Mergers and Acquisitions, Diversification, and Downside Risk

Jonathan Keen

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Abstract

I find that diversifying acquirers experience an increase in downside risk in the medium-term after deal completion. The returns of recent diversifiers are significantly more sensitive to target industry downturns than those of non-diversifying bidders over the first five years post-M&A. Specifically, during downturns, as target industry return decreases by an additional 1pp, the return of recently diversified firms decreases by 1.80pp, while that of recent non-diversifiers decreases by 0.79pp. This difference in sensitivity is not seen in downturns and decreases over the long-term. I show that the risk differential is attributable to operational inexperience and integration.

1 Introduction

Diversification is an often discussed motivation for merger activity. In portfolio theory, it is achieved through combining securities with less-than-perfect correlations to reduce risk. From the investor's perspective, any firm-specific risk can be diversified away, and thus is not relevant to decision-making. In the case of mergers and acquisitions, similarly, a firm may want to purchase a target if that target's idiosyncratic shocks offset their own on average. What if, however, the process of undergoing a diversifying merger exposes the merged firm to a unique risk that did not affect either the pre-merger target or acquirer? In this paper, I show that acquirers which undergo diversifying mergers face increased downside risk relative to their non-diversifying counterparts, as a result of their decision to diversify.

I argue that diversifying acquirers are less familiar with the target industry than non-diversifying acquirers (who operate in the same industry as their targets). This "unfamiliarity" adversely affects the diversifier's ability to maintain performance during crises, leading to increased downside risk. To show this, I examine the sensitivity of firm returns to target and acquirer industry returns in both upturns ("good times") and downturns ("bad times"). I find that during downturns, recent diversifiers (those acquirers with different 2-digit SIC codes than their target) show increased sensitivity to target industry returns relative to non-diversifiers. Specifically, during a downturn in the target industry, a 1pp decrease in industry returns is associated with a 1.01pp larger decrease in firm returns for diversifiers, on average over the first five years after the completion of the transaction.

To confirm this mechanism, I attempt to vary the degree of unfamiliarity, both within a time period and across time periods and show that the magnitude of the effect changes accordingly. First, I remain in the first five years after the transaction, but alter the identification of diversifying transactions. Instead of focusing on transactions in which the acquirer and target have different 2-digit SIC codes, I more strictly identify diversifying transactions as those in which the acquirer and target have different 3-digit SIC codes, but the same 2-digit SIC codes. In these transactions, the acquirer and target industries can be expected to be more similar than in the 2SIC case. In this sample, as the degree of acquirer unfamiliarity decreases, the magnitude of the effect decreases as well.

Next, I allow for the possibility of learning by the acquiring firm as they have time to operate in the target industry and gain experience. I compare, for both identifications of diversification the magnitude of the effect in years 1-5 after the transaction to that in years 6-10. I find that, again, the effect decreases in magnitude as acquirers are able to learn more about the target industry. I then show that this risk is idiosyncratic via a comparison of systematic risk exposures before and after the transaction. The downside risk is unique to diversifiers in my sample, and thus should appear as a change in factor loadings around the event if it is systematic. However, I find no increase in factor loadings that is unique to diversifiers, leading me to conclude that this risk is idiosyncratic.

This risk being unsystematic has several implications. For well-diversified investors, it is of no concern, as they can diversify it away on their own. However, it can affect several aspects of the merged firm itself. First, the increased risk may impact the firm's ability to secure external funding. This could be even more impactful, as the firm will have recently undergone a merger, and thus may be low on internal capital. Also, because it is downside risk, it could increase a firm's likelihood to violate covenants in existing debt, because it harms performance precisely when times are already bad. This risk is particularly interesting because it arises as a consequence of the merger event, rather than being something brought through by either party. Thus, potential acquirers may want to consider their familiarity with the target industry when deciding whether or not to undertake a merger.

2 Literature Review

Merger Motivations

Trautwein (1990) provides a summary of theoretical motivations for M&A activity as the result of rational choices. He discusses four main theories. Efficiency theory encapsulates the often-discussed idea of synergies. He describes three types: financial, where the firm's cost of capital is lowered through acquisitions, operational, where the combined firm can offer products, services, or competitive prices that the individual segments could not, and managerial, where the incoming managers are more effective at running the target firm than the existing managers.

Monopoly theory motivates mergers via their ability to help the acquiring firm gain a larger market share. This can be through acquiring competition or cross-subsidization of products between successful and failing segments.

Managers who enter a transaction because they believe they have better information about the target's value than the stock market would be acting under Valuation Theory. These managers choose targets which they believe are undervalued, with hopes of owning them when their value rises. The average non-diversifying merged firm in my sample has a significantly lower loading on the size factor than the pre-transaction portfolio firm, implying this as a driving motivation for non-diversifying mergers. This suggests that the the average merged firm is larger than the sum of its pre-transaction parts (a heavier lean toward the "big" leg of the SMB factor).

The well-researched Empire-Building theory, first discussed by Jensen (1986), describes a manger's incentive to grow a firm beyond optimal size. This motivation for mergers implies that the merged firm's value will be harmed by the manager's decisions. The mechanism can differ, such as Black (1989) suggesting that managers are too confident and will overpay for the target, but the overall prediction should remain the same: firm value is harmed by this managerial activity.

Baker et al (2005) survey CFOs to M&A party firms about the motivating factors for their activity. They find that 77.3% of survey participants cite diversification as a motive for a merger. 92% cite synergies as another motivation, with operating synergies being claimed by an overwhelming majority of participants (89.9%) to be the most important type of synergy. I provide evidence of decreased market β through diversifying transactions, suggesting that acquirers succeed in attaining this goal, as their risk decreases. However, my results indicate that there is an additional source of unsystematic risk faced by diversifiers that acts as a counter to the decrease seen in the β_{MKT}s.

Diversification Discount

The Diversification Discount is a well-researched phenomenon in which conglomerate firms appear to be worth less, in market cap terms, than a portfolio of standalone firms in the same industry. Berger and Ofek (1995) estimate standalone values for individual business segments and compare them to the values of the total firm. They find that the firm's actual values imply, on average, a 13-15% discount during the sample period of 1986-1991.

Lamont and Polk (2001) generate, via a model, some predictions about the cash flows and returns of diversified firms. They argue that the diversification discount must be due to either changes in future expected returns, changes in expected future cash flows, or some combination of the two. They find that, when compared to standalone firms, diversified firms have higher future expected returns, on average. This finding, according to their estimates, accounts for slightly less than half of the diversification discount.

