# Essays on the Value and Transferability of Intangible Assets

by

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**Abstract**

In the first essay, I investigate whether bidders pay for acquired targets' organization capital (OC), defined as the processes and systems that firms use to efficiently mix their capital and labor, in merger and acquisition (M&A) transactions. I also investigate whether the acquired OC is transferable and productive. I use a sample of completed U.S. M&A deals from 1990 to 2013. First, depending on the measure of recorded intangible assets employed, I find that bidders pay between 9 and 25 cents for one dollar of target OC. Second, I find that acquired OC is positively related to post-acquisition bidders' return on assets, sales growth, and asset turnover in same-industry transactions. The returns on acquired OC in the first and second fiscal years after transaction completion are 15% and 12%, respectively. These findings support the idea that OC is a valuable asset that is transferable between firms.

In the second essay, I examine whether organization capital is transferable across different industries. Using a sample of Compustat segment data from 1976 to 2014, I find results consistent with diversified firms benefitting more from their organization capital than do non-diversified firms when studying the relation between organization capital and each of return on assets, sales growth and asset turnover ratio. These findings support the transferability of organization capital across industries and thus suggest that investments in OC can transcend the industries in which they are made.

In the third essay, I investigate whether acquired targets' corporate social responsibility (CSR) is a transferable asset in merger and acquisition transactions. Using a sample of U.S. M&A deals from 1991 to 2013, I find a negative relation in same-industry deals between the acquired targets' CSR index and both scaled intangible assets booked by the bidders and bidders' post-acquisition return on assets. These relations imply that acquired targets' CSR acts more like a liability than an asset as it reduces the value of intangible assets recorded in M&A deals.

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# Chapter 1. Introduction

A rising factor of production over the last two decades has been intangible capital. Corrado and Hulten (2010) estimate that total investments in intangible capital ($1.6 trillion) amounted to 11.3 percent of GDP in 2007. While this amount alone is considerable, the relatively little we know about valuing intangible capital only adds to its significance. In this thesis, I study two intangible assets, namely organization capital, defined as the processes and systems that firms use to efficiently mix their capital and labor, and corporate social responsibility. In the first two essays, I study whether organization capital has a price and is a transferable asset between firms. In the third essay, I study whether corporate social responsibility is a transferable asset between firms.

In the first essay, I use the setting of mergers and acquisitions (M&A) to investigate whether bidders pay for acquired targets' organization capital. In doing so, I address the theoretical frameworks of Bahk and Gort (1993) and Carlin, Chowdhry, and Garmaise (2012), who suggest that organization capital is transferable by selling the firm. I also help to resolve the ongoing debate in this literature by showing empirically that organization capital is an asset that has a price, is transferable, and is not completely idiosyncratic. Following Eisfeldt and Papanikolaou (2013), I measure organization capital by cumulating and depreciating SG&A expenditures.

I investigate whether bidders pay for target organization capital by studying the relation between booked intangibles and the measure of organization capital. I also investigate whether the acquired organization capital is productive by studying the relation between two measures of organization capital and post-acquisition return on assets, sales growth, and asset turnover ratios. Using a sample of completed U.S. M&A deals from 1990 to 2013, I first find that bidders pay between 9 and 25 cents for one dollar of target organization capital. Second, I find that acquired organization capital is positively related to post-acquisition bidders' return on assets, sales growth, and asset turnover in same-industry transactions. These findings support the idea that organization capital is a valuable asset that is transferable between firms.

In the first essay, the small number of cross-industry acquisitions in my sample did not allow me to make meaningful conclusions regarding the transferability of organization capital between industries. I thus extend the work to the second essay by investigating whether the organization capital of a diversified firm, defined as one that operates in one or more business segment(s) in more than one industry, is associated with that firm's future profitability. If that is indeed the case, then it is consistent with organization capital being productive and transferable across segments/industries.

Using segment data from Compustat, I show evidence that organization capital is positively associated with ROA, sales growth, and asset turnover ratios. Second, I show that diversified firms benefit more from their OC than do their non-diversified counterparts. The findings are consistent with organization capital being a transferable asset between industries and nicely complements the finding of within-industry transferability in the previous essay.

In the third essay, I investigate whether acquired targets' corporate social responsibility (CSR) is a transferable asset in merger and acquisition transactions. I follow Servaes and Tamaro (2013) by computing a CSR index using data from the MSCI ESG KLD Stats dataset. Using the M&A data and methodology from the first essay, I find, in same-industry deals, a negative relation between the acquired targets' CSR index and both scaled intangible assets booked by the bidders and bidders' post-acquisition return on assets after controlling for acquired OC. These relations imply that acquired targets' CSR reduces the value of intangible assets recorded in M&A deals and is thus value decreasing. In this context, target CSR acts more like a liability than an asset.

# Chapter 2. The Price of Acquired Measured Organization Capital

## 2.1 Introduction

Intangible capital is becoming increasingly vital as a factor of production. Corrado and Hulten (2010) estimate that intangible assets formed 34% of firms' aggregate invested capital over the period 1995-2007 and that total investments in intangible capital ($1.6 trillion) amounted to 11.3 % of GDP in 2007. Peters and Taylor (2017) find in a sample of Compustat firms from 1975 to 2011 that almost half of the dollar value of total capital comes from intangible capital and that 76% of this intangible capital stems more specifically from organization capital. Organization capital – the methods that the firm uses to combine its physical and human capital – is thus an essential part of a firm's intangible capital. Organization capital includes a firm's information technology and growth strategies as well as its investments in human resources, distribution channels, and customer relationships.

Much of the existing research in the organization capital literature attempts to establish that organization capital is an asset and has focused primarily on documenting a positive relation between measures of organization capital and measures of future firm performance (see Black and Lynch, 2005; Lev and Radhakrishnan, 2005; De and Dutta, 2007; Tronconi and Vittucci Marzetti, 2011; Eisfeldt and Papanikolaou, 2013). Taking a different approach, Peters and Taylor (2017) show that measures of organization capital and physical capital have similar effects on firms' investments. I contribute to this literature by estimating a market value for organization capital. The existing measures used to create estimates of the dollar amount of organization capital are based on the aggregation of past Selling, General, & Administrative expenses. While these numbers are informative about the dollars invested in organization capital, they are much less informative about its market value. I exploit the accounting for merger and acquisition (M&A) to provide evidence on the market value of organization capital. To the best of my knowledge, this is the first paper to show evidence on the market price of organization capital.

In M&A deals, the bidders record the fair market value of net identifiable tangible assets acquired, identifiable intangible assets acquired, and goodwill. Goodwill represents the future economic benefit from acquired non-identifiable intangible assets. Under the joint hypothesis that organization capital is an asset and that it is transferable between firms, I argue that the value of intangible assets acquired – mainly goodwill – captures the value of organization capital. Thus, I investigate whether bidders pay for targets' organization capital in M&A transactions by examining whether the price paid for a target firm in excess of the value attributed to tangible and identifiable intangible assets not related to organization capital is associated with the value of the targets' measured organization capital.

Organization capital does not appear directly as an asset on a firm's balance sheet. However, there is this unique opportunity to (indirectly) ascertain its value – when an acquisition is made under the purchase method of accounting.[1] Under this method, the Statement of Financial Accounting Standards (SFAS) 141(r) A25 requires bidders to record the value of the non-identifiable intangible assets of the target firms as goodwill. While SFAS 141(r) does not explicitly mention organizational capital, to the extent that organizational capital is an intangible asset that bidders pay for, its value will be included in the goodwill booked at the time of the transaction. Thus, the M&A setting is well suited for this study.

Using acquisition data to estimate the market value of organization capital implicitly allows me to investigate empirically the transferability of organization capital, an issue of some debate in the literature. The theoretical frameworks of Bahk and Gort (1993) and Carlin, Chowdhry, and

[1] This is the only accounting method used for acquisitions since July 1st, 2001.

Garmaise (2012) suggest that organization capital is transferable by selling the firm. Atkeson and Kehoe (2005), Prescott and Visscher (1980), and Eisfeldt and Papanikolaou (2013), among others, argue that organization capital is transferable at a cost. On the other hand, Lev and Radhakrishnan (2005) argue that organization capital is very difficult to transfer. I help to resolve the debate in this literature by showing empirically that organization capital is an asset that is transferable and is not completely idiosyncratic.

In this chapter, I first test the hypothesis that the organization capital of the target firm has a market price. Evidence of bidders paying for target organizational capital is consistent with it being transferable between firms. I provide further evidence consistent with the transferability by examining whether the acquired organization capital is productive post-acquisition. I do this by studying the relation between bidders' return on assets and acquired targets' organization capital in the two years following acquisition completion. A positive relation implies that bidders are employing targets' organization capital following acquisition and confirms that organization capital is transferable.

In order to study the price and transferability of organization capital, I require an appropriate measure of it. Although organization capital has long been recognized as an economic asset (Marshall, 1920), accounting standards require the expensing of investments in organization capital. To date, the accounting and finance literatures have measured organization capital as a function of selling, general, and administrative expenses (SG&A) and have found this construct to be asset-like.[2] I follow Eisfeldt and Papanikolaou (2013) and measure organization capital by cumulating SG&A and depreciating SG&A expenditures. Since SG&A also includes research and

[2] See, for example, Lev and Radhakrishnan (2003) and (2005); Eisfeldt and Papanikolaou (2013); Peters and Taylor (2017).

development (R&D) and advertising expenses, I create an alternate measure of organization capital by cumulating SG&A after the removal of both R&D and advertising expenses.

My first hypothesis is that if bidders pay for targets' organization capital, then there should be a positive relation between targets' organization capital and transacted goodwill. My measure of OC is broad and can contain both non-identifiable and identifiable intangibles. Therefore, in addition to goodwill, I also consider other measures of intangible assets acquired in the transaction. I test this hypothesis by studying the relation between different values of scaled transacted intangible assets and each of the two measures of organization capital that I estimate, both scaled by total assets. Positive and significant coefficient estimates of scaled organization capital indicate that bidders pay for target organization capital, provide an estimate of the market price of organization capital, and validate the use of the cumulative SG&A model to measure investment in intangible assets.

My second hypothesis is that the acquired organization capital is productive. I test this hypothesis by studying the relation between bidders' post-acquisition return on assets and each of the two measures of acquired targets' organization capital scaled by bidders' lagged total assets. I expect the coefficient estimate on each of the two scaled measures to be positive and significant, implying that bidders are employing their acquired targets' organization capital productively. I also study the relation between bidders' post-acquisition sales growth (asset turnover ratio) and each of the two measures of acquired targets' organization capital scaled by bidders' lagged sales (lagged total assets). A positive and significant coefficient estimate on each of the latter variables implies that acquired organization capital is positively associated with bidders' sales and assets' efficiency, respectively.

Using a sample of completed U.S. M&A deals from 1990 to 2013, I find results consistent with my expectations. First, depending on the measures of booked intangible assets and organization capital used, I find that bidders pay between 9 and 25 cents, on average, per dollar of the targets' organization capital. Second, in subsample analysis, I find a positive relation between acquired targets' organization capital and bidders' post-acquisition ROA in same-industry (same two-digit SIC code) transactions. The returns on acquired targets' organization capital in the first and second fiscal years following the completion of the transaction are 15% and 12%, respectively. Third, I find a positive relation between acquired targets' organization capital and bidders' sales growth in the first fiscal year following the completion of the transactions. Fourth, I find that acquired targets' organization capital has a positive relation with bidders' asset turnover ratios in the first two fiscal years following the completion of the transactions.

The finding that targets' organization capital is related to the market price that bidders pay for targets, as well as bidders' future ROA, sales growth, and asset turnover ratio, is evidence that organization capital is an asset that is not completely idiosyncratic. In summary, my results show that organization capital has a price and is both productive and transferable. These findings also provide evidence on the construct validity of the measure of organization capital. By directly linking market values of unidentifiable intangibles (goodwill) as well as identifiable intangible assets (RD in process, workforce in place, brands) to the measure of organization capital, I show that this measure is statistically significantly related to assets that are not currently booked.

Thus, this study also contributes to the literature that recommends the capitalization of intangible expenses. Banker, Huang, and Natarajan (2011), Hulten and Hao (2008) and Enache and Srivastava (2018), among others, suggest that these investments in long-term intangible assets, which are expensed in the income statement, should be capitalized since capitalized intangibles explain equity values and can reduce overly-inflated Q values.[3]

The remainder of the paper is organized as follows: I summarize the related literature and develop the hypotheses in the next section. Section 2.3 describes the construction of the dataset and sample. Section 2.4 presents the results and section 2.5 concludes.

## 2.2 Research Background and Hypothesis Development

### 2.2.1 Organization Capital and Intangible Assets

Organization capital (OC) can be described as the firm's combination of knowledge, processes, and systems between labor and capital that leads to greater efficiency (Eisfeldt and Papanikolaou, 2013; Li, et al., 2018). Even though this notion of OC has been around for over a century and has been described by various researchers, there is still no absolute consensus regarding its precise definition or measure.[4] While Marshall (1920) states that training can improve the efficiency of employees, leading to superior organization, Prescott and Visscher (1980) are the first to define OC as information related to the firm's employees. Lev and Radhakrishnan (2005) and Lev, Radhakrishnan and Zhang (2009) describe OC as the unique way in which firms match their factors of production. Other definitions of OC include higher quality management, innovative processes, and the accumulation of knowledge capital through learning-by-doing.[5] These definitions sum to the idea that OC is an intangible asset related to human capital (management and key employees), processes, and knowledge, and that it is associated with higher firm value.

[3] See also Corrado, Hulten, and Sichel (2005), Corrado, Hulten, and Sichel (2009), Corrado and Hulten (2010), McGrattan and Prescott (2010), and Peters and Taylor (2017).
[4] See, for example, Prescott and Visscher (1980), Atkeson and Kehoe (2005), Lev and Radhakrishnan (2005), Eisfeldt and Papanikolaou (2013), and Li et al. (2018).
[5] See also Arrow (1962), Rosen (1972), Bahk and Gort (1993), Coff (2002), Atkeson and Kehoe (2005), De and Dutta (2007), and Corrado, Hulten and Sichel (2009).

The empirical literature on OC has focused primarily on the relationship between OC and future firm performance, and the value creation of OC.[6] For example, Eisfeldt and Papanikolaou (2013) find that high-OC firms have higher average stock returns and are more productive than low-OC firms. Lev and Radhakrishnan (2005) find that OC is associated with future abnormal earnings and can explain the difference between market value and book value of equity. Li et al. (2018) find that, compared to low-OC bidders, high-OC bidders have higher announcement abnormal returns and better post-acquisition operating and stock performance. High-OC firms are associated with the following characteristics: higher productivity, more labor intensity, higher quality management, smaller firm size, higher cash flow, higher IT expenditures, higher sales performance, higher Q ratios, and more (less) investment in intangible (physical) assets. Moreover, high-OC firms are more likely to list the loss of key employees as a risk factor in their annual reports (Black and Lynch, 2005; Lev and Radhakrishnan, 2005; De and Dutta, 2007; Tronconi and Vittucci Marzetti, 2011; Eisfeldt and Papanikolaou, 2013; Li et al., 2018). These firms are constantly developing and adopting new processes to increase their efficiency and competitiveness.

While earlier papers view OC as embodied in either key employees (Prescott and Visscher, 1980; Ranft and Lord, 2000) or the firm itself (Atkeson and Kehoe, 2005), recent papers such as Lustig, Syverson and Van Nieuwerburgh (2011) and Eisfeldt and Papanikolaou (2013) view OC as embodied in both key talent and the firm itself. Whether OC is embedded in key personnel or the firm itself (or both) can significantly influence its transferability. On one hand, Lev and Radhakrishnan (2005) argue that OC is very difficult to transfer because it is implicit in the firm. Another school of thought argues that OC is transferable at a cost (Prescott and Visscher, 1980;

[6] There are also papers which model OC for example, Atkeson and Kehoe (2005), Bahk and Gort (1993), Carlin, Chowdhry, and Garmaise (2012), Faria (2008), Lustig, Syverson, and Van Nieuwerburgh (2011), and Rosen (1972).

Atkeson and Kehoe, 2005; Eisfeldt and Papanikolaou, 2013). In the theoretical frameworks of Bahk and Gort (1993), Atkeson and Kehoe (2005), Faria (2008), and Carlin, Chowdhry, and Garmaise (2012), OC is transferable through selling the entire firm. This paper contributes to the OC literature by providing empirical evidence supporting the transferability of OC.

To find the market price of OC and to show empirically that it is transferable, I require an appropriate measure of OC. However, the lack of a precise definition of OC makes finding a true measure challenging, especially when it should also include values for experience and learning-by-doing (Arrow, 1962; Atkeson and Kehoe, 2005). Lev and Radhakrishnan (2003) estimate OC as the residual of a regression of sales growth on physical capital growth, labor growth, and R&D growth. This measure of OC contributes to the explanation of market value of firms and since it is strongly correlated with SG&A, they use SG&A as an instrumental variable that proxies for investments in OC.[7] Eisfeldt and Papanikolaou (2013) measure OC by cumulating annual SG&A expenses using the perpetual inventory method. This measure is later used by Li et al. (2018) and it is the OC measure which I employ in this study.

### 2.2.2 Mergers and Acquisitions and OC

In the theoretical framework of Bahk and Gort (1993) and Atkeson and Kehoe (2005), OC is transferable through selling the entire firm. Thus, I use the M&A setting to find the market price and study the transferability of OC. This paper is related to the vast M&A literature by showing the acquisition of OC as an additional motive for acquisitions.[8]

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[7] Based on the amalgamation of definitions of OC, the following are some of the investments in OC: information technology expenses, costs of training employees, advertising, payments to strategy consultants, the processes in which the firm invests, the unique systems the firm uses in productions and sales, the way firms reward their employees, and so on [see, e.g., Lev and Radhakrishnan (2005), De and Dutta (2007), Eisfeldt and Papanikolaou (2013), and Li et al (2018)]. These sources of investments in OC are subsumed into SG&A.

[8] I refer the reader to Chapter 19 of Copeland and Weston (1988) for different theories of M&A.

To the extent that OC is embedded in the firm, the only way to purchase it is to acquire the whole target firm [see, e.g., Bahk and Gort (1993), Atkeson and Kehoe (2005), Faria (2008), and Carlin, Chowdhry, and Garmaise (2012)]. If OC is embedded in both the firm and its key employees, then the bidder must acquire the target in its entirety and retain its key employees. Alternatively, if OC is embedded only in key employees (Prescott and Visscher, 1980), then the bidder can acquire OC solely by hiring the key employees of the target. Given that the overall OC literature suggests that the value of OC extends beyond just key employees, the M&A setting thus provides a unique opportunity to study the acquisition of OC. Moreover, this setting is also valuable because the single way for OC to appear on a balance sheet is when an acquisition is done under the purchase method of accounting. Under this method, if bidders pay for the targets' OC, the acquired OC is captured on the bidder's balance sheet in the booked goodwill or booked identifiable intangible assets associated with the transaction. According to SFAS 141(r) A25:

> "*The acquirer subsumes into goodwill the value of an acquired intangible asset that is not identifiable as of the acquisition date. For example, an acquirer may attribute value to the existence of an assembled workforce, which is an existing collection of employees that permits the acquirer to continue to operate an acquired business…the assembled workforce is not an identifiable asset to be recognized separately from goodwill, any value attributed to it is subsumed into goodwill.*"

This accounting standard indicates that non-identifiable intangible assets (like OC) are subsumed into goodwill. Though the statement does not mention the term OC, it uses the existence of an assembled workforce (which is a component of OC) as an example. Thus, the statement implies that the OC of a target firm is subsumed into the booked goodwill associated with the acquisition if the bidder pays for target OC. The value of goodwill therefore represents the future economic benefits of the non-identifiable intangible assets, including OC.

In Exhibit 1, I provide excerpts from a sample of acquiring-firm 10Ks where the bidders describe the components of goodwill. The two main components of goodwill are OC and synergies, and the components of OC include, but are not limited to, items such as assembled workforces, technology, and key personnel. More specifically, the following OC-related items are referred to in the goodwill literature as being components of goodwill: organization costs, reputation, better quality workforce, customer lists, cost of development, managerial talent, customer service, economies of scale, and great market position among others (Nelson, 1953; Falk and Gordon, 1977; Chauvin and Hirschey, 1994).[9]

Since I am using transacted goodwill, one can argue that the goodwill recorded is related to managerial hubris (Roll, 1986) rather than the acquisition of OC. There are three reasons that alleviate this concern. First, if goodwill represents managerial hubris, then there should be no relation between goodwill and the target's investment in OC. However, my results indicate that there is indeed a relation between the two. Second, even if managerial hubris is present, it should be orthogonal to the target's OC, mitigating this concern. Third, if goodwill reflects hubris, then the announcement of goodwill impairment should have no effect on stock price, assuming the market is efficient. However, Bens, Heltzer and Segal (2011) find a negative market reaction to the announcement of goodwill impairment, indicating that goodwill is an intangible asset of the firm.

[9] Note that in an M&A transaction, the bidder may record identifiable intangible assets like workforce and non-compete agreements, which are part of OC. I account for these in my measures of acquired intangible assets when I study the market price of OC.

