Risk Factors Similarity and Mergers and Acquisitions

Lei Chen[a]
Southwestern University of Finance and Economics

Allen H. Huang[b]
Hong Kong University of Science and Technology

Xinlu Wang[c]
Jinan University

Liang Xu[d]
Nanjing University

Current Draft: February, 2021

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[*] We thank Chen Lin, Jarrad Harford, Jose-Miguel Gaspar, Peng Huang, Shuping Chen, Wuyang Zhao, Henri Servaes, Stefano Cascino, Lin Zhou (discussant), Stenven Utke (discussant) and workshop and conference participants at Bocconi University, Chinese University of Hong Kong, Southern University of Science and Technology, Hong Kong University of Science and Technology, Shanghai University of Finance and Economics, SKEMA Business School, AAA 2020 annual meeting, and HARC 2021 annual meeting for comments. All errors remain our own.
[a] *Email:* leichen@swufe.edu.cn, School of Accounting, Southwestern University of Finance and Economics.
[b] *Email:* allen.huang@ust.hk, The Hong Kong University of Science and Technology, Clear Water Bay, Hong Kong.
[c] *Email:* xlwang@jnu.edu.cn, School of Management, Jinan University.
[d] *Email:* liangxu@nju.edu.cn, School of Business, Nanjing University.

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Abstract

In the M&A process, uncertainty impairs acquirers' ability to assess targets' intrinsic value as well as the expected synergy created from business combinations. We conjecture that similarity between merging firms' potential business downsides, measured with qualitative risk factor disclosures, reflects acquirers' familiarity with potential downsides of targets' business, thus can mitigate uncertainty and improve M&A quality. We first show that existing similarity measures have limited explanatory power for business downsides similarity and firm-pairs with higher business downsides similarity are more likely to have extreme negative returns, but not extreme positive returns in the future, which validates that our measure captures similarity in a unique aspect of business. We document that similarity between merging firms' business downsides is positively related to merger announcement returns, especially when acquirers face a greater level of uncertainty. We also find that business downsides similarity improves operating performance and reduces the likelihoods of incurring goodwill impairment and high restructuring costs in the post-merger period. Acquirers are more likely to pair with targets with more similar business downsides, more likely to complete deals with such targets, and pay less in equity in such deals, consistent with less uncertainty facilitating target selection and deal negotiation.

Keywords: M&A quality, firm-pair similarity, business downsides, risk factor disclosure, textual analysis

1. Introduction

Mergers and acquisitions (M&As) are arguably the most important and complex investment activities for firms, creating or destroying significant value in the process (Datta, Iskandar-Datta, and Raman, 2001; Fuller, Netter and Stegemoller, 2002). Prior research shows that M&As have better outcomes when acquirers are more familiar with the target.[1] Acquirers do not have complete understanding of targets' businesses prior to the transactions due to information asymmetry. One aspect of the targets' business that is particularly opaque to the acquirers and can greatly affect M&A outcomes is the targets' potential significant business downsides. Consequently, M&A consultants and financial journalists have always been advocating that acquirers must know the key factors that can undermine the target's operations, financial condition and potential value while undertaking the deals. These factors include but are not limited to the target's contingent liabilities, problematic contracts, litigation risk, customer/supplier concentration, key employee retention, regulatory environment and intellectual property issues.[2] In this paper, we explore how acquirers' familiarity with targets' potential significant business downsides affects M&A quality.

Studying potential significant business downsides' role in M&As is important for several reasons. To start, M&A outcomes can have substantial impacts on managers' compensation and career and negative outcomes matter significantly more than do positive ones (Lehn and Zhao,

[1] For example, M&A quality is higher when targets have higher quality financial reporting (e.g., Skaife and Wangerin, 2013; Martin and Shalev, 2017; Chen et al., 2018), when acquirers and targets follow more similar accounting rules (Francis, Huang and Khurana, 2016) or share auditors, directors, creditors, or advisors (Ivashina et al., 2009; Cai and Sevilir, 2012; Agrawal et al., 2013; Cai et al., 2016; Dhaliwal et al., 2016).

[2] https://www.forbes.com/sites/allbusiness/2018/08/27/mergers-and-acquisitions-key-considerations-when-selling-your-company/?sh=497c90841020;

https://deloitte.wsj.com/cfo/files/2012/06/DFPORH2011120500001.pdf

2006; Bens, Goodman and Neamtiu, 2012). In addition to the asymmetric payoff, prospect theory suggests that individuals place greater weights on losses than on gains in their utility functions (Kahneman and Tversky, 1979). Consequently, investors and managers should be more sensitive to information about events that can lead to negative outcomes than to other information. Second, despite the importance of negative prospects, prior research shows that managers tend to overestimate their ability to avoid negative events and underestimate risks due to overconfidence (Malmendier and Tate 2005; Kallunki and Pyykkö, 2012; Ho, Huang, Lin and Yen, 2016; Hribar and Yang, 2016), which contributes to the well-documented winner's curse in M&As (Langer, 1975; Roll 1986; Malmendier and Tate 2008). Third, acquirers may know less about targets' potential downsides than their potential upsides. The higher asymmetry of downside information is because targets have strong incentives to disclose potential upsides during M&A to increase valuation (Brennan, 1999; Lobo, Xie and Yan, 2020), but they are much less forthcoming regarding potential downsides. Furthermore, acquirers may have difficulty in estimating the likelihood and impact of potential significant downsides which, unlike regular events, occur less frequently and are less familiar to managers (Hertwig et al., 2004; Hertwig et al., 2005; Hau et al., 2008). Last, while acquirers usually emphasize M&As' potential upsides such as strategic benefits and synergy (Kimbrough and Louis, 2011) and prior studies on how similarity improves M&A quality also focuses either on potential upsides or regular business (Hoberg and Phillips, 2010; Bena and Li, 2014; Lee, Mauer and Xu, 2018), little is known about the importance of significant business downsides in M&As.

We expect that acquirers that are more familiar with targets' significant downsides have informational advantages to gauge the potential impacts of such downsides, which enables them to more accurately value target business, predict merger synergy, and avoid post-merger integration problems, leading to higher quality M&As. We measure acquirers' familiarity with the targets using the similarity between two firms' risk factor disclosures.

The SEC requires firms to disclose the most significant factors that make the company speculative or risky (Regulation S–K, Item 305(c), SEC 2005) in Item 1A of 10-K filings. The risk factor disclosure is the most comprehensive discussions about potential events or developments that could harm the firm's business, financial condition, and results of operations.[3] Note that we do not argue that acquirers learn about targets' significant business downsides through targets' risk factor disclosure. Instead, we use the similarity in risk factor disclosure to measure whether acquirers' business has similar potential significant downsides and thus their managers are more familiar with targets' significant business downsides.[4]

Empirically, we measure acquirers' familiarity with the targets' potential significant business downsides using the word-based cosine similarities between two firms' disclosed risk factors (hereafter SRF). To validate that SRF captures commonalities in firm-pairs' significant business downsides, we explore how it relates to other similarity measures used in the literature, and to the firm-pair's co-occurrence of future negative returns.

First, we regress SRF on existing similarity measures including product market similarity, industry relatedness, human capital relatedness, geographic proximity, asset valuation similarity, size closeness, return correlations, and disclosure style similarity, and show that their levels and

[3] Although Regulation S-K does not explicitly mandate risk factors to be "negative", in practice, Item 1A almost exclusively lists potential events that could adversely affect the firm's business and financial positions (Campbell et al., 2014; Huang, Shen and Zang, 2021, also see excerpts of risk factor disclosures in Appendix II).

[4] As firms do not disclose the likelihood of significant adverse events or their potential impacts, using risk factor disclosure to determine how these significant downside risks can affect M&A remains challenging. For example, a firm may disclose, in its Item 1A, that a failure to obtain government authorization to export certain products imposes a significant risk. However, to understand how this risk may impact future operations requires knowledge of how the government decides whether to authorize export, what action firms can do to facilitate the process, and possible remedial actions if the government denies authorization.

changes only explain 35% and 0.6% of the variations in SRF respectively.[5] Second and more importantly, we find that firm-pairs with higher SRF are more likely to have extreme negative returns in the same week over the next year, but there is no relation between SRF and co-experiencing extreme positive returns. In economic terms, a one-standard-deviation increase in SRF increases the odds of two firms co-experiencing extreme negative returns by 10% (0.05% relative to the sample mean of 0.5%). In sum, the results from the validation tests confirm that SRF captures similarity in a distinct aspect of firm business, namely the potential significant downsides.

Using the SRF measure, we find that in line with our expectation, acquirers' familiarity with targets' significant business downsides is positively related to M&A quality, measured with the combined return during M&A announcements. This positive relation is economically significant. A one-standard-deviation increase in SRF is associated with 0.80% higher combined abnormal returns over the three-day window centered on the announcement date, equivalent to a gain of $275 million USD for the average deal in our sample.

Next, we conduct cross-sectional analyses to explore the variations in the effect of familiarity with significant downsides on M&A quality. We show that this effect is primarily driven by deals in which the acquirers face greater uncertainty about targets, i.e., when they are further away geographically, when they are in unrelated industries, when the acquirer's CEO has no prior experience in the target's industry, when the target has low analyst coverage, or when acquirers and targets do not share the same auditor. These findings provide further support to our

[5] In Section 3.2, we provide examples of firm-pairs with high value in existing similarity measures but low SRF, and vice versa.

story that acquirers' familiarity with targets' significant business downsides improves M&A quality by reducing information asymmetry.

In addition to using M&A announcement returns to measure deal quality, we also use several post-merger operating performances and find similar results as in our main tests. First, we find that mergers with higher SRF have larger improvement in profitability, measured with the change in industry-adjusted ROA, compared to those with lower SRF. Economically, when their SRF increases by one standard deviation, merged firms' profitability is 1.3% higher in each of the two years post-merger, which is 17% of their pre-deal profitability. Second, we show that mergers with higher SRF are less likely to incur deal-specific goodwill impairment and high restructuring costs. In terms of economic magnitude, a one-standard-deviation increase in SRF reduces the odds of goodwill impairment by 18% (4.3% relative to the unconditional likelihood of 23.8%) and those of high restructuring cost by 23% (8.5% relative to the unconditional likelihood of 36.9%). Both results corroborate our main finding based on market reaction and suggest that better understanding of targets' downsides can meaningfully reduce the chances of failed acquisitions.

Further, we explore how SRF affects M&A likelihood of M&As and deal characteristics such as completion likelihood and payment methods. First, we examine whether acquirers are more likely to propose deals to firms when they are more familiar with these firms' significant downsides. We match each actual target with a pseudo target that is in the same product market, has the same industry relatedness with the acquirer, and is closest in size and asset valuation, and regress the actual target indicator on SRF. We find that SRF is positively associated with the likelihood of being an actual target. Economically, a one-standard-deviation increase in potential target's SRF with the acquirer increases the odds of being an actual target by 13.2% (6.6%

relative to the unconditional likelihood of 50%). This finding suggests that similarities in business downsides play a significant role in target selection.

Second, if familiarity with potential targets' significant downside reduces acquirers' information asymmetry and helps them value target business and predict synergy, proposed deals with higher SRF should be more likely to be completed. Furthermore, we expect that lower information asymmetry reduces acquirers' use of stocks as payments because they are less likely to require target shareholders to share M&A risks (Hansen, 1987; Fishman, 1989; Eckbo, Giammarino, and Heinkel, 1990; Raman, Shivakumar and Tamayo, 2013). The results are consistent with both predictions. Specifically, among announced M&As, high SRF deals are more likely to complete than low SRF ones, and in completed deals, acquirers use lower percentage of equity payment in high SRF ones. In terms of economic magnitude, a one-standard-deviation increase in SRF increases the odds of deal completion by 5.4% (4.6% relative to the unconditional completion rate of 85.3%) and decreases the percentage of equity payments in completed deals by 13.3% (3.4% relative to the average percentage of equity payments of 25.6%). Collectively, these results echo our evidence on market reactions and post-merger operating performance and provide additional support that acquirers' familiarity with targets' business downsides mitigates the information asymmetry in M&As.