There has been some pushback against the existence of the Diversification Discount, however. Campa and Kedia (2002) argue that the discount which had been studied up to that point was actually a result of insufficient controls. The authors use several techniques to control for the endogeneity of the merger decision, upon which the discount disappears.

Similarly, Graham et al (2002) find that much of the discount is due to firms acquiring already-discounted business segments, and argue that "the ... assumption that conglomerate divisions can be benchmarked to ... stand-alone firms should be carefully reconsidered."

These positions are also supported by Chevalier (2004). She addresses previous research which has attributed the discount to cross-subsidization of business segments (the monopoly theory discussed by Trautwein (1990)). Relying on previous links between investment patterns and cross-subsidization, she finds that these same investment patters are present between acquirer-target pairs *before* the transaction, and thus that there is some selection bias in the sample. Overall, while heavily researched, the existence of the Diversification Discount is by no means an agreed-upon result.

While several papers have addressed issues with the diversification discount, the most relevant for the findings of this paper is Custodio (2014). The author shows that accounting treatment of mergers leads to a portion of the diversification discount. Specifically, she argues that targets are recorded on acquirer books at transaction value, which is artificially inflated. This increased book value would increase the B/M of the merged firm, resulting in it being more likely to be included in the long leg of the HML factor (high minus low B/M). This is reflected in my factor model estimation by the significantly positive difference between the HML loading of the merged firm relative to the portfolio firm.

3 Data Collection

I collect a sample of 3,415 M&A events from Thomson Refinitiv/SDC Platinum. I use the following filters to select transactions from the sample period 1985-2016:

- Target and Acquirer Nation: United States
- Target and Acquirer Public Status: Public
- Deal Value: >= $5M
- Deal Status: Completed
- % of Shares Owned after Transaction: >= 50%

I first begin by identifying them as either "diversifying" or "non-diversifying", using acquirer and target SIC codes. I will primarily identify a transaction as diversifying when the target and acquirer have different 2-digit SIC codes. Custodio (2014) uses this definition to identify "unrelated" diversification. I will also use different 3-digit SIC codes as identification in additional tests of the robustness of my findings.

Next, from CRSP, I collect annual return data for the merged firm, as well as the acquirer and target industries for the five years after the transaction completion. I am studying the differences between diversifiers and non-diversifiers during upturns and downturns, so some definition of a downturn is necessary. My primary results define a downturn as the industry in question being in the bottom 67th percentile of standardized industry returns in a given year, though results for downturns as the bottom 50^{th} percentile are reported in the Appendix (Table A5). I standardize the returns before calculating the percentiles to account for some industries being overall more volatile than others.

Since some of my secondary tests involve a comparison of factor loadings before and after the merger event, I download the values of the 5 monthly Fama-French factors from Ken French's website, and merge this to the monthly time series of returns both before and after the transaction, gathered from CRSP. To estimate the factor loadings, I will use event time notation. The month before the "announcement month" is defined as month -1, and the month after the "effective month" is defined as month +1. I avoid using the time between the announcement and effective dates (on average about 4.7 months) to alleviate any concerns about announcement effects in the estimation of the factor model.

Summary Statistics: Firm Return in Different States

Variable	Mean	Std. Dev.	5pct	95pct
Target Upturn	0.17	0.45	-0.51	1.00
Target Downturn	-0.003	0.42	-0.67	0.67
Acquirer Upturn	0.19	0.46	-0.48	1.04
Acquirer Downturn	-0.01	0.41	-0.67	0.65

Summary Statistics: Transaction Count by Time Period

Period	# of Transactions	2SIC Diversifying	3SIC Diversifying
1985-1990	423	162	230
1991-1995	441	130	232
1996-2000	1,105	335	514
2001-2005	647	171	257
2006-2010	427	144	184
2011-2016	372	91	142
Total	3,415	1,033	1,559

4 Estimation

The Ideal Estimation

The ideal estimation for testing my hypothesis would require a decomposition of the firm into its target and acquirer segments. I am attempting to show that firm inexperience in the target industry leads to higher downside risk, and thus would want to be able to distinguish between the portions of firm operations where the firm is more or less experienced. Thus, I would be interested in observing the target segment's sensitivity to its own industry returns in comparison with the acquirer segment's sensitivity to the returns of its own industry.

This test would allow me to show that the target (unfamiliar) segment of the firm is subject to the risk I am documenting, and the existing acquirer (familiar) segment is not subject to this risk. Written in equations, I would like to separately estimate:

$$R_{A,t} = \beta_0 + \beta_1 R_{AI,t} + \beta_2 R_{AI,t} * Down_{AI,t} + \beta_3 R_{AI,t} * Div_t + \beta_4 R_{AI,t} * Down_{AI,t} * Div_t + \varepsilon_{A,t} \quad (1)$$

and

$$R_{T,t} = \gamma_0 + \gamma_1 R_{TI,t} + \gamma_2 R_{TI,t} * Down_{TI,t} + \gamma_3 R_{TI,t} * Div_t + \gamma_4 R_{TI,t} * Down_{TI,t} * Div_t + \varepsilon_{T,t} \quad (2)$$

Where $R_{A,t}$ and $R_{T,t}$ are the unobservable returns of the acquirer and target segments post-merger, respectively, and $R_{AI,t}$ and $R_{TI,t}$ are the returns of the acquirer and target industries, respectively. $Down_{AI,t}$ and $Down_{TI,t}$ are indicators equal to 1 if the acquirer and target industries are in a downturn (defined as being in the bottom 2/3 of standardized returns in a given year) and 0 otherwise, and Div is an indicator equal to 1 if the transaction is diversifying (different 2-digit SIC codes).

I am interested in the difference between diversifiers and non-diversifiers in both upturns and downturns. Specifically, I am interested in seeing if this difference is limited to the firm's sensitivity to target industry returns. I am arguing that diversifier unfamiliarity with their new industry leads them to be more sensitive to industry returns. Regardless of whether or not they are diversifying, acquiring firms are familiar with their home industry, as this is where they have already been operating, so diversifiers and non-diversifiers should have similar sensitivities to the returns of their own industries.

As the interpretation of these difference coefficients can be confusing, it is valuable to provide a more detailed explanation. The total sensitivity of firm returns to acquirer (target) industry returns in upturns is given by β_1 and $\beta_1+\beta_3$ (γ_1 and $\gamma_1+\gamma_3$), for diversifiers and non-diversifiers, respectively. Similarly, the total sensitivity to acquirer (target) industry returns in downturns is given by $\beta_1+\beta_2$ and $\beta_1+\beta_2+\beta_3+\beta_4$ ($\gamma_1+\gamma_2$ and $\gamma_1+\gamma_2+\gamma_3+\gamma_4$), for diversifiers and non-diversifiers, respectively. Thus, the differences in sensitivities to acquirer (target) industry returns can be expressed by β_3 and $\beta_3+\beta_4$ (γ_3 and $\gamma_3+\gamma_4$) in upturns and downturns, respectively.

