly relates to future cross-sectional returns in Fama-Macbeth regressions. We show that the relation between size and expected returns changes from negative to positive upon including the takeover characteristic along with other standard characteristics linked to cross-sectional return patterns. In other words, after controlling for takeover exposure, larger firms earn, if anything, higher average returns relative to smaller firms, in contrast to the conventional negative relation documented in previous studies. This key result holds for several variations of the characteristic, including a version covering an extended sample period from the mid-1960s onward, as well as a 'real-time' version based on model coefficients estimated using a backward rolling window.

We next consider the asset pricing performance of models that include a "takeover factor" constructed as a hedge portfolio based on the takeover likelihood characteristic, following Cremers et al. (2009). Takeover factor returns correlate positively with SMB returns. Both factors tend to perform relatively well during economic expansions, but poorly just prior to and during economic recessions. However, the premium for the takeover factor is substantially larger than that for the size factor, especially over the most recent three decades. For example, during our main sample period from 1990–2020, the annualized takeover factor premium is around 8%, whereas the annualized size premium is around 1.5%. Consequently, although the factors seem closely related, the takeover factor is much more resilient than the size factor over the past few decades.[3]

We follow Barillas and Shanken (2017) and regress excess takeover factor returns on factor returns associated with various benchmark models in order to directly test whether the takeover factor is priced by the factors in these models.[4] We consider a wide variety of alternative benchmark factor specifications, most of which include a size factor. Alpha estimates are positive and significant in all cases, indicating that none of the benchmark models price the takeover factor. Estimated alphas are economically significant and range from approximately 0.3–0.9% per month. Augmenting the benchmark models with the takeover factor significantly increases the maximum obtainable Sharpe ratio. These results are robust to considering real-time versions of the takeover factor that estimate takeover likelihood model parameters recursively to avoid any look-ahead bias, as well as to examining an extended historical sample that includes data from the 1960s onward.

Finally, we conduct a second set of excluded factor regressions to test whether the SMB

[3] Several papers point out that SMB factor returns have diminished in recent decades (see, e.g., Alquist et al. (2018) and Smith and Timmermann (2021)). The takeover factor also earns a higher premium than the size factor over an extended historical sample from the early 1960s onward.

[4] Barillas and Shanken (2017) show that, in comparing the relative merits of return-based asset pricing factor models, what matters is the ability of one set of factors to price the other, and vice versa. This insight motivates the 'excluded factor regressions' that we conduct.

factor remains relevant upon including the takeover factor. When the benchmark model does not include the takeover factor, we typically obtain a positive alpha estimate for the SMB factor. This estimate is larger and often significant when the 'quality' factor of Asness et al. (2019) is included in the model. However, when the the takeover factor is added to the benchmark model, SMB alpha estimates typically become economically small, statistically insignificant, and are frequently negative in sign.

Broadly, our results indicate that the traditional size factor can be interpreted as an indirect form of the takeover factor, in the sense that the size factor implicitly embeds exposure to underlying state variables that drive time-varying takeover activity. The proposed takeover factor earns a much higher premium than the size factor, especially over recent decades. Asset pricing tests consistently favor the takeover factor relative to the size factor. Our results further highlight the surprisingly high-dimensional nature of the space of stock return anomalies (e.g., Jensen et al. (2021)). In contrast to studies that derive new factors from large sets of anomaly characteristics using criteria that emphasize explaining return variation (e.g., principal components), the takeover factor derives from an economic conjecture that links characteristics to the cross section of returns via their informativeness regarding takeover exposure.

2 Related Literature

Our paper perhaps relates most directly to Cremers et al. (2009), who develop a theoretical link between heterogeneity in exposure to takeover activity and expected returns, and analyze a takeover factor similar to that proposed in this paper. Before highlighting differences between our paper and Cremers et al. (2009), we note that the empirical asset pricing literature following Cremers et al. (2009) seems reluctant to take up a takeover factor or takeover likelihood as a characteristic related to the cross-section of returns. For example, none of the recently proposed extensions of the traditional Fama-French three factor model, including the Fama-French five and six factor models (Fama and French (2015) and Fama and French (2018), respectively), the four-factor model of Stambaugh and Yuan (2017), and the Q-factor model of Hou et al. (2015) includes a takeover factor. Moreover, several recent papers study large sets of firm characteristics associated with return anomalies, a phenomenon sometimes referenced as the 'anomaly zoo.' However, few of these studies explicitly include estimated takeover likelihood as a potentially relevant characteristic and therefore a fresh inquiry seems warranted.[5]

A number of aspects of our paper are novel relative to Cremers et al. (2009). The ex post decomposition of average returns for size-based hedge portfolios (and other anomaly portfolios) into an M&A component and a residual is, to our knowledge, new to the literature. Motivated by our return decomposition results, our asset pricing analysis focuses on whether factor models that include the size factor price the takeover factor, and conversely whether models that include the takeover factor price the size factor. Cremers et al. (2009) consider the Fama-French-Carhart four factor model as a benchmark specification. Subsequent literature proposes new investment and profitability-based factors, and explores approaches for extracting factors from a large universe of anomalies. Traditional investment represents an alternative means for expanding firm size and scope, and prominent anomaly characteristics such as past returns, profitability and idiosyncratic volatility are linked to takeover likelihood (e.g.,Bhagwat et al. (2016)). Thus, it is reasonable to conjecture that models that include factors extracted from these characteristics will price the takeover factor. However, we demonstrate that this is not the case.

Several other recent papers address different aspects of the relation between takeovers, asset prices, and macroeconomic conditions. Bennett and Dam (2019) note that stock prices

[5]The relatively broad anomaly sets analyzed by Novy-Marx and Velikov (2015), McLean and Pontiff (2016), and Kozak et al. (2020) do not include the takeover likelihood characteristic. Chen and Zimmermann (2020) include a 'takeover vulnerability' characteristic from Cremers and Nair (2005). This characteristic differs from that in Cremers et al. (2009) and takes the form of a score based on the presence or absence of various takeover deterrents, such as poison pills. Harvey et al. (2016) include the takeover characteristic of Cremers et al. (2009) in their catalog of over 300 factors proposed in the literature; however, they do not specifically re-visit the performance of this factor.

embed the anticipation of future acquisition and estimate that 10% of the value of a typical stock derives from this source. These results imply that measured gains from mergers based on premiums associated with deal announcements understate the total gain from mergers. Heath and Mitchell (2020) examine the relation between merger completion and aggregate stock market conditions. Lattanzio and Sanati (2021) study the impact of merger activity on the U.S. listing gap and Erel et al. (2021) study the relations between cash holdings, macroeconomic conditions, and acquisition activity.

Our results concerning M&A news, takeover activity, and the size premium contribute to a large literature regarding the sources of the size premium and the importance and resiliency of the size factor. We do not attempt to comprehensively review this literature, but note that interest in the topic remains active, including relatively recent studies such as Van Dijk (2011), Fama and French (2012), Alquist et al. (2018), Asness et al. (2018), and Smith and Timmermann (2021).

3 Data

We obtain data on mergers and acquisitions from SDCs U.S. Mergers and Acquisitions Database. Generally following Netter et al. (2011), our sample selection process applies the following filters:

1. All acquisitions from 01/01/1990 (or 01/01/1980 in robustness checks) to 12/31/2020
2. Disclosed and Undisclosed [deal value] Mergers and Acquisitions (Deal Type: 1, 2)
3. Percentage of Shares Acquired in Transaction is greater than or equal to 50%
4. Percentage of Shares Held by Acquirer Six Months Prior to Announcement: 0 to 49%
5. Domestic (U.S.) acquirer or target
6. Deal Status is Completed

As our objective is to recover the M&A announcement component for long-short portfolios involving positions in hundreds of firms, it is important to have relatively comprehensive deal coverage, as well as accurate deal announcement dates. Prior studies document limited coverage of domestic deals by SDC prior to around 1990 (see, e.g., Netter et al. (2011)).[6] Consequently, our main analysis restricts attention to the period 1990–2020. However, in robustness checks we relax the first filter to include SDC deal data from the 1980s as well. The third and fourth criteria limit our analysis to transactions with an explicit change of control: The acquirer must purchase 50% or more of the target's shares in the transaction and own less than 50% of the target prior to the transaction. Our interest lies in aggregating valuation effects for publicly listed U.S. firms and thus, the fifth criterion eliminates deals that do not involve domestic firms. Our main results restrict attention to completed deals or 'successful bids' (the sixth criterion). However, we also consider the role of unsuccessful takeover contests in extensions and robustness checks described below. In contrast to some M&A studies, we do not impose a filter pertaining to deal size. This is because we explicitly wish to analyze the extent to which potentially large M&A announcement returns associated with targets (or acquirers) impact the returns of common long-short hedge portfolios analyzed in asset pricing. Given our central question, it is important to include all deals involving public U.S. firms and not exclude deals involving smaller targets.

After applying these screens and eliminating duplicate observations we have 225,243 transactions for the 1990–2020 sample.[7] We adjust all dollar values to 2020 dollars by the Consumer Price Index (CPI). We collect the following SDC deal attribute data for the transactions that remain following our screening criteria: date announced (DA) and date effective (DE), the percentage of cash (PCT_CSH) and stock (PCT_STK) paid in the deal,

[6] Netter et al. (2011) compare the number of domestic deals announced according to SDC and W. T. Grimm & Co. for transactions occurring from 1980 to 1991. In 1985, SDC reports only around 55% the number of deals relative to W. T. Grimm & Co. However, by 1990, this becomes around 200% and Netter et al. (2011) conclude that SDC coverage is nearly universal.

[7] We eliminate duplicate observations based on all of the following variables: announcement and effective date, acquirer and acquirer parent name, deal value, target and acquirer SIC code, and percentage stock as method of payment.

and deal value (VAL). We also collect the following data for both acquirer and target: market value four weeks prior to announcement (AMV and TMV), public status codes (APUBC and TPUBC), 4-digit primary SIC codes (ASICP and TSICP), and acquirer and target identifiers (CUSIPs).[8] Table 1 summarizes the SDC M&A sample data and the screens we apply. We begin with 225,243 deals involving a domestic acquirer or target. Panel A breaks down the characteristics of these deals by sub-sample. The attributes of the deals are consistent with prior research (Netter et al. (2011)). Most deals are small (less than $1 million) and involve non-public firms. Among larger deals of $50 million or more, around 60% involve either a public target or acquirer (or both).

We aim to construct measures of the portion of stock market returns attributable to M&A news. To this end, we match SDC CUSIP data for public targets' and acquirers' CUSIPs with the Chicago Research in Security Prices (CRSP) database CUSIPs and associated PERMNOs. In the analysis that follows, we retain only deals for which a match is obtained, and for which either the acquirer or target (or both) is listed on NYSE, NYSEMKT (AMEX), or Nasdaq at the deal announcement date per CRSP's exchange code (EXCHCD) field. We also require a non-missing daily return (RET) field over the event window $[-1, 1]$ that includes the announcement date (or, if announced on a non-trading day, the trading day prior to it), as well as one trading day before and after this date.

We obtain, when available, market capitalization and return data for acquirers and targets extending from 100 trading days prior to the deal announcement date to 10 trading days afterward. Panel B of Table 1 shows the filtering process that delivers our final sample of deals for analysis. Restricting to deals involving a public target or public acquirer with price data in the Chicago Research in Security Prices (CRSP) database on the merger announcement date leaves approximately 46,900 deals. Among these, around 85% involve a public acquirer and private target. Roughly 8.5% involve a non-public acquirer and public target, and the remainder (around 5.5%) involve both a public target and public acquirer. The mean deal

[8]Our screens imply that at least one of the acquirer or target nation codes correspond to the U.S., but not necessarily both.

value among deals involving a U.S. public firm is approximately \$0.7 billion. Deals involving public acquirers and non-public targets average around \$236 million in size, while the much smaller proportion of deals involving both public targets and public acquirers have a much larger average deal value of \$1.8 billion.

4 Acquisition Announcements and Factor Premia

In this section, we decompose the average return or premia associated with common asset pricing factors and anomaly portfolios into a component associated with news concerning takeover deals and a residual component.