We conduct a sensitivity analysis to investigate whether the positive association between SRF and market reaction is due to shareholders' incentives to increase firm risk to expropriate bondholders' wealth (Jensen and Meckling, 1976; Asquith and Kim, 1982). We find no relation between SRF and the change in the merging firms' stock return volatility, suggesting that this explanation is unlikely.

Our paper contributes to three streams of literature. First, as one of the most complex and significant investments made by firms, M&As frequently suffer from severe information asymmetry. Although prior studies show that better target information, e.g., more disclosure or higher quality financial reporting, and commonalities between targets and acquirers including common lenders, board members, and information intermediaries such as auditors, advisors and analysts, can mitigate information asymmetry (e.g., Ivashina et al., 2009; Cai and Sevilir 2012; Agrawal et al., 2013; Skaife and Wangerin, 2013; Cai et al., 2016; Martin and Shalev, 2017; Chen et al., 2018; Cortes and Marcet, 2018), most do not delve into the nature of such information. Our paper is an important addition to this line of research by documenting how acquirers' familiarity with a specific type of target information, namely potential significant downsides of target's business, alleviates uncertainty and improves M&A quality.

Second, we contribute to the theory of mergers by offering additional evidence that similarity between firms increases M&A quality. Prior literature such as Grossman and Hart (1986), Hart and Moore (1990) and Rhodes-Kropf and Robinson (2008) argues that similar firms merge to put complementary assets under common control and reduce hold-up problems and underinvestment. Follow-up studies focus on similarities in merger-pairs' potential upsides or general operations such as products, technology and human capital (Hoberg and Phillips, 2010; Bena and Li, 2014; Lee, Mauer and Xu, 2018). Our study broadens the applicability of this theory of merger by showing the first evidence that combining two firms with similar significant business downsides can also improve deal quality.

Third, this paper enriches our knowledge on risk factor disclosures. Risk factor disclosures represent a key reason that accounts for the substantial increase in 10-K length in the last decade (Dyer, Lang and Stice-Lawrence, 2017). Prior literature shows that they are related to firm risks and future adverse outcomes, informative to investors and stakeholders, and can lower shareholder litigation risks (Kravet and Muslu, 2013; Campbell et al., 2014; Hope, Hu and Lu, 2016; Gaulin, 2019; Chiu, Guan and Kim, 2018; Hanley and Hoberg, 2019; Huang, Shen and Zang, 2021). We add to the literature by showing that risk factor disclosures can be used to predict M&A market reactions and post-merger operating performance. Thus, our results have practical implications for investors that they can use risk factors to evaluate M&A quality.

2. Literature review

2.1 Literature on acquirer-target similarity, M&A uncertainty, and M&A quality

Most research on acquirer-target similarity has its roots in the property rights theory of the firm, which claims that complementary assets should be under common control to reduce holdup problems (Grossman and Hart, 1986; Hart and Moore, 1990). In line with this theory, empirical studies document that mergers of firms with similar assets, products, or those with complementary relations generate significantly positive wealth effects (Fan and Goyal, 2006; Rhodes-Kropf and Robinson, 2008; Hoberg and Phillips, 2010; Lee, Mauer and Xu, 2018)

Another stream of literature examines M&A through the lens of information asymmetry or information uncertainty. Consistent with better target disclosure mitigating information asymmetry/uncertainty and improving M&A quality, prior research shows that better-quality financial reporting, more firm-specific information and greater financial statement comparability at the target firm facilitate deal completion and synergy creation (Skaife and Wangerin, 2013; Martin and Shalev, 2017; Chen et al., 2018).[6] Similarly, other studies document an increase in

[6] Also see Raman, Shivakumar and Tamayo (2013), Marquardt and Zur (2015), McNichols and Stubben (2015) and Chen (2019) for other evidence on the impacts of target firm's disclosure quality on M&A occurrence and deal

M&A activity and higher value creation during M&A when two firms share commonalities that might lower information asymmetry/uncertainty such as common lender, board members and auditors (Ivashina et al., 2009; Cai and Sevilir 2012; Agrawal et al., 2013; Cai et al., 2016; and Cortes and Marcet, 2018). At the country level, cross-border M&A volume is found to be larger when the target country follows better accounting standards (Rossi and Volpin, 2004), and when pairs of countries follow similar GAAP (Francis, Huang and Khurana, 2016). Altogether, prior research offers ample evidence that M&As considerably benefit from lower information uncertainty.

2.2 Literature on risk factor disclosure

Prior research provides strong evidence that narrative risk disclosures are related to the volatility of a firm's expected future cash flows and informative to capital market participants (e.g., shareholders, creditors, analysts) as well as other stakeholders (e.g., suppliers). Kravet and Muslu (2013) and Campbell et al. (2014) document that risk factor disclosures are associated with investors and analysts' risk perceptions. Similarly, other studies document that risk factor disclosures benefit equity and debt market investors (Hope, Hu and Lu, 2016; Chiu, Guan and Kim, 2018). More recently, Hanley and Hoberg (2019), Gaulin (2019) and Cohen, Malloy and Nguyen (2020) show that risk factors can predict future earnings, return volatility, and adverse outcomes such as bankruptcy.

structure.

3. Empirical measurement, sample selection procedure, and research design

3.1 Measurement of similarity in significant business downsides

Our key variable (i.e., SRF) is the word-based cosine similarity of two firms' risk factor disclosures (Hoberg and Phillips, 2010; Brown and Tucker, 2011), indicating to what extent the two firms use similar words to describe significant downsides of their business. The value of SRF ranges from zero for two firms that do not share any words in their risk factor disclosure, to one when they use the same list of words with the same proportional frequency. To calculate SRF, we use firms' risk factor disclosures, i.e., Item 1A of their 10-K filings. More specifically, we first download all 108,492 10-Ks between 2006 and 2018 from the SEC's EDGAR database. We are able to extract 83,564 Item 1As using section title, HTML tags, CSS style, or their combinations. Following Campbell et al. (2014) and Gaulin (2019), we remove all tables, HTML tags, and exhibits in Item 1A. Next, we construct a dictionary of all words used in these risk descriptions, including 4,707 unique words.[7] We then represent each risk factor disclosure j with a 4,707 by one-dimension vector ($V_j = [w_{1,j}, w_{2,j},..., w_{4707,j}]$) to denote how much it uses each word from the dictionary. We apply the Term Frequency-Inverse Document Frequency (TF-IDF) method to weight each word by how frequently it appears in all risk factor disclosures. Specifically, for a word i in a risk factor disclosure j, we multiply the number of times word i appears in j, i.e., the original word frequency ($tf_{i,j}$), by the inverse prevalence of word i in all documents $log\left(\frac{1+N}{1+df_i}\right)$, where N is the total number of risk factor disclosures and df_i is the

[7] We lemmatize each word to get their original form. For instance, "walk," "walked," "walks" and "walking" would be treated as "walk." We also exclude stop words (from the customized stop word list for 10-Ks provided by Loughran and McDonald (2014)) such as "a," "the" and "by" from the dictionary. Last, we remove words that appear in less than 1% or more than 99% of the risk factor documents.

number of risk factor disclosures that contain word i, and use it to denote the use of word i in j. That is, $w_{i,j} = tf_{i,j} \times log\left(\frac{1+N}{1+df_i}\right)$.

The SRF between two firm-year observations (A and B) is the cosine similarity between the word vectors representing their risk factor disclosures (V_A and V_B). That is,

$$SRF_{A,B} = \frac{\boldsymbol{V_A} \cdot \boldsymbol{V_B}}{\|\boldsymbol{V_A}\|\|\boldsymbol{V_B}\|} = \frac{\sum_{i=1}^{4707} V_{i,A}V_{i,B}}{\sqrt{\sum_{i=1}^{4707} V_{i,A}^2}\sqrt{\sum_{i=1}^{4707} V_{i,B}^2}}$$

3.2 Determinants of SRF and SRF's relation with co-occurrence of extreme negative returns

Two firms may have potential business downsides that are highly distinct, despite commonalities in other aspects of business. For example, consider the deal between AmSurg Corp and Team Health Holdings Inc. These two firms are from vertically related industries, and are operating in the same product market as identified by Hoberg and Philips (2006) using text-based product similarity score. However, their SRF is only 0.262, which is below the 5th percentile of SRF in our M&A sample. The opposite can also be true. Take the deal between Cintas Corp and G&K Services Inc for example. SRF between these two firms is 0.783, above the 75th percentile of SRF in our M&A sample. Yet these two firms are not in the same/related industries or offer similar products. In this section, we investigate what SRF measures and how it differs from similarities in other aspects of business. First, we examine the determinants of SRF by estimating the following ordinary least squares model:

$$SRF_t = \alpha + \beta_1\, ProductSimilarity_t + \beta_2 RelatedInd_t + \beta_3\, RelatedHR_t +$$

$$\beta_4 SameState_t + \beta_5 Q\_diff_t + \beta_6 Size\_diff_t + \beta_7 Ret\_corr_t + \beta_8 MDA\_simi_t + \varepsilon. \qquad (1)$$

The indepdennt variables contain a set of firm-pair business similarities used in prior M&A literature, including product market similarity ($ProductSimilarity$, Hoberg and Phillips, 2010), asset valuation similarity (Q_diff, Rhodes-Kropf and Robinson, 2008), industry relatedness ($RelatedInd$, Fan and Goyal, 2006), human capital relatedness ($RelatedHR$, Lee, Mauer and Xu, 2018), geographic proximity ($SameState$, Kang and Kim, 2008; Li et al., 2020). We also include firm size differences ($Size\_diff$) and stock return correlations (Ret_corr), which might capture similarities in other aspects of firm business, and MD&A similarity (MDA_simi, Brown and Knechel, 2016) to control for similarity in firm disclosure style. Detailed variable definitions are in Appendix I. We include all possible firm-pairs (42,357,768 unique firm-pair-years) during 2006 to 2018 in this analysis. Our sample period starts from 2006 because the SEC mandated risk factor disclosure in 2005.

We report summary statistics in Table 1 Panel A. Table 1 Panel B displays the regression results of estimating Model 1. More specifically, Column 1 uses the specification without fixed effects while Columns 2 and 3 further include firm fixed effects and firm and year fixed effects respectively. Two findings emerge: first, the coefficients on most independent variables are significant, consistent with firms similar in business upsides or general operations, as captured by existing proxies, also demonstrate overlaps in potential business downsides; second and more importantly, the adjusted R^2s range from 34.6% in the model without fixed effects to 74.8% in the model with firm and year fixed effects, indicating that considerable amount of the variations in SRF cannot be explained by the models. We further modify Model 1 by replacing all the dependent and independent variables with their corresponding changes from year t-1 to year t. As Panel C indicates, the explanatory power of the change model is even lower – the adjusted R^2s is only 0.6% without fixed effects and 9.4% when firm and year fixed effects are included. Taken together, SRF captures certain aspect of firm business similarity that is distinct from those covered by prior measures.