### 2.2.3 Hypothesis Development and Variable Definition

Since it is virtually impossible to trade the firm's OC as a free-standing asset, in order to procure the OC of a target firm, the acquiring firm must purchase the target firm in its entirety. If bidders acquire target OC in an M&A transaction, then OC should have a price. Thus, I should observe a positive relation between the recorded intangible assets like goodwill and the target's OC. The variable of interest is *Scaled OC (Scaled OCnet),* where I scale *OC* (*OCnet*) by targets' total assets, $TA_{T,t-1}$, which are measured at the last fiscal year end prior to the completion of the acquisition, and *OC* is measured as follows:

$$OC_{i,t} = (1 - Depr_{OC})OC_{i,t-1} + \frac{SG\&A_{i,t}}{cpi_t} \tag{2.1}$$

$$OC_{i,0} = \frac{SG\&A_{i,1}}{g + Depr_{OC}} \tag{2.2}$$

where $OC_{i,t}$ is the measured OC of firm *i* at time *t*, $Depr_{oc}$ is the depreciation rate of OC set to 15%, and *g* is the average real growth rate of firm-level SG&A set to 10% as in Eisfeldt and Papanikolaou (2013). $cpi_t$ is the Consumer Price Index at time *t* with July 2010 as the base.[10] I use the same method to compute my alternative measure of OC, which I refer to as *OCnet*, except that I use SG&A net of both R&D and advertising expenses.

My measure of OC is broad and not all OC-related items are recorded as goodwill.[11] Some items are recorded separately as identifiable intangible assets when their values are material and identifiable; otherwise, their values are subsumed into goodwill. Since these are amounts paid to target shareholders for acquired measured OC, I should account for these in pricing acquired OC. Excluding the value of these intangibles and using only goodwill underestimates how much

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[10] https://fred.stlouisfed.org/

[11] These intangible assets are investments in OC in terms of the way the firms do their marketing, create and maintain their customer base lists, tradename, customer relations, and their own idiosyncratic way of maintaining their technologies.

bidders pay for OC and potentially leads to inconsistency or misrepresentation. I measure acquired intangible assets as follows:

- *AcqIntan1* is the sum of booked goodwill and all identifiable intangible assets recorded in the deal.
- *AcqIntan2* is *AcqIntan1* less both in-process R&D and patents.
- *AcqIntan3* is the sum of booked goodwill and workforce as well as non-compete agreements.
- *GDWL* is booked goodwill alone

The first hypothesis is:

*H1: OC is an asset that has a price.*

Implicit in this hypothesis is the assumption that cumulative SG&A measures OC. I test the above hypothesis using the following deal-level regression:

$$\frac{Y_{B,T,t}}{TA_{T,t-1}} = \alpha_0 + \beta_1 \frac{OC_{T,t-1}}{TA_{T,t-1}} + \beta_2 CASH + \beta_3 CAR_B + \beta_4 PREMIUM + Indus_{FF17} \,\&\, Yr\ FE + \varepsilon_{B,T,t} \quad (2.3)$$

where *Y* is *AcqIntan1, AcqIntan2, AcqIntan3,* or *GDWL*. The subscript *B* is for the bidder, *T* is for the target, and time *t* is the fiscal year during which the transaction was completed. The dependent variables are *Scaled AcqIntan1, Scaled AcqIntan2, Scaled AcqIntan3,* and *Scaled GDWL,* respectively. The variable of interest is *Scaled OC* (hereafter *OC*), and in separate regressions, I replace *OC* in Eq. (2.3) with *Scaled OCnet* (hereafter *OCnet*). The coefficient estimates of the two measures of OC are expected to capture the price that bidders pay, on average, for one dollar of acquired target measured OC (*OC* and *OCnet*).

*$CASH_{B,T,t}$* is a dummy variable which takes the value of 1 for 100% cash-financed deals, and 0 otherwise. *$CAR_B$*, is the cumulative announcement abnormal return (*CAR*) of the bidder, in percentage, for the three days (-1, +1) around the acquisition announcement date. The market model is used to estimate the abnormal stock return. The equally-weighted CRSP market return is used to estimate alpha and beta of the market model. Following Betton and Eckbo (2000), I calculate *PREMIUM* as the initial offer price scaled by target stock price 60 days prior to the announcement minus one, all multiplied by 100. In line with the notion of managerial hubris (Roll, 1986), I expect the coefficient estimates of *$CAR_B$* and *PREMIUM* to be negative and positive, respectively. *$Indus_{FF17}$ & Yr FE* are fixed effects for the Fama-French 17-industry classifications (Fama and French, 1997) and year, respectively. In my tests, standard errors are clustered by industry.[12] All variables are as described in Appendix 2. A timeline of the acquisition event is provided in Figure 1.

My second hypothesis addresses the productivity of acquired OC. An alternative approach to investigating whether OC is transferable is to examine the relation between targets' OC and bidders' future ROA. Thus my second hypothesis is:

> *H2: There is a positive relation between acquired targets' OC and bidders' future operating returns.*

I run regressions with ROA as the dependent variable and acquired *OC* (*OCnet*) scaled by lagged total assets as the variable of interest to study this relationship as follows:

$$\frac{OIBDP_{B,t+1}}{TA_{B,t}} \cdot 100 = \alpha_0 + \beta_1 \cdot \frac{OC_{T,t-1}}{TA_{B,t}} + \beta_2 \cdot \frac{OC_{B,t}}{TA_{B,t}} + \beta_3 \cdot \frac{1}{TA_{B,t}} + \beta_4 \cdot \frac{OIBDP_{B,t}}{TA_{B,t-1} + TA_{T,t-1}} \cdot 100 + Indus_{FF17} \,\&\, Yr\ FE + \varepsilon_{B,t+1} \tag{2.4}$$

[12] Since OC has a strong industry effect, I follow Petersen (2009) and cluster standard errors at the industry level.

where $OIBDP_{B,t+1}$ is bidder's operating income before depreciation for the fiscal year following the transaction completion year; $OC_{T,t-1}$ is acquired target *T*'s *OC*. All variables are as described in Appendix 2. Note that at time *t*, the operating income reported by the bidder includes the operating income of the target. Thus, I scale $OIBDP_{B,t}$ by the sum of bidder and target total assets. Eq. (2.4) is an augmented version of Banker, Huang, and Natarajan (2011), who study the value created by SG&A. If acquired OC is productive for the bidder, then it should be positively associated with bidders' future operating returns and the coefficient estimate of *OC* is expected to be positive and significant. A positive relationship between acquired OC and future profitability implies that bidders acquire and employ targets' OC.

I also study whether the observed relation between ROA and acquired OC arises via sales growth. I alter the Eq. (2.4) with sales to investigate this relation as follows:

$$\frac{SALE_{B,t+1}-SALE_{B,t}}{SALE_{B,t}} \cdot 100 = \alpha_0 + \beta_1 \frac{OC_{T,t-1}}{SALE_{B,t}} + \beta_2 \frac{OC_{B,t}}{SALE_{B,t}} + \beta_3 + \beta_4 \frac{SALE_{B,t}-SALE_{B,t-1}-SALE_{T,t-1}}{SALE_{B,t-1}+SALE_{T,t-1}} \cdot 100 + Indus_{FF17}\,\&\, Yr\ FE + \varepsilon_{B,t+1} \qquad (2.5)$$

where *SALE* is sales and all the other variables are as described earlier and in appendix 2. The dependent variable is bidders' *Sales Growth* and the variable of interest, $OC_{T,t-1}/SALE_{B,t}$, is the acquired OC scaled by lagged bidders' sales. While the bidder's sales at time *t* include the target sales during that year, this is not the case in year *t-1*. Therefore, when computing the increase in sales for year *t*, I deduct target sales at *t-1* and scale by the sales of both target and bidder combined.

Lastly, I study the relation between asset turnover and acquired target OC by modifying Eq. (2.4) as follows:

$$\frac{SALE_{B,t+1}}{TA_{B,t}} = \alpha_0 + \beta_1 \frac{OC_{T,t-1}}{TA_{B,t}} + \beta_2 \frac{OC_{B,t}}{TA_{B,t}} + \beta_3 \frac{1}{TA_{B,t}} + \beta_4 \frac{SALE_{B,t}}{TA_{B,t-1}+TA_{T,t-1}} \cdot 100 + Indus_{FF17}\,\&\, Yr\ FE + \varepsilon_{B,t+1} \qquad (2.6)$$

The dependent variable is bidders' *Asset Turnover* and the variable of interest, $OC_{T,t-1}/TA_{B,t}$, is the acquired OC scaled by lagged bidders' book value of total assets. All other variables are as described above and in Appendix 2.

### 2.3 Data and Sample Description

The sample of M&A deals is obtained from the Thomson Reuters Securities Data Company (SDC). I obtain the accounting and stock price data from the Compustat and Center for Research in Security Prices (CRSP) databases, respectively, for the acquiring and target firms. The SDC sample covers deals made by U.S. public bidders with announcement dates from January 1, 1990 and effective dates ending on or before December 31, 2013. Over that period, there are 87,297 completed deals, excluding repurchases and self-tenders. After matching and eliminating acquiring firms for which accounting data is not available, the sample size is reduced to 63,878 deals.

Since this study requires financial data for the target firms, I limit the sample to U.S. public targets. This criterion reduces the sample to 5,571 deals. Following the literature (Fuller, Netter, and Stegemoller, 2002; Cai, Song, and Walking, 2011), I exclude deals where at least one of the two firms is in the financial (SIC codes 6000 to 6999) or public utility sector (SIC codes 4900 to 4999). I drop deals where the transaction value listed in SDC is less than $1 million (inflation-adjusted using July 2010 as the base). Following Masulis, Wang, and Xie (2007), I keep deals where (1) the bidder owns less than 50% of the target shares outstanding prior to the announcement date and owns 100% of the target after the transaction is completed, and (2) the transaction value disclosed in SDC is at least one percent of the bidder's market capitalization measured on the $11^{th}$ trading day before the announcement date. To ensure that these targets are later delisted due to M&A activity, I verify that the CRSP delisting codes for the target firms are in the 200s (M&A-

related) within 150 days around the effective date. These criteria reduce the sample to 1,768 deals.[13]

The final selection criterion is that the acquired goodwill, a component of the first main dependent variable, is reported on the bidder's balance sheet in the first annual report following the effective date of the acquisitions.[14] Instead of using the goodwill amount provided in Compustat, I choose to use recorded goodwill on a deal-level basis for the following reasons. Most importantly, using bidder-level regressions would lead to an error in the independent variable and would violate the zero-conditional-mean assumption of OLS, resulting in a biased and inconsistent OLS estimator. I describe this error-in-independent variable problem in detail in Appendix 1 and show that the best solution is to hand-collect goodwill data for each deal from the bidders' annual reports from the Security Exchange Commission (SEC) website and use deal-level regressions.[15] Moreover, using deal-level data not only preserves the variation in the data but also allows me to differentiate between cross- and within-industry transactions. Using deal-level data results in a sample size of 999 deals.

In the second part of this chapter, I investigate the relationship between acquired OC and bidders' post-acquisition profitability, ROA, to provide confirmatory evidence on the transferability of OC. Unlike goodwill, ROA is measured at the bidder level and cannot be disaggregated to the transaction level. Therefore, I must aggregate acquired OC. However, aggregating acquired OC is problematic when the bidder makes acquisitions of private targets. I

[13] There are no target firms with delisted codes in the 300s (share exchange-related) in this sample.
[14] Prior to 2001, there were two methods of accounting for M&A – the pooling-of-interest method and the purchase method. Under the former method, assets and liabilities were recorded on a "historical cost" basis while under latter, the bidder records the transaction at the price actually paid. Goodwill is recorded only under the purchase method. In January 2001, the Financial Accounting Standards Board (FASB) made the purchase method the only method of accounting starting July 1, 2001. I exclude transactions in the sample that use the pooling-of-interest method as goodwill amounts for these deals would not be available. See Weston, Mitchell, and Mulherin (2003).
[15] https://www.sec.gov/edgar/searchedgar/companysearch.html

solve this issue by using deals where the bidder made only one acquisition in a given fiscal year and the acquired target is a public firm. This sample has 365 observations. To ensure that the ROA of the bidders are not contaminated by other acquisitions, I drop observations where the bidder made acquisitions in the fiscal year following the completion of the deal in question. This removal of confounding events leads to a sample of size of 271 observations in year *t+1*. Applying this procedure to the second fiscal year following the completion of the deal reduces the sample size to 193 observations. Table 2.1 provides a summary of the construction of the sample.

## 2.4 Results

### 2.4.1 Summary Statistics

While most of the variables used in the empirical tests of this study are scaled by total assets, I start by presenting the summary statistics of the unscaled versions of the main variables and some reference variables in Panel A1 of Table 2.2. I do this to provide a better view of the significance of my results and some statistics regarding the dollar amount of intangible assets recorded in M&A deals. I present the statistics for the Full sample first, followed by the Cross- and Same-Industry samples, respectively. The Same- (Cross-) Industry sample consists of observations where the bidder and target (do not) share the same two-digit SIC codes. For the Full sample, the means (medians) of *AcqIntan1*, *AcqIntan2*, *AcqIntan3*, and *GDWL* are $1.20 ($0.28), $1.08 ($0.26), $0.89 ($0.20) and $0.88 ($0.20) billion, respectively. Overall, these numbers show that a large dollar amount, on average, is being recorded as intangible assets acquired in an M&A deal.[16]

[16] Note that in 445 observations, the bidder recorded in-process R&D and patents and they have a combined mean of $0.4 billion. In 590 observations, the bidder recorded advertising-related intangible assets (*AcqIntan2 - AcqIntan3*) and this variable has a mean of $0.3 billion. In 106 observations, the bidder recorded workforce and non-compete agreements and they have a combined mean of $0.09 billion. When considering the mean of each of the scaled

The dollar amount of my measure of OC has a mean (median) of \$0.84 (\$0.27) billion. The dollar amount of *OCnet* has a mean (median) of \$0.70 (\$0.21) billion. The mean market value of equity (*ME*) and book value of total assets (*TA*) of the targets, measured at the most recent pre-acquisition fiscal year-end, are around \$1 billion in all three samples. The mean *ME* and *TA* of the bidders in the Full sample are about \$10 and \$8 billion, respectively. The bidders in the Cross-Industry sample are, on average, larger than those in the Same-Industry sample.

In Panel A2, I present the summary statistics of the above variables scaled by targets' total assets measured at the last fiscal year end prior to the completion of the acquisition. The mean (median) of *Scaled AcqIntan1* is 1.91 (1.22) in the Full sample, implying that the average amount attributed to intangible assets in a transaction in this sample is almost double that of the targets' total assets. In the Full sample, the means (medians) of *Scaled AcqIntan2* and *Scaled AcqIntan3* are 1.63 (1.04) and 1.36 (0.83), respectively, while the mean (median) of *Scaled GDWL* is 1.35 (0.83). This figure indicates that the average amount of goodwill recorded in a transaction in this sample is about 135% of the total assets of the target. The magnitude of the booked goodwill and *Scaled GDWL* suggests that goodwill is an important asset recorded in M&A transactions. The means of scaled acquired intangibles are significantly higher in Cross- than in Same-Industry deals.

*Scaled OC* and *Scaled OCnet* have means (medians) of 1.86 (1.40) and 1.43 (1.08), respectively.[17] The median level of *Scaled OC* in this sample is comparable to that in the fourth quintile (Table III) of Eisfeldt and Papanikolaou (2013), suggesting that the targets in this sample

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intangibles in Panel A2, I find that the means of *Scaled AcqIntan1*, *Scaled AcqIntan2,* and *Scaled AcqIntan3* are statistically larger than the mean of *Scaled GDWL* in the Full sample. This implies that the sum of the different measures of acquired identifiable intangible assets net of goodwill are, at least statistically, valuable assets.

[17] There is no statistical difference in the level of *Scaled OC* and *Scaled OCnet* between Cross- and Same-Industry deals.

are, on average, high OC firms. The means (medians) of *Scaled Bidder OC* and *Scaled Bidder OCnet* (where I use the *OC* and *OCnet* of the bidders) are 1.17 (0.93) and 0.90 (0.68), respectively. On average, *Scaled OC* is larger than *Scaled Bidder OC* and the difference is economically and statistically significant. In this sample, I can conclude that, on average, the targets are more OC-intensive than are the bidders. In this sample, about 40% of the deals are financed solely with cash. The mean of $CAR_B$ is -1.17% for the Full sample, and -1.50% and -1.04% for the Cross- and Same-Industry samples respectively.[18] The average *PREMIUM* is 49%. These statistics are consistent with Betton et al. (2008).

As mentioned earlier, in the second part of this chapter, I study the relation between acquired targets' OC and the following three post-acquisition variables – bidders' return on assets (*ROA*), *Sales Growth*, and *Asset Turnover*. The mean and median of post-acquisition bidder *ROA* are approximately 10% and 11% per year for the first and second fiscal years, respectively. The average *Sales Growth* in the first fiscal year following acquisition completion is around 15%. However, in the second fiscal year, the average *Sales Growth* is -1.55%. The *Asset Turnover* of the bidders is about 1, on average, in each of the first two fiscal years following the completion of the acquisition. The means of acquired *OC* (*OCnet*) scaled by bidders' *TA* in the first and second years following the completion of the acquisition are 0.41 (0.31) and 0.46 (0.33), respectively. Scaling these two variables instead by bidders' sales in the first and second year following acquisition completion are 0.77 (0.52) and 0.59 (0.40), respectively.

Consistent with my hypothesis *H1*, from the correlation matrix in Panel B1 of Table 2.2, I find that all the different measures of acquired scaled intangible assets have a positive and significant correlation with both *Scaled OC* and *Scaled OCnet*. In line with the notion of

[18] The difference in *CAR* between Same- and Cross-Industry samples is statistically insignificant.

managerial hubris (Roll, 1986), I find a positive and significant correlation coefficient between *PREMIUM* and the different scaled intangible asset variables. Both *Scaled OC* and *Scaled OCnet* have a positive and significant correlation with both *CASH* and *PREMIUM*. These results imply that, on average, when acquiring high OC targets, bidders tend to use cash as the method of payment and pay a higher premium. This result may also suggest that bidders account for the targets' OC positively when calculating the premium to pay in M&A deals. The variable $CAR_B$ has a positive and significant correlation with cash financing as the method of payment, indicating that the market reacts, on average, less negatively to deals financed solely with cash. Similar observations are made from the Same-Industry sample in Panel B2.

From the correlation matrix in Panel B3, I find that both scaled acquired *OC* and scaled acquired *OCnet* are significantly negatively correlated with *ROA* for each of the two fiscal years following the completion of the acquisitions, while these coefficients are insignificant in Panel B4 (Same-Industry sample). In Panel B5, I find that both acquired *OC* and acquired *OCnet* scaled by sales are positively (negatively) correlated with *Sales Growth* in year $t$+1 ($t$+2). In Panel B6, a similar observation is made for year $t$+1 in the Same-Industry sample. In Panel B7, I find that both scaled acquired *OC* and scaled acquired *OCnet* are positively correlated with *Asset Turnover* for each of the two fiscal years following the completion of the acquisitions. Similar observations are made in Panel B8 where I consider the Same-Industry sample.

### 2.4.2 The Price of OC

In Table 2.3, I present the results of Eq. (2.3) starting with *Scaled AcqIntan1* as the dependent variable in the first three columns and end with *Scaled GDWL* in the last three columns. I thus start with the aggregate of all acquired intangible assets booked in an M&A transaction and then remove the identifiable intangible assets and subsequently use solely the non-identifiable intangible assets. In the first three columns of Table 2.3, the coefficient estimates of *OC* are positive and significant. From the Full sample, I can interpret this coefficient estimate simply as follows: *Scaled AcqIntan1* increases by 0.14 when *OC* increases by one. More intuitively, though, if I multiply both sides by total assets, then I can interpret this coefficient as the price that bidders pay on average for one dollar of acquired targets' measured OC. In this case, when considering all booked intangible assets in a deal, bidders pay 14 cents, on average, per dollar of acquired targets' measured OC. The corresponding amounts for the Cross-Industry and Same-Industry samples are 14.6 and 16.4 cents per dollar, respectively.[19] These results are consistent with my observations from the correlation matrices and, more importantly, my hypothesis that OC is an asset that has a market price and that bidders pay for acquired target OC in M&A deals. These results also validate the use of a cumulative SG&A measure of OC.

The coefficient estimate of *CASH* is positive in all samples and significant in the Full and Cross-Industry samples only, implying that for a given level of book value of total assets, more intangible assets are recorded, on average, when the deal is 100% cash financed. The coefficient estimate of $CAR_B$ is negative in all samples and significant in the Full and Same-Industry samples only. This result implies that there is a negative relation between bidders' stock price reaction and the amount of scaled intangible assets booked in a transaction. As expected, the coefficient estimates of *PREMIUM* are positive in all samples, but significant in the Full and Same-Industry samples only. Consistent with my expectations, similar observations are made when using the different measures of acquired intangible assets. Taken together, the negative coefficient of $CAR_B$ and the positive coefficient of *PREMIUM* can be interpreted as a proxy for managerial hubris, a component of goodwill (Roll, 1986).

[19] The difference in the price of OC between Cross- and Same-industry subsamples is statistically insignificant in all models in this Table.

One may argue that intangibles such as in-process R&D and patents are associated with R&D expenses but not specifically with OC and thus these amounts should not be included in my dependent variable. I address this issue by using *Scaled AcqIntan2* as the dependent variable – *AcqIntan2* is the sum of acquired intangible assets that are unrelated to R&D expenses. I present the results in the next three columns of Table 2.3. Consistent with my hypothesis that OC has a price, the coefficient estimate of *OC* is still positive in all samples but significant in the Full and Same-Industry samples only. The coefficient estimates of the control variables are similar to those under the previous model.