4.1 Empirical Methods

We measure firm-level daily returns attributable to acquisition announcements using standard event study methods. Aggregate acquisition-related abnormal returns for a particular portfolio are then computed in the same manner as traditional value-weighted (or equal-weighted) portfolio returns, except using the acquisition-related abnormal returns as opposed to total returns.

Let $e = 1, ..., E$ denote a set of deal announcements. We focus on deal announcements because these news events are most likely to generate large valuation effects that can be reliably attributed to merger news.[9] The specific announcements included in our analysis consist of SDC-recorded M&A deal announcements during the period 1990–2020. The total number of included events E therefore equals the 46,905 announcement events involving public targets or acquirers following the additional data screens that we apply (see Panel B of Table 1). Associated with each deal announcement is the SDC-recorded announcement

[9] Other forms of news may influence prices in part due to revised assessments of merger likelihoods. Even the *absence* of news following a deal announcement is informative about the likelihood of deal completion, although market participants appear to under-react to this lack of news (Giglio and Shue (2014)). We elect to focus on deal announcements because price movements around these announcements can most credibly and reliably be attributed to merger news.

date. We denote the trading day coinciding with the announcement date, or the next trading day in those cases for which the recorded announcement date is not a trading day, as $\tau_e = 0$ in event time, measured in trading days.

We designate an event window measured in trading days encompassing each M&A announcement as $[\tau_1, \tau_2]$, with $\tau_1 \leq 0 \leq \tau_2$. For each announcement, we decompose the daily returns of the target and/or acquirer associated with the announcement into normal and abnormal returns for each trading day within the event window:

$$R_{i,\tau_e} = AR_{i,\tau_e} + NR_{i,\tau_e}, \ \tau_e \in [\tau_1, \tau_2] \tag{1}$$

where R_{i,τ_e} denotes the (observed) return for firm i (the acquirer or target) and AR_{i,τ_e} and NR_{i,τ_e} represent the abnormal return and normal return, respectively. We apply the market model for normal returns. Our main conclusions are robust to common variations on this approach (see the Online Appendix). We set the event window to $+/-1$ trading days for acquirers and to $-30/+1$ trading days for targets. The longer window for target firms accommodates the well-known 'run-up effect' for targets (see, e.g., Schwert (1996)) and follows many previous studies that examine cumulative abnormal returns associated with mergers (see, e.g., Eckbo (2009))). We explore the impact of alternative event windows in robustness checks described below.

Table 2 shows summary statistics for cumulative abnormal returns (CARs) associated with the deals in our sample as a comparison point with prior literature. Statistics are computed for all deals involving a U.S. public firm as target or acquirer. The acquirer (target) CAR is computed using a $[-1, +1]$ ($[-30, +1]$) day window around the SDC deal announcement date using market adjusted daily returns. Panel A provides aggregate statistics for CARs. The general features of average CARs documented in Table 2 are similar to patterns established for U.S. acquisitions involving public firms in prior literature. The mean acquirer CAR for all deals involving a public firm is slightly positive and statistically significant (Netter et al. (2011)). Panel B results show that average acquirer CARs involving public targets are negative, whereas acquirer CARs involving non-public targets are positive on average, and the difference is statistically significant (Fuller et al. (2002)). Consistent with many previous studies, average target CARs are positive, significant, and economically large (see e.g., Jensen and Ruback (1983), Jarrell and Poulsen (1989), Betton et al. (2008)). The average target CAR is over 30% for the full sample of public firms. Average CARs are slightly larger when the acquirer is public (see Panel B). The sub-sample breakdown provided in Panel C shows that target CARs have increased over the past 30 years, with the average CAR during the most recent decade exceeding that during the 1990s by about 5 percent.[10]

The next step of our analysis involves creating a panel data set of daily firm-level decomposed stock returns. This involves mapping abnormal returns identified in event time back to calendar time, and ensuring that there is no 'double counting' due to time series clustering of events at the firm level. More specifically, for each firm i that appears as an acquirer or target (or both) in the filtered SDC M&A event set $e = 1, ..., E$, we initialize the daily time series of abnormal returns as zeros. For each event $e = 1, ..., E$, we then map the event window associated with this event into calendar time, and assign the associated daily abnormal returns for the target (when the target is public) and acquirer (when the acquirer is public) based on AR_{i,τ_e}, unless the corresponding abnormal return is already nonzero. The final caveat ensures that we do not inappropriately double (or triple) count certain M&A-driven abnormal returns due to time series clustering of events at the firm level.[11] Whenever a trading day does not fall within the specified event window associated with an M&A deal involving a particular stock, the M&A news component of the return is set to zero and the residual component simply equals the observed daily return for the stock.

[10] Eaton et al. (2021) show that deal premium estimates using traditional fixed windows are biased downward, especially for deals with long processes. Since the deal process length has increased over time, our results concerning the secular increase in average CARs are likely conservative.

[11] As a hypothetical example illustrating the concern, suppose that firm ABC acquires two different firms with the same SDC announcement date. In this case, our process would assign the associated abnormal returns in calendar time for the first announcement e in the dataset, but not for the second, because the associated abnormal return is already nonzero. The event windows we apply are relatively narrow and consequently time series clustering of this sort at the firm level is rare.

Finally, given a particular factor or anomaly portfolio of interest, we first replicate daily returns for the factor or anomaly portfolio. We then compute the daily M&A component for that portfolio by applying the portfolio weights for each stock to the daily M&A return components for the stocks in the portfolio. We further decompose the M&A component of portfolio returns into target and acquirer returns. As a concrete illustration, consider the size factor SMB constructed by Fama and French (1993). We first replicate daily returns for this factor and retain the corresponding portfolio weights for each stock. We then apply these weights to the daily stock-level panel of M&A return components in order to construct the daily M&A component of the SMB factor return, and further decompose this into target and acquirer returns. The residual component of the SMB portfolio equals the difference between the total return and the M&A component.

4.2 Return Decomposition Results

Table 3 reports average value-weighted return components for various size-sorted portfolios and factors. For ease of interpretation, we annualize all average daily return components by multiplying by 250. Column (1) lists the portfolios. Column (2) reports the average total return for the portfolio. Columns (3) and (4) break down the average total value-weighted return into a component attributable to M&A deal news and the residual component. Columns (5) and (6) further break down the acquisition component of average returns into sub-components associated with acquirer and target announcement returns, respectively. Column (2) shows that average value-weighted returns are generally decreasing in size in our sample as expected given the well-documented size effect (e.g., Banz (1981), Fama and French (1992), and Fama and French (1993)). The average return of the hedge portfolio that is long the smallest quintile of firms and short the largest is around 1% per year. Similarly, the average return of the hedge portfolio that is long firms with below median market capitalization and short firms with above median market capitalization equals approximately 1.09%. The relatively small premia associated with these size-based hedge portfolios is consistent with several papers documenting a reduction in the size premium over recent decades (see, e.g., Alquist et al. (2018) and Smith and Timmermann (2021)).

The decomposition of average returns in an M&A component and residual shows that the M&A component is relatively large for small-cap portfolios. For example, the smallest decile and quintile portfolios both have average M&A return components of approximately 1.7% per year. In contrast, the M&A average return component for the largest decile and quintile portfolios are close to zero. This implies that conventional size-based long-short portfolios exhibit a significant, positive M&A-driven average return component. This component ranges from 1.12% for the long-short portfolio based on median size to around 1.65% for the long-short portfolio based on deciles. All of these average M&A return components exceed the average total return component for the long-short portfolios, implying that the average residual component for the portfolios is negative (but statistically insignificant). Columns (5) and (6) show that the portion attributable to targets accounts for the majority of the return difference. However, the acquirer component of the average return for size-based long-short portfolios is positive and statistically significant. This accords with prior evidence of a negative relation between market capitalization and acquirer announcement returns. Although the acquirer average return component is smaller than the target component, it accounts for roughy 20–30% of the average total portfolio return and is therefore economically significant.

The popular "SMB" factors proposed by Fama and French (1993) and Fama and French (2015) are not pure size-sorted portfolios. Instead, they are based on double-sorts involving size and other firm characteristics. For example, the three-factor SMB (also referred to as the $SMB_{(HML)}$ factor) is constructed using six value-weight portfolios formed on size and book-to-market.[12] The five-factor SMB proposed in Fama and French (2015) is equal to the average return on three sets of portfolios constructed based on double sorts involving size and book-to-market, size and investment, and size and profitability, respectively. In the final

[12]The $SMB_{(HML)}$ return equals the average return on the three small portfolios (Small Value, Small Growth, and Small Neutral), minus the average return on the three big portfolios (Big Value, Big Growth, and Big Neutral). The small/big break point is based on median market capitalization, and the value/neutral/growth break points are based on book-to-market terciles.

two rows of Table 3, we replicate these popular SMB factors and report their average value-weighted return components. The average total return for the SMB factors is slightly higher than those for the pure size-based hedge portfolios (around 1.5% per year). Again, the M&A return component for these portfolios is positive, statistically significant, and relatively large. Estimates of the average M&A return component are around 75% of the average total return for these factors and the average residual component is insignificantly different from zero. Together, these results indicate that the M&A component explains most of the measured premium for these popular size factors.

Tables 4 and 5 provide additional insight regarding the sources of the significant average M&A return component for size-based hedge portfolios. Table 4 presents two measures of the intensity of takeover activity for size-sorted portfolios. The first measure, reported on the left-hand side of the table, is defined as the percentage of targets or acquirers that appear in corresponding portfolio. The second measure, reported on the right-hand side of the table, equals the percentage of firms per year in the corresponding portfolio that become targets or acquirers. Acquirer results are shown for all deals and for the subset of deals involving public targets. Not surprisingly, target firms tend to be members of small capitalization portfolios. Nearly 50% of takeovers of public firms occur for firms in the smallest size decile portfolio, and nearly two-thirds of takeovers involve targets in the smallest size quintile portfolio. Similarly, the realized takeover rate is considerably larger for small capitalization portfolios relative to large capitalization portfolios. For example, the average annual takeover rate for the small cap quintile is around 4.5% whereas the corresponding rate for the large cap quintile is around 1.9%. This implies an 'odds ratio' of approximately 2.4, i.e., small cap quintile firms around 2.4 times more likely to be acquired than large quintile firms. Consequently, targets are over-represented in the long leg of size-based hedge portfolios. In contrast, results on the right-hand side of Table 4 show that small cap firms are relatively less likely to act as acquirers. The odds ratio of acquiring a firm for the small cap quintile relative to the large cap quintile is around one-third, and the odds ratio of acquiring a public firm is approximately one-tenth.[13]

In Table 5, we compare average CARs for targets and acquirers associated with different size-based portfolios. Average target CARs are larger for small targets relative to big targets. For example, the average CAR for targets in the smallest size quintile is around 35%, whereas the average CAR for targets in the largest size quintile is around 19%. The difference is highly significant. Average acquirer CARs are also significantly higher for small cap firms. The difference in average acquirer CARs between firms in the smallest versus largest capitalization portfolio is around 2.3% (3.0%) for portfolios based on size quintiles (deciles). This explains the source of the positive acquirer average return component in size-based hedge portfolios: despite the fact that large firms are relatively more likely to acquire, the corresponding average CARs are close to zero, whereas the small-firm average acquirer CAR is significantly positive. Collectively, Tables 4 and 5 illustrate that the economically significant average M&A return component we observe for size-based hedge portfolios is driven both by differences in the intensity of takeover activity and by differences in the magnitude of CARs associated with deal announcements.

4.3 Merger News and the Size Premium Prior to 1990

Our decomposition of the average return associated with size-based hedge portfolios is based on a narrow window event study approach. The validity of the approach is predicated on the observation of essentially all deals involving U.S. public firms and the ability to obtain accurate deal announcements dates that form the basis for our event windows. SDC data begin around 1980 and omit a significant fraction of deals prior to 1990 (Netter et al. (2011)). Other potential sources of information regarding M&A activity in earlier periods, such as delisting activity and delisting codes from CRSP, do not contain accurate deal announcement dates. These factors limit our ability to perform a precise average return decomposition over

[13] It may seem puzzling that the percentage of acquirers on the left-hand side of Table 4 is highest for small cap portfolios. This occurs because the standard size-sorting cutoffs are based on NYSE firms, implying that small cap portfolios consist of considerably more firms relative to large cap portfolios.

a very long history. The estimated size premium over the 1990–2020 period is smaller than estimates over longer historical samples. This raises the question of whether M&A activity still explains a significant share of the (larger) size premium in earlier data. Here we provide evidence that it does.