This conclusion is intuitive because existing similarity measures are about firm characteristics that can either positively or negatively impact business and the magnitude of the impact varies. In contrast, risk factor disclosures only discuss potential events or developments that could harm the firm's business and financial results significantly. That is, SRF exclusively captures similarities in downsides, especially those of large or catastrophic proportion, of all areas of business. Therefore, firms with more similar risk factor disclosures (i.e., higher SRF) anticipate similar events to cause significant negative impacts to their business. To lend further support to this argument, we examine whether firm-pairs with higher SRF are more likely to experience significant negative returns during the same period compared to those with lower SRF.

We create an indicator variable $CoDown$ that equals one if both firms experience extreme negative returns in the same week during the year and zero otherwise. Following the stock crash risk literature (Kim et al. 2011a, 2011b), we define weekly returns as extremely negative if the raw weekly returns are at least 3.2 standard deviations below the mean raw weekly returns during the previous year.[8] We estimate a probit model with $CoDown$ as the dependent variable and SRF and other similarity measures as the independent variables. Because firm-pairs may have different fiscal year ends, we measure $CoDown$ based on calendar years. Given independent variables are computed for firm-pairs based on fiscal years, to completely avoid look-ahead biases, namely, firms that have already experienced common negative events disclose similar risk factors in subsequent 10-Ks, we use values of fiscal year t-2 for all independent variables to explain $CoDown$ in year t.[9] More formally, we estimate the following

[8] Our results are qualitatively similar when we use 3 standard deviations as alternative cutoffs or use market adjusted returns to define this variable.

[9] For example, a firm's fiscal year may end on March 31. The fiscal year 2000 of this firm would naturally include

Probit model:

$$CoDown_t = \alpha + \beta_1\, SRF_{t-2} + \beta_2\, ProductSimilarity_{t-2} + \beta_3 RelatedInd_{t-2} +$$

$$\beta_4\, RelatedHR_{t-2} + \beta_5 SameState_{t-2} + \beta_6 Q_{diff_{t-2}} + \beta_7 Size\_diff_{t-2} +$$

$$\beta_8 Ret\_corr_{t-2} + \beta_9 MDA\_simi_{t-2} + \varepsilon. \tag{2}$$

Table 2 Panel A presents summary statistics for the variables used in this analysis. The regression results are reported in Panel B Column 1. We find that, as expected, the coefficient of SRF is positive and significant at the 1% level. In economic terms, a one-standard-deviation increase in SRF increases the likelihood of $CoDown$ being one by 0.05 percent points, which is 10% relative to the mean of 0.55%. $ProductSimilarity$ also has a positive sign, however, its economic impact is only half as SRF, with a one-standard-deviation increase raising the likelihood of $CoDown$ being one by 0.04 percent points, which is 7.3% relative to the mean. Among other similarity measures, only $Size\_diff$ has the expected sign.

We also conduct a placebo test that uses co-occurrence of extreme positive returns ($CoUp$, defined similarly as $CoDown$) and report the results in Panel B Column 2. As shown, the estimated coefficient of SRF is not significant in this regression, further confirming that SRF only measures similarity in events that may have significant negative impacts. It is worth noting that $ProductSimilarity$ continues to be positive and significant, and its predictive power for $CoUp$ is even greater than that for $CoDown$, as a one-standard-deviation increase in $ProductSimilarity$ increases the likelihood of $CoUp$ being one by 0.05 percent points, which is 10% relative to the mean. Taken together, evidence in Table 2 confirms that, unlike proxies from

three months of 2001. We thus regress a firm-pair's $CoDown$ in calendar year 2002 on SRF (and other control variables) measured based on their fiscal year 2000's 10-Ks.

prior literature that measure similarities in business areas that can have both upsides and downsides, SRF captures similarity in a unique aspect of business, i.e., significant downsides.

3.3 *M&A sample selection and summary statistics*

Table 3 Panel A summarizes our sample selection process. Our initial sample includes 2,438 U.S. domestic M&A deals announced between 2006 and 2018 in the Thomson Reuters' SDC database where both the acquirer and the target are public firms.[10] We begin the sample period from 2006 because the SEC mandated risk factor disclosure in 2005. Following prior literature such as Dhaliwal et al. (2016), we restrict the sample to 2,411 M&As where the acquirer possesses less than 50% of the target before the deal and seeks to own more than 50% post-merger. We then retain 1,109 deals where both the acquirer and the target have stock return data in CRSP, financial statement data in Compustat, as well as risk factor disclosures in 10-K reports from SEC's EDGAR database. Last, we exclude deals involving firms in financial and utility industries (SIC code 6000-6999 and 4000-4949 respectively) because M&As are highly regulated in these industries (e.g., Edmans, Goldstein, and Jiang, 2012). Our final sample consists of 696 M&A deals. We measure SRF between an acquirer and a target using their most recent risk factor disclosures prior to the M&A announcement date. For illustration, Appendix II provides excerpts of risk factor disclosures of firms involved in high and low SRF deals (top and bottom quartiles respectively). We report the sample distribution by year and by industry in Panels B and C of Table 3 respectively. Most of the acquirers are in manufacturing and service industries (61.6% and 22.5% respectively). In contrast, the distribution across time is less concentrated.

[10] We also require that the deal is classified as a merger, an acquisition of majority interest, or an acquisition of assets.

Table 4 Panel A reports descriptive statistics of the dependent and the independent variables for our M&A sample. The mean (median) of SRF is 0.586 (0.611). As a comparison, Brown, Tian, and Tucker (2018) find that the mean (median) similarity between a firm's risk factor disclosures in the current and previous periods is 0.898 (0.946). In line with the results from Table 1, the magnitude of Pearson (Spearman) correlation coefficients between SRF and other firm similarity measures is moderate (as reported in Panel B of Table 4), suggesting that SRF is not merely driven by similarity or relatedness in product market, industry classification, human resource, location, asset valuation, firm size, stock returns or disclosure style. The primary measurement of M&A quality $CCAR$ has a mean (median) of 0.027 (0.015), not significantly different from zero, with a standard deviation of 0.064, indicating that although M&As do not create value on average, there is substantial variation in M&A quality.

3.4 *Research designs*

To test the effect of SRF on M&A quality, we estimate the following ordinary least squares regression model

$$M\&A\ Quality = \alpha + \beta_1\, SRF_t + \beta_2\, ProductSimilarity_t + \beta_3 RelatedInd_t + \beta_4\, RelatedHR_t + \beta_5 SameState_t + \beta_6 Q_{diff_t} + \beta_7 RelativeSize_t + \beta_7 Ret\_corr_t + \beta_8 MDA\_simi_t + \gamma\, Controls + \epsilon \quad (3)$$

Following extent literature (e.g., Hoberg and Phillips, 2010; Cai et al., 2016; Martin and Shalev, 2017; Lee, Mauer and Xu, 2018), we use the value-weighted three-day cumulative abnormal returns of both the acquirer and the target surrounding the deal announcement date ($CCAR$) as the primary measure of M&A quality. We expect a positive coefficient on SRF. The control variables include all firm-pair business similarity measures discussed in Section 3.2, i.e., product market similarity ($ProductSimilarity$), industry relatedness ($RelatedInd$), human capital relatedness ($RelatedHR$), geographic proximity ($SameState$), asset valuation similarity (Q_diff), relative firm size ($RelativeSize$), stock return correlations (Ret_corr), and MD&A similarity (MDA_simi).[11] Following prior research (e.g., Cai and Sevilir, 2012; Harford, Humphery-Jenner, and Powell, 2012; Lee, Mauer and Xu, 2018), we also include commonly used deal characteristic as control variables, such as payment method ($AllCash$ and $Stock$), and a high technology firms indicator ($HighTech$). Last, we include several firm characteristics of both acquirer and target as control variables, such as stock returns ($Runup$), firm size ($Size$), Tobin'q (Q), leverage ($Leverage$), free cash flow (FCF), cash holding ($Cash$), and return on assets (ROA), all measured in the pre-announcement window. Model 3 does not include firm fixed effects because most acquirers appear once in our sample.

In addition to M&A announcement returns, we also use post-merger operating performance, including change in return on assets (ROA_chg), the occurrence and amount of deal-related goodwill impairment ($GoodwillImpairment(Occurence)$ and $GoodwillImpairment(Amount)$), and whether the acquirer incurs high post-merger restructuring cost ($HighRestructuringCost$) to measure M&A quality. Similarly, we expect that higher SRF deals will have better subsequent operating performance, i.e., larger increase in ROA, less occurrence and amount of deal-related goodwill impairment, and smaller likelihood of incurring high restructuring costs.

[11] In the regression using M&A sample, we control for RelativeSize (i.e., the ratio of the target's market value of equity to the acquirer's market value of equity as of 11 days before the M&As announcement date) to be consistent with the literature (e.g., Lee, Mauer and Xu 2018). In contrast, we control for Size_diff (i.e., the absolute value of difference between two firms' market value in logarithm) in the regression using all possible firm-pairs, as it is unclear which firm's market value should be used as the denominator/numerator.

4. Main results

4.1 SRF *and merger announcement returns*

Table 5 reports the relation between SRF and merger announcement returns. We first report the result of estimating Model 3 with SRF being the only independent variable in Column 1, then further include other similarity measures in Column 2. Finally, we include all control variables in Column 3. Results from all columns show that SRF is positively related (significant at the 1% level or 5% level) to market assessment of M&A quality. These findings are consistent with our expectation that the market interprets mergers in which the two firms have more similar significant business downsides have better quality. The effect of SRF on M&A quality is economically significant, with a one-standard-deviation increase in SRF increasing the three-day combined return of the acquirer and the target by 0.80%, translating into an increase of market value of $275 million using the average market capitalization of the merger pairs in our sample.[12]

To provide evidence that SRF improves M&A quality through reducing acquirer's uncertainty about target, we separately estimate the model with all control variables for subgroups of M&As with high and low uncertainty, and expect that SRF's effect on M&A quality should be stronger when acquirer has more uncertainty about the target. We proxy for M&A uncertainty using several measures. First, we use geographic distance between two merging firms as prior literature suggests that distance is positively related to information

[12] Following Bena and Li (2014), we measure two firms' technological overlap using patent counts in different technology classes. The patent data is obtained from UVA Darden Global Corporate Patent Dataset (https://patents.darden.virginia.edu/). Due to the availability of patent data, we can calculate the technological overlap for only 330 observations out of our M&A sample, leading to a reduction in our sample size by more than 50%. If we control for technological overlap, we obtain an insignificant estimation for SRF, though still positive. This is not due to technological overlap absorbing the explanatory power of SRF, but the sample size reduction. If we run our model without controlling for technological overlap using the subsample where technological overlap is available, SRF is still insignificant. Moreover, we find that the correlation between SRF and technological overlap is quite low (0.13, significant at the 5% level) in our sample.

acquisition cost and information asymmetry (Sufi, 2007; Butler, 2008; Bae, Stulz and Tan, 2008; Costello, 2013; Hollander and Verriest, 2016). Specifically, we use $ShortDistance$, an indicator variable that equals one if the distance between the headquarters of the two firms is less than 500 miles, and zero otherwise (Lerner, 1995).[13] The second proxy for M&A uncertainty is the industry relatedness between the acquirer and the target (i.e., $RelatedInd$) motivated by the intuition that the acquirer is either already more familiar with the target or can more easily collect information about the target when they are in the same or related industries (Raman, Shivakumar and Tamayo, 2013). Third, we construct an indicator variable, $CEOTargetExpr$, which equals one if the acquirer's CEO has worked in the target's industry previously, and zero otherwise. Prior studies show that acquirer CEO's experience in target's industry not only leads to better target selection and M&A contract terms, but also improves post-merger integration of the two firms (Custódio and Metzger, 2013). Fourth, in the spirit of Lang and Lundholm (1996), we capture uncertainty using $HighAnalystCoverage$, an indicator variable that equals one if the number of analyst following the target is above the sample median and zero otherwise. Our last measure of information uncertainty is $CommonAuditor$, which equals one if both firms are audited by the same audit firm in the year prior to the M&A announcement, and zero otherwise. According to Cai et al. (2016), a common auditor serves as an important information intermediary, helping merging firms reduce uncertainty throughout the acquisition process and allowing managers to allocate capital more efficiently.