Another argument that can be made is that *AcqIntan2* includes intangibles related to advertising investment but are not specifically related to OC and I should thus exclude these amounts from my dependent variable. I address this issue by using *AcqIntan3*, which is the sum of *GDWL*, workforce, and non-compete agreements, as my dependent variable and present the results in the next three columns of Table 2.3. The coefficient estimate of *OC* is again positive in all samples and significant in the Full and Same-Industry samples only, implying that bidders pay 10.8 cents and 12.5 cents, on average, per dollar of acquired OC, when considering *AcqIntan3*. The coefficient estimates of the control variables are qualitatively similar to those observed in the previous model, although *CASH* is significant only in the Cross-Industry sample.

In the final three columns of Table 2.3, I use scaled *GDWL*, which does not include any in-process R&D, patents, advertising investments, workforce, and non-compete agreements, as the dependent variable. For the Full sample, the coefficient estimate of *OC* is positive and significant, implying that bidders pay 11 cents, on average, per dollar of acquired targets' measured OC through goodwill. In horizontal deals, bidders pay 12.5 cents, on average, per dollar of acquired targets' measured OC through booked goodwill. For the Cross-Industry subsample, the coefficient estimate of *OC* is positive but insignificant, as in the last two models. Thus, I fail to conclude that bidders pay for their acquired targets' OC in cross-industry deals. However, the Cross-Industry sample is very small in size and the presence of both industry and year fixed effects potentially removes significant valuable variation in the data (see Gormley and Matsa, 2014). Excluding the industry fixed effects in the Cross-Industry sample in these models results in a positive and significant (p-value of about 0.08) coefficient estimate of *OC*.

Since the coefficient estimates of *OC* in the first two models (namely those using *Scaled AcqIntan1* and *Scaled AcqIntan2*) are significant and larger in magnitude than those in the *Scaled GDWL* model, it implies that acquired measured OC is also related to the other mentioned intangible assets. From this table, I can make three conclusions: (1) the value of acquired targets' measured OC is reflected in the value of intangible assets recorded in M&A deals, (2) bidders pay for acquired targets' OC, and (3) the market value of targets' OC is reflected in the purchase price of target firms.

It should be noted that the dependent variables in Eq. (2.3) are censored from below since recorded intangible assets do not take negative values in my sample. As a result, the Tobit model is more appropriate than the traditional OLS regression. In untabulated results, I find that the Tobit model produces results that are comparable to those using the OLS regressions and, thus for ease of exposition, I present only the output from the OLS regressions. Additionally of note, while the industry fixed effects used are based on Fama-French 17-industry classification, following Eisfeldt and Papanikolaou (2013), these results are robust to using fixed effects based on two-digit SIC codes.[20]

[20] The results of the Tobit model as well as the results using 2-digit SIC codes are available upon request.

Since both R&D and advertising expenses are included in SG&A expenses (the input in my measure of OC), it is natural to ask whether my results are being driven by these potentially significant expense amounts. To address this question, I note that in an M&A deal, any material R&D and advertising values should be recorded by the bidder as an identifiable item such as in-process R&D, and, for advertising expenses, the value of brand names or trademarks. Since these values should not be added into the amount of recorded goodwill, any component of R&D or advertising subsumed into goodwill should thus be immaterial. Therefore, when using *Scaled GDWL* as the dependent variable in Table 2.3, the relation that I observe is not due to any material R&D or advertising expenses. On the other hand, if these investments are material, they are captured in *Scaled AcqIntan1*, which comprises all intangible assets. Indeed, the coefficient estimates of *OC* are larger in this model compared to those from that using *Scaled GDWL*.

To further address this issue, I use an alternative measure of OC in which I capitalize SG&A net of both R&D and advertising expenses, defined earlier as *OCnet*. I then replicate Table 2.3 using *OCnet* instead of *OC* and present the results in Table 2.4. If R&D or advertising expenses do indeed drive the results that I have shown so far, then the coefficient estimate of *OCnet* should be insignificant in Table 2.4.

In Table 2.4, the coefficient estimates of *OCnet* are positive and significant in all samples and all models. In the first three columns, this estimate implies that, when considering *AcqIntan1*, bidders pay 13.3 cents, on average, per dollar of acquired targets' measured *OCnet*, while the corresponding amounts for the Cross-Industry and Same-Industry samples, are 14.2 and 14 cents per dollar, respectively.[21] These results are consistent with my hypothesis that OC is an asset that has a market price and that bidders pay for acquired target OC in M&A deals. The estimates of the

[21] The difference in the price of OC between Cross- and Same-industry subsamples is statistically insignificant.

control variables are similar to those in the corresponding model in Table 2.3, with the exception of $\beta_2$, which is not significant in the Same-Industry sample.

In columns 4 to 6 of Table 2.4, bidders pay 15 cents, on average, per dollar of acquired measured *OCnet* in the Full sample when considering *AcqIntan2*. In the Cross- and Same-Industry samples, they pay 15 and 17 cents, on average, respectively. In columns 7 to 9, bidders pay 13 cents, on average, per dollar of acquired *OCnet* when using *Scaled AcqIntan3* as the dependent variable in the Full sample. In cross-industry acquisitions, they pay 11 cents, on average, and 15 cents in horizontal deals.

In the final three columns, bidders pay 13 cents, on average, per dollar of acquired *OCnet* through *GDWL* in the Full sample. In the Cross- and Same-Industry samples, the corresponding amount are 9 and 15 cents on average, respectively. The coefficient estimates of the control variables in the last three models are qualitatively similar to those in the corresponding models in Table 2.3.

When using *OCnet* in Table 2.4, the results consistently support that bidders do pay for targets' OC in cross-industry transactions. In the last two models in particular, both the dependent variable and the variable of interest are free of any material component of R&D and advertising. These findings confirm that R&D and advertising expenses are not driving the results observed in Table 2.3, and are in line with Lev and Radhakrishnan (2005), who argue that non-R&D firms maintain their competitive advantage through OC generated by SG&A. The takeaway from this table is that bidders pay for acquired targets' OC in M&A deals and that these results are not being driven by the R&D and advertising expenses included in SG&A, the input to measure OC. Moreover, the value of OC is subsumed into the recorded amount of goodwill.

In the current setting, I argue that the bidder uses the acquired OC, an intangible asset, in combination with its own assets to generate future cash flow. Thus far, I have shown evidence that bidders pay for acquired OC. Ceteris paribus, a larger bidder will pay more for a unit of OC if that unit provides greater benefit through economies of scale. Alternatively, if the OC is scarce and can be withheld from a bidder, then it is a bargaining game. I test whether the bidder's size has any effect on the price of the acquired measured OC. In untabulated results, I fail to find evidence supporting the contention that the price of acquired target OC is a function of bidder size.[22]

Next, I examine whether the price of acquired target OC is a function of the bidders' own OC. For instance, bidders with high levels of OC may not be interested in buying more if their own is sufficient. Alternatively, these bidders may be willing to buy their targets' OC since they are more familiar with investments in OC and know its importance. Finally, it is possible that acquired OC is not a function of bidders' OC. The answer to this question is an empirical one, which I test by augmenting Eq. (2.3) with the interaction of *OC* and scaled bidder OC as follows:

$$\frac{GDWL_{B,T,t}}{TA_{T,t-1}} = \alpha_0 + \beta_1 \frac{OC_{T,t-1}}{TA_{T,t-1}} + \beta_2 \frac{OC_{B,t-1}}{TA_{B,t-1}} + \beta_3 \frac{OC_{T,t-1}}{TA_{T,t-1}} \cdot \frac{OC_{B,t-1}}{TA_{B,t-1}} + \beta_4 CASH + \beta_5 CAR_B + \beta_6 PREMIUM + Indus_{FF17} \,\&\, Yr\ FE + \varepsilon_{B,T,t} \tag{2.7}$$

I report the results with *Scaled GDWL* as the dependent variable in Table 2.5. In the first three columns of Table 2.5, I present the results using *OC* in the interaction term and in the last three columns, replacing *OC* with *OCnet*.

In the first column of Table 2.5, the coefficient estimate of *OC* is positive and significant while that of the interaction term is negative and significant. Taken together, these estimates imply that bidders pay for acquired target OC in an acquisition and that high OC bidders tend to pay less

[22] I do this by controlling for the bidders' size using bidders' total assets as a proxy in Eq. (2.3) and interacting *OC* with bidders' size. The coefficient of the interaction term is the variable of interest in this model. Similar results are obtained when I use *OCnet* instead of *OC*.

for it than do bidders with low levels of OC. At the mean of scaled bidders' OC, the price per dollar of acquired target OC through *GDWL* is 15 cents. No significance is found in the Cross-Industry sample for *OC* or the interaction term, while the latter in the Same-Industry sample suggests that as bidders' *Scaled OC* increases, they pay less per dollar of acquired *OC*. At the mean of bidders' *Scaled OC*, bidders pay 17 cents, on average, through booked *GDWL* per dollar of acquired target OC.

In the next model, I replace *OC* by *OCnet* and find that the coefficient estimates of *OCnet* are similar to those obtained when using *OC*. The interaction term is insignificant in all specifications, implying that the bidders' own *OCnet* is not a determinant of the price of *OCnet*. The takeaway from this table is that bidders do pay for targets' OC in an acquisition (using either *OC* or *OCnet*). Using *OC* as the measure, there is some evidence that low-OC bidders pay more for acquired targets' measured OC than do high-OC bidders. However, it does not appear that bidders' own OC influences the price paid for targets' OC when using *OCnet* as a measure of OC.[23]

In the next section, I study the productivity of acquired targets' OC by analyzing the relation between the bidders' post-acquisition ROA and acquired targets' OC. Since annual post-acquisition *ROA* is the dependent variable, for consistency, I can use either aggregate acquired targets' OC within a fiscal year as the independent variable of interest or deals where the bidder makes only one public acquisition in a fiscal year. However, using aggregating acquired OC will result to an error-in-independent variable problem leading to a biased and inconsistent OLS estimator when the bidder makes any acquisitions of private targets.[24] Therefore, to avoid this

[23] I obtain similar results when using each of the other three measures of scaled acquired intangible assets as the dependent variable.
[24] Please refer to Appendix 1 for a detailed econometric rationale.

problem, I use deals where the bidders make a single acquisition in a fiscal year and the target is a public firm. Thus, in this section, my regressions are on a deal-level basis.

Before I test the productivity of acquired OC, I verify whether the bidders who made a single public acquisition in a fiscal year pay for acquired OC. Ex ante, there is no reason to expect these bidders do not pay for their acquired OC. I replicate Tables 2.3 and 2.4 using this subsample and show the results in Tables 2.6 and 2.7, respectively.

In Table 2.6, I find that the coefficient estimates of *OC* are positive and significant only in the Same-Industry sample in all models, with bidders paying about 19 cents, on average, for a dollar of acquired target OC. When using *OCnet* in Table 2.7, I find that the coefficient estimates of *OCnet* are positive and significant in both Full and Same-Industry samples in all models, with bidders paying about 23 cents, on average, per dollar of acquired *OCnet* in horizontal deals. The takeaway from this and the previous table is that bidders making a single acquisition in a fiscal year pay for their acquired targets' OC in horizontal deals. Depending on the measure of OC and the measure of acquired intangible assets used, I find that the price of OC varies between 18 cents and 25 cents per dollar of acquired OC. Though these prices paid may seem low, it must be noted that not all of SG&A amounts are investments in OC. Hulten and Hao (2008), Eisfeldt and Papanikolaou (2014), and Peters and Taylor (2017) use 30% of SG&A as investment in OC. If I consider 30% of SG&A as the investment in OC, then the per-dollar price of acquired OC varies between 60 cents and 83 cents in my sample.

### 2.4.3 The Productivity of Acquired OC

Thus far, I have provided ample evidence supporting the notion that bidders pay for acquired targets' OC in M&A transactions. I now provide confirmatory evidence on the transferability of OC by showing a positive relation between acquired target OC and the following three ratios: (1) return on assets (*ROA*), (2) sales growth (*Sales Growth*) and (3) asset turnover (*Asset Turnover*). I begin by examining ROA since there is evidence in this literature that OC is associated with higher profitability (see, e.g., Banker et al., 2011; Li et al., 2017). Showing that acquired target OC is positively related to post-acquisition bidders' ROA implies that bidders employ their acquired OC and that the acquired OC is a transferable asset.

I show the results of Eq. (2.4) in Table 2.8.[25] In the first six and last six columns, respectively, I present the results for the first and second fiscal year following the completion of the acquisition.[26] In the first three columns, I exclude *OC* and find that bidders' own lagged scaled OC is insignificant, implying that the bidders' own OC is not productive for them. Adding in OC in the next three columns, I find it to be positive and significant in the Full and Cross-Industry samples, implying that one dollar of acquired measured OC is associated with 2.32 cents and 3.08 cents of operating income, on average, respectively. This figure may seem economically insignificant. Recall from Table 2.6 that these bidders pay 20 cents (Same-Industry sample, *Scaled AcqIntan1* model), on average, per dollar of acquired target OC. This figure translates into a return on acquired targets' *OC* of 15.4% in the first fiscal year following the completion of the transaction for horizontal deals. I find no significant relation between the bidders' ROA and their acquired OC in cross-industry deals, consistent with the finding in Table 2.6 that bidders do not pay for OC in cross-industry deals. However, given the small sample size, I cannot make strong conclusions for this sample.

[25] Note that in Eq. (2.4) I use acquired OC for simplicity instead of depreciated acquired OC. Factoring in the depreciation of OC will increase the magnitude of the coefficient estimates of $\beta_1$. I limit the observations to where *ROA* and *lagged ROA* are within 100%.

[26] Note that the sample size reduces significantly for these tests because I consider only observations where the bidder's sole acquisition in any particular year is a public target. Additionally, for the first fiscal year, I drop any observations where the bidder made an acquisition in that fiscal year. For the second fiscal year, I exclude any observations where the bidder made an acquisition in either of those two fiscal years.

In the second fiscal year, the coefficient estimates of *OC* are positive in all samples but significant only in the Same-Industry sample, where one dollar of acquired OC is associated with 2.49 cents of operating income, on average, making the return on acquired target OC 12.45%. The takeaway from this table is that when bidders pay for target OC, the latter is positively related to the bidders' post-acquisition operating income.

I use *OCnet* instead of *OC* to replicate Table 2.8 and show the results in Table 2.9.[27] In the first year following the completion of the transaction, I find no significant relation with *OCnet*. In the second fiscal year, one dollar of acquired *OCnet* in the Same-Industry sample is associated with 3.22 cents, on average, of operating income, generating a return on acquired target *OCnet* of 13.53% given that these bidders pay 23.8 cents (Table 2.7 – model *Scaled GDWL*). The takeaway from this table is that there is evidence that acquired *OCnet* is positively related to post-acquisition ROA.

In this section, I study whether the observed relation between ROA and acquired OC arises through sales growth. I use Eq. (2.5) to investigate this relation and I show the results in Table 2.10.[28] The results for the first and second fiscal years following the completion of the acquisition are provided in the first six and last six columns, respectively. In the first three columns, I report the results of Eq. (2.5) without including *OC*. I find that for these bidders, their own OC is negatively associated with their sales growth and these coefficient estimates are significant in the Full and Same-Industry samples. I find similar results when I incorporate *OC* in the next three columns. In the Same-Industry subsample, I find that that one dollar of acquired targets' OC is associated with a 2.47 cent, on average, increase in sales. In the second fiscal year, none of the

[27] I do not report the results for the regressions first without *OCnet* as they are qualitatively and statistically similar to the earlier results without *OC* in Table 2.8.
[28] I exclude observations where Sales Growth is in excess of 100%, which I consider as outliers.

coefficient estimates of *OC* are significant. The takeaway from this table is that there is evidence that acquired OC is positively associated with bidders' sales growth in the year following the completion of the acquisitions.

I re-estimate Eq. (2.5) with *OCnet* instead of *OC* and present the results in Table 2.11. My results imply that one dollar of acquired targets' *OCnet* is associated with a(n) 11.21 and 5.28 cents, on average, increase in sales in the Cross- and Same-Industry samples, respectively. In the second fiscal year, all coefficient estimates of *OCnet* are insignificant. The conclusion from this table is that there is some evidence that acquired *OCnet* is positively associated with bidders' sales growth in the year following the completion of the acquisitions.

I now study the relation between acquired target OC and asset turnover, a measure of efficiency indicating the amount of sales a company's assets are generating. I use Eq. (2.6) and present the results in Table 2.12. The first six and last six columns present the results for the first and second fiscal years following the completion of the acquisition, respectively. In the first fiscal year, the coefficient estimate of *OC* is positive and significant in the Full and Same-Industry samples. These estimates imply that one dollar of acquired OC (that costs 20.3 cents in the Same-Industry sample) is associated with 8.2 and 7.7 cents of sales, on average, in the Full and Same-Industry samples, respectively. In the second fiscal year, one dollar of acquired OC in the Full sample is associated with 3.3 cents of sales, on average, while in Cross-Industry deals, it is associated with 9.7 cents of sales. In the Same-Industry sample, one dollar of acquired OC is associated with 5.2 cents of sales. The takeaway from this table is that acquired OC is positively associated with bidders' sales and *Asset Turnover* following the completion of the acquisitions. The latter implies that acquired targets' OC contributes to the efficiency of total assets in generating sales.[29] The overall evidence that acquired targets' OC is positively related to future sales and income suggests that acquired OC is related to future cash flows and is therefore a valuable transferable asset.

A concern with both of my OC measures is that the initial value of OC, $OC_{i,0}$, depends significantly on the first available data on SG&A and thus may influence the results. Following Eisfeldt and Papanikolaou (2013) and Li et al. (2017), in additional tests, I drop observations where *OC* is in the first five years of the measured OC (that is, $OC_{i,0}$ to $OC_{i,t=4}$) to reduce the impact of the initial OC. While I do not report the results, they are economically and statistically similar.[30]

## 2.5 Concluding Remarks

In this study, I examine the value that bidders pay for the organization capital of target firms in mergers and acquisitions and investigate whether the acquired OC is transferable and productive. I first show evidence that bidders pay for targets' OC when making same-industry acquisitions. Depending on the measure of OC and measure of acquired intangible assets employed, I find the price that bidders pay varies between 9 and 25 cents per dollar of targets' OC. I do not observe these relations consistently in cross-industry transactions, however. To the best of my knowledge, this paper is the first to place an explicit value on the price paid for OC in an acquisition. Moreover, these findings validate the use of the cumulative SG&A model to measure investment in organization capital.

[29] I re-estimate Eq. (2.6) with *OCnet* instead of *OC* and present the results in Table 2.13. I find that that there is evidence of a positive relation between acquired *OCnet* and both bidders' sales and asset turnover following acquisition completion. I do not report the results for the regressions first without *OCnet* as they are qualitatively and statistically similar to the earlier results without *OC* in Table 2.12.
[30] Results are available upon request.

I further show a positive relation between acquired OC and bidders' future ROA, sales growth, and asset turnover in same-industry acquisitions following transaction completion. The returns on acquired OC in the first and second fiscal years after acquisition completion are 15% and 12%, respectively. The finding that target OC is related to both the price bidders pay and bidders' post-transaction ROA, sales growth, and asset turnover strongly supports the idea that OC is a transferable asset that has a price.

**Exhibit 1: Goodwill and OC**

This table presents evidence from the annual report of bidders following the completion of acquisition(s) supporting OC being subsumed into goodwill

| Bidder Name | Target Name | Completion Date | Comments regarding goodwill from annual report |
|---|---|---|---|
| Cadence Design Systems Inc. | Simplex Solutions Inc. | June 28, 2002 | "Cadence purchased Simplex to acquire key personnel and technology."[31] (p. 71) |
| The Stanley Works | The Black & Decker Corp. | March 12, 2010 | "Goodwill is calculated as the excess of the consideration transferred over the net assets recognized and represents the expected revenue and cost synergies of the combined business, assembled workforce, and the going concern nature of Black & Decker." (p. 74) |
| Equinix Inc. | Switch & Data Facilities Co Inc. | May 3, 2010 | "Goodwill is attributable to the workforce of Switch and Data and the significant synergies" (p. F-19) |
| Robbins & Myers Inc. | T-3 Energy Services Inc. | Jan. 10, 2011 | "Goodwill recognized from the acquisition primarily relates to the expected contributions of the entity to the overall corporate strategy in addition to synergies and acquired workforce, which are not separable from goodwill." (p. 38) |
| Viasystems Group Inc. | DDi Corp. | June 1, 2012 | "Goodwill of $53,694 was calculated as the excess of the purchase price over the fair value of net tangible and identifiable assets acquired; and represents the value of the assembled workforce, …" (p. 65) |
| Consolidated Communications Holdings Inc. | SureWest Communications Inc. | July 2, 2012 | "Goodwill recognized from the acquisition primarily relates to the expected contributions of the entity to the overall corporate strategy in addition to synergies and acquired workforce, which are not separable from goodwill" (p. F-16) |
| DTS Inc. | SRS Labs Inc. | July 23, 2012 | "Goodwill represents the excess of the purchase price over the fair value of the underlying net tangible and identifiable intangible assets, and it includes the value of the synergies between the acquired company and the Company and the acquired assembled workforce, neither of which qualifies as an identifiable intangible asset." (p. 80) |
| Office Depot Inc. | OfficeMax Inc. | Nov. 5, 2013 | "Goodwill is considered to represent the value associated with the workforce and synergies the two companies anticipate realizing as a combined company." (p. 73) |
| Bally Technologies Inc. | SHFL entertainment Inc. | Nov. 25, 2013 | "The goodwill recognized is attributable primarily to expected synergies and the assembled workforce of SHFL." (p. F-24). |

[31] Goodwill is 68% of net assets acquired in this transaction.