We first show that key forces contributing to the significant relation between deal activity and the size premium continue to operate in earlier decades. One necessary condition is relatively robust deal activity. (If there are few mergers, then merger announcement news is unlikely to explain the size premium.) Figure 1 plots two alternative measures of deal activity over a long history. The first is the annual proportion of firms reported by CRSP as delisting due to a merger or acquisition in the corresponding year. The second is the percentage of market capitalization that is acquired in each year based on CRSP delisting information, using market capitalization data from the previous December. Figure 1 shows evidence of aggregate merger waves as documented in previous studies. We highlight the fact that merger activity was robust during the decades preceding 1990. This period includes both the "conglomerate merger wave" of the late 1960s and the "refocusing merger wave" of the 1980s (Betton et al. (2008)).

Second, there must be a significant imbalance in the nature of takeover activity between the long and short legs of size-based hedge portfolios in order for M&A news to explain a significant share of the size premium. Table 6 shows pooled estimates of the odds ratio of acquisition for small cap firms versus large cap firms by decade for the 1960s through the 2010s. We pool firms in the small cap and large cap legs of benchmark size-based hedge portfolios and create an indicator for inclusion in the small cap portfolio. The reported odds ratio estimates and confidence intervals are based on a logistic regression of a firm-year acquisition indicator defined using CRSP delisting data on the small cap dummy. The odds ratios of becoming a target in a given year during the 1960s and 1970s are approximately 5.2 and 6.1, respectively, for size quintiles, and 6.0 and 9.4 for size deciles. The 1960s and 1970s odds ratios are considerably larger than the corresponding odds ratios over the most recent two decades. Odds ratios are lower during the 1980s and 1990s. However, the pooled odds ratio of acquisition for small cap firms relative to large cap firms is similar for the 1960s–1980s relative to the 1990-2020 SDC-based event study.

A third feature that contributes to the significant M&A component of the size premium is the negative relation between firm size and average CARs for targets and acquirers. Earlier studies of M&A gains to targets and bidders contain a wealth of evidence concerning the magnitude of average abnormal returns in samples prior to the 1990s. Jensen and Ruback (1983) summarize evidence from a set of event studies of deal announcements using data primarily from the 1960s and 1970s. They report average target returns of around 20% for mergers and 30% for tender offers. These estimates are relatively close to the average CARs reported in Table 2 for our SDC sample over the 1990–2020 period. In addition, early studies also find that average target and bidder CARs for small firms exceed those for large firms (Jarrell and Poulsen (1989)).[14]

As a final, direct check of the robustness of our conclusions over a longer historical period, we extend our event study-based decomposition of returns to a complete sample of SDC data from 1980–2020, despite the fact that deal data in the 1980s are likely to be incomplete. We obtain qualitatively similar results for this extended sample. Most importantly, we continue to find that the M&A component accounts for virtually the entire size premium over the extended sample period. Explicit results appear in the Online Appendix. Moreover, the Online Appendix shows that we obtain an economically and statistically significant M&A return component even for a sample limited to the 1980s and 1990s, which is the period with the *weakest* size imbalance in takeover activity (See Table 6). This strongly suggests that takeover activity also accounts for a significant proportion of the measured size premium during the 1960s and 1970s.

[14] Jarrell and Poulsen (1989) condition on the size of the target relative to the bidder and find a negative (positive) relation between relative size and target (acquirer) CARs using a sample of deals from the 1960s to the 1980s.

4.4 Additional Robustness Checks

We conduct a variety of robustness checks with respect to return decomposition results for size-based portfolios. First, we consider a range of alternative event windows for acquirers and targets and report selected results in the Online Appendix. Qualitatively similar results obtain for reasonable variations in the event windows. Effects tend to be economically smaller when the target event window is shorter, e.g., $[-10, +1]$ days rather than $[-30, +1]$ days, but we obtain similar results using even a $[-1, +1]$ window for targets. This indicates that the portfolio effects we document are primarily driven by large, 'granular,' announcement day returns as opposed to more gradual pre-announcement price run-up.[15] A second set of robustness checks considers alternative models for the 'normal return' component of event window returns. We consider the constant expected return model as well as a conventional single factor model and the Fama-French three factor model (Fama and French (1993)). All variations produce similar results.

We also conduct several variations of placebo tests. One such test retains the acquisition announcement dates but scrambles the firms involved in the deal by drawing a 'pseudo-target' and 'pseudo-acquirer' randomly from among firms with similar market capitalization. A second variation retains the actual target and acquirer firms, but scrambles the announcement date randomly. These placebo tests produce economically small and (typically) statistically insignificant estimates of M&A average return components for size-based hedge portfolios. Additional details and explicit results appear in the Online Appendix.

A final robustness analysis concerns M&A contests that result *without* a completed deal, including withdrawn deals. A potential concern is that negative target returns associated with withdrawn or incomplete deals might offset the effects of positive returns for completed deals in our analysis. However, it is notable that our main analysis excludes incomplete takeover contests entirely. For deals that are ultimately withdrawn, this implies that we

[15] In yet another robustness check, we consider a long target window of $[-90, +1]$, motivated by results in Eaton et al. (2021). This produces results that are similar to our main results using the $[-30, +1]$ window.

exclude positive target deal announcement returns (on average) for such deals, as well as potentially negative target returns associated with ultimate deal failure. As a robustness check, the Online Appendix analyzes the M&A component of size portfolio returns for withdrawn deals as well as a pooled sample of completed and withdrawn deals, where we include an additional $[-30, +30]$ window around the SDC-reported withdrawal date for withdrawn deals. We find insignificant effects for the sample of withdrawn deals and results very similar to our main results for the pooled sample of completed and withdrawn deals.

4.5 M&A Activity and Other Factors

This section briefly considers the question of whether M&A activity impacts measured expected returns for other prominent factors and anomaly long-short portfolios. Many of these hedge portfolios lack the particular characteristics exhibited by size-based hedge portfolios that drive significant M&A return components. As a concrete example, acquisition activity is relatively balanced across the long and short legs of standard hedge portfolios based on the book-to-market characteristic. Moreover, the market capitalization of the median firm in each of such portfolios is relatively similar. The circumstances imply that the M&A component of average returns is small for the value factor and related long-short portfolios based on book-to-market ratios. (See the Online Appendix for explicit results.)

The Online Appendix contains additional decomposition results for approximately 50 anomaly characteristics. Although many anomaly long-short portfolios do not exhibit a significant M&A average return component, there are some exceptions. For example, we find that an economically significant M&A return component exists for portfolios formed based on the gross profitability characteristic (Novy-Marx (2013)). In contrast to size, the average M&A component for long-short portfolios based on gross profitability is *negative* rather than positive. This occurs because less profitable firms that appear in the short leg of the gross profitability hedge portfolios tend to be smaller and more likely to become targets. Other anomalies that exhibit a significant M&A expected return component include idiosyncratic volatility, net issuance, price, and several multi-characteristic strategies that involve profitability (e.g., value-profitability). There is a significant difference in the market capitalization of firms in the long versus the short leg for each of these characteristics.

5 Takeover Exposure and Expected Returns

This section shifts from an ex post to an ex ante perspective. We test whether a characteristic reflecting differences in takeover exposure robustly relates to cross-sectional differences in expected returns, and we evaluate the performance of factor models that include a factor constructed from this takeover characteristic.

Fama and French (2018) note that "in the absence of discipline from theory, factor models degenerate into long lists of factors that come close to spanning the ex post mean-variance efficient tangency portfolio of a particular period." From a theoretical perspective, Cremers et al. (2009) consider two potential motivations for acquisitions, one involving agency problems, which are exacerbated when free cash flow is higher, the other driven by synergy values, which are higher when the (time-varying) price of risk is low. Under the agency motivation, acquisition premia are increasing in fundamental (cash flow) shocks reflected in the SDF and firms with greater takeover exposure have higher expected returns. The synergy motivation also generates a non-zero covariance between takeover premia and the SDF; however, the expected return effect is ambiguous due to potential intertemporal hedging demands.[16]

5.1 Estimated Takeover Likelihood

We first construct a firm-level characteristic measuring exposure to takeover activity. This characteristic equals the estimated likelihood that a firm will be acquired within the next year. Following previous literature (e.g., Palepu (1986) and numerous subsequent papers), firm-level estimates of takeover likelihood are based on a logistic regression model. The

[16]Empirically, Cremers et al. (2009) find that greater takeover exposure leads to higher average returns.

dependent variable is a target indicator variable that takes the value of one if a firm is a target in that year. We estimate several versions of the model with alternative sets of explanatory variables. Table 7 presents estimation results. Column (1) shows results for a model that includes *only* size (log market capitalization) as a predictor in addition to year-fixed effects that are included in all models. The slope coefficient on size is negative and significant; however, the model has limited predictive ability as measured by the max rescaled R^2-statistic (around 1.70%). Thus, although small firms are more likely to be acquired, there is not an overly strong relation between size and takeover probability.

Column (2) provides results for a benchmark set of explanatory variables based on a similar model estimated by Cremers et al. (2009). These variables include the return on assets of the firm (ROA), firm leverage (book debt to asset ratio), cash (the cash and short-term investments to assets ratio), firm size (the natural logarithm of market capitalization), Q (the market-to-book ratio for the firm), and asset structure (PPE, measured by the property, plant, and equipment to assets ratio). The model also includes two dummy variables. The first, denoted BLOCK, equals one when an external blockholder exists and zero otherwise.[17] The second dummy variable, denoted 'Industry (CNJ),' takes the value one if at least one acquisition occurred within the industry during the prior year. Industry identification is based on the Fama-French 48 industries (Fama and French (1997)). All Compustat variables are industry-adjusted and continuous variables are winsorized at the 1% and 99% levels. Higher market capitalization and Q are associated with lower takeover likelihood, whereas blockholder presence, prior industry acquisition activity, and leverage are associated with higher takeover likelihood, all else equal.

Columns (3) and (4) consider additional explanatory variables that other studies relate to takeover likelihood (e.g., Palepu (1986), Edmans et al. (2012), and Bhagwat et al. (2016)). Column (3) includes an additional firm dummy variable, denoted Dividend, that takes the value of one if the firm issues a dividend and zero otherwise. Column (3) also considers an

[17] The presence of block ownership is measured using institutional shareholdings data from Thomson/CDA and a 5% ownership take threshold.

alternative industry activity variable, denoted Industry (BDA), that takes the value of one if the industry experienced above median acquisition activity over the preceding two years and zero otherwise. Dividend payers are less likely to be takeover targets and above median industry acquisition activity is associated with higher takeover likelihood. Column (4) includes a measure of momentum in the form of the cumulative return over the preceding year, and a measure of the idiosyncratic volatility of returns, defined as the realized volatility of daily returns over the previous year.[18] Both variables are highly significant and negatively related to takeover likelihood, similar to results in, e.g., Palepu (1986) and Bhagwat et al. (2016). Column (5) swaps out gross profitability for ROA. The additional conditioning variables included in the models of columns (3)–(5) improve model fit significantly. Finally, column (6) removes banks from the sample based on SIC code due to their unusual financial statements. The magnitude of coefficients associated with several characteristics increases, including those for the block shareholder indicator, the leverage measure, and the dividend indicator. Moving forward, we reference the alternative takeover models via the corresponding column number, e.g., 'Model 4' references the model corresponding to column (4) of Table 7.