I am most interested in the magnitudes of $\beta_3+\beta_4$ and $\gamma_3+\gamma_4$. $\gamma_3+\gamma_4$ being significantly positive will mean that diversifiers are riskier than non-diversifiers during target industry downturns. However, this does not rule out the possibility that firms which undergo diversifying mergers and acquisitions are riskier overall in downturns. The magnitude of $\beta_3+\beta_4$ will help to clarify this point. If a diversifying acquirer's unfamiliarity with their new industry is the driving factor, then $\beta_3+\beta_4$ should be close to 0. This would suggest that diversifiers and non-diversifiers are similarly risky in downturns in the acquirer industry, where they have already operated for some time.

The Achievable Estimation

Unfortunately, the LHS of equations (1) and (2) are unobservable. To get around this, I combine the two equations to get a proxy of the merged firm. I begin by suggesting that the (observable) returns of the total firm can be expressed as a weighted average of the returns to the two segments $R_{Firm} = w_A R_A + w_T R_T$. I will approximate the weights using the last available market caps of the acquirer and target pre-announcement (using pre-announcement weights alleviates any concerns about the target firm being over-weighted due to announcement effects). The approximate weights are thus $w_i = \frac{MV_i}{MV_A+MV_T}$ where i can be either the acquirer (A) or target (T) firm. Plugging equations (1) and (2) into this approximation results in the (lengthy) full equation:

$$R_{Firm,t} = \delta_0 + \delta_1 w_A R_{AI,t} + \delta_2 w_T R_{TI,t} + \delta_3 w_A R_{AI,t} * Down_{AI,t} + \delta_4 w_T R_{TI,t} * Down_{TI,t} \\ +\delta_5 w_A R_{AI,t} * Div_t + \delta_6 w_T R_{TI,t} * Div_t + \delta_7 w_A R_{AI,t} * DownAI,t * Div_t + \delta_8 w_T R_{TI,t} * \\ Down_{TI,t} * Div_t + \varepsilon_{Firm,t} \quad (3)$$

This equation can be estimated successfully, as all variables on the LHS and RHS are observable! For clarity of interpretation, the analogous estimates to $\beta_3+\beta_4$ and $\gamma_3+\gamma_4$ are $\delta_5+\delta_7$ and $\delta_6+\delta_8$. Thus, I would expect $\delta_5+\delta_7$ to be close to zero and $\delta_6+\delta_8$ to be significantly positive. Tables 1 and 2 in the **Results** section report the regression coefficients and the total effects, respectively.

Additional Analysis

Different Definitions of Diversifying

As further evidence to support my "unfamiliarity" hypothesis, I offer an additional set of tests, both of which employ the same regression as the primary estimation. Since I am arguing that diversifiers being unfamiliar with their new industry is the driving mechanism behind this risk, I propose a distinction within the set of diversifying mergers between those in which the target and acquirer industries are more or less similar.

To do this, I will alter the definition of the indicator *Div* to take on a value of 1 if the acquirer and target industries have different 3SIC codes while **also** having the same 2SIC codes, and 0 otherwise.

By focusing on those transactions which are diversifying under the 3SIC definition, but not the 2SIC definition, I am able to draw a distinction between transactions in which the target and acquirer industries are more similar than those in the previous sample. My hypothesis implies that the effect should be smaller in magnitude for these transactions, as the acquirer can be expected to be more familiar with the target industry, as they are in the same 2SIC industry.

Allowing for Learning

The "unfamiliarity" hypothesis leads itself naturally to an additional implication about a firm's ability to learn. My hypothesis implies the effect should decrease as diversifying firms are given the chance to become more familiar with their new industry. I can easily test this by extending the sample from years 1-5 after the transaction to years 6-10. This test should be equally applicable to both the 2SIC and 3SIC definitions of diversification. I would expect to see the effect decrease in magnitude, as diversifying firms are able to familiarize themselves with their new industry over time.

I expect $\delta_6+\delta_8$ (the difference in total effect between diversifiers and non-diversifiers in target industry downturns) to decrease in magnitude, as the new-to-industry firms gain experience. Similarly, I would expect $\delta_5+\delta_7$ (the difference in total effect between diversifiers and non-diversifiers in acquirer industry downturns) to remain similar in magnitude, as both types of acquirers are still experienced in their own industries, whether it is 5 years or 10 years after the transaction.

Is This Risk Systematic?

It is not immediately clear whether or not this increased source of downside risk is systematic. For this, a comparison between the levels of systematic risk before and after the transaction would be useful. To achieve this, I offer a comparison between the loadings on the Fama-French five factors (Fama, French 2015) from before and after the event. Significant changes in the loadings would suggest changes in systematic risk. I show through the above estimation that diversifiers face increased risk, and this test will help to clarify what type of risk this is.

I estimate, for each transaction, the factor loadings (βs in Eq. 4 below) for the acquirer and target pre-transaction, and that of the remaining merged firm in the post period.

$$\mathrm{R}^e_{i,t} = \alpha + \beta_1(Mkt - RF)_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t + \varepsilon_{i,t} \quad (4)$$

I keep only those transactions for which all three of these estimations are possible, given the CRSP data. There are 3,383 of these "cleaned transactions", 1,547 of which are diversifying under the 3SIC definition, though the results are similar for the 2SIC definition.

For each transaction in the "pre" sample, I use the last available market caps for the target and acquirer to construct the value-weighted sum of the factor loadings of the two parties, with weights, again, defined as $w_i = \frac{w_i}{w_A + w_T}$ where i can either be the acquirer (A) or target (T). I use two-tailed t-tests to test the significance of the difference between the estimates for the merged firms and portfolio firms.

5 Results

Downside Risk Estimates

Table 1, Column (6) presents the results from the full regression described above, and Table 2 reports the total effects of $w_T R_{TI}$ and $w_A R_{AI}$ on R_{Firm}. These are the sum of the coefficients in Table 1 Column (6) for the various combinations of values for the indicator variables. For example, Row (2) Column (1) of Panel A reports the sum of all coefficients on

$w_T R_{TI}$ when $Down_{TI} = 1$ and $Div = 0$ (-0.12+0.92=0.80). In words, this is the total effect of target industry returns on firm returns for recently non-diversifying firms during target industry downturns. Rows (1)-(2) and Columns (1)-(2) are similarly defined. Row (3) and Column (3) report the differences between rows and columns, respectively. For each sum and difference estimate, the standard errors are calculated as: $SE_{Dif} = \sqrt{SE_1^2 + SE_2^2}$ because these are sums of regression coefficients, and thus already orthogonal to one another.