**Table 2.1: Sample construction**

| **Selection Criteria** | **No. of transactions** |
|---|---|
| Completed acquisitions by U.S public acquirers[32] (1990-2013) | 87,297 |
| Matched acquirers' *PERMNO* and *GVKEY* | 63,878 |
| Public targets | 6,814 |
| U.S targets | 5,571 |
| Exclude transactions in: | |
| Financial sector (SIC 6000-6999)<br>Public utilities (SIC 4900-4999) | 3,331 |
| SDC transaction value greater than $1m (July 2010 dollars) | 3,093 |
| Acquirers' ownership of targets: | |
| Prior to the announcement date: less than 50%<br>After the completion: 100% | 2,409 |
| Matched targets' *PERMNO* and *GVKEY* | 1,986 |
| Transaction value greater than 1% of bidder's market value of equity 11 days prior to announcement date | 1,804 |
| Target's delisting code in CRSP is in the 200s | 1,768 |
| Transactions with hand-collected goodwill | 999 |
| Observations with target OC and target total assets | 927 |
| | |
| Subsample for productivity test | |
| Single transaction in a fiscal year | 365 |
| Excluding confounding events in year *t+1* | 271 |
| Excluding confounding events in year *t+1* and *t+2* | 193 |

[32] Excluding repurchases and self-tenders.

**Table 2.2: Summary statistics and correlation coefficients**

The sample consists of 927 completed M&A deals from 1990 to 2013 satisfying the criteria in Table 2.1 and all the variables are as described in Appendix 2. *Same- (Cross-) Industry* are observations where the bidder and the target (do not) share the same two-digit SIC codes. All dollar values are inflation-adjusted using July 2010 as the base year, and are in billions of dollars. All variables are trimmed at the top and bottom 1%. Panel A1 shows the summary statistics of some reference and some unscaled variables. Panel A2 shows the summary statistics of the variables used in this study. Panels B1 to B8 show the pairwise correlation of the variables. Superscripts x, y, and z represent the statistical significance at the 1, 5, and 10% levels, respectively. Superscripts a, b, and c represent the statistical significance at the 1, 5, and 10% levels, respectively, between the Cross- and Same-Industry.

*Panel A1: Summary Statistics of Reference & Unscaled Variables*

| | **Full** | | | **Cross-Industry** | | | **Same-Industry** | | |
|---|---|---|---|---|---|---|---|---|---|
| **Variables** | N | Mean | Median | N | Mean | Median | N | Mean | Median |
| *AcqIntan1* | 918 | 1.203 | 0.284 | 267 | 1.217 | 0.359 | 651 | 1.197 | 0.252 |
| *AcqIntan2* | 918 | 1.079 | 0.257 | 267 | 1.135 | 0.314 | 651 | 1.055 | 0.225 |
| *AcqIntan3* | 918 | 0.886 | 0.204 | 266 | 0.898 | 0.248 | 652 | 0.881 | 0.182 |
| *GDWL* | 918 | 0.875 | 0.199 | 266 | 0.867 | 0.248 | 652 | 0.879 | 0.181 |
| *OC* | 909 | 0.841 | 0.270 | 264 | 0.825 | 0.260 | 645 | 0.848 | 0.280 |
| *OCnet* | 909 | 0.695 | 0.212 | 266 | 0.752 | 0.187 | 643 | 0.672 | 0.218 |
| $ME_{T,t-1}$ | 909 | 1.035 | 0.257 | 263 | 0.984 | 0.287 | 646 | 1.056 | 0.239 |
| $ME_{B,t-1}$ | 894 | 10.241 | 1.986 | 255 | 16.001 | 3.022 | 639 | 7.943 | 1.758 |
| $TA_{T,t-1}$ | 908 | 0.932 | 0.220 | 265 | 1.100 | 0.223 | 643 | 0.863 | 0.219 |
| $TA_{B,t-1}$ | 895 | 7.789 | 1.565 | 258 | 11.533 | 2.152 | 637 | 6.273 | 1.236 |

*Panel A2: Summary Statistics of variables used in this chapter*

| | Full | | | Cross-Industry | | | Same-Industry | | |
|---|---|---|---|---|---|---|---|---|---|
| **Variables** | N | Mean | Median | N | Mean | Median | N | Mean | Median |
| ***Variables related to the acquisition of OC*** | | | | | | | | | |
| *Scaled AcqIntan1* | 918 | 1.913 | 1.224 | 265 | 2.133 | 1.371 | 653 | $1.823^{c}$ | 1.200 |
| *Scaled AcqIntan2* | 918 | 1.634 | 1.041 | 265 | 1.889 | 1.214 | 653 | $1.530^{b}$ | 1.024 |
| *Scaled AcqIntan3* | 918 | 1.364 | 0.833 | 265 | 1.586 | 0.938 | 653 | $1.274^{b}$ | 0.800 |
| *Scaled GDWL* | 918 | 1.352 | 0.831 | 265 | 1.564 | 0.914 | 653 | $1.266^{b}$ | 0.799 |
| *Scaled OC* | 909 | 1.855 | 1.400 | 264 | 1.829 | 1.333 | 645 | 1.865 | 1.453 |
| *Scaled OCnet* | 908 | 1.426 | 1.081 | 264 | 1.384 | 1.077 | 644 | 1.443 | 1.081 |
| **Control Variables** | | | | | | | | | |
| *CASH* | 927 | 0.389 | 0.000 | 269 | 0.409 | 0.000 | 658 | 0.381 | 0.000 |
| $CAR_B$ | 889 | $-1.172^{x}$ | -0.602 | 258 | $-1.499^{x}$ | -0.806 | 631 | $-1.039^{x}$ | -0.549 |
| *PREMIUM* | 891 | $49.473^{x}$ | 40.234 | 258 | $51.888^{x}$ | 42.238 | 633 | $48.488^{x}$ | 39.165 |
| *Scaled Bidder OC* | 882 | 1.172 | 0.931 | 252 | 1.062 | 0.851 | 630 | $1.215^{b}$ | 0.958 |
| *Scaled Bidder OCnet* | 882 | 0.899 | 0.684 | 252 | 0.812 | 0.651 | 630 | $0.933^{b}$ | 0.699 |
| **Variables related to the productivity of acquired OC** | | | | | | | | | |
| $ROA_{t+1}$ | 267 | $9.524^{x}$ | 10.534 | 75 | $9.370^{x}$ | 10.959 | 192 | $9.584^{x}$ | 10.498 |
| $ROA_{t+2}$ | 190 | $10.695^{x}$ | 10.786 | 53 | $11.298^{x}$ | 11.049 | 137 | $10.461^{x}$ | 10.614 |
| $Sales\ Growth_{t+1}$ | 261 | $14.586^{x}$ | 10.123 | 76 | $14.890^{x}$ | 8.490 | 185 | $14.460^{x}$ | 10.650 |
| $Sales\ Growth_{t+2}$ | 180 | -1.554 | -0.954 | 51 | -2.742 | -1.520 | 129 | -1.084 | -0.368 |
| $Asset\ Turnover_{t+1}$ | 266 | 0.946 | 0.844 | 74 | 1.002 | 0.866 | 192 | 0.925 | 0.828 |
| $Asset\ Turnover_{t+2}$ | 190 | 0.971 | 0.856 | 53 | 0.943 | 0.883 | 137 | 0.983 | 0.845 |
| $OC_{T,t-1}/TA_{B,t}$ | 267 | 0.409 | 0.230 | 75 | 0.383 | 0.183 | 192 | 0.420 | 0.244 |
| $OCnet_{T,t-1}/TA_{B,t}$ | 267 | 0.313 | 0.186 | 76 | 0.286 | 0.138 | 191 | 0.324 | 0.195 |
| $OC_{T,t-1}/TA_{B,t+1}$ | 191 | 0.462 | 0.236 | 54 | 0.531 | 0.203 | 137 | 0.435 | 0.258 |
| $OCnet_{T,t-1}/TA_{B,t+1}$ | 189 | 0.327 | 0.195 | 53 | 0.267 | 0.135 | 136 | 0.351 | 0.210 |
| $OC_{T,t-1}/SALE_{B,t}$ | 257 | 0.769 | 0.304 | 74 | 0.720 | 0.258 | 183 | 0.789 | 0.374 |
| $OCnet_{T,t-1}/SALE_{B,t}$ | 257 | 0.521 | 0.260 | 75 | 0.470 | 0.212 | 182 | 0.541 | 0.272 |
| $OC_{T,t-1}/SALE_{B,t+1}$ | 181 | 0.587 | 0.270 | 53 | 0.629 | 0.213 | 128 | 0.569 | 0.284 |
| $OCnet_{T,t-1}/SALE_{B,t+1}$ | 180 | 0.395 | 0.228 | 52 | 0.340 | 0.202 | 128 | 0.417 | 0.248 |

*Panel B1: Pairwise Pearson Correlation Coefficients for variables related to the acquisition of OC*

| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|---|
| 1 | *Scaled AcqIntan1* | 1 | | | | | | | |
| 2 | *Scaled AcqIntan2* | $0.943^{x}$ | 1 | | | | | | |
| 3 | *Scaled AcqIntan3* | $0.928^{x}$ | $0.978^{x}$ | 1 | | | | | |
| 4 | *Scaled GDWL* | $0.926^{x}$ | $0.976^{x}$ | $0.997^{x}$ | 1 | | | | |
| 5 | *Scaled OC* | $0.123^{x}$ | $0.125^{x}$ | $0.113^{x}$ | $0.113^{x}$ | 1 | | | |
| 6 | *Scaled OCnet* | $0.081^{y}$ | $0.109^{x}$ | $0.100^{x}$ | $0.099^{x}$ | $0.936^{x}$ | 1 | | |
| 7 | *CASH* | $0.092^{x}$ | $0.082^{y}$ | 0.036 | 0.040 | $0.082^{y}$ | $0.067^{y}$ | 1 | |
| 8 | *$CAR_B$* | $-0.060^{z}$ | -0.042 | -0.040 | -0.041 | 0.009 | 0.025 | $0.179^{x}$ | 1 |
| 9 | *PREMIUM* | $0.099^{x}$ | $0.081^{y}$ | $0.088^{x}$ | $0.087^{x}$ | $0.070^{y}$ | $0.056^{z}$ | 0.026 | 0.015 |

*Panel B2: Pairwise Pearson Correlation Coefficients for variables related to the acquisition of OC*

| | | | **SAME-INDUSTRY** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
| | 1 | *Scaled AcqIntan1* | 1 | $0.936^{x}$ | $0.923^{x}$ | $0.923^{x}$ | $0.130^{x}$ | $0.087^{y}$ | $0.070^{y}$ | $-0.091^{y}$ | $0.141^{x}$ |
| | 2 | *Scaled AcqIntan2* | $0.957^{x}$ | 1 | $0.980^{x}$ | $0.980^{x}$ | $0.136^{x}$ | $0.121^{x}$ | 0.059 | $-0.077^{y}$ | $0.122^{x}$ |
| **C** | 3 | *Scaled AcqIntan3* | $0.938^{x}$ | $0.972^{x}$ | 1 | $0.999^{x}$ | $0.124^{x}$ | $0.115^{x}$ | 0.009 | $-0.075^{y}$ | $0.123^{x}$ |
| **R** | 4 | *Scaled GDWL* | $0.933^{x}$ | $0.967^{x}$ | $0.992^{x}$ | 1 | $0.124^{x}$ | $0.115^{x}$ | 0.010 | $-0.075^{y}$ | $0.124^{x}$ |
| **O** | 5 | *Scaled OC* | $0.110^{z}$ | $0.104^{z}$ | 0.088 | 0.087 | 1 | $0.936^{x}$ | $0.087^{y}$ | 0.040 | $0.086^{y}$ |
| **S** | 6 | *Scaled OCnet* | 0.073 | 0.084 | 0.067 | 0.063 | $0.938^{x}$ | 1 | $0.067^{z}$ | 0.042 | $0.076^{y}$ |
| **S** | 7 | *CASH* | $0.138^{y}$ | $0.127^{y}$ | 0.093 | $0.106^{z}$ | 0.071 | 0.068 | 1 | $0.200^{x}$ | $0.047^{x}$ |
| | 8 | *$CAR_B$* | 0.015 | 0.042 | 0.046 | 0.047 | -0.067 | -0.023 | $0.130^{y}$ | 1 | 0.042 |
| | 9 | *PREMIUM* | -0.011 | -0.0278 | -0.010 | -0.018 | 0.028 | -0.003 | -0.031 | -0.059 | 1 |

*Panel B3: Pairwise Pearson Correlation Coefficients for variables related to ROA*

| | | | Year t+2 | | | | |
|---|---|---|---|---|---|---|---|
| | | | 1 | 2 | 3 | 4 | 5 |
| ***Y*** | 1 | *ROA* | 1 | -0.195[x] | -0.169[y] | -0.132[z] | -0.110 |
| ***e*** | 2 | $OC_{T,t-1}/TA_B$ | -0.175[x] | 1 | 0.526[x] | 0.921[x] | 0.334[x] |
| ***a*** | 3 | $OC_B/TA_B$ | -0.118[z] | 0.435[x] | 1 | 0.493[x] | 0.924[x] |
| ***r*** | 4 | $OCnet_{T,t-1}/TA_B$ | -0.152[y] | 0.958[x] | 0.430[x] | 1 | 0.354[x] |
| ***t+1*** | 5 | $OCnet_B/TA_B$ | -0.022 | 0.390[x] | 0.935[x] | 0.433[x] | 1 |

*Panel B4: Pairwise Pearson Correlation Coefficients for variables related to ROA in Same-Industry deals*

| | | | Year t+2 | | | | |
|---|---|---|---|---|---|---|---|
| | | | 1 | 2 | 3 | 4 | 5 |
| ***Y*** | 1 | *ROA* | 1 | -0.007 | -0.053 | -0.029 | -0.001 |
| ***e*** | 2 | $OC_{T,t-1}/TA_B$ | -0.089 | 1 | 0.561[x] | 0.963[x] | 0.435[x] |
| ***a*** | 3 | $OC_B/TA_B$ | -0.113 | 0.487[x] | 1 | 0.572[x] | 0.911[x] |
| ***r*** | 4 | $OCnet_{T,t-1}/TA_B$ | -0.086 | 0.973[x] | 0.478[x] | 1 | 0.509[x] |
| ***t+1*** | 5 | $OCnet_B/TA_B$ | 0.015 | 0.425[x] | 0.930[x] | 0.510[x] | |

*Panel B5: Pairwise Pearson Correlation Coefficients for variables related to Sales Growth*

| | | | Year t+2 | | | | |
|---|---|---|---|---|---|---|---|
| | | | 1 | 2 | 3 | 4 | 5 |
| **Y** | 1 | *Sales Growth* | 1 | -0.193$^{y}$ | -0.026 | -0.142$^{z}$ | 0.070 |
| ***e*** | 2 | $OC_{T,t-1}/SALE_B$ | 0.184$^{x}$ | 1 | 0.432$^{x}$ | 0.942$^{x}$ | 0.373$^{x}$ |
| ***a*** | 3 | $OC_B/SALE_B$ | -0.090 | 0.498$^{x}$ | 1 | 0.426$^{x}$ | 0.933$^{x}$ |
| ***r*** | 4 | $OCnet_{T,t-1}/SALE_B$ | 0.295$^{x}$ | 0.935$^{x}$ | 0.392$^{x}$ | 1 | 0.409$^{x}$ |
| ***t+1*** | 5 | $OCnet_B/SALE_B$ | -0.065 | 0.474$^{x}$ | 0.953$^{x}$ | 0.491$^{x}$ | 1 |

*Panel B6: Pairwise Pearson Correlation Coefficients for variables related to Sales Growth in Same-Industry deals*

| | | | Year t+2 | | | | |
|---|---|---|---|---|---|---|---|
| | | | 1 | 2 | 3 | 4 | 5 |
| **Y** | 1 | *Sales Growth* | 1 | -0.031 | -0.132 | -0.009 | 0.005 |
| ***e*** | 2 | $OC_{T,t-1}/SALE_B$ | 0.176$^{y}$ | 1 | 0.497$^{x}$ | 0.961$^{x}$ | 0.519$^{x}$ |
| ***a*** | 3 | $OC_B/SALE_B$ | -0.109 | 0.549$^{x}$ | 1 | 0.490$^{x}$ | 0.916$^{x}$ |
| ***r*** | 4 | $OCnet_{T,t-1}/SALE_B$ | 0.274$^{x}$ | 0.959$^{x}$ | 0.425$^{x}$ | 1 | 0.551$^{x}$ |
| ***t+1*** | 5 | $OCnet_B/SALE_B$ | -0.062 | 0.571$^{x}$ | 0.953$^{x}$ | 0.491$^{x}$ | 1 |

*Panel B7: Pairwise Pearson Correlation Coefficients for variables related to Asset Turnover*

| | | | Year t+2 | | | | |
|---|---|---|---|---|---|---|---|
| | | | 1 | 2 | 3 | 4 | 5 |
| ***Y*** | 1 | *Asset Turnover* | 1 | 0.137[z] | 0.277[x] | 0.182[y] | 0.388[x] |
| ***e*** | 2 | $OC_{T,t-1}/TA_B$ | 0.090 | 1 | 0.526[x] | 0.921[x] | 0.334[x] |
| ***a*** | 3 | $OC_B/TA_B$ | 0.176[x] | 0.435[x] | 1 | 0.493[x] | 0.924[x] |
| ***r*** | 4 | $OCnet_{T,t-1}/TA_B$ | 0.157[y] | 0.958[x] | 0.430[x] | 1 | 0.354[x] |
| ***t+1*** | 5 | $OCnet_B/TA_B$ | 0.301[x] | 0.390[x] | 0.935[x] | 0.433[x] | 1 |

*Panel B8: Pairwise Pearson Correlation Coefficients for variables related to Asset Turnover in Same-Industry deals*

| | | | Year t+2 | | | | |
|---|---|---|---|---|---|---|---|
| | | | 1 | 2 | 3 | 4 | 5 |
| ***Y*** | 1 | *Asset Turnover* | 1 | 0.141 | 0.280[x] | 0.224[x] | 0.422[x] |
| ***e*** | 2 | $OC_{T,t-1}/TA_B$ | 0.139[z] | 1 | 0.561[x] | 0.963[x] | 0.435[x] |
| ***a*** | 3 | $OC_B/TA_B$ | 0.171[y] | 0.487[x] | 1 | 0.572[x] | 0.911[x] |
| ***r*** | 4 | $OCnet_{T,t-1}/TA_B$ | 0.238[x] | 0.973[x] | 0.478[x] | 1 | 0.509[x] |
| ***t+1*** | 5 | $OCnet_B/TA_B$ | 0.304[x] | 0.425[x] | 0.930[x] | 0.510[x] | 1 |

**Table 2.3: The price of acquired measured OC**

This table presents the results from the estimation of the following OLS regression:

$$\frac{Y_{B,T,t}}{TA_{T,t-1}} = \alpha_0 + \beta_1 \frac{OC_{T,t-1}}{TA_{T,t-1}} + \beta_2 CASH + \beta_3 CAR_B + \beta_4 PREMIUM + Indus_{FF17} \,\&\, Yr\ FE + \varepsilon_{B,T,t}$$

where *Y = AcqIntan1, AcqIntan2, AcqIntan3, GDWL*. *AcqIntan1* is transacted goodwill plus all other acquired intangible assets. *AcqIntan2* is *AcqIntan1* less both in-process R&D and patents. *AcqIntan3* is transacted goodwill plus work force and non-compete agreements. *GDWL* is the transacted goodwill. *TA* is book value of total assets. The sample consists of 927 completed M&A deals from 1990 to 2013 satisfying the criteria in Table 2.1 and all the variables are as described in Appendix 2. Same- (Cross-) Industry are observations where the bidder and the target (do not) share the same two-digit SIC codes. All dollar values are inflation-adjusted using July 2010 as the base year. All variables are trimmed at the top and bottom 1%. Residuals are clustered by the target Fama-French 17-Industry classifications and p-values are in parentheses.

| **Model** | ***Scaled AcqIntan1*** | | | ***Scaled AcqIntan2*** | | | ***Scaled AcqIntan3*** | | | ***Scaled GDWL*** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Full | Cross-Industry | Same-Industry | Full | Cross-Industry | Same-Industry | Full | Cross-Industry | Same-Industry | Full | Cross-Industry | Same-Industry |
| $\beta_1$ | 0.140 | 0.146 | 0.164 | 0.123 | 0.119 | 0.140 | 0.108 | 0.097 | 0.125 | 0.106 | 0.084 | 0.125 |
| | (0.008) | (0.036) | (0.001) | (0.024) | (0.146) | (0.004) | (0.029) | (0.124) | (0.006) | (0.029) | (0.114) | (0.007) |
| $\beta_2$ | 0.238 | 0.347 | 0.148 | 0.206 | 0.253 | 0.145 | 0.091 | 0.218 | 0.014 | 0.111 | 0.296 | 0.015 |
| | (0.012) | (0.041) | (0.142) | (0.036) | (0.088) | (0.157) | (0.217) | (0.038) | (0.869) | (0.098) | (0.028) | (0.857) |
| $\beta_3$ | -0.028 | -0.005 | -0.038 | -0.019 | 0.005 | -0.029 | -0.016 | 0.004 | -0.025 | -0.016 | 0.003 | -0.025 |
| | (0.042) | (0.890) | (0.000) | (0.041) | (0.862) | (0.000) | (0.056) | (0.876) | (0.000) | (0.065) | (0.906) | (0.000) |
| $\beta_4$ | 0.005 | 0.003 | 0.006 | 0.004 | 0.002 | 0.004 | 0.004 | 0.002 | 0.004 | 0.003 | 0.002 | 0.004 |
| | (0.036) | (0.334) | (0.004) | (0.060) | (0.497) | (0.010) | (0.036) | (0.440) | (0.003) | (0.035) | (0.533) | (0.003) |
| $\alpha_0$ | 0.500 | 1.085 | 0.922 | 0.600 | 1.316 | 0.840 | 0.410 | 0.988 | 0.645 | 0.416 | 0.971 | 0.646 |
| | (0.396) | (0.001) | (0.000) | (0.144) | (0.000) | (0.000) | (0.207) | (0.000) | (0.000) | (0.210) | (0.001) | (0.000) |
| $Indus_{FF17}$ & *Yr FE* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *N* | 834 | 241 | 593 | 834 | 241 | 593 | 834 | 241 | 593 | 834 | 241 | 593 |
| $R^2$ | 0.155 | 0.208 | 0.191 | 0.130 | 0.210 | 0.147 | 0.117 | 0.174 | 0.138 | 0.118 | 0.179 | 0.137 |