Sorting on estimated takeover likelihood produces economically meaningful differences in realized takeover activity. For example, realized takeovers involve targets in the high (estimated) takeover probability quintile around 25-35% of the time, and targets in the low (estimated) takeover probability quintile around 15% of the time. We compute time-series averages of of cross-sectional correlations between three versions of the takeover likelihood characteristic and each of the component characteristics in the underlying models. These pairwise correlations (not separately reported) are moderate in magnitude, falling approx-

[18]We follow Bhagwat et al. (2016) in constructing both variables. We measure cumulative 12-month returns as of the end of the prior calendar year. Idiosyncratic volatility is measured as the 12-month realized volatility of daily returns as of the end of month $t-2$ in the prior year. This construction avoids a mechanical connection between firm return volatility and rumors of an acquisition announcement. Edmans et al. (2012) provides further evidence of a causal impact of financial prices on takeover activity using mutual fund redemptions as an instrument for price changes. Bhagwat et al. (2016) find that a firm is less likely to be acquired if its prior stock volatility is high and link this aversion to deal-level interim uncertainty.

imately in the [-0.5,0.5] interval. This confirms that estimated takeover likelihood is *not* dominated by a single component characteristic (it is not "just size" or "just profitability") and is instead a distinct attribute of firms.

5.2 Takeover Likelihood and Expected Returns

We next analyze the relation between cross-sectional stock returns and the model-implied likelihood of a takeover within the next year. Benchmark results define the takeover likelihood characteristic using Model 4 in Table 7. Results are generally robust to using any of the models in columns (2)–(6) in Table 7. (See additional results in the Online Appendix.) We compute three versions of the takeover characteristic as follows:

1. "Main SDC sample:" This version of the takeover characteristic is computed using the variables and coefficient estimates from Model 4 of Table 7. The sample period is 1990–2020.

2. "Extended sample:" This version of the takeover characteristic covers an extended time series period (1963–2020) by applying estimates from the SDC coverage period (1990–2020) to earlier characteristics data. With two exceptions, all of the firm variables included in the takeover model can be computed from 1963–2020. The first exception is the industry activity variable: we cannot accurately measure industry activity prior to 1990 using our SDC data. From 1981–1989, the extended takeover factor is constructed using all dependent variables in Model 4 of Table 7 except $Industry$. The second problematic variable is the block shareholder measure (BLOCK). Because Thomson Reuters data begins in 1980, we cannot measure a firm's institutional share holdings prior to 1980. Prior to 1980, the takeover factor is constructed using all dependent variables in Model 4 of Table 7 except $BLOCK$ and $Industry$. These iterations of Model 4 are estimated using the 1990–2020 sample. Estimated coefficients for the remaining dependent variables are nearly identical to those reported in Table 7.

3. "Real-time rolling window:" Although firm characteristics that serve as inputs to the previous versions of the takeover characteristic are available to investors in real time, model coefficients are estimated using the 1990–2020 sample. Consequently, we consider an alternative 'real-time' version of the takeover likelihood characteristic that uses only data that would be available to an investor in real time. Real-time takeover model coefficients are based on estimates of Model 4 in Table 7 using a rolling 10-year window procedure. This version of the takeover characteristic covers the years 2000–2020.

Table 8 shows results from standard Fama and MacBeth (1973) cross-sectional regressions. The dependent variable in these regressions equals the one-year-ahead excess return for the corresponding stock. The independent variables include a constant and set of explanatory firm variables that vary across specifications. All Compustat-based variables are measured as of the end of the prior calendar year. Market return data is measured as of the end of June, and is used to explain the annual return from July through June of the following year. The table reports the time series average of annual coefficient estimates with Newey-West corrected t-statistics in parentheses. Panel A shows results for the main SDC sample. Panels B and C show results for the extended sample and the sample covered by the real-time version of the takeover likelihood characteristic, respectively.

Columns (1) and (2) of Table 8 show results of univariate Fama-Macbeth regressions based on the takeover likelihood characteristic and size, respectively. The estimated coefficient in column (1) associated with the takeover likelihood characteristic is positive and significant, indicating a positive cross-sectional relation between takeover likelihood and expected returns.[19] The estimate in column (2) indicates that firm size negatively relates to cross-sectional returns, consistent with many earlier studies. The model reported in column (3) conditions on the takeover characteristic, firm size, and other prominent characteris-

[19] As a robustness check, we also analyze portfolios sorted by the takeover likelihood characteristic. We compute raw returns and alphas for portfolios sorted into quintiles based on estimates of takeover likelihood, and find that average portfolio returns and alphas increase from Quintile 1 (lowest predicted takeover likelihood) firms to Quintile 5. In addition, we estimate alphas for sorted portfolios with respect to the Fama and French (2015) five-factor model. These alphas are monotonically increasing from Quintile 1 firms to Quintile 5. Further details and explicit results appear in the Online Appendix.

tics associated with the cross-section of returns. These include book-to-market, investment growth, idiosyncratic volatility, turnover, and past returns features including measures of momentum, and short- and long-run reversal. The coefficient estimate associated with takeover likelihood remains positive and significant with roughly similar magnitude in this richer model. In contrast, the coefficient estimate associated with firm size switches from a negative to positive sign, implying that, conditional on takeover probability and other prominent characteristics, larger firms earn *higher* average returns.

Similar results obtain for the extended sample period covered in Panel B of Table 8. The slope coefficient on firm size in column (5) is positive, similar to the column (3) results, but is economically small and statistically insignificant. These results provide additional indirect evidence that merger activity remains an important driver of the size effect during the period from the early 1960s through the 1980s, when the measured size premium is larger. Panel C shows that using the real-time version of the takeover characteristic produces qualitatively similar results to those in Panel A. The size of the slope coefficient on the takeover characteristic falls somewhat, but remains highly significant. The coefficient on firm size becomes positive and significant in column (7), similar to results in column (3). To summarize, we find a robust, positive relation between the takeover likelihood characteristic and expected returns in the cross-section of stocks, and the relation between firm size and expected returns becomes, if anything, positive after conditioning on takeover likelihood and other prominent characteristics.

5.3 A Takeover Factor Versus the Size Factor

Following Cremers et al. (2009), we construct a "takeover factor" as a long-short portfolio based on extreme takeover likelihood quintiles or deciles. In light of our earlier decomposition results for the size premium, our asset pricing analysis focuses on contrasting the takeover factor with the traditional size factor. Portfolios defining the takeover factor are rebalanced at the end of June in each year using market return data measured at the end of June and

Compustat data from the prior fiscal year end. We use the shorthand 'TMA' (target minus acquirer) to denote the factor.[20] Results in the main paper focus on factors constructed using the takeover likelihood characteristic based on Model 4 in Table 7 and we obtain qualitatively similar results using alternative models of takeover likelihood.[21] The TMA factor is based on the main SDC sample and is available from 1990–2020 (monthly). We also consider an alternative extended-sample version of the factor that covers 1963–2020 (TMA^{ES}) that is constructed using the corresponding extended sample takeover characteristic described in Section 5.2. Finally, we construct a strictly real-time version of the factor (TMA^{RT}) using the real-time, rolling window version of the takeover likelihood characteristic. The latter factor is available over the period 2000–2020.

Figure 2 compares the TMA factor over the extended sample period with the SMB factor. Panel A contrasts rolling 12-month returns for the two factors. NBER recession periods are shaded grey. TMA factor returns tend to be pro-cyclical. There is clear positive co-movement between the rolling annual TMA and SMB factor returns. This co-movement appears to be stronger prior to the 1990s, and weaker, although still positive, thereafter. Indeed, the sample correlation between rolling annual TMA and SMB returns is around 0.65 (0.35) before (after) 1990. Returns for both factors are pro-cyclical, tending to be higher during economic expansions and lower just before or during recession periods including the financial crisis. Although the SMB factor tends to perform poorly just before or during recession periods similar to TMA, it also performs poorly for extended periods during relatively healthy economic times, such as the late 1990s and following the financial crisis.

Panel B compares the performance of the two factors over a longer, rolling 5-year window. The solid blue line depicts the five year rolling average of the monthly excess return for the

[20]In additional robustness checks, we form alternative TMA factors following a procedure similar to Fama and French (1993) in which we first sort firms into terciles according to book-to-market and then form within-tercile quartiles or deciles based on estimated takeover probabilities and then subsequently define the factor as the equal-weighted return on long-short takeover portfolios within each book-to-market tercile. These factors produce qualitatively similar results in our main asset pricing tests.

[21]Results are *not* robust to using Model 1 in Table 7, but that is because this simple benchmark model conditions only on size, and therefore the resulting factor is simply a size factor.

SMB. The dashed (dotted) red (green) line shows the five-year rolling average return for the extended TMA factor constructed using extreme decile (quintile) portfolios based on estimated takeover likelihood using Model 4. The rolling average TMA factor return is positive for most of the sample period and consistently exceeds that of the SMB factor. The financial crisis is the only period for which average SMB factor returns exceed TMA factor returns. The average return dynamics of the TMA and SMB factors are relatively similar. Returns for both factors fall during the late 1990s, increase following the dot-com bust, and then fall again during the financial crisis. However, the TMA factor earns a substantially higher average return than SMB, especially since 1990. The figure also includes two measures of the intensity of takeover activity. The first (dashed purple line) equals the 5-year rolling average of the number of completed M&A events.[22] The second measure (solid orange line) equals the 5-year rolling average of the number of firms that delisted due to M&A (based on CRSP delisting codes), divided by the total number of firms in CRSP in that month. Time-variation in the TMA premium, as well as differences in the differential premium between TMA and SMB, appears to relate to the intensity of acquisition activity. For example, the TMA factor return significantly exceeds that of the SMB factor during the relatively heavy merger activity of the late 1990s and early 2000s.

We compute correlations between monthly takeover factor returns and returns for a range of prominent return-based factors in the literature, including the factors of the Fama-French five factor model (Fama and French (2016)), the momentum factor (UMD), the 'betting against beta' (BAB) factor of Frazzini and Pedersen (2014), the 'quality minus junk' (QMJ) factor of Asness et al. (2019), and the MGMT and PERF mispricing factors of Stambaugh and Yuan (2017). Various versions of the TMA factor correlate positively with SMB returns and the corresponding sample correlations are in the 0.11–0.65 range, depending on the particular sample period and version of TMA. Acquisitions offer an alternative channel for firm asset growth relative to capital expenditures and our takeover models indicate that high

[22] This is similar to Giovanni (2005), who uses the number of M&A deals each year as a measure of M&A activity. This measure is available for the SDC data period.

investment firms are less likely to be targets. However, we observe only weak correlations between various TMA factor versions and the CMA factor, suggesting that the factors are quite distinct. Pairwise correlations with other prominent factors are generally small in magnitude (see Online Appendix).

To analyze the asset pricing performance of the takeover factor relative to the size factor, we follow Barillas and Shanken (2017), who show that, in assessing the relative performance of tradeable factor models, what matters is the extent to which each model is able to price the factors in the other model. The first set of tests conduct 'excluded factor' regressions where takeover factor returns are regressed on factors from comparison models that exclude the takeover factor:

$$R_{TMA,t} = \alpha_{TMA} + \beta'_{TMA} R_{BF,t} + \epsilon_t, \tag{2}$$

where R_{TMA} denotes the return on the takeover factor, R_{BF} denotes a $K \times 1$ vector of returns on the factors for the specified benchmark factor model, and α_{TMA} and β_{TMA} denote the alpha and vector of betas for the excluded takeover factor. The null hypothesis is $\alpha_{TMA} = 0$, i.e., a zero alpha in a regression of omitted TMA factor on the specified factors. Under this null hypothesis, the positive average excess return associated with the TMA factor is fully explained by exposure to the benchmark model factors.

Table 9 reports results. Rows correspond to alternative factor models described in the row labels. The first column reports the estimated alpha and corresponding t-statistic of the spanning regression. Two additional statistics shed light on the economic importance of results. The statistic $Sh^2(f)$ shows the squared maximum Sharpe ratio obtainable from the benchmark (right-hand-side) factors. The statistic $\alpha^2/s^2(\epsilon)$ is the squared ratio of the estimated alpha to the estimated standard deviation of the regression residuals. This statistic conveys the increase in squared Sharpe ratio that results from augmenting the benchmark factors with the TMA factor. The benchmark models include popular characteristics-based factor models, such as the Fama-French five factor model, and additional factor models distilled from a large set of anomaly variables, including the 'factors that fit' proposed by

Lettau and Pelger (2020) and a factor set based on Kozak et al. (2020).