Table 1: Sensitivity of Firm Returns to Industry Downturns

Variable	(1)	(2)	(3)	(4)	(5)	(6)
(1) $w_a R_{AI}$	0.93***		0.80***	0.73***	0.81***	0.74***
	(60.13)		(45.88)	(30.67)	(36.66)	(24.11)
(2) $w_T R_{TI}$		2.30***	1.03***	1.00***	0.88***	0.92***
		(40.53)	(17.20)	(12.89)	(12.24)	(9.84)
(3) $w_a R_{AI} * Down_{AI}$				0.14***		0.14***
				(3.97)		(3.05)
(4) $w_T R_{TI} * Down_{TI}$				0.0420		-0.12
				(0.36)		(-0.86)
(5) $w_a R_{AI} * Div$					-0.02	-0.03
					(-0.67)	(-0.69)
(6) $w_T R_{TI} * Div$					0.60***	0.25
					(4.43)	(1.45)
(7) $w_a R_{AI} * Down_{AI} * Div$						0.03
						(0.45)
(8) $w_T R_{TI} * Down_{TI} * Div$						0.76***
						(2.84)

Table 1 presents the regression coefficients from the estimation of Eq. (3). The important coefficients for testing my hypothesis are those in Columns (5)+(7) and (6)+(8). These sums, 0.00 and 1.01, respectively, represent the difference in total effects between diversifiers and non-diversifiers during acquirer and target industry downturns.

In Panel A, a large difference can be seen between diversifiers and non-diversifiers during target industry downturns. The magnitude of the total effect is 1.01 (t-stat=2.52). This implies that during a target industry downturn, a 1pp further decrease in target industry return is associated with a 1.01pp **larger** decrease in firm return for diversifiers relative to non-diverisifiers. The average annual return during a target industry downturn itself is 1%, so this is certainly an economically large effect.

This can be contrasted with Panel B, which reports the total effects of acquirer industry returns on firm returns. The differences between diversifiers and non-diversifiers are close to 0, with the estimate during downturns actually being equal to 0.00.

Table 2: Total Effects

A: Target Industry	(1) Div=0	(2) Div=1	(3) Difference
(1) Down_{TI}=0	0.92***	1.17***	0.25
	(9.84)	(5.94)	(1.15)
(2) Down_{TI}=1	0.80***	1.81***	1.01**
	(4.61)	(4.99)	(2.52)
(3) Difference	-0.12	0.63	
	(-0.64)	(1.53)	
B: Acquirer Industry	**(1) Div=0**	**(2) Div=1**	**(3) Difference**
(1) Down_{AI}=0	0.74***	0.71***	-0.03
	(24.11)	(12.99)	(-0.50)
(2) Down_{AI}=1	0.88***	0.88***	0.00
	(16.19)	(8.93)	(0.00)
(3) Difference	0.14**	0.17	
	(2.18)	(1.49)	

Table 2 shows the total effects for various combinations of the indicator variables used in Eq. (3), for the target industry (Panel A) and acquirer industry (Panel B). The primary estimate of interest is Panel A, Row (2), Column (3). This shows that, during target industry downturns, a 1pp decrease in industry return is associated with a 1.01pp larger decrease in firm returns for diversifiers compared to non-diversifiers. This is in contrast with the analogous estimate for the acquirer industry in Panel B, which shows no difference between the two types of acquirers. The total effect for non-diversifiers is similar for the target and acquirer industry (0.80 compared to 0.88), showing that the difference is driven by increased risk for diversifiers rather than decreased risk for non-diversifiers.

Figures 1A and 1B give a visual representation of Table 2 by plotting firm return against industry return. The x-axis is constructed to be illustrative, such that an industry return less than zero represents a downturn, while values greater than zero represent an upturn.

The total effects of industry returns on firm returns during upturns and downturns are represented by the slopes of the lines in the negative and positive portions of the x-axis, respectively (a steeper slope indicates a higher sensitivity). In each panel, the blue and red lines represent diversifying and non-diversifying transactions, respectively.

The total effect of target industry returns on firm returns, illustrated in Figure 1A, is similar during upturns for diversifiers and non-diversifiers (1.17 compared to 0.92, t-stat of difference=1.15), while during downturns, the absolute and relative steepness of the diversifier return increases (now 1.81 compared to 0.80, t-stat of difference=2.52). This shows, visually, the implication of the "unfamiliarity" risk I document in Table 1. Specifically, it shows that the sensitivities of firm returns to target industry returns for diversifiers and non-diversifiers are similar during upturns, but that diversifiers face increased risk during downturns.

Figure 1A: Firm Return vs. Target Industry Return

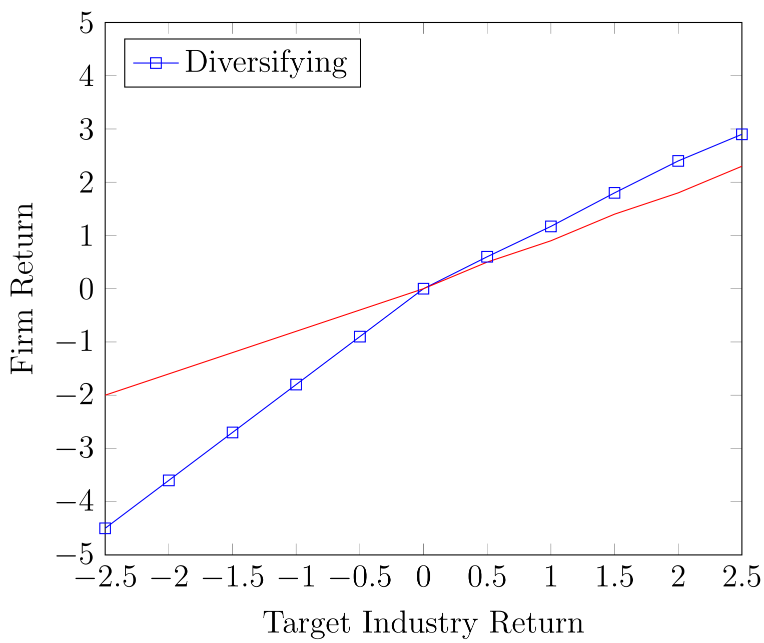
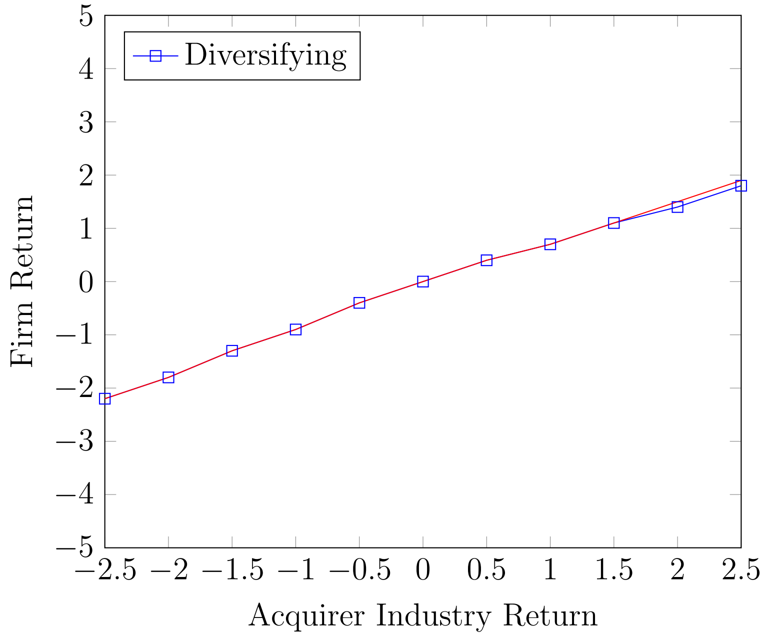