**Table 2.4: The price of acquired measured OC net of both R&D & advertising expenses**

This table present the results from the estimation of the following OLS regression:

$$\frac{Y_{B,T,t}}{TA_{T,t-1}} = \alpha_0 + \beta_1 \frac{OCnet_{T,t-1}}{TA_{T,t-1}} + \beta_2 CASH + \beta_3 CAR_B + \beta_4 PREMIUM + Indus_{FF17} \,\&\, Yr\ FE + \varepsilon_{B,T,t}$$

where *Y* = *AcqIntan1, AcqIntan2, AcqIntan3, GDWL*. *AcqIntan1* is transacted goodwill plus all other acquired intangible assets. *AcqIntan2* is *AcqIntan1* less both in-process R&D and patents. *AcqIntan3* is transacted goodwill plus work force and non-compete agreements. *GDWL* is the transacted goodwill. *TA* is book value of total assets. The sample consists of 927 completed M&A deals from 1990 to 2013 satisfying the criteria in Table 2.1 and all the variables are as described in Appendix 2. Same- (Cross-) Industry are observations where the bidder and the target (do not) share the same two-digit SIC codes. All dollar values are inflation-adjusted using July 2010 as the base year. All variables are trimmed at the top and bottom 1%. Residuals are clustered by the target Fama-French 17-Industry classifications and p-values are in parentheses.

| **Model** | ***Scaled AcqIntan1*** | | | ***Scaled AcqIntan2*** | | | ***Scaled AcqIntan3*** | | | ***Scaled GDWL*** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Full | Cross-Industry | Same-Industry | Full | Cross-Industry | Same-Industry | Full | Cross-Industry | Same-Industry | Full | Cross-Industry | Same-Industry |
| $\beta_1$ | 0.133 | 0.142 | 0.140 | 0.152 | 0.148 | 0.166 | 0.133 | 0.114 | 0.147 | 0.129 | 0.091 | 0.148 |
| | (0.000) | (0.011) | (0.000) | (0.000) | (0.039) | (0.000) | (0.000) | (0.051) | (0.000) | (0.000) | (0.050) | (0.000) |
| $\beta_2$ | 0.247 | 0.364 | 0.141 | 0.204 | 0.253 | 0.138 | 0.091 | 0.219 | 0.009 | 0.111 | 0.301 | 0.010 |
| | (0.006) | (0.055) | (0.093) | (0.028) | (0.087) | (0.123) | (0.183) | (0.051) | (0.902) | (0.079) | (0.045) | (0.890) |
| $\beta_3$ | -0.029 | -0.007 | -0.038 | -0.020 | 0.004 | -0.030 | -0.017 | 0.004 | -0.025 | -0.017 | 0.003 | -0.025 |
| | (0.030) | (0.847) | (0.000) | (0.027) | (0.891) | (0.000) | (0.039) | (0.897) | (0.000) | (0.047) | (0.927) | (0.000) |
| $\beta_4$ | 0.005 | 0.003 | 0.006 | 0.004 | 0.002 | 0.004 | 0.004 | 0.002 | 0.004 | 0.003 | 0.002 | 0.004 |
| | (0.036) | (0.330) | (0.005) | (0.055) | (0.496) | (0.008) | (0.032) | (0.438) | (0.002) | (0.031) | (0.534) | (0.002) |
| $\alpha_0$ | 0.504 | 1.106 | 0.990 | 0.610 | 1.305 | 0.905 | 0.428 | 0.987 | 0.702 | 0.433 | 0.977 | 0.703 |
| | (0.400) | (0.000) | (0.000) | (0.148) | (0.000) | (0.000) | (0.212) | (0.000) | (0.000) | (0.214) | (0.001) | (0.000) |
| $Indus_{FF17}$ & *Yr FE* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *N* | 833 | 241 | 592 | 833 | 241 | 592 | 833 | 241 | 592 | 833 | 241 | 592 |
| $R^2$ | 0.153 | 0.204 | 0.186 | 0.128 | 0.208 | 0.144 | 0.115 | 0.173 | 0.136 | 0.115 | 0.178 | 0.135 |

**Table 2.5: The price of acquired OC and the effect of bidders' OC**

This table presents the results from the estimation of the following OLS regressions:

$$\frac{GDWL_{B,T,t}}{TA_{T,t-1}} = \alpha_0 + \beta_1 \frac{OC_{T,t-1}}{TA_{T,t-1}} + \beta_2 \frac{OC_{B,t-1}}{TA_{B,t-1}} + \beta_3 \frac{OC_{T,t-1}}{TA_{T,t-1}} \cdot \frac{OC_{B,t-1}}{TA_{B,t-1}} + \beta_4 CASH + \beta_5 CAR_B + \beta_6 PREMIUM + Indus_{FF17} \,\&\, Yr\ FE + \varepsilon_{B,T,t}$$

$$\frac{GDWL_{B,T,t}}{TA_{T,t-1}} = \alpha_0 + \beta_1 \frac{OCnet_{T,t-1}}{TA_{T,t-1}} + \beta_2 \frac{OCnet_{B,t-1}}{TA_{B,t-1}} + \beta_3 \frac{OCnet_{T,t-1}}{TA_{T,t-1}} \cdot \frac{OCnet_{B,t-1}}{TA_{B,t-1}} + \beta_4 CASH + \beta_5 CAR_B + \beta_6 PREMIUM + Indus_{FF17} \,\&\, Yr\ FE + \varepsilon_{B,T,t}$$

*GDWL* is the transacted goodwill and *TA* is the book value of total assets. The sample consists of 927 completed M&A deals from 1990 to 2013 satisfying the criteria in Table 2.1 and all the variables are as described in Appendix 2. Same- (Cross-) Industry are observations where the bidder and the target (do not) share the same two-digit SIC codes. All dollar values are inflation-adjusted using July 2010 as the base year. All variables are trimmed at the top and bottom 1%. Residuals are clustered by the target Fama-French 17-Industry classifications and p-values are in parentheses.

| **Model** | | ***OC*** | | | ***OCnet*** | |
|---|---|---|---|---|---|---|
| | Full | Cross-Industry | Same-Industry | Full | Cross-Industry | Same-Industry |
| $\beta_1$ | 0.253 | 0.133 | 0.266 | 0.229 | 0.110 | 0.254 |
| | (0.001) | (0.284) | (0.018) | (0.035) | (0.309) | (0.081) |
| $\beta_2$ | 0.107 | -0.006 | 0.126 | -0.026 | -0.202 | 0.051 |
| | (0.086) | (0.970) | (0.145) | (0.875) | (0.330) | (0.765) |
| $\beta_3$ | -0.085 | -0.048 | -0.079 | -0.057 | -0.022 | -0.066 |
| | (0.002) | (0.467) | (0.030) | (0.445) | (0.744) | (0.485) |
| $\beta_4$ | 0.076 | 0.332 | -0.032 | 0.094 | 0.378 | -0.024 |
| | (0.281) | (0.101) | (0.759) | (0.181) | (0.061) | (0.791) |
| $\beta_5$ | -0.019 | -0.004 | -0.026 | -0.019 | -0.006 | -0.026 |
| | (0.039) | (0.887) | (0.000) | (0.043) | (0.832) | (0.000) |
| $\beta_6$ | 0.003 | 0.002 | 0.004 | 0.003 | 0.002 | 0.004 |
| | (0.034) | (0.517) | (0.003) | (0.033) | (0.541) | (0.002) |
| $\alpha_0$ | 0.290 | 0.973 | 0.539 | 0.443 | 1.135 | 0.705 |
| | (0.417) | (0.001) | (0.001) | (0.317) | (0.001) | (0.000) |
| $Indus_{FF17}$ & $Yr$ $FE$ | Yes | Yes | Yes | Yes | Yes | Yes |
| $N$ | 806 | 233 | 573 | 802 | 230 | 572 |
| $R^2$ | 0.128 | 0.181 | 0.148 | 0.121 | 0.183 | 0.139 |

**Table 2.6: The price of acquired OC for firms that made a single transaction in a fiscal year**

This table presents the results from the estimation of the following OLS regression:

$$\frac{Y_{B,T,t}}{TA_{T,t-1}} = \alpha_0 + \beta_1 \frac{OC_{T,t-1}}{TA_{T,t-1}} + \beta_2 CASH + \beta_3 CAR_B + \beta_4 PREMIUM + Indus_{FF17} \,\&\, Yr\ FE + \varepsilon_{B,T,t}$$

where *Y* = *AcqIntan1, AcqIntan2, AcqIntan3, GDWL*. *AcqIntan1* is transacted goodwill plus all other acquired intangible assets. *AcqIntan2* is *AcqIntan1* less both in-process R&D and patents. *AcqIntan3* is transacted goodwill plus work force and non-compete agreements. *GDWL* is the transacted goodwill. *TA* is book value of total assets. The sample consists of 365 completed M&A deals from 1990 to 2013 satisfying the criteria in Table 2.1, where the bidders made a single acquisition in a fiscal year, and all the variables are as described in Appendix 2. Same- (Cross-) Industry are observations where the bidder and the target (do not) share the same two-digit SIC codes. All dollar values are inflation-adjusted using July 2010 as the base year. All variables are trimmed at the top and bottom 1%. Residuals are clustered by the target Fama-French 17-Industry classifications and p-values are in parentheses.

| **Model** | ***Scaled AcqIntan1*** | | | ***Scaled AcqIntan2*** | | | ***Scaled AcqIntan3*** | | | ***Scaled GDWL*** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Full | Cross-Industry | Same-Industry | Full | Cross-Industry | Same-Industry | Full | Cross-Industry | Same-Industry | Full | Cross-Industry | Same-Industry |
| $\beta_1$ | 0.123 | -0.027 | 0.203 | 0.125 | -0.025 | 0.192 | 0.121 | -0.002 | 0.186 | 0.122 | -0.002 | 0.188 |
| | (0.110) | (0.671) | (0.032) | (0.145) | (0.704) | (0.062) | (0.109) | (0.973) | (0.040) | (0.109) | (0.971) | (0.039) |
| $\beta_2$ | 0.149 | 1.204 | -0.493 | 0.204 | 1.069 | -0.338 | 0.069 | 0.841 | -0.398 | 0.071 | 0.843 | -0.394 |
| | (0.512) | (0.307) | (0.048) | (0.341) | (0.267) | (0.115) | (0.660) | (0.392) | (0.080) | (0.649) | (0.390) | (0.082) |
| $\beta_3$ | -0.027 | 0.013 | -0.037 | -0.018 | 0.020 | -0.028 | -0.014 | 0.025 | -0.024 | -0.015 | 0.025 | -0.025 |
| | (0.296) | (0.749) | (0.000) | (0.287) | (0.474) | (0.000) | (0.374) | (0.457) | (0.002) | (0.366) | (0.461) | (0.001) |
| $\beta_4$ | 0.005 | -0.013 | 0.009 | 0.002 | -0.014 | 0.005 | 0.002 | -0.012 | 0.005 | 0.002 | -0.012 | 0.005 |
| | (0.475) | (0.046) | (0.217) | (0.675) | (0.020) | (0.266) | (0.574) | (0.028) | (0.222) | (0.575) | (0.027) | (0.222) |
| $\alpha_0$ | 0.373 | 2.866 | -0.486 | 0.748 | 3.303 | -0.168 | 0.478 | 2.317 | -0.212 | 0.483 | 2.314 | -0.207 |
| | (0.704) | (0.082) | (0.659) | (0.336) | (0.038) | (0.843) | (0.449) | (0.140) | (0.791) | (0.442) | (0.140) | (0.795) |
| $Indus_{FF17}$ & $Yr$ $FE$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $N$ | 331 | 87 | 244 | 331 | 87 | 244 | 331 | 87 | 244 | 331 | 87 | 244 |
| $R^2$ | 0.159 | 0.408 | 0.277 | 0.128 | 0.413 | 0.214 | 0.116 | 0.342 | 0.206 | 0.115 | 0.343 | 0.206 |

**Table 2.7: The price of acquired measured *OCnet* for firms that made single transaction in a fiscal year**

This table presents the results from the estimation of the following OLS regression:

$$\frac{Y_{B,T,t}}{TA_{T,t-1}} = \alpha_0 + \beta_1 \frac{OCnet_{T,t-1}}{TA_{T,t-1}} + \beta_2 CASH + \beta_3 CAR_B + \beta_4 PREMIUM + Indus_{FF17} \,\&\, Yr\ FE + \varepsilon_{B,T,t}$$

where *Y* = *AcqIntan1, AcqIntan2, AcqIntan3, GDWL*. *AcqIntan1* is transacted goodwill plus all other acquired intangible assets. *AcqIntan2* is *AcqIntan1* less both in-process R&D and patents. *AcqIntan3* is transacted goodwill plus work force and non-compete agreements. *GDWL* is the transacted goodwill. *TA* is book value of total assets. The sample consists of 365 completed M&A deals from 1990 to 2013 satisfying the criteria in Table 2.1, where the bidders made a single acquisition in a fiscal year, and all the variables are as described in Appendix 2. Same- (Cross-) Industry are observations where the bidder and the target (do not) share the same two-digit SIC codes. All dollar values are inflation-adjusted using July 2010 as the base year. All variables are trimmed at the top and bottom 1%. Residuals are clustered by the target Fama-French 17-Industry classifications and p-values are in parentheses.

| **Model** | ***Scaled AcqIntan1*** | | | ***Scaled AcqIntan2*** | | | ***Scaled AcqIntan3*** | | | ***Scaled GDWL*** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Full | Cross-Industry | Same-Industry | Full | Cross-Industry | Same-Industry | Full | Cross-Industry | Same-Industry | Full | Cross-Industry | Same-Industry |
| $\beta_1$ | 0.183 | -0.117 | 0.216 | 0.208 | -0.093 | 0.252 | 0.192 | -0.054 | 0.237 | 0.192 | -0.054 | 0.238 |
| | (0.003) | (0.508) | (0.005) | (0.004) | (0.647) | (0.006) | (0.003) | (0.746) | (0.004) | (0.003) | (0.747) | (0.004) |
| $\beta_2$ | 0.130 | 1.088 | -0.593 | 0.176 | 0.954 | -0.411 | 0.044 | 0.732 | -0.465 | 0.047 | 0.734 | -0.462 |
| | (0.562) | (0.410) | (0.011) | (0.397) | (0.378) | (0.038) | (0.771) | (0.515) | (0.028) | (0.760) | (0.513) | (0.029) |
| $\beta_3$ | -0.028 | 0.013 | -0.037 | -0.019 | 0.020 | -0.029 | -0.015 | 0.025 | -0.025 | -0.015 | 0.025 | -0.025 |
| | (0.266) | (0.762) | (0.000) | (0.252) | (0.496) | (0.000) | (0.337) | (0.469) | (0.002) | (0.330) | (0.473) | (0.001) |
| $\beta_4$ | 0.005 | -0.013 | 0.009 | 0.002 | -0.014 | 0.005 | 0.003 | -0.012 | 0.005 | 0.003 | -0.012 | 0.005 |
| | (0.451) | (0.059) | (0.198) | (0.646) | (0.027) | (0.238) | (0.550) | (0.040) | (0.197) | (0.551) | (0.039) | (0.198) |
| $\alpha_0$ | 0.294 | 3.401 | -0.500 | 0.700 | 3.793 | -0.176 | 0.464 | 2.755 | -0.217 | 0.470 | 2.751 | -0.212 |
| | (0.750) | (0.159) | (0.644) | (0.340) | (0.110) | (0.831) | (0.457) | (0.233) | (0.783) | (0.450) | (0.233) | (0.788) |
| $Indus_{FF17}$ & *Yr FE* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *N* | 329 | 87 | 242 | 329 | 87 | 242 | 329 | 87 | 242 | 329 | 87 | 242 |
| $R^2$ | 0.169 | 0.415 | 0.285 | 0.133 | 0.422 | 0.221 | 0.121 | 0.352 | 0.212 | 0.121 | 0.352 | 0.211 |

## Table 2.8: Acquired OC and post-acquisition profitability

This table presents the results from the estimation of the following OLS regressions:

$$\frac{OIBDP_{B,t+1}}{TA_{B,t}} \cdot 100 = \alpha_0 + \beta_1 \frac{OC_{T,t-1}}{TA_{B,t}} + \beta_2 \frac{OC_{B,t}}{TA_{B,t}} + \beta_3 \frac{1}{TA_{B,t}} + \beta_4 \frac{OIBDP_{B,t}}{TA_{B,t-1} + TA_{T,t-1}} \cdot 100 + Indus_{FF17}\ \&\ Yr\ FE + \varepsilon_{B,t+1}$$

$$\frac{OIBDP_{B,t+2}}{TA_{B,t+1}} \cdot 100 = \alpha_0 + \beta_1 \frac{OC_{T,t-1}}{TA_{B,t+1}} + \beta_2 \frac{OC_{B,t+1}}{TA_{B,t+1}} + \beta_3 \frac{1}{TA_{B,t+1}} + \beta_4 \frac{OIBDP_{B,t+1}}{TA_{B,t}} \cdot 100 + Indus_{FF17}\ \&\ Yr\ FE + \varepsilon_{B,t+2}$$

where *OIBDP* is operating income before depreciation and *TA* is the book value of total assets. The sample consists of 271 and 193 completed M&A deals from 1990 to 2013 satisfying the criteria in Table 2.1 for year *t+1* and *t+2*, respectively. All the variables are as described in Appendix 2. Same- (Cross-) Industry are observations where the bidder and the target (do not) share the same two-digit SIC codes. All dollar values are inflation-adjusted using July 2010 as the base year and are in billions of dollars. All variables are trimmed at the top and bottom 1%. Residuals are clustered by the target Fama-French 17-Industry classifications and p-values are in parentheses.

| Model | | | $ROA_{t+1}$ | | | | | | $ROA_{t+2}$ | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Full | Cross-Industry | Same-Industry | Full | Cross-Industry | Same-Industry | Full | Cross-Industry | Same-Industry | Full | Cross-Industry | Same-Industry |
| $\beta_1$ | | | | 2.319 | -1.273 | 3.079 | | | | 0.481 | 2.533 | 2.486 |
| | | | | (0.036) | (0.425) | (0.009) | | | | (0.309) | (0.132) | (0.000) |
| $\beta_2$ | -0.069 | -0.172 | 0.205 | -0.393 | 0.099 | -0.410 | -0.000 | 0.063 | 0.643 | -0.129 | -0.561 | -0.160 |
| | (0.820) | (0.617) | (0.708) | (0.174) | (0.758) | (0.301) | (1.000) | (0.968) | (0.345) | (0.863) | (0.712) | (0.752) |
| $\beta_3$ | 0.092 | 0.266 | -0.169 | -0.019 | 0.768 | -0.317 | -0.232 | -0.808 | -0.100 | -0.290 | -1.325 | -0.242 |
| | (0.434) | (0.613) | (0.250) | (0.891) | (0.022) | (0.106) | (0.189) | (0.098) | (0.539) | (0.066) | (0.013) | (0.205) |
| $\beta_4$ | 0.719 | 0.646 | 0.720 | 0.738 | 0.588 | 0.740 | 0.703 | 0.816 | 0.671 | 0.705 | 1.003 | 0.671 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\alpha_0$ | -2.938 | 4.028 | -3.077 | -3.416 | 5.291 | -3.360 | 5.869 | 58.248 | 5.244 | 5.923 | 62.566 | 5.132 |
| | (0.046) | (0.213) | (0.172) | (0.016) | (0.096) | (0.152) | (0.009) | (0.002) | (0.003) | (0.009) | (0.003) | (0.003) |
| $Indus_{FF17}$ & $Yr$ $FE$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $N$ | 247 | 63 | 186 | 247 | 63 | 186 | 182 | 47 | 131 | 182 | 47 | 131 |
| $R^2$ | 0.693 | 0.804 | 0.734 | 0.703 | 0.837 | 0.750 | 0.692 | 0.856 | 0.737 | 0.693 | 0.874 | 0.751 |