The estimated alphas associated with TMA factor returns are positive, statistically significant, and economically significant in magnitude for all of the excluded factor regressions in Table 9. The positive α estimates associated with the excluded (left-hand side) TMA returns are reasonably stable as we consider richer factor models. For example, the estimated monthly α for the TMA factor based on the main SDC sample with respect to the CAPM equals around 0.8%, the α estimate with respect to the Fama-French 5 factor model is around 0.78% per month, and the α with respect to the 'factors that fit' proposed by Lettau and Pelger (2020) is around 0.68%. The (unreported) adjusted R^2-values from the spanning regressions in Table 9 show that a significant portion of the time series variation in the takeover factor is unexplained by the various benchmark factor models. Finally, the $Sh^2(f)$ and $\alpha^2/s^2(\epsilon)$ statistics show that adding TMA to the benchmark factors delivers economically significant improvements in the sense of substantially increasing the maximum Sharpe ratio associated with the factors. As a concrete example, consider the final row of results in Panel A corresponding to the KNS factor model as the benchmark. The $Sh^2(f)$ statistic for this model equates to an annualized maximum Sharpe ratio of around 1.07. The $\alpha^2/s^2(\epsilon)$ statistic of around 0.09 implies that the annualized maximum obtainable Sharpe ratio increases to just under 1.5 upon adding TMA to the set of available factors. Overall, the results strongly favor models that include the takeover factor relative to analogs that omit this factor.

Next, we explore whether there remains support for the inclusion of a size factor once the takeover factor is included. To address this question, we run another set of excluded factor regressions, in which we regress monthly returns for the *SMB factor* on factor returns for various benchmark models. Table 10 presents results for 1963–2020 and for a partition of this longer period. Each pair of rows in the table contrasts a benchmark model without and with the takeover factor included. The main takeaway is that including the TMA factor significantly decreases the alpha associated with the SMB factor and often flips the sign of the estimated alpha from positive to negative. Consider, for example, the results in rows 3 and 4 of the table. Row 3 includes the market factor and the QMJ factor proposed by Asness et al. (2019). Consistent with results in Asness et al. (2019), controlling for the 'quality' factor produces a positive and significant alpha for the SMB factor. Row 4 adds the TMA factor. This addition causes the SMB alpha estimate to become negative and insignificant. This general pattern plays out across a wide variety of benchmark models.

The $Sh^2(f)$ statistics for the benchmark models that include TMA (even rows) are substantially larger than the analogs that exclude TMA (odd rows). The $\alpha^2/s^2(\epsilon)$ statistics convey the economic significance of adding SMB to the corresponding model. These statistics become very small in most cases whenever the takeover factor is added to the model. The subsample results show that, for models that exclude TMA, SMB alphas and estimates of the economic value associated with including SMB are larger in the 1960s–1980s. Even during this period, however, adding TMA to the model reduces SMB alphas and often results in economically small $\alpha^2/s^2(\epsilon)$ statistics. Collectively, the results indicate that versions of popular models modified to include TMA can either price the SMB factor portfolio, or benefit relatively little from the addition of this factor.

5.4 Additional Robustness Checks and Extensions

The takeover model includes a variety of firm characteristics associated with cross-sectional return patterns (e.g., firm size, book-to-market, and ROA). The logistic regression model applies a nonlinear transformation to these characteristics. To determine whether the nonlinear transformation is essential to the asset pricing success of the TMA factor, we apply an alternative linear probability model (LPM) using the same firm variables included in Model 4 of Table 7. We obtain qualitatively similar asset pricing results using this version of the takeover characteristic and the corresponding factor. The nonlinear logistic transformation is therefore not an essential feature. Additional tests reported in the Online Appendix show that the relation between the takeover characteristic and cross-sectional expected returns is not driven by any *single* characteristic included in the takeover model. Consequently, the TMA factor can be viewed as a factor constructed from a relatively high dimensional set of characteristics (the inputs to the takeover model) with weights determined via a particular *economic* criterion (the ability to capture takeover exposure). This approach contrasts with popular approaches that derive factors from a large set of characteristics using statistical criteria, such as principal components analysis. The fact that the TMA factor is not priced even by sophisticated models extracted from large sets of anomaly portfolios using statistical criteria highlights the surprisingly high-dimensional nature of the space of stock return anomalies (e.g., Jensen et al. (2021)). It is possible that other useful factors could be derived via alternative economic criteria in the spirit of our approach.

The asset pricing comparisons in our main results focus on factor-spanning regressions in the spirit of Barillas and Shanken (2017). As a robustness check, we consider an alternative approach that evaluates the magnitude of pricing errors for a specified set of 'left-hand-side' test assets. We focus on relatively broad sets of test assets defined as portfolios associated with anomaly characteristics and/or industry portfolios. In general, models that include TMA as opposed to SMB produce smaller pricing errors for most sets of test assets examined (see the Online Appendix). The asset pricing results reported in Tables 8–10 focus on a specific model (Model 4) for takeover activity from Table 7. However, we obtain similar results by relying on any of Models 2–6 in Table 7.

Novy-Marx and Velikov (2015) argue that transaction costs reduce the profitability of trading strategies based on many anomalies. Our TMA factor is re-balanced annually. We confirm that this implies low turnover relative to many anomalies (Novy-Marx and Velikov (2015)). Therefore, transactions costs are unlikely to 'explain' TMA factor alphas. Finally, it is important to address concerns related to data-mining (Harvey et al. (2016), Giglio et al. (2021), Harvey and Liu (2021)). From this perspective, we emphasize that the takeover factor is *not*, in fact, a newly proposed factor. Moreover, there is relatively little overlap between our sample and the sample period examined by Cremers et al. (2009), who originally propose and study such a factor. Thus, our analysis effectively represents a new *out-of-sample* test regarding the performance of a takeover factor.

6 Conclusion

We decompose the average returns associated with size-based hedge portfolios and other common anomaly portfolios into an 'M&A' and a residual component. M&A announcement returns account for virtually the entire size premium. This occurs because of a substantial imbalance of exposure to merger activity between the long and short legs of size-based portfolios. Targets predominantly appear within the long leg of the hedge portfolio. In addition, target and acquirer CARs are larger for small cap firms relative to large cap firms.

We construct a firm-level characteristic based on the estimated likelihood that a firm will become a takeover target in the next year. This characteristic relates positively and robustly to cross-sectional returns. We then form a takeover factor that is long stocks with a high takeover likelihood and short stocks with a low takeover likelihood. Asset pricing tests indicate that the inclusion of the takeover factor materially improves various benchmark models' ability to explain return premia. In contrast, the traditional size factor adds little explanatory power to factor models that include the takeover factor. These results suggest that standard factor models should replace the traditional size factor with a takeover factor.

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Figure 1: **Merger and Acquisition Activity**

This figure reports annual measures of merger and acquisition activity. The first activity measure (solid blue line, 'M&A / Total Firms') is defined as the number of firms that delisted due to a merger or acquisition in a given year, divided by the total number of firms in CRSP in that year. The second activity measure (dashed red line, 'M&A / Mkt Cap') is defined as the total market capitalization of firms that delisted due to a merger or acquisition in a given year, divided by the total market capitalization in that year, using market capitalization data from the end of the previous December.

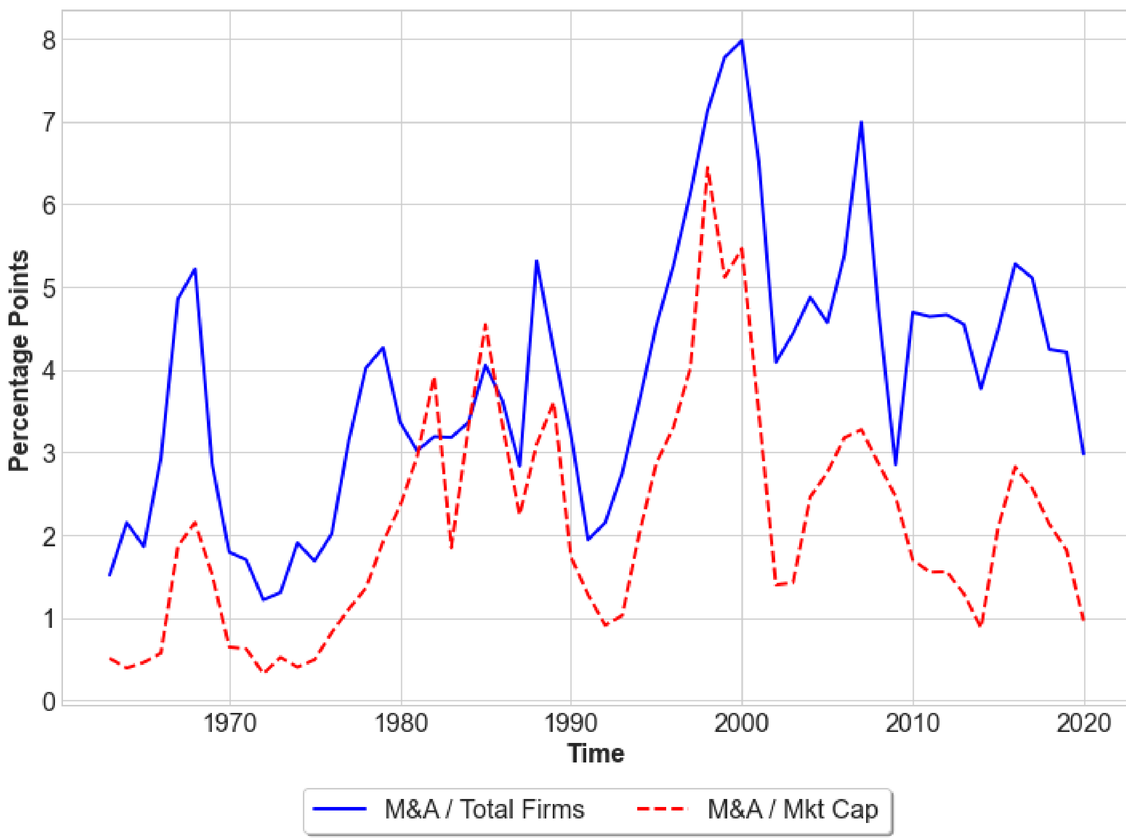

Figure 2: **Time-Series Variation in TMA Factor Returns**

These figures report rolling averages of various TMA factor returns, as well as the rolling averages of the SMB factor return and of merger and acquisition activity. Panel A uses a one-year window to calculate the averages. Panel B uses a five-year window to calculate the averages. All rolling averages are backward-looking, so that the reported value in Panel B on December, 1995, is the monthly average from January, 1991, through December, 1995. Two measures of M&A activity are included in Panel B. 'M&A activity: SDC Data (#)' is defined as the number of M&A events announced each month. Deals that are never completed are excluded. 'M&A activity: CRSP Delisting Codes (%)' is defined as the number of firms that delisted due to a merger or acquisition in a given month, divided by the total number of firms in CRSP in that month. In both Panels, takeover likelihood is calculated using a backward-extended version of Model 4 that includes data from 1963–2020. TMA^{Quint} is calculated using the highest and lowest quintiles of takeover probability to define 'high' and 'low'. TMA^{Decile} is calculated using the highest and lowest deciles of takeover probability to define 'high' and 'low'. The TMA and SMB factors are indexed to the left axis in both panels, and rolling average factor returns are expressed in percentage points. Shaded areas in Panel A highlight the NBER recession periods. M&A activity measures in Panel B are indexed to the right axes. Vertical lines in both figures identify the beginning of the BLOCK data (1980) and the SDC data (1990) used to estimate takeover likelihood.