The results (tabulated in Table 6) show that the positive effect of SRF on M&A quality is driven entirely by sub-samples of M&As with high uncertainty. Specifically, SRF is significantly

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[13] Our results are qualitatively similar when we define $ShortDistance$ using the sample median of the geographic distance (676 miles) between the two headquarters as the threshold. Our inference also remains if we divide our sample based on the SameState indicator.

positive only in M&As when two firms are further away (Column 2), when they are not in same industries or related industries (Column 4), when acquirer CEOs do not have experience in target industry (Column 6), when analyst coverage of the target is low (Column 8), and when the two merging firms do not share the same auditor (Column 10). In contrast, SRF does not have a significant association with $CCAR$ in the sub-samples with low M&A uncertainty (Columns 1, 3, 5, 7 and 9). Chi-Square tests also show that the coefficients of SRF are significantly higher when uncertainty is measured with $RelatedInd$ and $CEOTargetExpr$ at the 1% and 5% levels respectively. Overall, our results are consistent with M&As with similar business downsides creating value through mitigating the uncertainty faced by acquirers, lending further support to our previous results.

4.2 *SRF and post-M&A operating performance*

In this section, we provide supporting evidence on the relation between SRF and M&A quality using post-merger operating performance to measure the latter. We use four measures of post-merger operating performance. First, we calculate the change in size-weighted industry-adjusted return on assets (ΔROA) for the merger pair from pre- to post-merger (Lin, Officer and Zou, 2011; Goodman et al., 2014; Cai et al., 2016). Our next three measures are based on how well acquirers integrate targets post-merger. Firms are also required to write down their goodwill when the merger synergy fails to materialize. Thus, following Ben-David, Bhattacharya and Jacobsen (2020), we manually collect the deal-related goodwill impairment data from the "Goodwill and Other Intangible Assets" note in the 10-K filings and define two variables, $GoodwillImpairment(Occurence)$ and $GoodwillImpairment(Amount)$. These two variables capture the occurrence and amount of deal-related goodwill impairment in the post-merger period, respectively. Last, integration failure often leads to firms incurring considerable costs for restructuring their operations. In line with Pan, Siegel, and Wang, (2020), we construct an indicator variable to capture restructuring activities (i.e., $HighRestructuringCost$), which equals one if the post-merger restructuring cost in the M&A year is in the top tercile of the sample, and zero otherwise.

Table 7 presents the regression results of SRF 's impact on post-merger operating performance. We find that SRF is positively related to ROA changes in the two years following M&As (both significant at the 5% level), and negatively associated with the occurrence and amount of deal-related goodwill impairment (significant at the 5% or 10% level respectively) and the likelihood of restructuring costs (significant at the 5% level), with sizable economic magnitude. For example, a one-standard-deviation increase in SRF is associated with an increase in ROA change by 1.3 percent points both in the first and the second post-merger years, respectively, which is 17% relative improvements compared to the average pre-merged ROA of 7.5%. Similarly, a one-standard-deviation increase in SRF is followed by a 4.3% (8.5%) decrease in the likelihood of deal-related goodwill impairment (incurring high restructuring costs), which is 18% (23%) relative to the 23.8% (36.9%) unconditional likelihood of goodwill impairment (incurring high restructuring costs). Overall, the results based on alternative measures of deal outcomes provide additional evidence that similarity in business downsides is associated with better quality M&As.

4.3 *SRF and M&A target selection and characteristics*

In this section, we shed lights on the relations between SRF and other aspects of the M&A process such as target selection, deal completion and payment method. First, to examine M&A target selection, we match each target in our M&A sample with three pseudo targets using a procedure similar to that used in Lee, Mauer and Xu (2018). Specifically, for each completed deal, we use the following steps to identity pseudo targets: (1) pseudo targets belong to the same product market as the real target, based on the product market classification of Hoberg and Phillips (2010); (2) pseudo targets have the same industry relatedness (in relative to the acquirer) as the real target has, so that a real related (unrelated) merger is matched with pseudo related (unrelated) firm-pairs; (3) pseudo merging firm pairs must not engage in M&As in years t-1 and t; (4) we identify the three firms that have the closest market capitalization to the target; (5) we select one firm with the closest market-to-book ratio (M/B) to the target. We calculate SRF between pseudo merger pairs using their latest 10-K filings prior to the actual M&A announcement dates and estimate a probit model in which the dependent variable ($Target$) is an indicator variable that equals one for real targets and zero for pseudo targets. As tabulated in Table 8 Column 1, the estimated coefficient on SRF is positive and significant at the 1% level. In terms of economic significance, the marginal effect of SRF shows that a one-standard-deviation increase in SRF results a 13.2% higher odds of being selected as a target (6.6% relative to an unconditional likelihood of 50% in the sample). In comparison, one-standard-deviation increases in $ProductSimilarity$ and Ret_corr are associated with 37.2% and 15.4% higher odds of being selected as a target respectively. Further, we compare the likelihoods of the models with and without SRF, and find that the model with SRF performs significantly better in identifying targets (Likelihood-Ratio test is significant at the 1% level).

We next investigate the associations between SRF and deal completion and payment methods. First, we use $\mathrm{Completion}$, an indicator variable that equals one if the M&A is completed and zero if it is withdrawn, as the dependent variable, and find that the estimated coefficient on SRF is positive and significant at the 1% level. This is consistent with that familiarity with the target's business downsides mitigates acquirer's uncertainty and improves deal completion likelihood. Economically, a one-standard-deviation increase in SRF is associated with an increase in completion probability by 4.6%, relative to the unconditional likelihood of 85.7%. Second, we use the percentage of equity used in M&A payment ($\mathrm{StockPct}$) as the dependent variable, and find that SRF is negatively associated with the percentage of equity used in payment (significant at the 10% level). In terms of economic magnitude, a one-standard-deviation increase in SRF increases the odds of deal completion by 5.4% (4.6% relative to the unconditional completion rate of 85.3%) and decreases the percentage of equity payments in deals by 13.3% (3.4% relative to the average percentage of equity payments of 25.6%). This result is consistent with that acquirers face less uncertainty when targets have more similar significant business downsides, and thus have less need to use equity to share the risk of overpayment with target's shareholders (Raman, Shivakumar and Tamayo, 2013). Collectively, these tests lend further supports to that similarity in a distinct aspect of the business, namely the downsides, mitigates uncertainty faced by acquirers and improves M&A quality.

4.4 SRF *and change in stock return volatility*

Finance theory suggests that shareholders have incentives to increase firm risk to expropriate bondholders' wealth (Jensen and Meckling, 1976; Asquith and Kim, 1982), including undertaking investments such as risk-increasing M&As (Agrawal and Mandelker, 1987, Datta, Iskandar-Datta and Raman, 2001). Thus, an alternative explanation for the favorable market reactions to mergers of firms with high SRF is that such transactions may lead to greater risk in the combined entities. Therefore, we examine whether the change in acquirer's stock return volatility is related to SRF. We use two measures in this test. First, following Datta, Iskandar-Datta and Raman (2001), we use the change in acquirers' stock return volatility from the pre- to the post-merger period as the dependent variable ($Volatility\_chg$) and re-estimate

Model 3. Our second measure is an indicator variable ($Volatility\_increase$) that equals one if acquirer's stock return volatility in post-merger is greater than acquirer's stock return volatility in pre-merger, and zero otherwise. As tabulated in Table 9, the estimated coefficient on SRF is insignificantly different from zero for both dependent variables. Thus, we do not find evidence supporting that the positive market reactions to M&As with higher SRF are driven by acquirers in these deals taking more risks.

5. Conclusion

In the M&A process, uncertainty hinders acquirers' ability to value targets and to assess potential synergy. One aspect of uncertainty that has been under-explored is target businesses' downsides. We show that similarities in risk factor disclosures capture similarity in a unique aspect of business, i.e., significant downsides, that is not captured by existing measures of business similarity. We also find that consistent with our expectation, SRF is only associated with a firm-pair's likelihood of co-experiencing extreme negative returns but not that of extreme positive returns.

We find that, controlling for business similarity measures from prior literature, higher SRF between two merging firms increases merger announcement returns, especially when acquirers face higher uncertainty about the target, and leads to better post-merger operating performance measured with profitability, goodwill impairment and restructuring costs. Additional analyses show that acquirers are more likely to select targets exhibiting similar potential downsides, and deals with higher SRF are more likely to complete and use less equity in payment. Altogether, our results suggest that commonality in business downsides narrows the information gap between acquirers and targets and improves M&A outcomes.

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Appendix I: Variable Definitions

Variables	Definitions
Main variables:	
SRF	The cosine similarity in word vectors between two firms' risk factor section (Item 1A) in 10-K fillings.
$CCAR$	The value-weighted three-day cumulative abnormal returns of both the acquirer and the target surrounding the deal announcement date. We first estimate Fama-French three-factor model parameters over the period from 210 days before to 11 days before the M&As announcement date for merging firms, and calculate abnormal stock return as a firm's raw stock return minus the predicted return from the Fama-French three-factor model. Then, CCAR is calculated as the average of 3-day cumulative abnormal returns of merging firms, weighted by their respective market value of equity as of 11 days before the M&As announcement date.
Firm Similarity Variables:	
$ProductSimilarity$	The cosine similarity in word vectors between two firm's business description section in 10-K fillings (Hoberg and Phillips, 2010). We obtain this measure from Hoberg-Phillips Data Library.
$RelatedInd$	An indicator variable that equals to one if two firms are classified as vertically related or horizontally related, and zero otherwise. Following Fan and Goyal (2006), two firms are vertically related if they are from different industries but exhibit vertical relatedness with the 1% cutoff. Two firms are horizontally related if they are from same industry.
$RelatedHR$	The cosine similarity of firms' human capital profile vectors derived from industry segment occupation profile between two firms (Lee, Mauer and Xu, 2018).
$SameState$	An indicator variable that takes value of one if two firms are headquartered at the same state, and zero otherwise.
Q_diff	The absolute value of difference between two firms' q, as a proxy for valuation similarity.
$Size\_diff$	The absolute value of difference between two firms' market value in logarithm.
Ret_corr	The correlation of two firms' raw stock returns in the same calendar year. In the M&A sample, the correlation of the acquirer's and the target's raw stock returns is calculated using the 12-month period ending two months prior to M&A announcement date.
MDA_simi	The cosine similarity in word vectors between two firm's MDA section in 10-K fillings.
$RelativeSize$	The ratio of the target's market value of equity to the acquirer's market value of equity as of 11 days before the M&As announcement date.
Deal-level characteristics:	
$AllCash$	An indicator variable that equals to one if the M&A deal is financed with cash only, and zero otherwise.
$Stock$	An indicator variable that equals to one if the M&A deal is partially financed with equity, and zero otherwise.
$HighTech$	An indicator variable that equals to one if both the acquirer and the target are from technology industries, and zero otherwise. Following Harford, Humphery-Jenner, and Powell (2012), tech industries include computer hardware (SIC codes 3571, 3572, 3575, 3577, 3578); communications equipment (3661,3663,3669); electronics (3671, 3672, 3674, 3675, 3677, 3678, 3679); navigation equipment (3812); measuring and controlling devices (3823, 3825, 3826, 3827, 3829); medical instruments (4812, 4813); telephone equipment (4899) and software (7371, 7372, 7373, 7374, 7375, 7378, 7379).
Firm-level characteristics:	
$Runup$	The buy-and-hold abnormal stock returns during the period from 210 days before to 11