## Table 2.9: Acquired *OCnet* and post-acquisition profitability

This table presents the results from the estimation of the following OLS regressions:

$$\frac{OIBDP_{B,t+1}}{TA_{B,t}} \cdot 100 = \alpha_0 + \beta_1 \frac{OCnet_{T,t-1}}{TA_{B,t}} + \beta_2 \frac{OCnet_{B,t}}{TA_{B,t}} + \beta_3 \frac{1}{TA_{B,t}} + \beta_4 \frac{OIBDP_{B,t}}{TA_{B,t-1} + TA_{T,t-1}} \cdot 100 + Indus_{FF17} \,\&\, Yr\ FE + \varepsilon_{B,t+1}$$

$$\frac{OIBDP_{B,t+2}}{TA_{B,t+1}} \cdot 100 = \alpha_0 + \beta_1 \frac{OCnet_{T,t-1}}{TA_{B,t+1}} + \beta_2 \frac{OCnet_{B,t+1}}{TA_{B,t+1}} + \beta_3 \frac{1}{TA_{B,t+1}} + \beta_4 \frac{OIBDP_{B,t+1}}{TA_{B,t}} \cdot 100 + Indus_{FF17} \,\&\, Yr\ FE + \varepsilon_{B,t+2}$$

where *OIBDP* is operating income before depreciation and *TA* is the book value of total assets. The sample consists of 271 and 193 completed M&A deals from 1990 to 2013 satisfying the criteria in Table 2.1 for year *t+1* and *t+2*, respectively. All the variables are as described in Appendix 2. Same- (Cross-) Industry are observations where the bidder and the target (do not) share the same two-digit SIC codes. All dollar values are inflation-adjusted using July 2010 as the base year and are in billions of dollars. All variables are trimmed at the top and bottom 1%. Residuals are clustered by the target Fama-French 17-Industry classifications and p-values are in parentheses.

| **Model** | | $ROA_{t+1}$ | | | $ROA_{t+2}$ | |
|---|---|---|---|---|---|---|
| | Full | Cross-Industry | Same-Industry | Full | Cross-Industry | Same-Industry |
| $\beta_1$ | 1.429 | -2.709 | 1.594 | 1.854 | 4.264 | 3.222 |
| | (0.187) | (0.216) | (0.303) | (0.022) | (0.254) | (0.009) |
| $\beta_2$ | -0.034 | 0.319 | 0.165 | -0.418 | -0.929 | -0.392 |
| | (0.946) | (0.309) | (0.823) | (0.665) | (0.612) | (0.613) |
| $\beta_3$ | -0.024 | 0.426 | -0.231 | -0.352 | -1.106 | -0.220 |
| | (0.869) | (0.431) | (0.193) | (0.025) | (0.015) | (0.266) |
| $\beta_4$ | 0.716 | 0.607 | 0.712 | 0.710 | 0.935 | 0.676 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\alpha_0$ | -3.195 | 5.358 | -3.333 | 5.723 | 12.718 | 3.640 |
| | (0.023) | (0.102) | (0.169) | (0.017) | (0.281) | (0.088) |
| $Indus_{FF17}$ & $Yr\ FE$ | Yes | Yes | Yes | Yes | Yes | Yes |
| $N$ | 247 | 63 | 185 | 179 | 41 | 134 |
| $R^2$ | 0.707 | 0.811 | 0.750 | 0.685 | 0.850 | 0.753 |

**Table 2.10: Acquired OC and post-acquisition sales growth**

This table presents the results from the estimation of the following OLS regressions:

$$\frac{SALE_{B,t+1} - SALE_{B,t}}{SALE_{B,t}} \cdot 100 = \alpha_0 + \beta_1 \frac{OC_{T,t-1}}{SALE_{B,t}} + \beta_2 \frac{OC_{B,t}}{SALE_{B,t}} + \beta_3 \frac{1}{SALE_{B,t}} + \beta_4 \frac{SALE_{B,t} - SALE_{B,t-1} - SALE_{T,t-1}}{SALE_{B,t-1} + SALE_{T,t-1}} \cdot 100$$

$$+ Indus_{FF17} \,\&\, Yr\ FE + \varepsilon_{B,t+1}$$

$$\frac{SALE_{B,t+2} - SALE_{B,t+1}}{SALE_{B,t+1}} \cdot 100 = \alpha_0 + \beta_1 \frac{OC_{T,t-1}}{SALE_{B,t+1}} + \beta_2 \frac{OC_{B,t+1}}{SALE_{B,t+1}} + \beta_3 \frac{1}{SALE_{B,t+1}} + \beta_4 \frac{SALE_{B,t+1} - SALE_{B,t}}{SALE_{B,t}} \cdot 100$$

$$+ Indus_{FF17} \,\&\, Yr\ FE + \varepsilon_{B,t+2}$$

where *SALE* is sales. The sample consists of 271 and 193 completed M&A deals from 1990 to 2013 satisfying criteria in Table 2.1 for year *t+1* and *t+2*, respectively. All variables are as described in Appendix 2. Same- (Cross-) Industry are observations where the bidder and target do (not) share the same two-digit SIC codes. All dollar values are inflation-adjusted using July 2010 as the base year and are in billions of dollars. All variables are trimmed at the top and bottom 1%. Residuals are clustered by the target Fama-French 17-Industry classifications and p-values are in parentheses.

| **Model** | ***Sales Growth$_{t+1}$*** | | | | | | ***Sales Growth$_{t+2}$*** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Full | Cross-Industry | Same-Industry | Full | Cross-Industry | Same-Industry | Full | Cross-Industry | Same-Industry | Full | Cross-Industry | Same-Industry |
| $\beta_1$ | | | | 2.272 | 3.541 | 2.474 | | | | -0.876 | -1.763 | 3.386 |
| | | | | (0.024) | (0.143) | (0.000) | | | | (0.758) | (0.581) | (0.203) |
| $\beta_2$ | -2.927 | -0.926 | -3.932 | -3.330 | -1.549 | -4.477 | 0.514 | -4.834 | 1.083 | 0.693 | -4.558 | -0.063 |
| | (0.000) | (0.668) | (0.000) | (0.000) | (0.529) | (0.000) | (0.833) | (0.397) | (0.693) | (0.798) | (0.401) | (0.985) |
| $\beta_3$ | -0.044 | -0.542 | -0.006 | -0.167 | -1.049 | -0.121 | -0.716 | -1.111 | -0.530 | -0.571 | -0.625 | -0.939 |
| | (0.202) | (0.003) | (0.937) | (0.017) | (0.000) | (0.054) | (0.120) | (0.134) | (0.097) | (0.299) | (0.685) | (0.016) |
| $\beta_4$ | -0.521 | -0.481 | -0.584 | -0.464 | -0.430 | -0.525 | 0.116 | -0.022 | 0.059 | 0.123 | -0.001 | 0.035 |
| | (0.000) | (0.027) | (0.002) | (0.001) | (0.030) | (0.005) | (0.062) | (0.854) | (0.498) | (0.132) | (0.993) | (0.719) |
| $\alpha_0$ | 0.159 | -13.743 | -22.021 | 0.819 | -12.973 | -21.187 | 8.190 | -15.200 | -20.806 | 8.224 | -13.238 | -20.079 |
| | (0.969) | (0.212) | (0.015) | (0.827) | (0.280) | (0.017) | (0.710) | (0.335) | (0.003) | (0.709) | (0.338) | (0.001) |
| $Indus_{FF17}$ & $Yr$ $FE$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $N$ | 246 | 67 | 179 | 246 | 67 | 179 | 173 | 47 | 125 | 173 | 47 | 125 |
| $R^2$ | 0.325 | 0.619 | 0.429 | 0.333 | 0.634 | 0.436 | 0.273 | 0.792 | 0.360 | 0.274 | 0.793 | 0.369 |

**Table 2.11: Acquired *OCnet* and post-acquisition sales growth**

This table presents the results from the estimation of the following OLS regressions:

$$\frac{SALE_{B,t+1}-SALE_{B,t}}{SALE_{B,t}}\cdot 100=\alpha_0+\beta_1\frac{OCnet_{T,t-1}}{SALE_{B,t}}+\beta_2\frac{OCnet_{B,t}}{SALE_{B,t}}+\beta_3\frac{1}{SALE_{B,t}}+\beta_4\frac{SALE_{B,t}-SALE_{B,t-1}-SALE_{T,t-1}}{SALE_{B,t-1}+SALE_{T,t-1}}\cdot 100$$
$$+\,Indus_{FF17}\,\&\,Yr\ FE+\ \varepsilon_{B,t+1}$$

$$\frac{SALE_{B,t+2}-SALE_{B,t+1}}{SALE_{B,t+1}}\cdot 100=\alpha_0+\beta_1\frac{OCnet_{T,t-1}}{SALE_{B,t+1}}+\beta_2\frac{OCnet_{B,t+1}}{SALE_{B,t+1}}+\beta_3\frac{1}{SALE_{B,t+1}}+\beta_4\frac{SALE_{B,t+1}-SALE_{B,t}}{SALE_{B,t}}\cdot 100$$
$$+Indus_{FF17}\,\&\,Yr\ FE+\varepsilon_{B,t+2}$$

where *SALE* is sales. The sample consists of 271 and 193 completed M&A deals from 1990 to 2013 satisfying criteria in Table 2.1 for year *t+1* and *t+2*, respectively. All variables are as described in Appendix 2. Same- (Cross-) Industry are observations where the bidder and target do (not) share the same two-digit SIC codes. All dollar values are inflation-adjusted using July 2010 as the base year and are in billions of dollars. All variables are trimmed at the top and bottom 1%. Residuals are clustered by the target Fama-French 17-Industry classifications and p-values are in parentheses.

| **Model** | ***Sales Growth$_{t+1}$*** | | | ***Sales Growth$_{t+2}$*** | | |
|---|---|---|---|---|---|---|
| | Full | Cross-Industry | Same-Industry | Full | Cross-Industry | Same-Industry |
| $\beta_1$ | 4.033 | 11.214 | 5.276 | -2.110 | -7.339 | 4.110 |
| | (0.185) | (0.011) | (0.025) | (0.706) | (0.686) | (0.366) |
| $\beta_2$ | -4.659 | -2.460 | -6.814 | 0.453 | -5.982 | -0.461 |
| | (0.003) | (0.598) | (0.000) | (0.915) | (0.395) | (0.930) |
| $\beta_3$ | -0.052 | -1.276 | 0.071 | -0.162 | -0.550 | -0.401 |
| | (0.559) | (0.000) | (0.611) | (0.661) | (0.814) | (0.314) |
| $\beta_4$ | -0.456 | -0.376 | -0.505 | 0.122 | -0.050 | 0.049 |
| | (0.000) | (0.059) | (0.004) | (0.133) | (0.820) | (0.583) |
| $\alpha_0$ | 5.744 | -13.466 | 3.731 | 6.769 | 42.608 | -20.923 |
| | (0.816) | (0.257) | (0.573) | (0.772) | (0.002) | (0.003) |
| $Indus_{FF17}$ & $Yr$ $FE$ | Yes | Yes | Yes | Yes | Yes | Yes |
| $N$ | 244 | 67 | 178 | 173 | 47 | 126 |
| $R^2$ | 0.332 | 0.642 | 0.424 | 0.277 | 0.830 | 0.366 |

**Table 2.12: Acquired OC and post-acquisition asset turnover**

This table presents the results from the estimation of the following OLS regressions:

$$\frac{SALE_{B,t+1}}{TA_{B,t}} = \alpha_0 + \beta_1 \frac{OC_{T,t-1}}{TA_{B,t}} + \beta_2 \frac{OC_{B,t}}{TA_{B,t}} + \beta_3 \frac{1}{TA_{B,t}} + \beta_4 \frac{SALE_{B,t}}{TA_{B,t-1} + TA_{T,t-1}} \cdot 100 + \ Indus_{FF17} \,\&\, Yr\ FE + \ \varepsilon_{B,t+1}$$

$$\frac{SALE_{B,t+2}}{TA_{B,t+1}} = \alpha_0 + \beta_1 \frac{OC_{T,t-1}}{TA_{B,t+1}} + \beta_2 \frac{OC_{B,t+1}}{TA_{B,t+1}} + \beta_3 \frac{1}{TA_{B,t+1}} + \beta_4 \frac{SALE_{B,t+1}}{TA_{B,t}} \cdot 100 + Indus_{FF17} \,\&\, Yr\ FE + \varepsilon_{B,t+2}$$

where *SALE* is sales and *TA* is the book value of total assets. The sample consists of 271 and 193 completed M&A deals from 1990 to 2013 satisfying the criteria in Table 2.1 for year *t+1* and *t+2*, respectively. All the variables are as described in Appendix 2. Same- (Cross-) Industry are observations where the bidder and the target do (not) share the same two-digit SIC codes. All dollar values are inflation-adjusted using July 2010 as the base year and are in billions of dollars. All variables are trimmed at the top and bottom 1%. Residuals are clustered by the target Fama-French 17-Industry classifications and p-values are in parentheses.

| **Model** | ***Asset Turnover$_{t+1}$*** | | | | | | ***Asset Turnover$_{t+2}$*** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Full | Cross-Industry | Same-Industry | Full | Cross-Industry | Same-Industry | Full | Cross-Industry | Same-Industry | Full | Cross-Industry | Same-Industry |
| *$\beta_1$* | | | | 0.082 | 0.266 | 0.077 | | | | 0.033 | 0.097 | 0.052 |
| | | | | (0.002) | (0.274) | (0.002) | | | | (0.045) | (0.075) | (0.001) |
| *$\beta_2$* | 0.023 | 0.068 | 0.025 | 0.009 | 0.039 | 0.008 | 0.013 | 0.052 | 0.034 | 0.004 | 0.022 | 0.017 |
| | (0.174) | (0.050) | (0.481) | (0.559) | (0.448) | (0.810) | (0.658) | (0.528) | (0.070) | (0.887) | (0.774) | (0.324) |
| *$\beta_3$* | 0.006 | 0.029 | -0.006 | 0.002 | 0.016 | -0.010 | 0.005 | -0.013 | 0.004 | 0.000 | -0.034 | 0.001 |
| | (0.253) | (0.133) | (0.324) | (0.737) | (0.393) | (0.190) | (0.358) | (0.644) | (0.031) | (0.884) | (0.109) | (0.513) |
| *$\beta_4$* | 0.829 | 0.902 | 0.787 | 0.840 | 0.938 | 0.795 | 0.927 | 0.816 | 0.886 | 0.927 | 0.865 | 0.886 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) | (0.000) | (0.000) | (0.000) | (0.000) |
| *$\alpha_0$* | 0.386 | -0.017 | 0.251 | 0.357 | -0.100 | 0.236 | 0.167 | 0.433 | 0.030 | 0.166 | 0.338 | 0.031 |
| | (0.000) | (0.941) | (0.004) | (0.000) | (0.737) | (0.006) | (0.201) | (0.187) | (0.779) | (0.204) | (0.262) | (0.772) |
| *$Indus_{FF17}$ & Yr FE* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *N* | 250 | 63 | 185 | 250 | 63 | 185 | 179 | 47 | 131 | 179 | 47 | 131 |
| *$R^2$* | 0.847 | 0.875 | 0.874 | 0.850 | 0.881 | 0.876 | 0.926 | 0.931 | 0.950 | 0.927 | 0.943 | 0.951 |

**Table 2.13: Acquired *OCnet* and post-acquisition asset turnover**

This table presents the results from the estimation of the following OLS regressions:

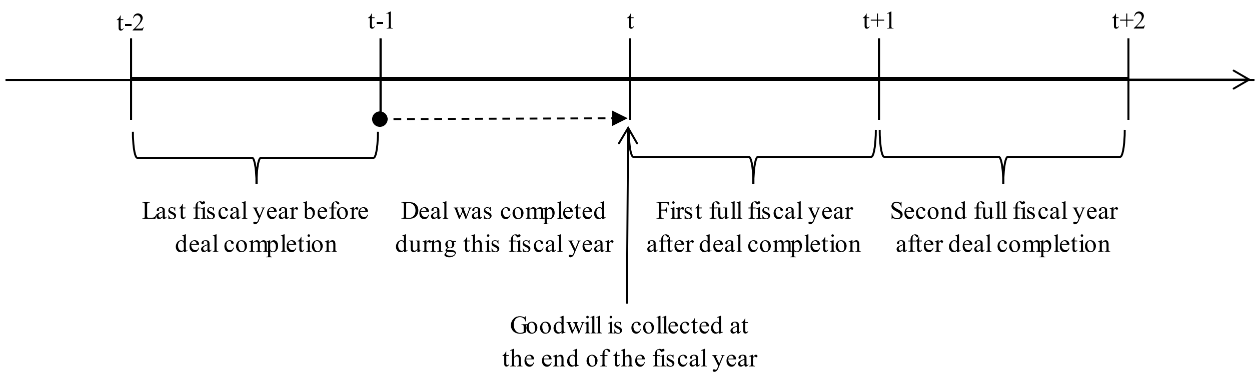
$$\frac{SALE_{B,t+1}}{TA_{B,t}} = \alpha_0 + \beta_1 \frac{OCnet_{T,t-1}}{TA_{B,t}} + \beta_2 \frac{OCnet_{B,t}}{TA_{B,t}} + \beta_3 \frac{1}{TA_{B,t}} + \beta_4 \frac{SALE_{B,t}}{TA_{B,t-1} + TA_{T,t-1}} \cdot 100 + \ Indus_{FF17}\ \&\ Yr\ FE + \ \varepsilon_{B,t+1}$$

$$\frac{SALE_{B,t+2}}{TA_{B,t+1}} = \alpha_0 + \beta_1 \frac{OCnet_{T,t-1}}{TA_{B,t+1}} + \beta_2 \frac{OCnet_{B,t+1}}{TA_{B,t+1}} + \beta_3 \frac{1}{TA_{B,t+1}} + \beta_4 \frac{SALE_{B,t+1}}{TA_{B,t}} \cdot 100 + Indus_{FF17}\ \&\ Yr\ FE + \varepsilon_{B,t+2}$$

where *SALE* is sales and *TA* is the book value of total assets. The sample consists of 271 and 193 completed M&A deals from 1990 to 2013 satisfying the criteria in Table 2.1 for year *t+1* and *t+2*, respectively. All the variables are as described in Appendix 2. Same- (Cross-) Industry are observations where the bidder and the target do (not) share the same two-digit SIC codes. All dollar values are inflation-adjusted using July 2010 as the base year and are in billions of dollars. All variables are trimmed at the top and bottom 1%. Residuals are clustered by the target Fama-French 17-Industry classifications and p-values are in parentheses.

| **Model** | ***Asset Turnover$_{t+1}$*** | | | ***Asset Turnover$_{t+2}$*** | | |
|---|---|---|---|---|---|---|
| | Full | Cross-Industry | Same-Industry | Full | Cross-Industry | Same-Industry |
| $\beta_1$ | 0.091 | 0.205 | 0.041 | 0.146 | 0.272 | 0.175 |
| | (0.083) | (0.649) | (0.548) | (0.111) | (0.048) | (0.083) |
| $\beta_2$ | 0.004 | 0.043 | 0.009 | -0.014 | -0.006 | -0.007 |
| | (0.856) | (0.586) | (0.843) | (0.783) | (0.951) | (0.899) |
| $\beta_3$ | 0.004 | 0.008 | -0.007 | -0.004 | -0.031 | -0.002 |
| | (0.403) | (0.724) | (0.301) | (0.234) | (0.106) | (0.333) |
| $\beta_4$ | 0.842 | 0.917 | 0.802 | 0.932 | 0.914 | 0.887 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\alpha_0$ | 0.355 | -0.187 | 0.248 | 0.100 | 0.008 | 0.183 |
| | (0.000) | (0.240) | (0.004) | (0.542) | (0.957) | (0.097) |
| $Indus_{FF17}$ & $Yr$ $FE$ | Yes | Yes | Yes | Yes | Yes | Yes |
| $N$ | 249 | 63 | 183 | 180 | 44 | 128 |
| $R^2$ | 0.850 | 0.875 | 0.876 | 0.915 | 0.922 | 0.936 |

**Figure 1: Timeline**



# Chapter 3. The Cross-Industry Transferability of Organization Capital

## 3.1 Introduction

In the second chapter of this thesis, I use the M&A setting to study whether organization capital is an asset that has a price and if it is transferable between firms within and across different industries. I find evidence consistent with organization capital being an asset that has a price. I further show a positive relation between acquired targets' organization capital and post-acquisition bidders' return on assets in horizontal acquisitions, thus providing evidence that organization capital is a transferable asset within industries. However, the small number of cross-industry acquisitions in my sample did not allow me to make meaningful conclusions regarding the transferability of OC *between* industries. Given the sheer importance of intangible assets (see, e.g., Peters and Taylor, 2017), determining whether these investments are able to transcend the industries in which they are made is a worthwhile exercise. Ceteris paribus, an asset that is transferable across different industries should be more valuable than one that is only transferable within industry since it can be traded and potentially has a demand across different industries. I thus extend the work of the previous chapter by investigating whether the organization capital of a diversified firm, defined as one that operates in one or more business segment(s) in more than one industry, is positively associated with that firm's future profitability. If that is indeed the case, then it is consistent with organization capital being productive and transferable across segments/industries.

In order to test this relation, I use segment data from Compustat and employ a modified version of the methodology used by Banker et al. (2011), who show that organization capital is associated with higher profitability. Given that the segment data from Compustat is extensive, I am able to overcome the small sample issue of the prior chapter, allowing me to now investigate whether diversified firms benefit from economies of scope from their organization capital. The presence of economies of scope in the current context implies that diversified firms benefit from employing their organization capital in their different industry segments. Showing that these economies of scope exist suggests that organization capital is transferable across different industries.