Panel A: One-Year Rolling Average

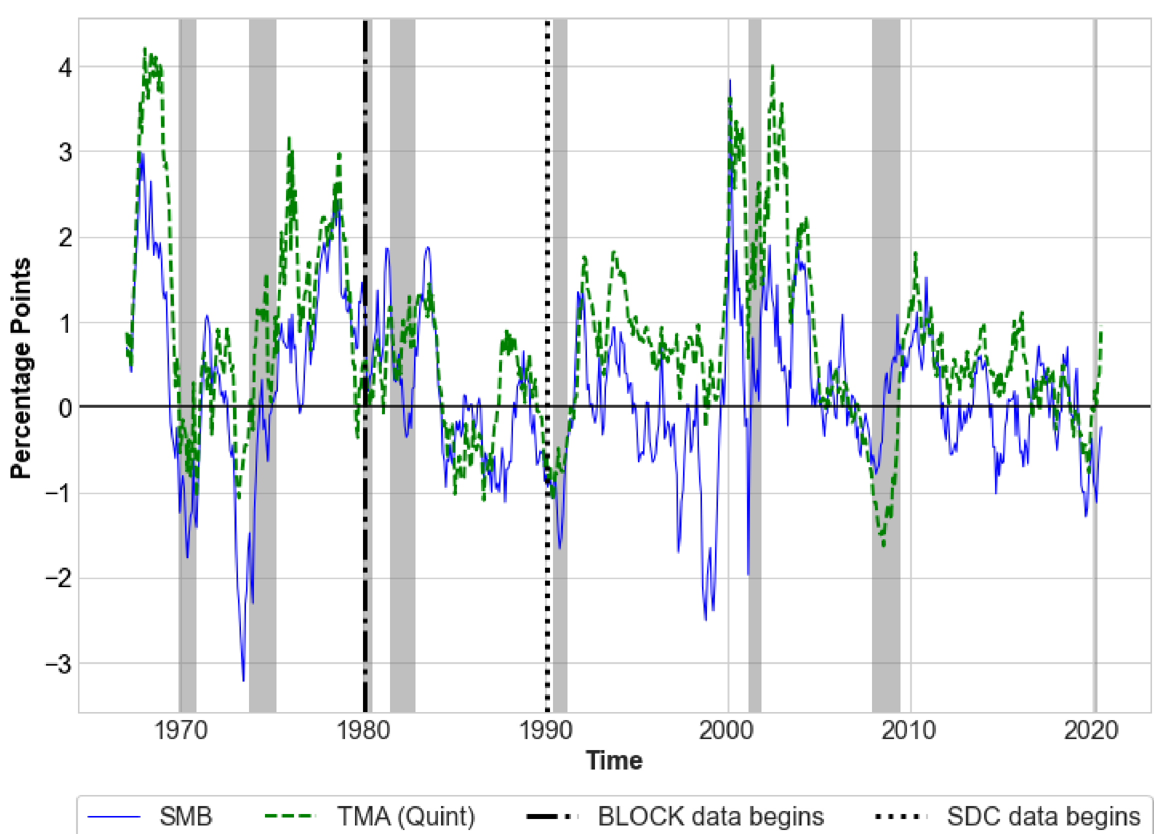

Figure 2 cont.

Panel B: Five-Year Rolling Average

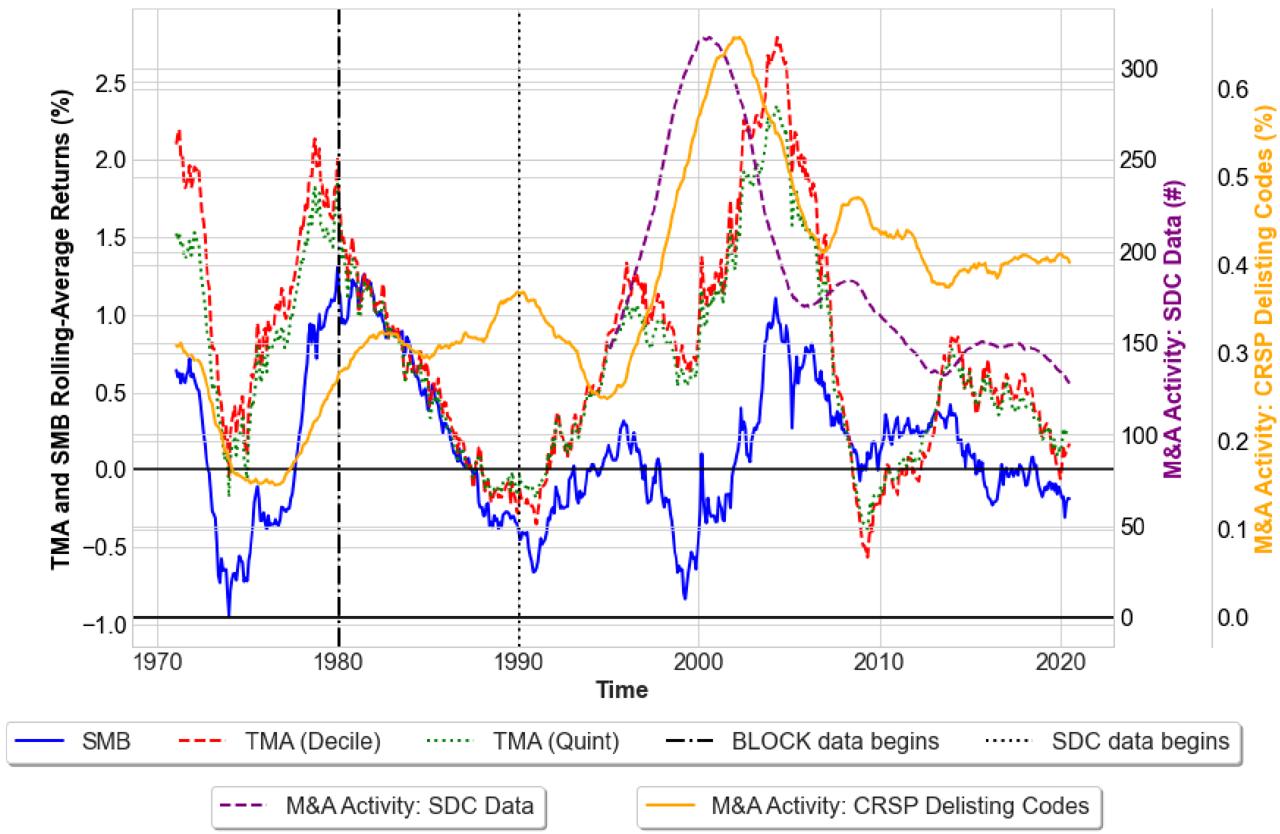

Table 1: **Descriptive Statistics for SDC Merger and Acquisition Data**

This table shows descriptive statistics for merger and acquisition deal data obtained from SDC. Panel A shows counts for deals satisfying the criteria listed in the row labels over several subsamples. Panel B shows counts for criteria among deals that involve at least one publicly listed firm (target or acquirer) and that match to the CRSP dataset, as well as the average and median deal value. Deal values are adjusted to 2020 dollars and are expressed in millions.

Panel A: All Completed M&A for Transactions Involving Either a U.S. Target or U.S. Acquirer

	(1) Restriction	(2) Number obs. 1990-2000	(3) Number obs. 2001-2010	(4) Number obs. 2011-2020	(5) Number obs. 1990-2020
(1)	Domestic acquirer or target	71,967	70,869	82,407	225,243
(2)	Deal value $\geq$ \$1 million	32,325	25,465	22,808	79,598
(3)	Deal value $\geq$ \$50 million	13,481	12,149	11,869	37,526
(3a)	*Public Acquirer and Public Target*	*1,648*	*1,201*	*914*	*3,763*
(3b)	*Public Acquirer and Non-Public Target*	*4,687*	*4,020*	*3,933*	*12,640*
(3c)	*Non-Public Acquirer and Public Target*	*1,863*	*1,485*	*907*	*3,933*
(3d)	*Non-Public Acquirer and Non-Public Target*	*5,443*	*5,443*	*6,142*	*16,868*

Panel B: Filters Imposed on SDC Data

	(1) Restriction	(2) Number of observations	(3) Mean Deal Value (\$M)	(4) Median Deal Value (\$M)
(1)	Domestic acquirer or target	225,243	425.58	38.16
(2)	Public Target or Public Acquirer with data in CRSP at Announcement	46,905	694.61	61.11
	Composition of (2) by public status			
(2a)	*Public Acquirer and Public Target*	*2,745*	*1,846.75*	*315.10*
(2b)	*Public Acquirer and Non-Public Target*	*40,074*	*236.50*	*36.88*
(2c)	*Non-Public Acquirer and Public Target*	*4,086*	*2,246.63*	*337.54*

Table 2: **Cumulative Abnormal Returns for SDC Merger and Acquisition Data**

This table shows cumulative abnormal returns (CARs), expressed in percentage points, for merger and acquisition deal data obtained from SDC. Robust standard errors are reported in parentheses and the number of observations are reported in italics. The acquirer CAR is defined over +/-1 day around announcement date. The target CAR is defined over -30/+1 days around announcement date. Both target and acquirer CARs are adjusted for the market return. Panel A reports CARs for the full sample. Panel B reports CARs for subsamples separated by target and acquirer public status. Panel C reports CARs for subsamples separated by decade. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Aggregate	Acquirer	Target			
	1.1346 *** (0.050) *42,593*	31.3778 *** (0.518) *6,619*			
Panel B: By Public Status	**Acquirer**	**Target**	**Differences:**	**Acquirer**	**Target**
(a) Both Acquirer and Target are Public	-1.1526 *** (0.175) *2,672*	33.0078 *** (0.775) *2,669*			
(b) Target is not Public	1.2877 *** (0.052) *39,921*		(a) - (b)	-2.4402 *** (0.182)	
(c) Acquirer is not Public		30.2764 *** (0.692) *3,950*	(a) - (c)		2.7315 *** (1.039)
Panel C: By Period	**Acquirer**	**Target**	**Differences:**	**Acquirer**	**Target**
(d) 1990-2000	1.2934 *** (0.063) *20,878*	29.3205 *** (0.676) *3,222*	(d) - (e)	0.4515 *** (0.095)	-3.4579 *** (1.232)
(e) 2001-2010	0.8419 *** (0.072) *12,148*	32.7784 *** (1.029) *2,063*	(e) - (f)	-0.3178 * (0.165)	-1.4025 (1.567)
(f) 2011-2020	1.1597 *** (0.149) *9,567*	34.1808 *** (1.182) *1,334*	(d) - (f)	0.1336 (0.828)	-4.8603 *** (1.362)

Table 3: **M&A Component of Size Portfolios**

This table reports value-weighted daily returns for various size portfolios, as well as a decomposition of the value-weighted returns into M&A and Residual components. Long/Short size portfolios are based on median, quintile, and decile sorts. All returns are annualized (scaling by 250 trading days per year) and expressed in percentage points. The Three-Factor SMB portfolio is constructed as in Fama and French (1993). The Five-Factor SMB portfolio is constructed as in Fama and French (2015). Robust standard errors are reported in parentheses. The acquirer return is defined as +/-1 day around announcement date. The target return is defined as -30/+1 days around announcement date. Both target and acquirer returns are adjusted for the market return. Acquirer and target returns add to the total M&A return; the M&A return and the Residual return add to the total return. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Description	Portfolio	Total Return	Residual	M&A	Acquirer	Target
	(1)	(2)	(3)	(4)	(5)	(6)
Below Median	(Small)	12.86	11.49	1.36	0.22	1.15
Above Median	(Big)	11.77	11.53	0.24	-0.01	0.26
Decile	1	12.45	10.72	1.72	0.22	1.50
Quintile	1	12.63	10.92	1.71	0.27	1.44
	2	12.78	11.50	1.28	0.20	1.07
	3	12.92	11.76	1.17	0.17	0.99
	4	13.12	12.36	0.76	0.09	0.68
Quintile	5	11.63	11.50	0.13	-0.04	0.16
Decile	10	11.46	11.39	0.07	-0.04	0.11
Long-Short	SMB	1.09	-0.03	1.12 ***	0.23 ***	0.89 ***
Median		(1.772)	(1.758)	(0.069)	(0.057)	(0.039)
Long-Short	1-5	1.00	-0.58	1.58 ***	0.30 ***	1.28 ***
Quintiles		(2.225)	(2.209)	(0.084)	(0.065)	(0.054)
Long-Short	1-10	0.98	-0.67	1.65 ***	0.26 ***	1.39 ***
Deciles		(2.345)	(2.327)	(0.095)	(0.077)	(0.058)
Three-Factor	SMB	1.35	0.30	1.05 ***	0.19 ***	0.87 ***
		(1.653)	(1.641)	(0.062)	(0.043)	(0.045)
Five-Factor	SMB	1.48	0.40	1.07 ***	0.22 ***	0.85 ***
		(1.666)	(1.654)	(0.063)	(0.047)	(0.041)