Figure 1B, alternatively, gives a visual representation of the total effect of acquirer industry returns on firm returns (the estimates from Panel B of Table 2). During upturns, as in Figure 1, the sensitivities of diversifiers and non-diversifiers are similar (0.71 compared to 0.74, t-stat of difference=-0.50). However, as is consistent with my hypothesis, the total effects during downturns is similar for diversifiers and non-diversifiers (0.88 for each t-stat of difference=0.00). These figures help to visualize my argument that the difference in risk between diversifiers and non-diversifiers is restricted to target industry downturns. This implies that diversifiers' unfamiliarity with their new industry only harms them in bad times when ability to effectively manage becomes more necessary.

Figure 1B: Firm Return vs. Acquirer Industry Return



In summary, there is an additional risk of poor performance faced by diversifiers during target industry downturns. This increase in risk is not present in upturns for either the target or acquirer industry, suggesting that when times are good, experience is less important for good performance. This, combined with the lack of an effect seen in the acquirer industry (the home industry with which diversifiers and non-diversifiers are already familiar), suggests that diversifier unfamiliarity with their new industry is the driving factor. Next, I will attempt to vary the familiarity level within the set of diversifying transactions, and see if the magnitude of the effect changes accordingly.

Additional Tests

Different Definitions of Diversifying

Tables 3 and 4 present the regression coefficients and total effects for the test using different 3SIC codes as the criteria for a transaction to be designated as diversifying. The coefficients of interest are again δ_6+δ_8 and δ_5+δ_7, which represent the sensitivity difference between diversifiers and non-diversifiers in acquirer and target downturns, respectively. These are Row (2) Column (3) of Panels A and B.

From Table 3, δ_6+δ_8=-0.22+0.53=0.31 (t-stat=0.72), which is less than one third of the magnitude seen for diversifying transactions under the 2SIC definition. This implies that by diversifying into a more similar industry, the acquiring firm decreases their exposure to this risk by 69%. On the other hand, δ_5+δ_7=-0.13-0.03=-0.16 (t-stat=-1.57), which is actually larger in magnitude than that seen for less similar transactions, though insignificantly different from zero.

Table 3: Sensitivity for 3SIC Diversification (Years 1-5)

Variable	(1)	(2)	(3)	(4)	(5)	(6)
(1) $w_a R_{AI}$	0.72***		0.61***	0.37***	0.64***	0.38***
	(55.32)		(43.80)	(18.05)	(42.36)	(15.71)
(2) $w_T R_{TI}$		1.73***	0.94***	0.73***	0.86***	0.68***
		(38.12)	(20.37)	(9.42)	(17.02)	(8.11)
(3) $w_a R_{AI} * Down_{AI}$				0.40***		0.41***
				(15.92)		(14.30)
(4) $w_T R_{TI} * Down_{TI}$				0.28***		0.27***
				(3.07)		(2.70)
(5) $w_a R_{AI} * Div$					-0.19***	-0.03
					(-5.44)	(-0.58)
(6) $w_T R_{TI} * Div$					0.43***	0.53**
					(3.41)	(2.08)
(7) $w_a R_{AI} * Down_{AI} * Div$						-0.13*
						(-1.86)
(8) $w_T R_{TI} * Down_{TI} * Div$						-0.22
						(-0.77)

Table 3 re-estimates Eq. (3), but changes the identification strategy for diversifying transactions. This estimation focuses on those transactions for which the acquirer and target have the same 2-digit SIC code, but different 3-digit SIC codes. This sample can be thought of as those transactions which are diversifying, but in which the target and acquirer industries are more similar than in the transactions studied in Tables 1 and 2. The important estimate is again those in Columns (5)+(7) and (6)+(8), which are -0.16 and 0.31, respectively. Specifically, they are interesting in their comparison to the estimates in Tables 1 and 2. The decrease in the magnitude of the difference between diversifiers and non-diversifiers supports the "unfamiliarity" hypothesis, as it shows that as the industries become more similar, the effect decreases.

In summary, I distinguish between diversifying transactions in which the acquirer and target industries are more or less similar (3SIC and 2SIC definitions). The magnitude of the sensitivity to target industry downturns is larger for 2SIC transactions where the industries of the two parties are more different. This acts as supporting evidence for my hypothesis as it shows that over the same time horizon after the transaction, the effect decreases as the acquirer familiarity with the target industry increases.

Table 4: Total Effects for 3SIC Diversification (Years 1-5)

A: Target Industry	(1) Div=0	(2) Div=1	(3) Difference
(1) Down_{TI}=0	0.68***	1.20***	0.53*
	(8.11)	(4.51)	(1.89)
(2) Down_{TI}=1	0.95***	1.25***	0.31
	(7.24)	(3.11)	(0.72)
(3) Difference	0.27*	0.05	
	(1.76)	(0.11)	
B: Acquirer Industry	**(1) Div=0**	**(2) Div=1**	**(3) Difference**
(1) Down_{AI}=0	0.38***	0.35***	-0.03
	(15.71)	(6.81)	(-0.47)
(2) Down_{AI}=1	0.79***	0.64***	-0.16
	(21.03)	(7.05)	(-1.57)
(3) Difference	0.41***	0.29***	
	(9.31)	(2.77)	

Table 4 shows the total effects of the target and acquirer industry returns on firm returns for diversifiers and non-diversifiers in Panels A and B, respectively. These estimates are the sums of the coefficients in Table 3 for the various combinations of indicator variables. The estimate in Panel A, Row (2), Column (3) shows that the difference in sensitivity, and therefore downside risk, has decreased to 0.31 when looking at "more similar" diversifying transactions. This shows that when diversifiers enter into an industry more closely related to their own, their "unfamiliarity" risk decreases, supporting my hypothesis of inexperience being the driving factor.