This study contributes to the organization capital literature by addressing the ongoing debate about the transferability of organization capital. One school of thought argues that organization capital is transferable at a cost (Atkeson and Kehoe, 2005; Prescott and Visscher, 1980; Eisfeldt and Papanikolaou, 2013). On the other hand, Lev and Radhakrishnan (2005) argue that organization capital is very difficult to transfer.

This study also contributes to the conglomerate literature, which has concentrated primarily on whether diversification creates or destroys value. For instance, John and Ofek (1995), Servaes (1996), and Denis et al. (1997), among others, show support for a diversification discount, whereby firms operating across different segments and industries have lower values than do their single-industry counterparts. Others such as Schipper and Thompson (1983), Matsusaka (1993), and Hubbard and Palia (2002) show support for a diversification premium, whereby operating across different segments and industries increases the value of the firm relative to those operating in a single industry. Taking a different approach, Morck and Yeung (2002) show that cross-industry diversification creates value in the presence of information-based assets. Their rationale is that once information-based assets are developed, they can be simultaneously applied to multiple segments. Defining research and development (R&D) and advertising expenses as investments in information-based assets, they study the relation between Tobin's Q and investment in their information-based asset measures for diversified and non-diversified firms. I use a similar approach in this chapter to examine the productivity and efficiency of investments in OC for diversified and non-diversified firms.

In this chapter, I hypothesize that organization capital is a transferable asset across different industries. I test this hypothesis by studying the relation between return on assets and the interaction of each of two organization capital measures with measures of diversification. I expect the coefficient estimate on each of the two interaction terms to be positive and significant, consistent with organization capital being transferable. I also study the relation between sales growth (asset turnover ratio) and each of the two interaction terms. A positive and significant coefficient estimate on each of these two variables implies that organization capital is positively associated with sales growth (asset efficiency).

Using a sample of Compustat segment data from 1976 to 2014, I find results consistent with diversified firms benefitting more from their organization capital than do non-diversified firms when studying the relation between organization capital and each of return on assets, sales growth and asset turnover ratio. These findings support the transferability of organization capital across industries and thus suggest that investments in OC can transcend the industries in which they are made. My findings suggest that greater recognition of this intangible asset should be given on the balance sheet (see Banker, Huang, and Natarajan , 2011; Hulten and Hao, 2008; and Enache and Srivastava, 2018, among others).

The remainder of the paper is organized as follows: I summarize the related literature and develop the hypotheses in the next section. Section 3.3 describes the construction of the dataset and sample. Section 3.4 presents the results and Section 3.5 concludes.

### 3.2 Research Background and Hypothesis Development

#### 3.2.1 Diversification and Intangible Assets

There is a vast literature on diversification addressing a variety of research questions.[33] Comment and Jarrell (1995) note that firms diversify to reap potential benefits from managerial economies of scale, economies of scope, and financial synergies. However, they find empirically that, as diversification increases, stock returns decrease. In theoretical models, Stein (1997) focuses on the financial benefits of diversified firms and shows that diversified firms can be shareholder-value maximizers. On the other hand, Scharfstein and Stein (2000) show how rent-seeking behavior can mitigate the benefits of internal capital markets. Meyer et al. (1992) show how failing segments can benefit from cross-subsidies in diversified firms.

There is an ongoing debate in the empirical literature on whether diversification destroys value (e.g. Comment and Jarrell, 1995; John and Ofek, 1995; Servaes, 1996; Denis et al. 1997); or creates it (e.g. Schipper and Thompson, 1983; Matsusaka, 1993; Hubbard and Palia, 2002). For instance, Lang and Stulz (1994) and Berger and Ofek (1995) argue that the diversification discount could be due to cross-subsidization. The findings of Hyun-Han and Stulz (1998) and Rajan et al. (2000) suggest that internal capital markets do not allocate resources efficiently. Using value weighting on diversified firms, Hund et al. (2012) find that these firms exhibit a diversification premium, not discount. Custódio (2014) employs merger accounting to explain part of the diversification discount of diversified firms.

In studies more closely related to this chapter (in addition to that of Morck and Yeung, 2002 described earlier), some researchers have linked diversification with intangible assets. Chatterjee and Wernerfelt (1991) find that diversified firms with more intangible assets have more

[33] While I include several studies here, the mentioned papers are by no means an exhaustive list. I invite the reader to refer to Maksimovic and Phillips (2013) for a comprehensive literature review.

related diversification. In their model, Maksimovic and Phillips (2002) show that diversified firms can benefit from managerial talent. Hoberg and Phillips (2017) find that most diversified firms are not truly diversified in the sense that they are connected by a common language that makes them more related and actually complementary to each other.

### 3.2.2 Hypothesis Development and Variable Definition

My measures of organization capital (OC) are *OC* and *OCnet*, which I describe in Chapter 2. Following Comment and Jarrell (1995), I use two sets of diversification (*Diver*) measures. The first set is based on the number of business/operating segments (a count measure) reported by firms and these measures are as follows:

- *U4*: the number of unique four-digit SIC code segments reported minus one. When *U4* is equal to zero, the firm is considered non-diversified and it operates in a single four-digit SIC code industry. A firm with *U4* of zero can still have multiple segments but all the segments are in the same four-digit SIC code. A non-zero *U4* means that the firm operates in multiple four-digit SIC code industry segments.
- *U2*: the number of unique two-digit SIC code segments reported minus one. When *U2* is equal to zero, the firm is considered non-diversified and it operates in a unique two-digit SIC code industry. A firm with *U2* of zero can still have multiple segments but all the segments are in the same two-digit SIC code. A non-zero *U2* means that the firm operates in multiple two-digit SIC code industry segments.
- *D·U4*: A dummy variable which takes the value of 1 when the number of business/operation segments reported is in more than one four-digit SIC code (*U4*>0) and zero otherwise.

- $D{\cdot}U2$: A dummy variable which takes the value of 1 when the number of business/operation segments reported is in more than one two-digit SIC code ($U2$>0) and zero otherwise.[34]

The second set of diversification measures involve a sales-based Herfindahl index ($HH$) where $HH$ is computed as follows:

$$HH_{it} = \sum_{j=1}^{N_{it}} \left( S_{jit} / \sum_{j=1}^{N_{it}} S_{jit} \right)^2$$

where $N_{it}$ is the number of reported segments for firm $i$ in fiscal year $t$, $S_j$ is sales of segment $j$. When $HH$ is equal to one, then the firm is non-diversified and reports only one segment. As $HH$ decreases, the firm is considered more diversified. Note that John and Ofek (1995) use this measure and find that sales of assets in diversified firms are associated with better future operating performance. To make this $HH$ measure compatible with the first set of measures, I use the inverse of $HH$ minus one as follows:

$$H^{-1} = \frac{1}{HH} - 1$$

When $H^{-1}$ is zero (the minimum), then the firm is non-diversified and $H^{-1}$ increases as the firm becomes more diversified. The different measures are as follows:

- $H^{-1}4$: $H^{-1}$ where segments are first aggregated into four-digit SIC codes and therefore each segment represents a unique four-digit SIC code industry. When $H^{-1}4$ is zero, the firm is not diversified.
- $H^{-1}2$: $H^{-1}$ where segments are first aggregated into two-digit SIC codes and therefore each segment represents a unique two-digit SIC code industry. When $H^{-1}2$ is zero, the firm is not diversified.

[34] Note that since my focus is on the cross-industry effect of OC, I do not include the number of reported segments as a measure of diversification by itself as this measure includes firms with different segments in the same industry. However, my results are robust to including this measure.

- $D{\cdot}H^{-1}4$: A dummy variable which takes the value of 1 when $H^{-1}4$ is non-zero and zero when $H^{-1}4$ is zero.
- $D{\cdot}H^{-1}2$: A dummy variable which takes the value of 1 when $H^{-1}2$ is non-zero and zero when $H^{-1}2$ is zero.

I apply the methodology used in studying the productivity of acquired OC in Chapter 2 to study whether OC is a transferable asset across different industries. My first hypothesis addresses the productivity of OC in diversified firms. I examine the ROA-OC relation between standalone and diversified firms. If OC is transferable across different industries, then I expect OC to be at least as productive in diversified firms as in non-diversified firms. My hypothesis is:

> *H1: The operating return-OC relation between diversified and non-diversified firms is non-negative.*

I use regression analysis with ROA as the dependent variable and the interaction of *Scaled OC* (hereafter *OC*) (and *Scaled OCnet*, hereafter *OCnet*) and a diversified firm variable (*Diver*) as the variable of interest to study this relationship as follows:

$$\frac{OIBDP_{i,t}}{TA_{i,t-1}} \cdot 100 = \alpha_0 + \beta_1 \cdot \frac{OC_{i,t-1}}{TA_{i,t-1}} + \beta_2 \cdot Diver + \beta_3 \cdot \frac{OC_{i,t-1}}{TA_{i,t-1}} \cdot Diver + \beta_4 \cdot \frac{1}{TA_{i,t-1}}$$

$$+ \beta_5 \cdot \frac{OIBDP_{i,t-1}}{TA_{i,t-2}} \cdot 100 + Indus_{FF17} \cdot Yr \,\&\, Firm\, FE + \varepsilon_{i,t}. \quad (3.1)$$

where $OIBDP_{i,t+1}$ is operating income before depreciation; $OC_{i,t-1}$ is OC, *TA* is total assets, *Diver* is a diversified firm measure which represents one of the eight measures described above, $Indus_{FF17} \cdot Yr$ *& Firm FE* are industry-by-year (where the Fama-French 17-industry classification is used) and firm fixed effects, respectively. The dependent variable is *ROA* and the variable of interest is the interaction term. In all regressions, standard errors are clustered by firm. All variables are as described in Appendix 2.

I expect the coefficient estimate of *OC* to be positive, implying that OC is productive and is positively associated with future operating returns. If diversified firms generate more (less) operating income than do standalone firms, then I expect the coefficient estimate of *Diver* to be positive (negative). A negative coefficient estimate on the interaction term implies that the OC of diversified firms is less productive than that of non-diversified firms, suggesting that OC is not transferable between industries. An insignificant (positive significant) coefficient estimate on the interaction term implies that the productivity of OC is equivalent between (higher in) diversified and (than) non-diversified firms, which is consistent with OC being transferable across industries.

My second hypothesis studies whether the observed relation between ROA and OC arises via sales growth. I alter Eq. (3.1) with sales to investigate this relation as follows:

$$\frac{SALE_{i,t} - SALE_{i,t-1}}{SALE_{i,t-1}} \cdot 100 = \alpha_0 + \beta_1 \cdot \frac{OC_{i,t-1}}{SALE_{i,t-1}} + \beta_2 \cdot Diver + \beta_3 \cdot \frac{OC_{i,t-1}}{SALE_{i,t-1}} \cdot Diver$$
$$+ \beta_4 \cdot \frac{1}{SALE_{i,t-1}} + \beta_5 \cdot \frac{SALE_{i,t-1} - SALE_{i,t-2}}{SALE_{i,t-2}} \cdot 100 + Indus_{FF17} \cdot Yr\&Firm\ FE + \varepsilon_{i,t} \quad (3.2)$$

where *SALE* is sales and all the other variables are as described earlier and in Appendix 2. The dependent variable is *Sales Growth* and the variable of interest is the interaction of OC scaled by lagged sales and *Diver*.

I expect the coefficient estimate of $\beta_1$ to be positive, implying that OC is positively associated with sales growth. I expect the coefficient estimate of $\beta_2$ to be positive (negative) if diversified firms create more (less) sales growth than do standalone firms. The coefficient estimate of the interaction term has the same interpretation as in Eq. (3.1) except with sales growth. If this coefficient is non-negative, it is consistent with OC being transferable between industries.

Lastly, I study the relation between asset turnover and acquired target OC by modifying Eq. (3.1) as follows:[35]

$$\frac{SALE_{i,t}}{TA_{i,t-1}} \cdot 100 = \alpha_0 + \beta_1 \cdot \frac{OC_{i,t-1}}{TA_{i,t-1}} + \beta_2 \cdot Diver + \beta_3 \cdot \frac{OC_{i,t-1}}{TA_{i,t-1}} \cdot Diver + \beta_4 \cdot \frac{1}{TA_{i,t-1}} + \beta_5 \cdot \frac{SALE_{i,t-1}}{TA_{i,t-2}} \cdot 100 + Indus_{FF17} \cdot Yr\&Firm\ FE + \varepsilon_{i,t} \tag{3.3}$$

where *SALE* is sales and *TA* is the book value of total assets. All the other variables are as described earlier and in Appendix 2. The dependent variable is bidders' *Asset Turnover*.

I expect the coefficient estimate of *OC* to be positive, implying that OC is positively associated with *Asset Turnover*, an asset efficiency measure. If the coefficient estimate on *Diver* is positive (negative), diversified firms are associated with higher (lower) *Asset Turnover* than are standalone firms. A negative coefficient estimate on the interaction term implies that the OC of diversified firms is less efficient than for non-diversified firms.

### 3.3 Data and Sample Description

The segment data are obtained from the Compustat database for the years 1976 to 2014. All dollar values are inflation-adjusted using July 2010 as the base year. I exclude firms in the financial (SIC codes 6000 to 6999) and public utility (SIC codes 4900 to 4999) sectors. I exclude segments with missing or non-positive sales. I use the universe of Compustat firms to compute the measures of *OC* and *OCnet*, and this methodology is described in Chapter 2. Given that the universe of Compustat firms includes many very small firms, these too would be included in my sample. However, to make the sample more meaningful, I exclude firms below the fifth percentile of total assets of the Compustat universe. I also exclude firms with ROA greater (less) than or

[35] Note that asset turnover is a component of ROA in DuPont analysis.

equal to 100% (-100%), and firms with either negative scaled SG&A ($\frac{SG\&A}{TA}$) or scaled SG&A greater than one. Table 3.1 provides a summary of the construction of the sample.

### 3.4 Results

#### 3.4.1 Summary Statistics

In Panel A of Table 3.2, I present the summary statistics of the variables used in this chapter. The mean and median of return on assets (*ROA*) are 13.29% and 13.17%, respectively. The mean (median) of *Sales Growth* is 5.81% (4.14%). The mean (median) of *Asset Turnover* is 1.39 (1.25). On average, these firms are profitable, have positive sales growth, and are using their assets efficiently to generate sales. The main independent variables in this study, *Scaled OC* and *Scaled OCnet*, have means (medians) of 1.49 (1.23) and 1.32 (1.06), respectively. The median level of *Scaled OC* in this sample is comparable to those in the third quintile (Table III) of Eisfeldt and Papanikolaou (2013), suggesting that the firms in this sample are, on average, medium-OC firms.

The mean of *U4* (*U2*) is 0.64 (0.48), indicating that when grouping segments by four- (two-) digit SIC code, firms operate, on average, in 1.64 (1.48) segments. However, the median of *U4* (*U2*) is zero, thus at least 50% of the companies operate as stand-alone firms in this sample. The mean of *D·U4* is 0.38 implying that 38% of the firms operate in multiple four-digit SIC code segments and the remaining 62% of firms are non-diversified. The mean and median of *D·U2* are similar to those of *D·U4* when examining segments by two-digit SIC codes.

The mean of $H^{-1}4$ ($H^{-1}2$) is 0.327 (0.219), implying that when grouping segments on four- (two-) digit SIC code, the average sales-based Herfindahl index is 0.75 (0.82) and at least 50% of the firms reported sales in only one four- (two-) digit SIC code industry. The mean of $D{\cdot}H^{-1}4$ is

0.38 implying that, 38% of the firms report sales in multiple four-digit SIC code segments, and 62% of the firms report sales in only one four-digit SIC code industry. These figures using two-digit SIC code are 32% and 68%, respectively. The mean (median) of lagged total assets (*TA*) is \$1.35 (\$0.237) billion. The mean (median) of lagged total sales (*SALE*) is \$1.47 (\$0.275) billion.

In Panel B of Table 3.2, I present the means (medians) of the main variables separately for diversified and non-diversified firms, using the count dummies. Using the dummies based on the Herfindahl index produces similar results. The means of *ROA* are significantly higher for the diversified than non-diversified firms. Sales growth and asset turnover are significantly higher in non-diversified than diversified firms, on average. Compared to diversified firms, non-diversified firms spend more on OC (OCnet), holding their size constant.

From the correlation matrix in Panel C, I find that both *OC* and *OCnet* are negatively correlated with *ROA* and positively correlated with *Asset Turnover*. These suggest that OC is negatively related to profitability and positively associated with asset efficiency. Moreover, all the diversification measures are positively correlated with *ROA*, while most are negatively correlated with *Asset Turnover*. I find all the variables are negatively correlated with *Sales Growth*.

### 3.4.2 The ROA-OC Relation

I show the results of Eq. (3.1) in Table 3.3. In the first four columns, I present the results where the diversification measures are based on the number of segments, while in the last four columns, the diversification measures use the sales-based Herfindahl index. First, I find that the coefficient estimates of *OC* are positive and statistically significant in all columns. This result implies that OC is positively related to future operating income and is consistent with OC being an asset. Second, the coefficient estimates of the different diversification measures are negative and significant in all columns, indicating that diversified firms have lower *ROA* compared to non-diversified firms, consistent with a diversification discount. This result contradicts the observations made from Panel B of Table 3.2, where the means of ROA are higher in the diversified samples, and is due to the firm fixed effects.

Third, the coefficient estimates on the interaction term are positive and significant in all columns. This is consistent with diversified firms benefiting more from their OC than do non-diversified firms. Given that in Panel B of Table 3.2 that diversified firms spend less on OC compared to non-diversified firms, these results suggest that diversified firms spend less on OC yet benefit more from these investments. Holding all else constant, (1) an increase in scaled OC benefits diversified firms more than non-diversified firms and (2) the more widely the firms are diversified, the more they benefit from their OC. Similar conclusions are made when I use the sales-based Herfindahl index to classify firms into diversified and non-diversified. These findings are consistent with OC being a transferable asset across industries.

Since both R&D and advertising expenses are included in SG&A expenses (the input into my measure of OC), it is natural to ask whether these results are being driven by these potentially-significant expense amounts. To address this issue, I use an alternative measure of *OC* where I capitalize SG&A net of both R&D and advertising expenses, defined earlier as *OCnet*. I then replicate Table 3.3 using *OCnet* instead of *OC* and present the results in Table 3.4. If R&D or advertising expenses do indeed drive the results shown in Table 3.3, then the coefficient estimate of *OCnet* should be statistically insignificant in Table 3.4. However, replacing *OC* with *OCnet* does not change the conclusions reached above. *OCnet* is positively related to future operating income, diversified firms benefit more from their *OCnet* when compared to non-diversified firms, and the evidence still suggests that diversified firms spend less on *OCnet* but are able to benefit more from their *OCnet*. Similar findings are also made when using the sales-based Herfindahl index to classify firms into diversified and non-diversified. Thus, R&D and advertising expenses do not drive the results in Table 3.3.

The takeaway from this section is that compared to non-diversified firms, the results are consistent with diversified firms spending less on their *OC* and *OCnet*, and benefitting more from these investments in terms of operating income. This result is in line with Morck and Yeung (2002), who find that cross-industry diversification increases firm value (Tobin's Q) in the presence of intangible assets. Overall, my findings are consistent with the notion of OC being a transferable asset between different industries.

**3.4.3 The Sales Growth-OC Relation**

In this section, I study whether the observed relation in Tables 3.3 and 3.4 arises via sales growth using Eq. (3.2), the results of which are presented in Tables 3.5 and 3.6, respectively. In the first four columns of Table 3.5, I present the results where the diversification measures are based on the number of segments, and in the last four columns, the diversification measures use the sales-based Herfindahl index. Similar to the previous tables, I find that the coefficient estimates of *OC* are positive and significant in all columns, indicating that *OC* is positively related to future sales growth. This result contradicts the negative correlation coefficient observed in Panel B of Table 3.2 and is due to the inclusion firm fixed effects. The coefficient estimates of the different measures of diversification are positive in all columns but mostly significant only when using the number of segments to classify firms. These results provide some evidence that diversified firms, on average, have higher sales growth than non-diversified firms.

In this table, the coefficient estimates of the interaction term are positive and significant in all columns, again indicating that diversified firms benefit more than non-diversified firms from their OC. Again, incorporating the evidence from Panel B of Table 3.2, on average, diversified firms spend less on OC yet benefit more from these investments. Similar observations are made when using the sales-based Herfindahl index to classify firms into diversified and non-diversified. In Table 3.6, I present the results using *OCnet* and find them to be qualitatively similar to those using *OC*. Overall, there is evidence that cross industry diversification increases future sales growth in the presence of OC and this is consistent with OC being transferable across industries. Moreover, the positive relation between ROA and OC observed earlier arises from higher sales growth.

### 3.4.4 The Asset Turnover-OC Relation

In this section, I study the relation between OC and asset turnover, a measure of efficiency indicating the value of sales a company's assets is generating. I study the relation using Eq. (3.3) and present the results in Table 3.7. In the first four columns, I present the results where the diversification measures are based on the number of segments, while in the last four columns, the diversification measures use the sales-based Herfindahl index. First, I find that the coefficient estimates of *OC* are positive and statistically significant in all columns implying that, on average, OC is positively related to future asset turnover ratio, indicating a positive association between OC and asset efficiency. Second, the coefficient estimates of the different measures of diversification are positive and significant in all columns. Thus, diversified firms have higher asset turnover ratios, on average, when compared to non-diversified firms. This finding contradicts (at least in part) the diversification discount.[36]

[36] In Table 3.3, I find evidence supporting the diversification discount but not in Table 3.5 or Table 3.7. This suggest that if I use a regression with profit margin as the dependent variable, most likely, the results will support the diversification discount due to the DuPont analysis.