Table 4: **Merger and Acquisition Activity Across Size Portfolios**

This table reports M&A activity for targets and acquirers in various size portfolios. Long/Short size portfolios are based on median, quintile, and decile sorts. In columns (2), (3), and (4) ('% of Targets or Acquirers'), M&A activity is measured as the number of targets (acquirers) in the corresponding portfolio in each period, divided by the total number of targets (acquirers) in the period. Differences in M&A activity between long and short size portfolios are reported in the final three rows of columns (2), (3), and (4). In columns (5), (6), and (7) ('Realized Takeover Rate'), M&A activity is measured as the number of targets or acquirers in the corresponding portfolio in each period, divided by the total number of firms in the portfolio in the period. Odds ratios for the likelihood that a firm in the 'small' size portfolio is involved in a merger or acquisition, relative to the likelihood that a firm in the 'big' size portfolio is involved in a merger or acquisition, are reported in the final three rows of columns (5), (6), and (7). All measures of M&A activity are computed annually, and time-series averages of each measure are expressed in percentage points. Robust standard errors are reported in parentheses, and 95% confidence intervals are reported in brackets. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

		% of Targets or Acquirers			Realized Takeover Rate		
Description	Portfolio	Targets	Acquirers (All Targets)	Acquirers (Public Targets)	Targets	Acquirers (All Targets)	Acquirers (Public Targets)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Below Median	(Small)	84.75	64.73	48.07	4.41	13.26	1.15
Above Median	(Big)	15.25	35.27	51.93	3.01	26.91	4.89
Decile	1	48.71	24.13	10.79	4.52	8.75	0.47
Quintile	1	63.50	37.16	20.86	4.54	10.47	0.70
	2	15.95	19.60	18.12	4.11	19.93	2.18
	3	10.11	15.21	16.70	3.88	23.21	3.05
	4	7.32	13.76	17.23	3.47	25.74	4.09
Quintile	5	3.13	14.27	27.08	1.89	30.11	6.95
Decile	10	1.21	7.47	16.24	1.54	32.36	8.53
		Long – Short: Differences			Long / Short: Odds Ratios		
Median	SMB	69.51 ***	29.46 ***	-3.87	1.47 ***	0.42 ***	0.22 ***
		(1.897)	(2.316)	(2.823)	[1.37, 1.58]	[0.40, 0.43]	[0.21, 0.24]
Quintiles	1-5	60.37 ***	22.89 ***	-6.22 ***	2.44 ***	0.27 ***	0.09 ***
		(1.732)	(1.971)	(2.149)	[2.12, 2.81]	[0.26, 0.29]	[0.08, 0.10]
Deciles	1-10	47.51 ***	16.66 ***	-5.45 ***	2.96 ***	0.20 ***	0.05 ***
		(1.923)	(1.415)	(1.687)	[2.37, 3.69]	[0.19, 0.22]	[0.04, 0.06]

Table 5: **Cumulative Abnormal Returns Across Size Portfolios**

This table reports cumulative abnormal returns (CARs), expressed in percentage points, for targets and acquirers across various size portfolios, as well as differences in CARs between long and short size portfolios. Long/Short size portfolios are based on median, quintile, and decile sorts. Robust standard errors are reported in parentheses and the number of observations are reported in italics. The acquirer CAR is defined over +/-1 day around announcement date. The target CAR is defined over -30/+1 days around announcement date. Both target and acquirer CARs are adjusted for the market return. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Description	Portfolio	Targets	Acquirers	Differences:	Targets	Acquirers
	(1)	(2)	(3)		(4)	(5)
Below Median	(Small)	33.3031 ***	1.5513 ***	Median	9.9131 ***	1.4250 ***
		(0.628)	(0.078)	(SMB)	(1.048)	(0.088)
		4,866	*21,422*			
Above Median	(Big)	23.3900 ***	0.1263 ***			
		(0.839)	(0.040)			
		839	*14,307*			
Quintile	1	34.8206 ***	2.2839 ***	Quintile	15.9859 ***	2.3455 ***
		(0.786)	(0.132)	(1-5)	(1.738)	(0.141)
		3,666	*11,795*			
	2	29.0362 ***	0.6880 ***			
		(0.983)	(0.077)			
		893	*6,808*			
	3	27.3041 ***	0.4796 ***			
		(1.133)	(0.081)			
		567	*5,440*			
	4	23.1277 ***	0.2169 ***			
		(1.184)	(0.066)			
		398	*5,484*			
Quintile	5	18.8347 ***	-0.0616			
		(1.551)	(0.051)			
		181	*6,202*			
Decile	1	35.8111 ***	2.9283 ***	Decile	21.4459 ***	2.9927 ***
		(0.950)	(0.200)	(1-10)	(8.802)	(0.209)
		2,785	*7,337*			
Decile	10	14.3652 ***	-0.0645			
		(2.244)	(0.061)			
		74	*3,575*			

Table 6: **Acquisition Odds Ratios Over Time**

This table reports odds ratios for the likelihood that a firm in the 'small' size portfolio delists due to a merger or acquisition (CRSP delisting code in the 200s), relative to the likelihood that a firm in the 'big' size portfolio delists due to a merger or acquisition. The small and big portfolios are defined using median, quintile, and decile breakpoints. Size breakpoints are estimated using all NYSE stocks with positive market equity. When available, size is defined as the firm's market capitalization as of the end of the prior June. For firms with a history in CRSP of less than one year, if prior June market cap is unavailable, then size is defined as market capitalization as of the end of the prior month. 95% confidence intervals are reported in brackets below odds ratios. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Sample	Median	Quintile	Decile
1963–2020	1.0984 ***	1.9742 ***	2.0503 ***
	[1.0563, 1.1423]	[1.7801, 2.1895]	[1.7575, 2.3918]
1963–1989	1.0637 *	2.3127 ***	2.0703 ***
	[0.9934, 1.1391]	[1.8965, 2.8203]	[1.5714, 2.7276]
1990–2020	1.1349 ***	1.8610 ***	2.0716 ***
	[1.0819, 1.1905]	[1.6481, 2.1015]	[1.7201, 2.4950]
1960s	1.8833 ***	5.2062 ***	6.0204 ***
	[1.4689, 2.4146]	[2.9053, 9.3292]	[2.4654, 14.7016]
1970s	1.7833 ***	6.1319 ***	9.3684 ***
	[1.4582, 2.1810]	[3.5362, 10.6329]	[3.4973, 25.0958]
1980s	0.8356 ***	1.2070	0.9581
	[0.7391, 0.9447]	[0.9582, 1.5206]	[0.7045, 1.3029]
1990s	0.9922	1.4102 ***	1.4633 ***
	[0.8961, 1.0987]	[1.1662, 1.7053]	[1.0955, 1.9546]
2000s	1.2114 ***	1.6691 ***	1.9181 ***
	[1.0848, 1.3527]	[1.3755, 2.0252]	[1.4314, 2.5704]
2010s	1.4185 ***	3.2252 ***	3.8832 ***
	[1.2476, 1.6129]	[2.4457, 4.2531]	[2.5079, 6.0128]

Table 7: **Takeover Probability Model**

This table provides MLE estimates of a logistic regression model for takeover probability similar to Cremers et al. (2009). The dependent variable is equal to one if an acquisition occurs in that calendar year and zero otherwise. Q, PPE, Cash, BLOCK, MktCap, Industry (CNJ), Leverage, and ROA are calculated as in Cremers et al. (2009). ROA is defined as net income divided by total assets. Leverage is defined as book debt divided by total assets. Cash is defined as cash and short-term investments, scaled by total assets. Size is defined as the natural logarithm of market capitalization. Q is defined as the market-to-book ratio for the firm. PPE is defined as property, plant, and equipment, scaled by total assets. BLOCK is a dummy variable that equals one when an external blockholder exists and zero otherwise, where the presence of block ownership is measured using institutional shareholdings data from Thomson/CDA using a 5% ownership take threshold. Industry (CNJ) is dummy variable that takes the value one if at least one acquisition occurred within the industry during the prior year. Industry (BDH) is an alternative industry dummy defined as in Bhagwat et al. (2016), where it is equal to one if the number of acquisitions within the industry over is above the median number of within-industry acquisitions over the preceding two calendar years. Industry identification is based on the Fama-French 48 industries for both industry dummies. Gross profitability is defined as revenue minus cost of goods sold, divided by total assets. Dividend is a dummy variable equal to one if the firm issues a dividend, and zero otherwise. LRET is a measure of momentum, defined as the cumulative 12-month return over the preceding year. Idiosyncratic volatility is defined as the realized standard deviation of daily returns over 12 months, measured as of the end of month $t-2$ of the preceding calendar year as in Bhagwat et al. (2016). All regressions include, but do not report, year dummies. Model (6) excludes all firms with SIC codes between 6000 and 6999 (i.e., banks). All dependent variables, except for volatility, are measured as of the end of the prior calendar year. All Compustat variables are industry-adjusted (mean) using the Fama French 48 industries. All continuous variables are winsorized at the 1% and 99% levels. Coefficients are reported with standard errors in parentheses and odds ratios in brackets. Standard errors are clustered by firm and year. The sample period extends from January 1990 through December 2020. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	All Firms					Exclude Banks
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-3.4053 ***	-3.7541 ***	-3.7709 ***	-3.2069 ***	-3.4357 ***	-3.8762 ***
	(0.1622)	(0.1781)	(0.1709)	(0.1879)	(0.1975)	(0.2192)
ln(MktCap)	-0.0426 ***	-0.0697 ***	-0.0678 ***	-0.0929 ***	-0.0777 ***	-0.0466 ***
	(0.00717)	(0.00792)	(0.00829)	(0.00899)	(0.00978)	(0.0110)
	[0.958]	[0.933]	[0.934]	[0.911]	[0.925]	[0.954]
Q		-0.00816 ***	-0.00707 **	-0.00726 **	-0.00780 ***	-0.0665 ***
		(0.00281)	(0.00287)	(0.00282)	(0.00277)	(0.00913)
		[0.992]	[0.993]	[0.993]	[0.992]	[0.936]
PPE		-0.1142 **	-0.1117 **	-0.1022 *	-0.0990 *	-0.0513
		(0.0538)	(0.0543)	(0.0546)	(0.0544)	(0.0576)
		[0.892]	[0.894]	[0.903]	[0.906]	[0.950]

ln(Cash)		-0.00859	-0.00998	-0.00651	-0.00775	0.0216
		(0.0116)	(0.0117)	(0.0117)	(0.0116)	(0.0133)
		[0.991]	[0.990]	[0.994]	[0.992]	[1.022]
BLOCK		0.3551 ***	0.3699 ***	0.3542 ***	0.3439 ***	0.4954 ***
		(0.0347)	(0.0348)	(0.0350)	(0.0351)	(0.0432)
		[1.426]	[1.448]	[1.425]	[1.410]	[1.641]
Industry (CNJ)		0.4439 ***				
		(0.0671)				
		[1.559]				
Industry (BDH)			0.4684 ***	0.4778 ***	0.4791 ***	0.3457 ***
			(0.0411)	(0.0412)	(0.0412)	(0.0437)
			[1.597]	[1.613]	[1.438]	[1.413]
Leverage		0.3227 ***	0.3221 ***	0.3602 ***	0.3635 ***	0.4704 ***
		(0.0777)	(0.0777)	(0.0780)	(0.0774)	(0.0881)
		[1.381]	[1.380]	[1.434]	[1.438]	[1.601]
ROA		0.1384 *	0.1186 *	0.0370		-0.00823
		(0.0713)	(0.0704)	(0.0728)		(0.0806)
		[1.148]	[1.126]	[1.038]		[0.992]
Gross Profitability					-0.00001 ***	
					(3.935E-6)	
					[1.000]	
Dividend			-0.0267	-0.0752 **	-0.0710 **	-0.2465 ***
			(0.0306)	(0.0316)	(0.0315)	(0.0385)
			[0.974]	[0.928]	[0.931]	[0.782]
LRET				-0.1962 ***	-0.1928 ***	-0.2238 ***
				(0.0256)	(0.0256)	(0.0282)
				[0.822]	[0.825]	[0.800]
Idiosyncratic Volatility				-5.3224 ***	-5.1218 ***	-1.7505 *
				(0.8525)	(0.8385)	(0.9849)
				[0.005]	[0.006]	[0.174]
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Max-Rescaled R^2	1.70%	2.23%	2.48%	2.76%	2.80%	3.11%
Observations	132,642					108,377
Targets	5,104					3,857