Evidence of Learning

Tables 5 and 6 present the total effects from the test over years 6-10 after the transaction, for the 2SIC and 3SIC definitions of diversification, respectively. I report the full regression estimation for both tests in the Appendix (Tables A1 and A2) in the interest of avoiding clutter, as the total effects are of primary interest.

Beginning with the 2SIC definition in Table 5, the difference between diverisifiers and non-diversifiers in target industry downturn has decreased from 1.01 in the previous sample of years 1-5, to 0.45 (t-stat=0.84) on average in years 1-6. This decrease of 56% implies that, as diversifiers become more familiar with their new industries, their exposure to this risk decreases.

Turning now to those transactions which are diversifying under the 3SIC definition, the difference in total effects between diversifiers and non-diversifiers decreases to -0.004 (t-stat=-0.02). This implies that there is no difference in sensitivity to target industry returns between the two types of acquirers, on average, in years 6-10 after undergoing a 3SIC diversifying transaction.

Table 5: Total Effects for 2SIC Diversification (Years 6-10)

A: Target Industry	(1) Div=0	(2) Div=1	(3) Difference
(1) Down_{TI}=0	0.73***	0.63**	-0.10
	(5.81)	(2.43)	(-0.33)
(2) Down_{TI}=1	0.91***	1.36***	0.45
	(3.93)	(2.83)	(0.84)
(3) Difference	0.18	0.73	
	(0.70)	(1.33)	

B: Acquirer Industry	(1) Div=0	(2) Div=1	(3) Difference
(1) Down_{AI}=0	0.47***	0.65***	0.18***
	(14.99)	(11.75)	(2.76)
(2) Down_{AI}=1	0.90***	0.78***	-0.12
	(15.54)	(7.47)	(-1.04)
(3) Difference	0.43***	0.13	
	(6.51)	(1.11)	

Table 5 presents the total effects over years 6-10 after the transaction, for those transactions which are diversifying under the 2SIC definition. This table can be contrasted with the results in Table 2. Specifically, the difference in the total effect of target industry returns on firm returns for diversifiers and non-diversifiers during downturns has decreased in magnitude from 1.01 to 0.45. This demonstrates that as diversifiers are able to gain experience in their new industry over time, their exposure to the "unfamiliarity" risk decreases.

Table 6: Total Effects for 3SIC Diversification (Years 6-10)

A: Target Industry	(1) Div=0	(2) Div=1	(3) Difference
(1) Down_{TI}=0	0.01	-0.02	-0.03
	(0.07)	(-0.09)	(-0.11)
(2) Down_{TI}=1	0.005	0.001	-0.004
	(0.03)	(0.00)	(-0.02)
(3) Difference	-0.01	0.02	
	(-0.03)	(0.06)	

B: Acquirer Industry	(1) Div=0	(2) Div=1	(3) Difference
(1) Down_{AI}=0	0.59***	0.55***	-0.04
	(20.81)	(8.59)	(-0.53)
(2) Down_{AI}=1	0.86***	0.94***	0.08
	(19.32)	(8.25)	(0.62)
(3) Difference	0.27***	0.39***	
	(5.18)	(2.97)	

Table 6 presents the total effects over years 6-10 after the transaction, for those transactions which are diversifying under the 3SIC definition. This table can be contrasted with the results in Table 4. Specifically, the difference in the total effect of target industry returns on firm returns for diversifiers and non-diversifiers during downturns has decreased in magnitude from 0.31 to -0.004. This demonstrates that as diversifiers are able to gain experience in their new industry over time, their exposure to the "unfamiliarity" risk decreases.

In summary, for both the 2SIC and 3SIC definitions of diversifying transactions, a decrease in the magnitude of the documented effect is seen over time. This evidence supports my hypothesis, as it is evidence that the effect decreases as acquiring firms get more familiar with their new industry.

Is the Risk Systematic?

Tables 7 and 8 present the resulting estimates from the additional tests designed to determine whether or not the downside risk faced by diversifying acquirers is systematic. I report estimations for the total sample (Table 7), while also splitting the sample into diversifying and non-diversifying transactions (Table 8, Panels A and B).

Each of the panels in Tables 7 and 8 has five columns of estimates. The first and second are the estimates for the acquiring and target firms, respectively. The third column is the values for the portfolio firm, while the fourth is the estimates for the remaining merged firm post-transaction. Lastly, the fifth column reports the difference between the estimates for the merged firm and the portfolio firm (Column 4 minus Column 3).

The return estimate in each column is the average monthly return for the firm combination associated with that column. The "pre" period is defined as the 60 months before the announcement month, while the "post" period is the 60 months after the effective month. Excluding the period between the announcement and effective months shields my results from concerns about announcement effects. T-statistics are reported under each estimate.

Full Sample

Table 7 reports estimates of the returns and factor loadings for the total sample. The significant differences in factor loadings appear in the market (MKT), size (SMB), and value (HML) factors. The MKT loading decreases by 0.04 (t-stat=-2.07), the SMB loading decreases by 0.08 (t-stat=-2.98), and the HML loading increases by 0.19 (t-stat=5.19).

By just examining the full sample, it is unclear whether the risk I document appears in the factor loadings, as this downside risk is faced only by diversifiers. However, by dividing the sample into diversifying and non-diversifying transactions, a clearer picture can be seen. The two subsamples are explored in the following subsection.

In summary, the changes in factor loadings for the total sample appear in the market (MKT), size (SMB), and value (HML) factors. There is a significant increase in β_{HML}, and a significant decrease in both β_{MKT} and β_{SMB}.