	days prior to the M&A announcement date.
$Size$	The natural logarithm of book value of total assets at the fiscal year-end immediately prior to the M&A announcement date.
Q	Book value of total assets divided by market value of equity plus book value of total assets minus book value of equity at the fiscal year-end immediately prior to the M&A announcement date.
$Leverage$	Book value of debt (long-term debt plus short-term debt) divided by market value of equity plus book value of total assets minus book value of equity at the fiscal year-end immediately prior to the M&A announcement date.
FCF	The ratio of operating income before depreciation minus interest expense minus income taxes minus capital expenditures to total assets at the fiscal year-end immediately prior to the M&A announcement date.
$Cash$	The ratio of cash holdings to total assets at the fiscal year-end immediately prior to the M&A announcement date.
ROA	The ratio of operating income before depreciation to total assets at the fiscal year-end immediately prior to the M&A announcement date.
Other Variables:	
$CoDown$	An indicator variable, equal to one if two firms experience extreme negative weekly return in at least one same week during a year. We define weekly returns as extremely negative if they are at least 3.2 standard deviations below the mean of raw weekly returns during the previous the year.
$CoUp$	An indicator variable, equal to one if two firms experience extreme positive weekly return in at least one same week during a year. We define weekly returns as extremely positive if they are at least 3.2 standard deviations above the mean of raw weekly returns during the previous year.
$ShortDistance$	An indicator variable that equals one if the distance between the headquarters of acquirer and target is less than 500 miles, and zero otherwise.
$CEOTargetExpr$	An indicator variable that equals one if the acquirer's CEO has worked in the target's industry, and zero otherwise.
$HighAnalystCoverage$	An indicator variable that equals one if the number of analyst following the target is above the sample median, and zero otherwise.
$CommonAuditor$	An indicator variable that equals one if acquirer and target are audited by the same audit firm in the year prior to the M&A announcement, and zero otherwise.
ROA_chg	The change in return on assets for the merger pair from pre- to post-merger. Pre-merger ROA is the size weighted average of industry-adjusted ROA of the two firms in the fiscal year preceding deal announcement. Post-merger ROA is the industry-adjusted ROA of the combined firm in the years following deal completion.
$GoodwillImpairment$ $(Occurence)$	An indicator variable that equals one if the acquirer has any deal-related goodwill impairment disclosed in the "Goodwill and Other Intangible Assets" note in the 10-K filings during the post-merger period, and zero otherwise.
$GoodwillImpairment$ $(Amount)$	The total amount of deal-related goodwill impairment disclosed in the "Goodwill and Other Intangible Assets" note in the 10-K filings during the post-merger period
$HighRestructuringCost$	an indicator variable, equals one if the restructuring cost in the M&A year is in the top tercile of the sample, and zero otherwise.
$Target$	An indicator variable that equals one for real targets and zero for pseudo targets. For each merging acquirer firm, we match it with three non-merging target firm (pseudo target) based on product market similarity, industry relatedness, market capitalization, and market-to-book ratio.
$Completion$	An indicator variable that equals one if the M&A is completed and zero if it is withdrawn.
$StockPct$	The percentage of equity used by the acquirer in M&A payment.
$Volatility\_chg$	Acquirer's stock return volatility in post-merger period minus acquirer's stock return volatility in the pre-merger period.

$Volatility\_increase$	An indicator variable that equals one if acquirer's stock return volatility in post-merger is greater than acquirer's stock return volatility in pre-merger, and zero otherwise.

Appendix II: Illustrations of acquirer and target risk factors with high and low similarity

This appendix illustrates examples of risk factors from acquirers and targets of two M&As, one with high SRF and one with low SRF. To ease comparisons, we highlight the keywords appearing in both firms' risk factors disclosure.

High SRF example: The acquisition of Oclaro, Inc. (NASDAQ: OCLR) by Lumentum Holdings Inc. (NASDAQ: LITE) in 2018. The SRF for this merger pair is 0.762.

Lumentum Holdings Inc. (NASDAQ: LITE)	Oclaro, Inc. (NASDAQ: OCLR)
*We depend on **a limited number of suppliers for raw materials**, packages and components, and any failure or delay by these suppliers in meeting our requirements could have an adverse effect on our business and results of operations.* *We rely on **a limited number of customers** for a significant portion of our sales; and the majority of our customers **do not have contractual purchase commitments**.* *The **manufacturing of our products** may be adversely affected if our contract manufacturers and suppliers fail to meet our **production requirements** or if we are unable to manufacture certain products in our manufacturing facilities.* *Our products may contain **defects** that could cause us to incur significant costs, divert our attention from product development efforts and result in a loss of customers.* *Our operating results may be subject to volatility due to fluctuations in foreign **currency**.* *We expect to change our **international** corporate structure in the near future in order to minimize our effective **tax rate**; however, if we are unable to adopt this structure or if it is challenged by U.S. or foreign tax authorities, we may be unable to realize such **tax savings** which could materially and adversely affect our operating results.* *Our ability to develop, market, and sell products could be harmed if we are unable to retain or hire **key personnel*** ……	*We depend on **a limited number of suppliers of raw materials and equipment** used to manufacture our products.* *We depend on **a limited number of customers** for a significant percentage of our revenues and the loss of a major customer could have a materially adverse impact on our financial condition. Many of our customers typically purchase our products pursuant to individual purchase orders or contracts that **do not contain purchase commitments**.* ***Customer requirements** for new **products** are increasingly challenging, which could lead to significant executional risk in designing and **manufacturing such products**.* *Despite quality assurance measures, defects may occur in our products. The occurrence of any **defects** in our products could give rise to liability for damages caused by such defects, including consequential damages.* *As a result of our global operations, our business is subject to **currency** fluctuations that may adversely affect our results of operations.* *We have a complex **multinational tax structure**, and changes in effective **tax rates** or adverse outcomes resulting from examination of our income tax returns could adversely affect our results.* *If we fail to attract and retain **key personnel,** our business could suffer.* ……

Low SRF example: The acquisition of Opower (NYSE: OPWR) by Oracle (NYSE: ORCL) in 2016. The SRF for this merger pair is 0.396.

Oracle Corporation (NYSE: ORCL)	Opower, Inc. (OPWR)
Economic, political and market conditions can adversely affect our business, results of operations and financial condition, including our revenue growth and profitability, which in turn could adversely affect our stock price. *We may experience foreign currency gains and losses. Changes in currency exchange rates can adversely affect customer demand and our revenue and profitability.* *We may fail to achieve our financial* ***forecasts*** *due to inaccurate sales forecasts or other factors.* *Our Oracle Cloud strategy, including our Oracle Software as a Service (SaaS), Platform as a Service (PaaS), Infrastructure as a Service (IaaS) and Data as a Service (DaaS) offerings, may adversely affect our revenues and profitability.* *Our success depends upon our ability to develop new* ***products*** *and* ***services****, integrate acquired* ***products*** *and* ***services*** *and enhance our existing products and services.* *Our software indirect sales channel could affect our future operating results.* *We may not be able to protect our intellectual property rights.* ……	*We have a history of losses and anticipate continued losses and negative operating cash flow in the future. We may not be able to achieve or sustain profitability on a quarterly or annual basis.* *Sales cycles and implementation times can be lengthy and unpredictable and require significant employee time and financial resources.* *We are dependent in part on regulations on the utility industry, and the changing regulatory landscape could alter our clients' buying patterns.* *If we fail to respond to evolving technological changes, our* ***products*** *and solutions could become obsolete or less competitive.* *Because we recognize subscription revenue over the term of the contract following the initial launch of our* ***services****, downturns or upturns in new sales will not be immediately reflected in our results of operations and may be difficult to discern.* *Many of our client agreements provide our clients with the ability to terminate the agreement for convenience, which may limit our ability to* ***forecast*** *our revenue accurately.* *If we fail to retain qualified personnel, our financial performance may suffer.* ……

Table 1: Determinants of Risk Factor Similarity

This table examines the determinants of risk factor similarity. Panel A shows the summary statistics for the sample. Panel B shows the regression results. We estimate the OLS regression: $SRF_t = f(ProductSimilarity_t, RelatedInd_t, RelatedHR_t, SameState_t, Q\_diff_t, Size\_diff_t, Ret\_corr_t, MDA\_simi_t) + \varepsilon$. Variable definitions are in Appendix I. The sample includes all possible firm-pairs between 2006 and 2018. We report t-stat (in parentheses) that are computed using robust standard errors. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively. All potentially unbounded variables are winsorized at 1% and 99% levels. Panel C presents results of change model. The dependent variable is the change of SRF from the prior period.

Panel A: Summary Statistics of the Sample

	N	Mean	SD	1%	Q1	Median	Q3	99%
SRF	42,357,768	0.302	0.134	0.075	0.203	0.284	0.381	0.689
$ProductSimilarity$	42,357,768	0.018	0.037	0.000	0.000	0.000	0.021	0.202
$RelatedInd$	42,357,768	0.079	0.270	0.000	0.000	0.000	0.000	1.000
$RelatedHR$	42,357,768	0.402	0.250	0.021	0.199	0.351	0.572	1.000
$SameState$	42,357,768	0.060	0.238	0.000	0.000	0.000	0.000	1.000
Q_diff	42,357,768	1.936	38.386	0.008	0.254	0.665	1.587	10.655
$Size\_diff$	42,357,768	2.166	1.629	0.034	0.868	1.835	3.128	6.931
Ret_corr	42,357,768	0.205	0.176	-0.092	0.069	0.177	0.319	0.663
MDA_simi	42,357,768	0.318	0.137	0.021	0.240	0.322	0.405	0.672

Panel B: Regression Results

Dep Var = SRF	(1)	(2)	(3)
$ProductSimilarity$	0.769***	0.982***	0.982***
	(23.28)	(32.10)	(29.99)
$RelatedInd$	0.009***	0.032***	0.032***
	(3.42)	(15.33)	(15.48)
$RelatedHR$	0.080***	0.053***	0.065***
	(11.81)	(17.37)	(27.35)
$SameState$	0.007***	0.008***	0.008***
	(3.07)	(8.34)	(8.81)
Q_diff	-0.000**	-0.000	-0.000
	(-2.18)	(-1.19)	(-1.59)
$Size\_diff$	0.003***	0.001	-0.000*
	(2.79)	(1.20)	(-2.08)
Ret_corr	0.064***	0.041*	0.028***
	(4.16)	(2.17)	(5.87)
MDA_simi	0.395***	0.279***	0.255***
	(17.66)	(14.78)	(14.03)
Firm1 FEs	No	Yes	Yes
Firm2 FEs	No	Yes	Yes
Year FEs	No	No	Yes
# of Obs.	42,357,768	42,357,768	42,357,768

Adjusted R^2	0.346	0.726	0.748

Panel C: Change Model

Dep Var = $\Delta \boldsymbol{SRF}$	(1)	(2)	(3)
$\Delta ProductSimilarity$	0.059***	0.057***	0.053***
	(3.62)	(4.24)	(4.83)
$\Delta RelatedHR$	-0.003*	-0.002	-0.001
	(-1.67)	(-1.05)	(-0.41)
ΔQ_diff	-0.000***	-0.000***	-0.000***
	(-4.08)	(-4.05)	(-7.99)
$\Delta Size\_diff$	0.001	0.001	0.000
	(1.59)	(1.42)	(0.54)
ΔRet_corr	0.012	0.011	0.005*
	(1.53)	(1.77)	(2.03)
ΔMDA_simi	0.041***	0.036***	0.034***
	(5.78)	(5.71)	(6.15)
Firm1 FEs	No	Yes	Yes
Firm2 FEs	No	Yes	Yes
Year FEs	No	No	Yes
# of Obs.	31,500,322	31,500,322	31,500,322
Adjusted R^2	0.006	0.084	0.094

Table 2: Risk Factor Similarity and Co-occurrence of Extreme Returns

This table examines the effect of risk factor similarity on the co-occurrence of extreme negative and positive returns. Panel A shows the summary statistics for the sample. Panel B shows the regression results. We estimate the Probit regression: $CoDown_t/CoUp_t = f(SRF_{t-2}, ProductSimilarity_{t-2}, RelatedInd_{t-2}, RelatedHR_{t-2}, SameState_{t-2}, Q\_diff_{t-2}, Size\_diff_{t-2}, Ret\_corr_{t-2}, MDA\_simi_{t-2}) + \varepsilon$. All regressions include firm and year fixed effects. Variable definitions are in Appendix I. The sample includes all possible firm-pairs between 2006 and 2018. We report *t*-stat (in parentheses) that are computed using robust standard errors. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively. All potentially unbounded variables are winsorized at 1% and 99% levels.