Table 8: **Fama MacBeth Regressions**

This table presents Fama MacBeth regressions of annual returns on takeover likelihood and other firm characteristics. The table reports average coefficient estimates with Newey-West corrected t-statistics in parentheses. In Panel A, takeover likelihood is calculated using the coefficients estimated in Model 4 in Table 7 and the SDC sample period (1990–2020). In Panel B, takeover likelihood is calculated using a backward-extended version of Model 4 that includes data from 1963–2020. In Panel C, takeover likelihood is calculated using the dependent variables in Model 4 in Table 7 and the 10-year rolling estimation window. Size, ROA, and Idiosyncratic volatility are defined as in Table 7. Book-to-Market is the natural logarithm of book equity divided by market equity, measured as of the end of the prior calendar year. Investment growth is the growth in total assets. Short-Term Reversal is the one-month return, measured as of the end of the current month t. Momentum is the eleven month return, measured as of the end of the prior month $t-1$. Long-Term Reversal is the 24-month return, measured as of the end of month $t-12$. Turnover is the natural logarithm of monthly trading volume divided by total shares outstanding, averaged over the prior twelve months. All Compustat data is measured as of the end of the prior calendar year. All market return data is measured as of the end of June, and is used to estimate the annual return from July through June of the following year. All explanatory variables are winsorized at the 1% and 99% levels. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: SDC Sample (1990–2020)			Panel B: Extended Sample (1963–2020)		Panel C: Rolling Window (2000–2020)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Takeover Likelihood	3.8636 ***		3.3105 ***	5.4203 ***	3.8505 ***	2.3527 ***	0.9988 ***
	(4.778)		(6.317)	(3.283)	(4.229)	(2.579)	(4.365)
Size		-0.0130 **	0.0129 ***		0.0019		0.0109 **
		(-2.433)	(4.429)		(0.313)		(2.236)
Book-to-Market			-0.0005		0.0106		0.0003
			(-0.056)		(1.377)		(0.020)
Investment Growth			-0.0254 ***		-0.0310 ***		-0.0265 ***
			(-3.474)		(-6.424)		(-2.980)
ROA			0.0836 ***		0.0590		0.1282 ***
			(2.964)		(1.231)		(12.169)
Idiosyncratic Volatility			3.4681 ***		2.5989 ***		2.9967 ***
			(12.388)		(4.842)		(7.960)
Short-Term Reversal			-0.1299 ***		-0.0543		-0.1680 ***
			(-3.891)		(-1.639)		(-9.146)
Momentum			-0.0299 *		0.0004		-0.0536 ***
			(-1.873)		(0.018)		(-5.367)
Long-Term Reversal			-0.0213 ***		-0.0198 **		-0.0127 **
			(-2.858)		(-2.215)		(-2.092)
Turnover			-0.0582 ***		-0.0556 ***		-0.0575 ***
			(-13.419)		(-12.431)		(-9.942)

Table 9: **Excluded Factor Regressions – TMA**

This table reports excluded monthly factor regression alphas for a variety of factor models, as in Barillas and Shanken (2017). Units are expressed in percentage points and robust t-statistics are reported in parentheses. In all regressions, the dependent variable is the takeover probability factor and the independent variables are the factors that correspond to the factor model in the row labels. MKT is the value-weighted market return. FF3 corresponds to the Fama French three-factor model (Fama and French (1993)). UMD is the Carhart (1997) momentum factor. FF5 corresponds to the Fama French five-factor model (Fama and French (2015)). BAB is the 'betting against beta' factor of Frazzini and Pedersen (2014). QMJ is the 'quality minus junk' factor of Asness et al. (2019). StY 4 corresponds to the four-factor model from Stambaugh and Yuan (2017). LP 5 corresponds to the five-factor RP-PCA model from Lettau and Pelger (2020). KNS 5 corresponds to the five-factor PCA model from Kozak et al. (2020). In Panel A, takeover likelihood is calculated using the coefficients from Model 4 in Table 7. In Panel B, takeover likelihood is calculated using a backward-extended version of Model 4 that includes data from 1963–2020. In Panel C, takeover likelihood is calculated using the dependent variables from Model 4 in Table 7 and the 10-year rolling estimation window. The TMA is formed using the highest and lowest quintiles of takeover probability to define 'high' and 'low'. α columns report the intercepts from the excluded factor regressions. $Sh^2(f)$ columns report the maximum squared Sharpe ratio from the tangency portfolio that includes the factors in the row labels (i.e., only the RHS factors). $\alpha^2/s^2(e)$ columns report the corresponding TMA factor's marginal contribution to $Sh^2(f)$, as in Fama and French (2018). ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: SDC Sample (1990–2020)			Panel B: Extended Sample (1963–2020)			Panel C: Rolling Window (2000–2020)		
	α	$Sh^2(f)$	$\alpha^2/s^2(e)$	α	$Sh^2(f)$	$\alpha^2/s^2(e)$	α	$Sh^2(f)$	$\alpha^2/s^2(e)$
MKT	0.7965 ***	0.0229	0.0942	0.8653 ***	0.0136	0.0608	0.6086 ***	0.0104	0.0575
	(5.212)			(6.030)			(3.315)		
FF3	0.7908 ***	0.0240	0.1215	0.7140 ***	0.0285	0.0672	0.5548 ***	0.0132	0.0574
	(6.140)			(6.460)			(3.528)		
FF3 + UMD	0.6750 ***	0.0532	0.0970	0.6196 ***	0.0719	0.0519	0.4895 ***	0.0208	0.0498
	(5.394)			(5.521)			(3.239)		
FF 5	0.7765 ***	0.1146	0.1182	0.6874 ***	0.0921	0.0622	0.4514 ***	0.1198	0.0385
	(6.033)			(5.897)			(2.941)		
FF 5 + UMD + BAB	0.6501 ***	0.1570	0.0965	0.5370 ***	0.1487	0.0386	0.3253 ***	0.1631	0.0292
	(4.926)			(4.393)			(2.586)		
FF 5 + UMD + QMJ	0.7941 ***	0.2352	0.1316	0.5851 ***	0.2291	0.0448	0.5450 ***	0.2039	0.0609
	(5.477)			(4.527)			(3.232)		
StY 4	0.6469 ***	0.1881	0.0807	0.4887 ***	0.2168	0.0305	0.4441 **	0.1297	0.0366
	(4.341)			(3.706)			(2.413)		
LP 5	0.6810 ***	0.1985	0.0967	0.4687 ***	0.3307	0.0282	0.4937 ***	0.1289	0.0472
	(4.850)			(3.373)			(2.976)		
KNS 5	0.6336 ***	0.0960	0.0904	0.6319 ***	0.1372	0.0480	0.3906 **	0.0733	0.0325
	(4.935)			(4.926)			(2.537)		

Table 10: **Excluded Factor Regressions – SMB**

This table reports excluded monthly factor regression alphas for a variety of factor models, as in Barillas and Shanken (2017). Units are expressed in percentage points and robust t-statistics are reported in parentheses. In all regressions, the dependent variable is the size factor, and the factor models (independent variables) replace the SMB factor with the corresponding TMA factor and/or with the QMJ factor of Asness et al. (2018). All independent variables are defined as in Table 9. The TMA factor is formed using the highest and lowest quintiles of takeover probability to define 'high' and 'low'. In Panel A, takeover likelihood is calculated using a backward-extended version of Model 4 that includes data from 1963–2020. In Panel B, takeover likelihood is calculated using the backward-extended version of Model 4 that includes data prior to the start of our SDC sample period (1963–1989). In Panel C, takeover likelihood is calculated using the coefficients from Model 4 in Table 7 and the SDC sample period (1990–2020). α columns report the intercepts from the excluded factor regressions. $Sh^2(f)$ columns report the maximum squared Sharpe ratio from the tangency portfolio that includes the factors in the row labels (i.e., only the RHS factors). $\alpha^2/s^2(e)$ columns report the SMB factor's marginal contribution to $Sh^2(f)$, as in Fama and French (2018). ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Extended Sample (1963–2020)			Panel B: Pre-SDC Sample (1963–1989)			Panel C: SDC Sample (1990–2020)		
	α	$Sh^2(f)$	$\alpha^2/s^2(e)$	α	$Sh^2(f)$	$\alpha^2/s^2(e)$	α	$Sh^2(f)$	$\alpha^2/s^2(e)$
MKT	0.0916	0.0136	0.0010	0.2451	0.0059	0.0078	-0.0090	0.0229	0.0000
	(0.820)			(1.507)			(-0.059)		
MKT + TMA	-0.3309 ***	0.0745	0.0192	-0.2016 *	0.0568	0.0109	-0.4580 ***	0.1174	0.0289
	(-3.516)			(-1.820)			(-2.718)		
MKT + QMJ	0.4482 ***	0.0851	0.0270	0.5212 ***	0.0576	0.0438	0.5064 **	0.1391	0.0313
	(3.532)			(3.414)			(2.515)		
MKT + QMJ + TMA	-0.0550	0.2012	0.0006	-0.0447	0.1785	0.0006	-0.0153	0.3283	0.0000
	(-0.547)			(-0.376)			(-0.085)		
FF 5 - SMB + UMD + TMA	-0.1032	0.1708	0.0022	0.0440	0.2967	0.0006	-0.1275	0.2323	0.0028
	(-1.125)			(0.359)			(-0.885)		
FF 5 - SMB + UMD + QMJ	0.5535 ***	0.1843	0.0443	0.7647 ***	0.2810	0.1012	0.4920 ***	0.1999	0.0347
	(4.713)			(4.886)			(3.006)		
FF 5 - SMB + UMD + TMA + QMJ	0.1049	0.2720	0.0024	0.2371 **	0.3824	0.0188	0.0799	0.3687	0.0011
	(1.083)			(2.203)			(0.473)		
LP 5 + TMA	-0.0515	0.3591	0.0010	0.2945 ***	0.7816	0.0615	-0.0260	0.2966	0.0002
	(-0.653)			(3.095)			(-0.259)		
LP 5 + QMJ	-0.0684	0.3672	0.0018	0.3420 ***	0.7573	0.0815	-0.0925	0.3017	0.0028
	(-0.838)			(3.544)			(-0.845)		
LP 5 + QMJ + TMA	-0.1309 *	0.3880	0.0071	0.2992 ***	0.7821	0.0656	-0.2105 **	0.4274	0.0152
	(-1.682)			(3.129)			(-1.980)		
KNS 5 + TMA	-0.0250	0.1856	0.0002	0.1725 *	0.3715	0.0154	-0.0657	0.1877	0.0012
	(-0.363)			(1.681)			(-0.669)		
KNS 5 + QMJ	0.2167 ***	0.2157	0.0144	0.5333 ***	0.4443	0.1288	0.1221	0.2052	0.0041
	(2.594)			(5.198)			(1.113)		
KNS 5 + QMJ + TMA	0.0348	0.3053	0.0004	0.3234 ***	0.5557	0.0578	0.0257	0.3772	0.0002
	(0.441)			(3.509)			(0.217)		