Table 7: Total Sample (3,383 Transactions)

Variable	(1) Acquirer	(2) Target	(3) Portfolio	(4) Merged	(5) Merged-Portfolio
(1) α	0.0047***	0.0084***	0.0048***	-0.0003	-0.0051***
	(8.70)	(9.70)	(9.68)	(-0.53)	(-6.78)
(2) β_{MKT}	1.0400***	0.9039***	1.0235***	0.9800***	-0.0435**
	(69.22)	(40.82)	(76.83)	(60.27)	(-2.07)
(3) β_{SMB}	0.5060***	0.7717***	0.5093***	0.4250***	-0.0843***
	(24.36)	(25.80)	(27.51)	(19.88)	(-2.98)
(4) β_{HML}	0.1214***	-0.0015	0.1066***	0.3008***	0.1942***
	(4.34)	(-0.03)	(4.25)	(10.85)	(5.19)
(5) β_{RMW}	-0.0982***	-0.3101***	-0.1014***	-0.1194***	-0.0180
	(-2.84)	(-5.91)	(-3.29)	(-3.43)	(-0.39)
(6) β_{CMA}	-0.1318***	-0.0763	-0.1158***	-0.0569	0.0589
	(-3.69)	(-1.38)	(-3.65)	(-1.60)	(1.24)

Table 7 presents the comparison of factor loadings between the merged and portfolio firms to examine the change in systematic risk around the merger event. Through the average transaction, an acquirer disproportionately increases their loading on the HML factor by 0.19, while disproportionately decreasing their loading on the MKT and SMB factors by 0.04 and 0.08, respectively.

Divided Sample

Panel A of Table 8 reports estimates of the same quantities as Table 7 for the subsample of diversifying transactions (under the 3SIC definition), while Panel B reports the estimates for those transactions identified as non-diversifying.

Columns (1) and (2) of both Panels suggest that the average acquirer of each type has a higher market beta than their targets, on average, with values of 1.07 (t-stat=48.43) and 0.91 (t-stat=28.30), respectively, for diversifiers, and values of 1.01 (t-stat=49.55) and 0.90 (t-stat=29.46) for non-diversifiers.

The change in β_{MKT} seen in Table 7 is driven by the subset of diversifying transactions. This is consistent with reducing risk as a motive for diversifying mergers, as described by Trautwein (1990) and Baker et al (2005), among others. The change in β_{HML} is present for both types, though slightly larger in magnitude for diversifying transactions. This change being present for both types of transactions is to be expected, as the accounting treatment of mergers documented by Custodio (2014) leads to inflated book values (and thus higher B/M), meaning the merged firm is more likely to be associated with the long leg of the factor portfolio, hence the difference.

The change in β_{SMB} is driven by the non-diversifying transactions. This would suggest that the merged firm in non-diversifying transactions tends to be larger than the sum of its pre-transaction parts. This could be interpreted as non-diversifiers being more likely to purchase undervalued targets which then grow as a part of the merged firm, but this is beyond the scope of this paper.

There is no increase in any loading that is unique to the diversifying transactions, which suggests that the risk I document is not systematic, and therefore can be diversified away by any investor wishing to purchase these firms. However, this risk is still faced by the firm itself.

Table 8 Panel A: Diversifying (1,547 Transactions)

Variable	(1) Acquirer	(2) Target	(3) Portfolio	(4) Merged	(5) Merged-Portfolio
(1) α	0.0034***	0.0083***	0.0035***	-0.0021**	-0.0056***
	(4.44)	(6.72)	(5.24)	(-2.55)	(-5.28)
(2) β_{MKT}	1.0735***	0.9070***	1.0500***	0.9715***	-0.0785**
	(48.43)	(28.30)	(54.48)	(39.80)	(-2.52)
(3) β_{SMB}	0.4800***	0.7742***	0.4789***	0.4260***	-0.0529
	(15.77)	(17.64)	(17.94)	(13.47)	(-1.28)
(4) β_{HML}	0.0888**	0.0215	0.0732**	0.2980***	0.2248***
	(2.15)	(0.37)	(2.02)	(7.10)	(4.05)
(5) β_{RMW}	-0.0759	-0.3023***	-0.0751*	-0.1151**	-0.0400
	(-1.53)	(-4.16)	(-1.73)	(-2.19)	(-0.59)
(6) β_{CMA}	-0.0782	-0.0417	-0.0630	-0.0168	0.0462
	(-1.53)	(-0.53)	(-1.40)	(0.32)	(0.67)

Table 8 Panel B: Non-Diversifying (1,836 Transactions)

Variable	(1) Acquirer	(2) Target	(3) Portfolio	(4) Merged	(5) Merged-Portfolio
(1) α	0.0059***	0.0085***	0.0058***	0.0012	-0.0046***
	(7.63)	(7.02)	(8.21)	(1.57)	(-4.42)
(2) β_{MKT}	1.0055***	0.9013***	1.0012***	0.9872***	-0.0140
	(49.55)	(29.46)	(54.43)	(45.29)	(-0.49)
(3) β_{SMB}	0.5278***	0.7695***	0.5351***	0.4242***	-0.1109***
	(18.58)	(18.84)	(20.87)	(14.61)	(-2.86)
(4) β_{HML}	0.1490***	-0.0208	0.1348***	0.3031***	0.1683***
	(3.91)	(-0.35)	(3.89)	(8.22)	(3.33)
(5) β_{RMW}	-0.1172***	-0.3167***	-0.1236***	-0.1230***	0.0006
	(-2.43)	(-4.26)	(-2.85)	(-2.66)	(0.01)
(6) β_{CMA}	-0.1770***	-0.1053	-0.1603***	-0.0905***	0.0698
	(-3.55)	(-1.37)	(-3.60)	(-18.70)	(1.06)

Table 8 repeats the estimates in Table 7, but separates diversifying and non-diversifying transaction (Panels A and B). Column (5) of the two panels shows that diversifying transactions drive the decrease in the loading on the MKT factor, while non-diversifying transactions drive the decrease in the loading on the SMB factor. It also shows that both diversifying and non-diversifying transactions show an increase in the loading on the HML factor, though the diversifiers show an insignificantly larger change (0.22 and 0.17). This demonstrates that the downside risk explored in Tables 1-6 is unsystematic, as there is no increase in systematic risk which is unique to diversifying transactions.

In summary, if the "unfamiliarity" risk I document were systematic, I would expect to find an increase in the loading on one of the systematic risk factor which only appears in the subsample of diversifying transactions. The only change seen just for diversifiers is a decrease in the loading on the market factor (β_{MKT}), suggesting that the risk I document is unsystematic. This implies that it is important for consideration by the firms themselves, but is of no consequence to well-diversified investors.

6 Conclusion

I document evidence that firms which undergo diversifying M&A transactions expose themselves to increased downside risk due to their unfamiliarity with their new industry. During target industry downturns, a decrease of 1pp in target industry returns is associated with a 1.01pp (t-stat=2.52) **larger** decrease in firm returns for diversifiers than for non-diversifiers.