Panel A: Summary Statistics of the Sample

	N	Mean	SD	1%	Q1	Median	Q3	99%
$CoDown$	31,971,429	0.005	0.074	0.000	0.000	0.000	0.000	0.000
$CoUp$	31,971,429	0.005	0.068	0.000	0.000	0.000	0.000	0.000
SRF	31,971,429	0.298	0.130	0.076	0.202	0.282	0.377	0.680
$ProductSimilarity$	31,971,429	0.017	0.033	0.000	0.000	0.000	0.021	0.200
$RelatedInd$	31,971,429	0.079	0.270	0.000	0.000	0.000	0.000	1.000
$RelatedHR$	31,971,429	0.405	0.251	0.021	0.201	0.355	0.578	1.000
$SameState$	31,971,429	0.060	0.237	0.000	0.000	0.000	0.000	1.000
Q_diff	31,971,429	1.353	1.939	0.008	0.252	0.660	1.589	10.558
$Size\_diff$	31,971,429	2.131	1.582	0.034	0.856	1.810	3.087	6.848
Ret_corr	31,971,429	0.217	0.178	-0.089	0.076	0.190	0.338	0.669
MDA_simi	31,971,429	0.318	0.140	0.020	0.238	0.321	0.405	0.670

Panel B: Regression Results

	(1)	(2)
Dep Var =	$\boldsymbol{CoDown}$	$\boldsymbol{CoUp}$
SRF	0.382**	-0.052
	(2.43)	(-0.89)
$ProductSimilarity$	1.236***	1.287***
	(4.08)	(4.54)
$RelatedInd$	0.009	0.043***
	(1.22)	(3.23)
$RelatedHR$	-0.049	0.088***
	(-1.57)	(3.96)
$SameState$	0.019	0.012*
	(1.22)	(1.65)
Q_diff	-0.001	-0.029***
	(-0.13)	(-2.66)
$Size\_diff$	-0.034***	-0.027***
	(-4.68)	(-3.59)
Ret_corr	0.16	0.162

	(1.02)	(1.34)
MDA_simi	-0.003	0.036
	(-0.03)	(0.53)
Firm1 FEs	Yes	Yes
Firm2 FEs	Yes	Yes
Year FEs	Yes	Yes
# of Obs.	31,971,429	31,971,429
Pseudo R^2s	0.410	0.243

Table 3: M&A Sample Selection and Distribution

This table presents the selection process and the distribution of the M&A sample. Panel A shows the sample selection process. Panel B shows our sample distribution over years. Panel C shows our sample distribution across industries based on two-digit SIC code.

Panel A: Sample Selection

Criteria	# of Obs.
U.S. domestic M&A deals between two public firms that are announced during 2006-2018 in the Thomson Reuters' SDC database	2,438
Require the acquirer possesses less than 50% of the target before the deal and seeks to own more than 50% post-merger	2,411
Require both the acquirer and the target have stock return data in CRSP, financial statement data in Compustat, as well as risk factor disclosures from 10-K reports	1,109
Exclude deals involving firms in financial industries (SIC code 6000-6999) or utility industries (SIC code 4000-4949)	696
Final sample	696

Panel B: Sample Distribution over Years

Year	Number of deals	Percentage of sample (%)
2006	44	6.32
2007	76	10.92
2008	66	9.48
2009	68	9.77
2010	59	8.48
2011	37	5.32
2012	43	6.18
2013	33	4.74
2014	50	7.18
2015	73	10.49
2016	61	8.76
2017	44	6.32
2018	42	6.03
Total	696	100.00

Panel C: Sample Distribution across Industries Based on Two-digit SIC Code

	Acquirer		Target		Percentage of firms in Compustat (%)
	Number of deals	Percentage of sample (%)	Number of deals	Percentage of sample (%)	
Agriculture, Forestry and Fishing	1	0.14	1	0.14	0.33
Mining	32	4.59	33	4.73	6.48
Construction	6	0.86	6	0.86	1.64
Manufacturing	429	61.55	412	59.11	55.61
Transportation, Communications, Electric, Gas and Sanitary service	2	0.29	3	0.43	0.76
Wholesale Trade	17	2.44	23	3.30	4.10
Retail Trade	46	6.60	37	5.31	7.99
Services	157	22.53	179	25.68	22.39
Non-classifiable	6	0.86	2	0.29	0.69
Total	696	100	696	100	100

Table 4: Summary Statistics and Correlation Matrix

This table presents summary statistics and correlation matrix of the main variables used for the M&A sample. Panel A shows summary statistics. Panel B shows Spearman correlation coefficients (the upper diagonal elements) and Pearson correlation coefficients (the lower diagonal elements) between the variables. Coefficients in bold font are significantly correlated (p-value < 0.1). Variable definitions are in Appendix I. All potentially unbounded variables are winsorized at 1% and 99% levels.

Panel A: Summary Statistics

	N	Mean	Std Dev	P25	Median	P75
Merger returns						
CCAR	696	0.027	0.064	-0.006	0.015	0.055
Acquirer-Target similarity measures						
SRF	696	0.586	0.174	0.475	0.611	0.716
ProductSimilarity	696	0.146	0.112	0.085	0.135	0.188
RelatedInd	696	0.526	0.500	0.000	1.000	1.000
RelatedHR	696	0.854	0.177	0.802	0.915	0.980
SameState	696	0.237	0.426	0.000	0.000	0.000
Q_diff	696	0.972	1.101	0.230	0.587	1.253
RelativeSize	696	0.287	0.398	0.037	0.135	0.392
Ret_corr	696	0.332	0.212	0.159	0.317	0.486
MDA_simi	696	0.524	0.196	0.447	0.557	0.650
Deal characteristics						
AllCash	696	0.511	0.500	0.000	1.000	1.000
Stock	696	0.339	0.474	0.000	0.000	1.000
HighTech	696	0.230	0.421	0.000	0.000	0.000
Acquirer characteristics						
Runup	696	0.054	0.291	-0.115	0.020	0.190
Size	696	8.367	1.965	6.990	8.358	9.961
Q	696	2.174	1.223	1.406	1.846	2.547
Leverage	696	0.132	0.128	0.036	0.106	0.177
FCF	696	0.051	0.103	0.028	0.070	0.100
Cash	696	0.197	0.172	0.062	0.139	0.292
ROA	696	0.126	0.109	0.095	0.135	0.178
Target characteristics						
Runup	696	0.058	0.574	-0.242	-0.038	0.206
Size	696	6.202	1.778	4.810	6.117	7.509
Q	696	2.080	1.328	1.250	1.677	2.419
Leverage	696	0.127	0.152	0.000	0.075	0.195
FCF	696	-0.046	0.248	-0.053	0.032	0.071
Cash	696	0.275	0.248	0.054	0.204	0.434
ROA	696	0.025	0.245	0.008	0.093	0.145

Panel B: Correlation Matrix

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	$CCAR$		**0.14**	**0.09**	0.06	0.05	-0.02	**-0.17**	**0.33**	**0.14**	**0.12**	0.00	0.02	0.04	**-0.11**
2	SRF	**0.14**		**0.41**	**0.34**	**0.30**	**0.19**	-0.05	**0.30**	**0.20**	**0.59**	**-0.17**	**0.19**	**0.19**	**-0.08**
3	$ProductSimilarity$	0.06	**0.35**		**0.36**	**0.14**	**0.15**	-0.01	**0.25**	**0.15**	**0.37**	**-0.18**	**0.21**	**0.09**	-0.04
4	$RelatedInd$	0.04	**0.33**	**0.28**		**0.31**	**0.08**	0.01	**0.10**	**0.09**	**0.27**	**-0.07**	**0.07**	**0.27**	-0.05
5	$RelatedHR$	0.03	**0.29**	**0.12**	**0.30**		0.02	-0.01	**0.10**	**0.09**	**0.23**	0.03	0.00	**0.20**	**-0.08**
6	$SameState$	-0.02	**0.17**	**0.19**	**0.08**	-0.01		**0.09**	**0.10**	0.05	**0.18**	**-0.07**	**0.10**	**0.11**	-0.05
7	Q_diff	**-0.15**	-0.05	-0.03	0.04	0.01	**0.08**		**-0.26**	**-0.21**	**-0.08**	**0.09**	**-0.10**	**0.08**	0.04
8	$RelativeSize$	**0.24**	**0.18**	**0.24**	**0.07**	0.06	**0.11**	**-0.17**		**0.33**	**0.36**	**-0.45**	**0.49**	-0.04	**-0.08**
9	Ret_corr	**0.16**	**0.18**	**0.16**	**0.10**	**0.11**	**0.08**	**-0.21**	**0.18**		**0.17**	**-0.16**	**0.15**	-0.02	-0.02
10	MDA_simi	**0.13**	**0.53**	**0.33**	**0.22**	**0.15**	**0.18**	**-0.09**	**0.22**	**0.14**		**-0.15**	**0.23**	**0.17**	0.00
11	$AllCash$	-0.01	**-0.14**	**-0.21**	**-0.07**	0.03	**-0.07**	0.05	**-0.36**	**-0.19**	**-0.13**		**-0.73**	**0.17**	0.02
12	$Stock$	0.03	**0.16**	**0.25**	**0.07**	0.01	**0.10**	**-0.07**	**0.38**	**0.17**	**0.20**	**-0.73**		**-0.10**	-0.03
13	$HighTech$	0.03	**0.20**	0.00	**0.27**	**0.15**	**0.11**	0.01	-0.05	-0.03	**0.18**	**0.17**	**-0.10**		-0.01
14	$Runup$ $(Acquirer)$	**-0.12**	**-0.07**	-0.02	-0.04	**-0.07**	-0.05	0.04	**-0.08**	-0.06	0.02	-0.03	0.04	-0.01	
15	$Size$ $(Acquirer)$	**-0.16**	**-0.27**	**-0.21**	**-0.06**	-0.04	-0.05	0.05	**-0.31**	**0.28**	**-0.37**	**0.20**	**-0.34**	**-0.13**	-0.01
16	Q $(Acquirer)$	**-0.16**	0.00	0.04	0.00	-0.02	0.05	**0.55**	**-0.17**	**-0.12**	-0.03	0.03	-0.04	0.04	0.05
17	$Leverage$ $(Acquirer)$	**0.18**	0.01	0.06	-0.01	0.02	**-0.08**	**-0.23**	**0.13**	**0.14**	0.06	**-0.12**	**0.14**	**-0.21**	**0.07**
18	FCF $(Acquirer)$	0.04	**-0.14**	**-0.17**	-0.05	-0.01	**-0.11**	-0.03	**-0.15**	0.06	**-0.18**	**0.23**	**-0.29**	**0.14**	**0.09**
19	$Cash$ $(Acquirer)$	**-0.09**	**0.09**	**0.08**	**0.09**	0.02	**0.09**	**0.25**	**-0.09**	**-0.17**	**0.13**	0.04	-0.02	**0.25**	0.02
20	ROA $(Acquirer)$	**0.08**	**-0.16**	**-0.13**	-0.01	-0.01	-0.06	**-0.07**	**-0.14**	**0.19**	**-0.17**	**0.17**	**-0.23**	0.03	0.04
21	$Runup$ $(Target)$	0.00	-0.03	-0.01	0.01	-0.01	0.00	0.04	-0.05	0.00	-0.04	0.05	-0.04	-0.03	**0.20**
22	$Size$ $(Target)$	**0.09**	0.03	0.05	0.01	0.00	0.06	**-0.19**	**0.30**	**0.64**	0.01	**-0.24**	**0.11**	**-0.15**	-0.03
23	Q $(Target)$	**-0.12**	**-0.08**	-0.03	0.05	0.05	**0.07**	**0.61**	**-0.12**	**-0.12**	**-0.13**	**0.09**	**-0.10**	-0.01	0.05
24	$Leverage$ $(Target)$	**0.11**	**0.08**	**0.11**	0.03	0.01	-0.04	**-0.21**	**0.15**	**0.23**	**0.13**	**-0.27**	**0.19**	**-0.27**	-0.01
25	FCF $(Target)$	**0.20**	0.02	-0.05	**-0.12**	-0.04	-0.06	**-0.33**	**0.17**	**0.26**	0.04	0.05	-0.04	**0.08**	0.00
26	$Cash$ $(Target)$	**-0.15**	0.04	**0.07**	**0.18**	**0.10**	**0.07**	**0.34**	**-0.20**	**-0.31**	-0.02	**0.14**	**-0.11**	**0.15**	0.00
27	ROA $(Target)$	**0.21**	0.03	-0.04	**-0.10**	-0.03	-0.03	**-0.33**	**0.19**	**0.32**	0.05	0.02	-0.02	0.03	-0.02