To support this hypothesis, I vary firm "familiarity" with the target industry along multiple dimensions, and find that as the acquirer is more familiar with the target industry, the magnitude of this downside risk decreases. Specifically, I show that for transactions in which the acquirer and target have the same 2-digit SIC code but different 3-digit SIC codes (a proxy for the parties' industries being more similar than in the strictly different 2SIC case), the magnitude of the effect decreases to 0.31 (t-stat=0.72).

Additionally, for both definitions of diversification (2SIC and 3SIC), I show that, on average, the effect decreases in magnitude over time to 0.45 (t-stat=0.84) and -0.004 (t-stat=-0.02), respectively. This demonstrates that familiarity is the driving source of the increased downside risk shown for diversifying acquirers, as it decreases when they are given time to learn.

I then examine whether this source of risk is systematic. I compare the Fama-French five factor loadings (Fama, French 2015) of the merged firm to those of the portfolio firm pre-transaction, and find no significant increase in the loading on any factor that is limited to only the subsample of diversifying transactions. Therefore, this downside risk is unsystematic. While this means that it is not relevant to a potential investor in the firms (they can diversify it away on their own), it is certainly relevant to the firm itself. This increased risk could impact their ability to secure external funding for projects, and may also increase their likelihood of violating any covenants on existing debt. Potential acquirers may want to consider this risk (and thus their familiarity with the prospective target industry) when deciding whether or not to undertake a given merger.

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Appendix

Table A1: Sensitivity Regression for 2SIC Diversification (Years 6-10)

Variable	(1)	(2)	(3)	(4)	(5)	(6)
(1) $w_a R_{AI}$	0.7626		0.6754	0.5528	0.6552	0.4729
	(44.43)		(35.61)	(23.43)	(26.63)	(14.99)
(2) $w_T R_{TI}$		2.0937	0.8459	0.5709	0.8332	0.7282
		(27.24)	(10.53)	(5.60)	(8.63)	(5.81)
(3) $w_a R_{AI} * Down_{AI}$				0.2958		0.4308
				(8.17)		(8.82)
(4) $w_T R_{TI} * Down_{TI}$				0.5314		0.1831
				(3.40)		(0.94)
(5) $w_a R_{AI} * Div$					0.0525	0.1751
					(1.43)	(3.87)
(6) $w_T R_{TI} * Div$					0.1605	-0.0957
					(0.89)	(-0.42)
(7) $w_a R_{AI} * Down_{AI} * Div$						-0.2995
						(-4.06)
(8) $w_T R_{TI} * Down_{TI} * Div$						0.5439
						(1.54)

Table A2: Sensitivity Regression for 3SIC Diversification (Years 6-10)

Variable	(1)	(2)	(3)	(4)	(5)	(6)
(1) $w_a R_{AI}$	0.7530		0.7530	0.5792	0.7645	0.5878
	(46.64)		(46.63)	(23.77)	(43.67)	(20.81)
(2) $w_T R_{TI}$		0.0965	0.0458	0.0180	0.0398	0.0138
		(0.44)	(0.23)	(0.09)	(0.20)	(0.07)
(3) $w_a R_{AI} * Down_{AI}$				0.2888		0.2734
				(9.48)		(7.93)
(4) $w_T R_{TI} * Down_{TI}$				-0.0082		-0.0085
				(-0.83)		(-0.81)
(5) $w_a R_{AI} * Div$					-0.0796	-0.0374
					(-1.76)	(-0.65)
(6) $w_T R_{TI} * Div$					-0.0086	-0.0313
					(-0.67)	(-1.04)
(7) $w_a R_{AI} * Down_{AI} * Div$						0.1135
						(1.30)
(8) $w_T R_{TI} * Down_{TI} * Div$						0.0269
						(0.83)

Table A3: Total Effects for 3SIC Diversification (Years 6-10)

A: Target Industry	(1) Div=0	(2) Div=1	(3) Difference
(1) Down_{TI}=0	0.01	-0.02	-0.03
	(0.07)	(-0.09)	(-0.11)
(2) Down_{TI}=1	0.005	0.001	-0.004
	(0.03)	(0.00)	(-0.02)
(3) Difference	-0.01	0.02	
	(-0.03)	(0.06)	

B: Acquirer Industry	(1) Div=0	(2) Div=1	(3) Difference
(1) Down_{AI}=0	0.59	0.55	-0.04
	(20.81)	(8.59)	(-0.53)
(2) Down_{AI}=1	0.86	0.94	0.08
	(19.32)	(8.25)	(0.62)
(3) Difference	0.27	0.39	
	(5.18)	(2.97)	

Table A4: Sensitivity with Downturn as Returns in Bottom 50th Percentile

Variable	(1)	(2)	(3)	(4)	(5)	(6)
(1) $w_a R_{AI}$	0.9346		0.7964	0.8109	0.8048	0.8041
	(60.13)		(45.88)	(31.30)	(36.05)	(24.30)
(2) $w_T R_{TI}$		2.2964	1.0278	1.0551	0.8692	0.9195
		(40.56)	(17.20)	(14.19)	(12.15)	(10.40)
(3) $w_a R_{AI} * Down_{AI}$				-0.0126		0.0233
				(-0.33)		(0.47)
(4) $w_T R_{TI} * Down_{TI}$				-0.0642		-0.1343
				(-0.50)		(-0.88)
(5) $w_a R_{AI} * Div$					-0.0027	0.0296
					(-0.08)	(0.55)
(6) $w_T R_{TI} * Div$					0.6315	0.5646
					(4.64)	(3.32)
(7) $w_a R_{AI} * Down_{AI} * Div$						-0.1016
						(-1.26)
(8) $w_T R_{TI} * Down_{TI} * Div$						0.3083
						(1.83)

Table A5: Total Effects with Downturn as Returns in Bottom 50th Percentile

A: Target Industry	(1) Div=0	(2) Div=1	(3) Difference
(1) Down_{TI}=0	0.92	1.48	0.56
	(10.40)	(7.74)	(2.67)
(2) Down_{TI}=1	0.79	1.66	0.87
	(4.45)	(5.58)	(2.53)
(3) Difference	-0.13	0.17	
	(-0.68)	(0.49)	

B: Acquirer Industry	(1) Div=0	(2) Div=1	(3) Difference
(1) Down_{AI}=0	0.80	0.83	0.03
	(24.30)	(13.19)	(0.42)
(2) Down_{AI}=1	0.83	0.76	-0.07
	(13.88)	(6.64)	(-0.56)
(3) Difference	0.02	-0.08	
	(0.34)	(-0.60)	