	Variable	15	16	17	18	19	20	21	22	23	24	25	26	27
1	$CCAR$	**-0.24**	**-0.17**	**0.07**	-0.03	**-0.07**	0.00	-0.02	**0.07**	**-0.12**	**0.07**	**0.17**	**-0.13**	**0.19**
2	SRF	**-0.28**	-0.03	-0.02	**-0.15**	0.06	**-0.13**	-0.01	0.06	**-0.06**	0.05	-0.06	0.05	-0.01
3	$ProductSimilarity$	**-0.25**	-0.01	-0.03	**-0.14**	**0.15**	**-0.07**	-0.04	0.03	-0.02	0.06	**-0.11**	**0.11**	**-0.07**
4	$RelatedInd$	**-0.07**	0.01	-0.04	0.02	**0.09**	0.05	0.01	0.01	0.05	0.01	**-0.15**	**0.15**	**-0.08**
5	$RelatedHR$	**-0.08**	0.02	0.03	0.06	0.03	0.06	-0.02	0.01	0.04	0.00	0.01	**0.09**	0.03
6	$SameState$	-0.05	0.05	**-0.09**	**-0.08**	**0.08**	-0.05	0.01	0.05	**0.08**	-0.05	-0.05	**0.08**	-0.04
7	Q_diff	0.02	**0.51**	**-0.26**	**0.17**	**0.29**	**0.11**	-0.05	**-0.22**	**0.39**	**-0.26**	**-0.18**	**0.32**	**-0.23**
8	$RelativeSize$	**-0.44**	**-0.27**	**0.12**	**-0.25**	**-0.14**	**-0.18**	0.04	**0.43**	**-0.15**	**0.26**	**0.28**	**-0.30**	**0.34**
9	Ret_corr	**0.28**	**-0.10**	**0.15**	**0.08**	**-0.18**	**0.17**	**0.09**	**0.64**	**-0.09**	**0.24**	**0.26**	**-0.29**	**0.37**
10	MDA_simi	**-0.35**	**-0.08**	-0.02	**-0.19**	**0.08**	**-0.13**	-0.03	**0.07**	**-0.15**	**0.12**	-0.02	-0.02	0.03
11	$AllCash$	**0.18**	**0.08**	**-0.09**	**0.23**	**0.07**	**0.16**	**0.07**	**-0.24**	**0.15**	**-0.29**	0.00	**0.17**	-0.05
12	$Stock$	**-0.33**	**-0.11**	**0.10**	**-0.27**	**-0.08**	**-0.20**	-0.05	**0.12**	**-0.13**	**0.20**	0.01	**-0.14**	0.06
13	$HighTech$	**-0.14**	**0.13**	**-0.22**	**0.14**	**0.29**	-0.04	0.02	**-0.16**	0.06	**-0.31**	0.00	**0.23**	**-0.11**
14	$Runup$ $(Acquirer)$	**0.08**	0.03	0.04	**0.08**	0.01	0.02	**0.25**	0.03	0.03	0.01	0.04	0.00	0.01
15	$Size$ $(Acquirer)$		0.03	**0.26**	**0.29**	**-0.19**	**0.28**	**0.15**	**0.47**	**0.24**	**0.07**	**0.11**	-0.06	**0.14**
16	Q $(Acquirer)$	**-0.07**		**-0.48**	**0.42**	**0.38**	**0.40**	-0.02	**-0.08**	**0.39**	**-0.28**	**-0.06**	**0.32**	**-0.14**
17	$Leverage$ $(Acquirer)$	**0.17**	**-0.40**		**-0.16**	**-0.55**	**-0.07**	0.03	**0.28**	**-0.20**	**0.39**	**0.11**	**-0.35**	**0.20**
18	FCF $(Acquirer)$	**0.30**	0.04	**-0.14**		**0.12**	**0.77**	**0.12**	**0.06**	**0.25**	**-0.17**	**0.21**	**0.14**	**0.13**
19	$Cash$ $(Acquirer)$	**-0.27**	**0.39**	**-0.44**	**-0.13**		-0.03	**-0.07**	**-0.26**	**0.18**	**-0.34**	**-0.23**	**0.51**	**-0.32**
20	ROA $(Acquirer)$	**0.37**	**0.06**	0.01	**0.82**	**-0.25**		**0.12**	**0.17**	**0.17**	-0.02	**0.18**	-0.01	**0.26**
21	$Runup$ $(Target)$	**0.15**	-0.02	0.00	**0.12**	**-0.08**	**0.15**		0.06	**0.07**	-0.05	**0.19**	-0.01	**0.15**
22	$Size$ $(Target)$	**0.49**	**-0.10**	**0.21**	**0.11**	**-0.25**	**0.23**	-0.05		**-0.11**	**0.46**	**0.34**	**-0.47**	**0.45**
23	Q $(Target)$	**0.22**	**0.32**	**-0.18**	**0.10**	**0.14**	0.05	**0.15**	**-0.14**		**-0.42**	**0.10**	**0.41**	0.05
24	$Leverage$ $(Target)$	0.02	**-0.23**	**0.44**	**-0.16**	**-0.27**	-0.03	-0.05	**0.36**	**-0.34**		0.03	**-0.57**	**0.18**
25	FCF $(Target)$	**0.09**	**-0.15**	**0.10**	**0.30**	**-0.23**	**0.32**	0.04	**0.39**	**-0.22**	0.02		**-0.30**	**0.83**
26	$Cash$ $(Target)$	**-0.09**	**0.31**	**-0.31**	**-0.09**	**0.47**	**-0.19**	**0.08**	**-0.47**	**0.39**	**-0.41**	**-0.43**		**-0.44**
27	ROA $(Target)$	**0.12**	**-0.18**	**0.14**	**0.27**	**-0.28**	**0.36**	0.02	**0.44**	**-0.22**	**0.09**	**0.96**	**-0.50**	

Table 5: Similarity in Risk Factors and Merger Announcement Returns

This table examines the relation between risk factor similarity and merger announcement returns. We estimate the OLS regression: $CCAR = f(SRF, ProductSimilarity, RelatedInd, RelatedHR, SameState, Q\_diff, RelativeSize, Ret\_corr, MDA\_simi, OtherControls) + \varepsilon$. $OtherControls$ include $AllCash$, $Stock$, $HighTech$, $Tender$, $Friendly$, $Toehold$, $Runup$ $(Acquirer)$, $Size$ $(Acquirer)$, Q $(Acquirer)$, $Leverage$ $(Acquirer)$, FCF $(Acquirer)$, $Cash$ $(Acquirer)$, ROA $(Acquirer)$, $Runup$ $(Target)$, $Size$ $(Target)$, Q $(Target)$, $Leverage$ $(Target)$, FCF $(Target)$, $Cash$ $(Target)$, and ROA $(Target)$. All regressions include industry and year fixed effects. Variable definitions are in Appendix I. We report t-stat (in parentheses) that are computed using robust standard errors. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively. All potentially unbounded variables are winsorized at 1% and 99% levels.

Dep Var = $\boldsymbol{CCAR}$	(1)	(2)	(3)
SRF	0.069***	0.050***	0.046**
	(4.39)	(2.62)	(2.43)
$ProductSimilarity$		-0.021	-0.017
		(-0.72)	(-0.59)
$RelatedInd$		0.001	0.003
		(0.18)	(0.46)
$RelatedHR$		-0.005	-0.009
		(-0.31)	(-0.63)
$SameState$		-0.005	-0.001
		(-0.89)	(-0.21)
Q_diff		-0.004*	0.002
		(-1.95)	(0.49)
$RelativeSize$		0.031***	0.019**
		(4.16)	(2.33)
Ret_corr		0.036***	0.044***
		(2.59)	(2.32)
MDA_simi		0.011	-0.003
		(0.86)	(-0.23)
$AllCash$			0.004
			(0.71)
$Stock$			-0.012
			(-1.57)
$HighTech$			0.002
			(0.25)
$Runup$ $(Acquirer)$			-0.030***
			(-3.00)
$Size$ $(Acquirer)$			-0.010***
			(-4.84)
Q $(Acquirer)$			-0.005
			(-1.55)
$Leverage$ $(Acquirer)$			0.112***
			(3.59)
FCF $(Acquirer)$			-0.099*

			(-1.92)
$Cash\ (Acquirer)$			0.009
			(0.48)
$ROA\ (Acquirer)$			0.155***
			(2.90)
$Runup\ (Target)$			0.006
			(1.36)
$Size\ (Target)$			0.002
			(0.85)
$Q\ (Target)$			0.002
			(0.60)
$Leverage\ (Target)$			0.004
			(0.18)
$FCF\ (Target)$			0.036
			(1.05)
$Cash\ (Target)$			-0.008
			(-0.52)
$ROA\ (Target)$			-0.023
			(-0.60)
Year & Industry FEs	Yes	Yes	Yes
# of Obs.	696	696	696
Adjusted R^2s	0.096	0.145	0.219

Table 6: Similarity in Risk Factors and Merger Announcement Returns - Cross-Sectional Analyses

This table examines the relation between risk factor similarity and merger announcement returns within subsamples. We form sub samples based on the level of M&A uncertainty, which is measured with *ShortDistance* (Columns 1 and 2), *RelatedInd* (Columns 3 and 4), *CEOTargetExpr* (Columns 5 and 6), *HighAnalystCoverage* (Columns 7 and 8) and *CommonAuditor* (Columns 9 and 10). For each subsample, we estimate the OLS regression: *CCAR = f(SRF, ProductSimilarity, RelatedInd, RelatedHR, SameState, Q_diff, RelativeSize, Ret_corr, MDA_simi, OtherControls) + ε. OtherControls* include *AllCash, Stock, HighTech, Tender, Friendly, Toehold, Runup (Acquirer), Size (Acquirer), Q (Acquirer), Leverage (Acquirer), FCF (Acquirer), Cash (Acquirer), ROA (Acquirer), Runup (Target), Size (Target), Q (Target), Leverage (Target), FCF (Target), Cash (Target),* and *ROA (Target).* All regressions include industry and year fixed effects. Variable definitions are in Appendix I. We report t-stat (in parentheses) that are computed using robust standard errors. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively. All potentially unbounded variables are winsorized at 1% and 99% levels.

Dep Var = CCAR	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	ShortDistance		***RelatedInd***		***CEOTargetExpr***		***HighAnalystCoverage***		***CommonAuditor***	
	Yes	**No**	**Yes**	**No**	**Yes**	**No**	**Yes**	**No**	**Yes**	**No**
SRF	0.017	0.066**	-0.019	0.099***	-0.081	0.055***	0.030	0.056**	-0.012	0.038*
	(0.55)	(2.34)	(-0.80)	(3.26)	(-1.29)	(2.62)	(0.97)	(2.08)	(-0.26)	(1.70)
ProductSimilarity	-0.010	-0.019	0.015	-0.069	-0.005	-0.024	-0.051	-0.001	0.071	-0.031
	(-0.29)	(-0.34)	(0.43)	(-1.12)	(-0.11)	(-0.59)	(-1.16)	(-0.02)	(1.15)	(-0.89)
RelatedInd	-0.012	0.006			0.025	0.006	0.001	0.002	-0.003	0.006
	(-1.21)	(0.73)			(1.31)	(0.84)	(0.07)	(0.26)	(-0.16)	(0.88)
RelatedHR	-0.005	-0.003	-0.014	-0.010	0.035	-0.015	-0.002	-0.011	0.061	-0.014
	(-0.23)	(-0.14)	(-0.46)	(-0.59)	(0.77)	(-0.87)	(-0.08)	(-0.57)	(1.10)	(-0.89)
SameState			-0.005	-0.003	0.003	-0.003	0.004	-0.006	0.008	-0.007
			(-0.63)	(-0.40)	(0.22)	(-0.50)	(0.48)	(-0.65)	(0.49)	(-1.11)
Q_diff	-0.004	0.005	0.003	0.006	0.002	0.001	-0.002	0.007	0.001	0.003
	(-0.83)	(1.19)	(0.75)	(1.45)	(0.32)	(0.31)	(-0.53)	(1.23)	(0.13)	(0.75)

RelativeSize	0.019	0.029*	0.009	0.033**	0.018	0.015	0.017	0.020	0.011	0.020**
	(1.60)	(1.95)	(0.76)	(2.40)	(0.96)	(1.60)	(1.49)	(1.56)	(0.51)	(2.22)
Ret_corr	0.066**	0.33	0.041	0.075***	0.027	0.036*	0.042	0.028	0.003	0.045**
	(2.05)	(1.28)	(132)	(2.74)	(0.50)	(1.71)	(1.43)	(0.89)	(0.05)	(2.14)
MDA_simi	-0.020	0.015	0.014	-0.003	-0.004	-0.003	0.007	-0.019	0.033	-0.013
	(-0.88)	(0.80)	(0.74)	(-0.17)	(-0.10)	(-0.20)	(0.36)	(-0.93)	(0.92)	(-0.85)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of Obs.	293	403	366	330	162	480	346	350	162	526
Adjusted R^2s	0.248	0.216	0.218	0.275	0.113	0.251	0.242	0.201	0.236	0.248
Test of diff. in *SRF*	*p*-value = 0.192		*p*-value = 0.001		*p*-value = 0.013		*p*-value = 0.481		*p*-value=0.218	

Table 7: Similarity in Risk Factors and Post-M&A Operating Performance

This table examines the relation between risk factor similarity and post-M&A operating performance. We estimate the regression: *PostMAPerformance* = *f(SRF, ProductSimilarity, RelatedInd, RelatedHR, SameState, Q_diff, RelativeSize, Ret_corr, MDA_simi, OtherControls) + ε. OtherControls* include *AllCash, Stock, HighTech, Tender, Friendly, Toehold, Runup (Acquirer), Size (Acquirer), Q (Acquirer), Leverage (Acquirer), FCF (Acquirer), Cash (Acquirer), ROA (Acquirer), Runup (Target), Size (Target), Q (Target), Leverage (Target), FCF (Target), Cash (Target),* and *ROA (Target). PostMAPerformance* is *ROA_chg* in Columns 1 and 2, *GoodwillImpairment (Occurrence)* and *GoodwillImpairment (Amount)* in Columns 3 and 4, and *HighRestructuringCost* in Column 5 respectively. All regressions include industry and year fixed effects. Variable definitions are in Appendix I. We report t-stat (in parentheses) that are computed using robust standard errors. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively. All potentially unbounded variables are winsorized at 1% and 99% levels.

	(1)	(2)	(3)	(4)	(5)
Dep Var =	*ROA_chg*		*Goodwill Impairment*		*HighRestructuringCost*
	t+1	**t+2**	*Occurrence*	*Amount*	
SRF	0.075**	0.077**	-1.054*	-1.758**	-1.841**
	(2.24)	(2.10)	(-1.71)	(-2.00)	(-2.12)
$ProductSimilarity$	0.018	0.043	-1.289*	-2.559**	-0.589
	(0.26)	(0.92)	(-1.64)	(-2.33)	(-0.54)
$RelatedInd$	-0.022**	-0.003	0.083	0.354	0.149
	(-2.38)	(-0.37)	(0.42)	(1.33)	(0.61)
$RelatedHR$	0.068**	0.031	0.665	0.763	0.649
	(2.37)	(1.33)	(1.36)	(1.36)	(0.88)
$SameState$	0.016*	0.007	-0.070	0.002	-0.056
	(1.71)	(0.71)	(-0.35)	(0.01)	(-0.23)
Q_diff	-0.009*	0.001	0.099	-0.003	0.521***

	(-1.69)	(0.19)	(0.73)	(-0.02)	(4.06)
$RelativeSize$	-0.041***	0.008	0.368	1.097**	1.802***
	(-2.98)	(0.44)	(1.40)	(2.28)	(3.08)
Ret_corr	0.022	0.012	-0.323	-0.094	-1.345*
	(0.85)	(0.42)	(-0.57)	(-0.12)	(-1.97)
MDA_simi	0.002	-0.034	0.313	1.410**	0.528
	(0.08)	(-1.34)	(0.58)	(2.10)	(0.78)
Other Controls	Yes	Yes	Yes	Yes	Yes
Year & Industry FEs	Yes	Yes	Yes	Yes	Yes
# of Obs.	480	412	446	472	271
Adjusted (Pseudo) R^2s	0.181	0.153	0.229	0.219	0.283

Table 8: Similarity in Risk Factors and M&A Target Selection and Characteristics

This table examines the relation between similarity in risk factors and M&A target selection and deal characteristics. We estimate the Probit and OLS regressions: *MACharacteristics = f(SRF, ProductSimilarity, RelatedInd, RelatedHR, SameState, Q_diff, RelativeSize, Ret_corr, MDA_simi, OtherControls) +* ε. *OtherControls* include *AllCash, Stock, HighTech, Tender, Friendly, Toehold, Runup (Acquirer), Size (Acquirer), Q (Acquirer), Leverage (Acquirer), FCF (Acquirer), Cash (Acquirer), ROA (Acquirer), Runup (Target), Size (Target), Q (Target), Leverage (Target), FCF (Target), Cash (Target),* and *ROA (Target)*. We further include *AllCash* and *Stock* as controls in Columns 1 and 2. *MACharacteristics* is *Target* in Column 1, *Completion* in Column 2 and *StockPct* in Column 3 respectively. All regressions include industry and year fixed effects. Variable definitions are in Appendix I. We report t-stat (in parentheses) that are computed using robust standard errors. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively. All potentially unbounded variables are winsorized at 1% and 99% levels.

	(1)	(2)	(3)
Dep Var =	***Target***	***Completion***	***StockPct***
SRF	1.055***	1.599***	-19.673*
	(3.00)	(2.70)	(-1.78)
ProductSimilarity	6.388***	1.286	30.207**
	(7.23)	(1.59)	(2.29)
RelatedInd	-0.547***	-0.072	2.775
	(-4.61)	(-0.39)	(0.76)
RelatedHR	1.025***	-0.148	-2.148
	(4.32)	(-0.32)	(-0.27)
SameState	0.079	-0.226	0.859
	(0.71)	(-1.11)	(0.25)
Q_diff	-0.030	-0.145	-1.345
	(-0.52)	(-1.22)	(-0.84)
RelativeSize	-0.034	-0.235	17.297**
	(-0.33)	(-0.95)	(2.13)
Ret_corr	0.466	-1.103*	-0.557
	(1.32)	(-1.84)	(-0.05)
MDA_simi	0.333	0.577	-4.420
	(1.04)	(1.06)	(-0.54)
Other Controls	Yes	Yes	Yes
Year & Industry FEs	Yes	Yes	Yes
# of Obs.	1012	568	554
Adjusted (Pseudo) R^2s	0.150	0.270	0.435

Table 9: Similarity in Risk Factors and Change in Stock Return Volatility

This table examines the relation between similarity in risk factors and changes in acquirer's stock return volatility. We estimate the OLS regression: *Volatility_chg (Volatility_increase) = f(SRF, ProductSimilarity, RelatedInd, RelatedHR, SameState, Q_diff, RelativeSize, Ret_corr, MDA_simi, OtherControls) + ε. OtherControls* include *AllCash, Stock, HighTech, Tender, Friendly, Toehold, Runup (Acquirer), Size (Acquirer), Q (Acquirer), Leverage (Acquirer), FCF (Acquirer), Cash (Acquirer), ROA (Acquirer), Runup (Target), Size (Target), Q (Target), Leverage (Target), FCF (Target), Cash (Target),* and *ROA (Target)*. All regressions include industry and year fixed effects. Variable definitions are in Appendix I. We report t-stat (in parentheses) that are computed using robust standard errors. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively. All potentially unbounded variables are winsorized at 1% and 99% levels.

	(1)	(2)
Dep Var =	***Volatility_chg***	***Volatility_increase***
SRF	0.001	0.916
	(0.15)	(1.26)
ProductSimilarity	0.002	-1.864**
	(0.38)	(-2.12)
RelatedInd	0.001	-0.121
	(0.49)	(-0.60)
RelatedHR	-0.002	0.219
	(-0.58)	(0.46)
SameState	-0.000	0.054
	(-0.08)	(0.25)
Q_diff	0.001	0.066
	(1.18)	(0.67)
RelativeSize	0.001	1.314***
	(0.35)	(3.01)
Ret_corr	0.001	-0.700
	(0.23)	(-1.15)
MDA_simi	0.002	0.503
	(0.83)	(0.91)
Other Controls	Yes	Yes
Year & Industry FEs	Yes	Yes
# of Obs.	501	418
Adjusted (Pseudo) R^2s	0.547	0.364