Next, the coefficient estimates of the interaction term are positive and significant in all columns save those using the dummy version of the classification variables. Since the marginal effect of OC on asset turnover is larger for diversified firms, these firms benefit more from their OC than do non-diversified counterparts. These results are not dependent on how diversification is measured.

In Table 3.8, I present the results of Eq. (3.3) using *OCnet* and find them to be qualitatively similar to those using *OC*. Thus, in this section, I show that in the presence of OC, an intangible asset, cross-industry diversification increases the asset turnover ratio. These results also imply that the higher ROA observed earlier is attributable to using assets more efficiently.

A concern with the measures of OC (*OCnet*) is that the initial value, $OC_{i,0}$ $(OCnet_{i,0})$, depends significantly on the first available data on SG&A and this may influence the results. Following Eisfeldt and Papanikolaou (2013) and Li et al. (2018), I drop observations where OC (*OCnet*) is in the first five years of the measured OC (*OCnet*) to reduce the impact of the initial OC. While I do not report the results, they are economically and statistically similar.[37] These results are also robust to using industry fixed effects based on four-digit (two-digit) SIC code (instead of Fama-French 17-industry classification), year (instead of industry-by-year) and firm fixed effects.

## 3.5 Concluding Remarks

In this study, I examine whether OC is transferable between industries using Compustat segment data. I first show evidence that OC is positively associated with ROA, sales growth, and asset turnover ratios. Second, I show that diversified firms benefit more from their OC than do their non-diversified counterparts. The findings that, in the presence of OC, diversification across

[37] Results are available upon request.

industries increases return on assets, sales growth, and asset efficiency, is consistent with OC being a transferable asset between industries and nicely complements the finding of within-industry transferability in the previous chapter.

**Table 3.1: Sample construction**

| Selection Criteria |
|---|
| Compustat segment data from 1976 to 2014 |
| Exclude segments with missing or non-positive sales |
| Exclude firms in: |
| Financial sector (SIC 6000-6999) |
| Public utilities (SIC 4900-4999) |
| ROA is within ± 100% exclusively |
| SG&A scaled by total assets is positive and less than 1. |
| Drop firms below the 5th percentile of total assets in July 2010 dollars. |

## Table 3.2: Summary statistics and correlation coefficients

The sample consists of all of Compustat segment data from 1976 to 2014 satisfying the criteria in Table 3.1 and all the variables are as described in Appendix 2. All dollar values are inflation-adjusted using July 2010 as the base year, and are in billions of dollars. All variables are trimmed at the top and bottom 1%. Panel A shows the summary statistics of the variables use in this study. Panel B shows the mean (median) and the difference in mean of the main variables for diversified and non-diversified firms. Panel C shows the pairwise correlation of some key variables. Superscripts x, y, and z represent the statistical significance at the 1, 5, and 10% levels, respectively.

*Panel A: Summary Statistics*

| Variables | N | Mean | Median |
|---|---|---|---|
| **Dependent Variables** | | | |
| *ROA* | 105,018 | 13.290 | 13.168 |
| *Sales Growth* | 102,752 | 5.815 | 4.141 |
| *Asset Turnover* | 105,018 | 1.390 | 1.251 |
| **Variables of Interest** | | | |
| *Scaled OC* | 105,018 | 1.485 | 1.231 |
| *Scaled OCnet* | 105,018 | 1.315 | 1.062 |
| $OC_{t-1}/SALE_{t-1}$ | 104,955 | 1.253 | 1.041 |
| $OCnet_{t-1}/SALE_{t-1}$ | 104,954 | 1.051 | 0.895 |
| *U4* | 103,102 | 0.638 | 0.000 |
| *U2* | 103,728 | 0.481 | 0.000 |
| *D·U4* | 103,102 | 0.380 | 0.000 |
| *D·U2* | 103,728 | 0.320 | 0.000 |
| $H^{-1}4$ | 103,024 | 0.327 | 0.000 |
| $H^{-1}2$ | 103,024 | 0.219 | 0.000 |
| $D{\cdot}H^{-1}4$ | 103,024 | 0.380 | 0.000 |
| $D{\cdot}H^{-1}2$ | 103,024 | 0.316 | 0.000 |
| **Control Variables** | | | |
| $AT_{t-1}$ | 105,018 | 1.352 | 0.237 |
| $SALE_{t-1}$ | 104,955 | 1.470 | 0.275 |

*Panel B: Summary Statistics by diversifying*

| **Variables** | ***D·U4=1*** | ***D·U4=0*** | ***Diff*** | ***D·U2=1*** | ***D·U2=0*** | ***Diff*** |
|---|---|---|---|---|---|---|
| *ROA* | 13.554 | 13.098 | -0.456$^{x}$ | 13.469 | 13.193 | -0.276$^{x}$ |
| | (13.443) | (12.931) | | (13.401) | (13.041) | |
| *Sales Growth* | 4.444 | 6.522 | 2.077$^{x}$ | 4.322 | 6.379 | 2.058$^{x}$ |
| | (3.253) | (4.653) | | (3.166) | (4.550) | |
| *Asset Turnover* | 1.379 | 1.405 | 0.026$^{x}$ | 1.397 | 1.393 | -0.004 |
| | (1.257) | (1.255) | | (1.275) | (1.245) | |
| *Scaled OC* | 1.382 | 1.558 | 0.176$^{x}$ | 1.372 | 1.543 | 0.171$^{x}$ |
| | (1.140) | (1.306) | | (1.130) | (1.292) | |
| *Scaled OCnet* | 1.220 | 1.318 | 0.098$^{x}$ | 1.220 | 1.306 | 0.086$^{x}$ |
| | (1.001) | (1.072) | | (0.996) | (1.063) | |
| $OC_{t-1}/SALE_{t-1}$ | 1.132 | 1.327 | 0.194$^{x}$ | 1.108 | 1.318 | 0.209$^{x}$ |
| | (0.954) | (1.102) | | (0.940) | (1.095) | |
| $OCnet_{t-1}/SALE_{t-1}$ | 0.985 | 1.091$^{x}$ | 0.106$^{x}$ | 0.970 | 1.086 | 0.116$^{x}$ |
| | (0.843) | (0.931) | | (0.833) | (0.926) | |
| *N* | 39,179 | 63,923 | | 33,193 | 70,535 | |

*Panel C: Pairwise Pearson Correlation Coefficients*

| **Variables** | ***ROA*** | ***Sales Growth*** | ***Asset Turnover*** |
|---|---|---|---|
| *Scaled OC* | -0.059$^{x}$ | - | 0.349$^{x}$ |
| *Scaled OCnet* | -0.044$^{x}$ | - | 0.403$^{x}$ |
| $OC_{t-1}/SALE_{t-1}$ | - | -0.036$^{x}$ | - |
| $OCnet_{t-1}/SALE_{t-1}$ | - | -0.049$^{x}$ | - |
| *U4* | 0.030$^{x}$ | -0.051$^{x}$ | -0.015$^{x}$ |
| *U2* | 0.017$^{x}$ | -0.046$^{x}$ | 0.001 |
| *D·U4* | 0.020$^{x}$ | -0.050$^{x}$ | -0.016$^{x}$ |
| *D·U2* | 0.012$^{x}$ | -0.048$^{x}$ | 0.003 |
| $H^{-1}4$ | 0.028$^{x}$ | -0.054$^{x}$ | -0.032$^{x}$ |
| $H^{-1}2$ | 0.013$^{x}$ | -0.047$^{x}$ | -0.017$^{x}$ |
| $D{\cdot}H^{-1}4$ | 0.019$^{x}$ | -0.049$^{x}$ | -0.015$^{x}$ |
| $D{\cdot}H^{-1}2$ | 0.010$^{x}$ | -0.046$^{x}$ | 0.003 |

## Table 3.3: The relation between ROA and OC

This table presents the results from the estimation of the following OLS regression:

$$\frac{OIBDP_{i,t}}{TA_{i,t-1}} \cdot 100 = \alpha_0 + \beta_1 \cdot \frac{OC_{i,t-1}}{TA_{i,t-1}} + \beta_2 \cdot Diver + \beta_3 \cdot \frac{OC_{i,t-1}}{TA_{i,t-1}} \cdot Diver + \beta_4 \cdot \frac{1}{TA_{i,t-1}} + \beta_5 \cdot \frac{OIBDP_{i,t-1}}{TA_{i,t-2}} \cdot 100 + Indus_{FF17} \cdot Yr\&Firm\ FE + \varepsilon_{i,t}$$

where *OIBDP* is operating income before depreciation and *TA* is total assets. *Diver* is a diversification measure, which represents one of the eight measures. The sample consists of all of Compustat segment data from 1976 to 2014 satisfying the criteria in Table 3.1 and all the variables are as described in the Appendix 2. All dollar values are inflation-adjusted using July 2010 as the base year, and are in billions of dollars. All variables are trimmed at the top and bottom 1%. Residuals are clustered by firm and p-values are in parentheses.

| **Diversification** Measure | ***U4*** | ***U2*** | ***D·U4*** | ***D·U2*** | ***$H^{-1}4$*** | ***$H^{-1}2$*** | ***$D·H^{-1}4$*** | ***$D·H^{-1}2$*** |
|---|---|---|---|---|---|---|---|---|
| $\beta_1$ | 0.969 | 1.004 | 0.951 | 0.987 | 0.980 | 0.997 | 0.952 | 0.993 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_2$ | -0.223 | -0.122 | -0.438 | -0.340 | -0.454 | -0.512 | -0.431 | -0.344 |
| | (0.005) | (0.189) | (0.010) | (0.050) | (0.000) | (0.003) | (0.012) | (0.048) |
| $\beta_3$ | 0.137 | 0.098 | 0.261 | 0.190 | 0.210 | 0.251 | 0.259 | 0.191 |
| | (0.006) | (0.098) | (0.006) | (0.050) | (0.011) | (0.022) | (0.007) | (0.051) |
| $\beta_4$ | 0.113 | 0.113 | 0.113 | 0.113 | 0.113 | 0.113 | 0.113 | 0.113 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_5$ | 0.494 | 0.495 | 0.494 | 0.494 | 0.494 | 0.494 | 0.494 | 0.494 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\alpha_0$ | 7.276 | 7.140 | 7.296 | 7.207 | 7.346 | 7.285 | 7.338 | 7.278 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| | | | | | | | | |
| $Indus_{FF17} \cdot Yr\&Firm\ FE$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *N* | 96,145 | 96,681 | 96,145 | 96,681 | 96,075 | 95,999 | 96,075 | 95,999 |
| $R^2$ | 0.658 | 0.658 | 0.658 | 0.658 | 0.658 | 0.658 | 0.658 | 0.658 |

### Table 3.4: The relation between ROA and *OCnet*

This table presents the results from the estimation of the following OLS regression:

$$\frac{OIBDP_{i,t}}{TA_{i,t-1}} \cdot 100 = \alpha_0 + \beta_1 \cdot \frac{OCnet_{i,t-1}}{TA_{i,t-1}} + \beta_2 \cdot Diver + \beta_3 \cdot \frac{OCnet_{i,t-1}}{TA_{i,t-1}} \cdot Diver + \beta_4 \cdot \frac{1}{TA_{i,t-1}} + \beta_5 \cdot \frac{OIBDP_{i,t-1}}{TA_{i,t-2}} \cdot 100 + Indus_{FF17} \cdot Yr\&Firm\ FE + \varepsilon_{i,t}$$

where *OIBDP* is operating income before depreciation and *TA* is total assets. *Diver* is a diversification measure, which represents one of the eight measures. The sample consists of all of Compustat segment data from 1976 to 2014 satisfying the criteria in Table 3.1 and all the variables are as described in the Appendix 2. All dollar values are inflation-adjusted using July 2010 as the base year, and are in billions of dollars. All variables are trimmed at the top and bottom 1%. Residuals are clustered by firm and p-values are in parentheses.

| **Diversification** Measure | ***U4*** | ***U2*** | ***D·U4*** | ***D·U2*** | ***$H^{-1}$4*** | ***$H^{-1}$2*** | ***D·$H^{-1}$4*** | ***D·$H^{-1}$2*** |
|---|---|---|---|---|---|---|---|---|
| $\beta_1$ | 1.097 | 1.132 | 1.077 | 1.115 | 1.108 | 1.121 | 1.078 | 1.123 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_2$ | -0.228 | -0.140 | -0.443 | -0.353 | -0.478 | -0.579 | -0.438 | -0.358 |
| | (0.004) | (0.132) | (0.009) | (0.039) | (0.000) | (0.001) | (0.010) | (0.038) |
| $\beta_3$ | 0.158 | 0.127 | 0.296 | 0.224 | 0.254 | 0.338 | 0.295 | 0.225 |
| | (0.005) | (0.056) | (0.006) | (0.039) | -0.008 | (0.006) | (0.006) | (0.039) |
| $\beta_4$ | 0.115 | 0.114 | 0.114 | 0.114 | 0.114 | 0.114 | 0.114 | 0.114 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_5$ | 0.492 | 0.492 | 0.492 | 0.492 | 0.492 | 0.492 | 0.492 | 0.492 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\alpha_0$ | 7.214 | 7.085 | 7.239 | 7.155 | 7.285 | 7.227 | 7.284 | 7.228 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $Indus_{FF17}$·*Yr&Firm FE* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *N* | 96,105 | 96,640 | 96,105 | 96,640 | 96,035 | 95,958 | 96,035 | 95,958 |
| $R^2$ | 0.657 | 0.657 | 0.657 | 0.657 | 0.657 | 0.657 | 0.657 | 0.657 |

## Table 3.5: The relation between sales growth and OC

This table presents the results from the estimation of the following OLS regression:

$$\frac{SALE_{i,t} - SALE_{i,t-1}}{SALE_{i,t-1}} \cdot 100 = \alpha_0 + \beta_1 \cdot \frac{OC_{i,t-1}}{SALE_{i,t-1}} + \beta_2 \cdot Diver + \beta_3 \cdot \frac{OC_{i,t-1}}{SALE_{i,t-1}} \cdot Diver + \beta_4 \cdot \frac{1}{SALE_{i,t-1}}$$
$$+\beta_5 \cdot \frac{SALE_{i,t-1} - SALE_{i,t-2}}{SALE_{i,t-2}} \cdot 100 + Indus_{FF17} \cdot Yr\&Firm\ FE + \varepsilon_{i,t}$$

where *SALE* is sales. *Diver* is a diversification measure, which represents one of the eight measures. The sample consists of all of Compustat segment data from 1976 to 2014 satisfying the criteria in Table 3.1 and all the variables are as described in the Appendix 2. All dollar values are inflation-adjusted using July 2010 as the base year, and are in billions of dollars. All variables are trimmed at the top and bottom 1%. Residuals are clustered by firm and p-values are in parentheses.

| **Diversification** Measure | ***U4*** | ***U2*** | ***D·U4*** | ***D·U2*** | ***$H^{-1}4$*** | ***$H^{-1}2$*** | ***$D \cdot H^{-1}4$*** | ***$D \cdot H^{-1}2$*** |
|---|---|---|---|---|---|---|---|---|
| $\beta_1$ | 1.392 | 1.408 | 1.377 | 1.372 | 1.365 | 1.409 | 1.383 | 1.385 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_2$ | 0.599 | 0.598 | 1.047 | 0.750 | 0.551 | 0.776 | 1.044 | 0.762 |
| | (0.007) | (0.022) | (0.021) | (0.108) | (0.141) | (0.130) | (0.022) | (0.106) |
| $\beta_3$ | 0.410 | 0.501 | 0.528 | 0.635 | 0.746 | 0.826 | 0.540 | 0.628 |
| | (0.016) | (0.017) | (0.080) | (0.052) | (0.011) | (0.041) | (0.073) | (0.056) |
| $\beta_4$ | 0.391 | 0.390 | 0.390 | 0.390 | 0.391 | 0.391 | 0.390 | 0.391 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_5$ | 0.156 | 0.156 | 0.156 | 0.156 | 0.156 | 0.156 | 0.156 | 0.156 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\alpha_0$ | 3.488 | 3.523 | 3.638 | 3.817 | 4.035 | 4.102 | 3.747 | 3.981 |
| | (0.179) | (0.156) | (0.160) | (0.123) | (0.112) | (0.110) | (0.137) | (0.117) |
| $Indus_{FF17} \cdot Yr\&Firm\ FE$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *N* | 91,776 | 92,309 | 91,776 | 92,309 | 91,665 | 91,618 | 91,665 | 91,618 |
| $R^2$ | 0.339 | 0.338 | 0.339 | 0.338 | 0.338 | 0.339 | 0.338 | 0.339 |

## Table 3.6: The relation between sales growth and *OCnet*

This table presents the results from the estimation of the following OLS regression:

$$\frac{SALE_{i,t} - SALE_{i,t-1}}{SALE_{i,t-1}} \cdot 100 = \alpha_0 + \beta_1 \cdot \frac{OCnet_{i,t-1}}{SALE_{i,t-1}} + \beta_2 \cdot Diver + \beta_3 \cdot \frac{OCnet_{i,t-1}}{SALE_{i,t-1}} \cdot Diver + \beta_4 \cdot \frac{1}{SALE_{i,t-1}}$$

$$+\beta_5 \cdot \frac{SALE_{i,t-1} - SALE_{i,t-2}}{SALE_{i,t-2}} \cdot 100 + Indus_{FF17} \cdot Yr\&Firm\ FE + \varepsilon_{i,t}$$

where *SALE* is sales. *Diver* is a diversification measure, which represents one of the eight measures. The sample consists of all of Compustat segment data from 1976 to 2014 satisfying the criteria in Table 3.1 and all the variables are as described in the Appendix 2. All dollar values are inflation-adjusted using July 2010 as the base year, and are in billions of dollars. All variables are trimmed at the top and bottom 1%. Residuals are clustered by firm and p-values are in parentheses.

| **Diversification** Measure | ***U4*** | ***U2*** | ***D·U4*** | ***D·U2*** | $H^{-1}4$ | $H^{-1}2$ | $D{\cdot}H^{-1}4$ | $D{\cdot}H^{-1}2$ |
|---|---|---|---|---|---|---|---|---|
| $\beta_1$ | 1.643 | 1.692 | 1.603 | 1.646 | 1.610 | 1.699 | 1.609 | 1.671 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_2$ | 0.510 | 0.541 | 0.844 | 0.654 | 0.376 | 0.583 | 0.838 | 0.652 |
| | (0.028) | (0.048) | (0.071) | (0.175) | (0.341) | (0.288) | (0.074) | (0.181) |
| $\beta_3$ | 0.555 | 0.618 | 0.804 | 0.813 | 1.035 | 1.135 | 0.822 | 0.817 |
| | (0.009) | (0.018) | (0.031) | (0.043) | (0.006) | (0.028) | (0.028) | (0.044) |
| $\beta_4$ | 0.392 | 0.391 | 0.391 | 0.390 | 0.392 | 0.391 | 0.391 | 0.391 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_5$ | 0.156 | 0.156 | 0.156 | 0.156 | 0.156 | 0.156 | 0.156 | 0.156 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\alpha_0$ | 3.237 | 3.232 | 3.423 | 3.546 | 3.796 | 3.799 | 3.539 | 3.695 |
| | (0.211) | (0.192) | (0.185) | (0.150) | (0.135) | (0.138) | (0.160) | (0.145) |
| $Indus_{FF17}{\cdot}Yr\&Firm\ FE$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *N* | 91,771 | 92,300 | 91,771 | 92,300 | 91,659 | 91,611 | 91,659 | 91,611 |
| $R^2$ | 0.339 | 0.339 | 0.339 | 0.338 | 0.339 | 0.340 | 0.339 | 0.339 |

## Table 3.7: The relation between asset turnover and OC

This table presents the results from the estimation of the following OLS regression:

$$\frac{SALE_{i,t}}{TA_{i,t-1}} \cdot 100 = \alpha_0 + \beta_1 \cdot \frac{OC_{i,t-1}}{TA_{i,t-1}} + \beta_2 \cdot Diver + \beta_3 \cdot \frac{OC_{i,t-1}}{TA_{i,t-1}} \cdot Diver + \beta_4 \cdot \frac{1}{TA_{i,t-1}} + \beta_5 \cdot \frac{SALE_{i,t-1}}{TA_{i,t-2}} \cdot 100$$
$$+ Indus_{FF17} \cdot Yr\&Firm\ FE + \varepsilon_{i,t}$$

where *SALE* is sales and *TA* is total assets. *Diver* is a diversification measure, which represents one of the eight measures. The sample consists of all of Compustat segment data from 1976 to 2014 satisfying the criteria in Table 3.1 and all the variables are as described in Appendix 2. All dollar values are inflation-adjusted using July 2010 as the base year, and are in billions of dollars. All variables are trimmed at the top and bottom 1%. Residuals are clustered by firm and p-values are in parentheses.

| **Diversification** **Measure** | ***U4*** | ***U2*** | ***D·U4*** | ***D·U2*** | ***$H^{-1}4$*** | ***$H^{-1}2$*** | ***$D{\cdot}H^{-1}4$*** | ***$D{\cdot}H^{-1}2$*** |
|---|---|---|---|---|---|---|---|---|
| $\beta_1$ | 0.144 | 0.145 | 0.146 | 0.146 | 0.145 | 0.145 | 0.146 | 0.146 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_2$ | 0.017 | 0.022 | 0.039 | 0.040 | 0.017 | 0.020 | 0.039 | 0.039 |
| | (0.001) | (0.000) | (0.000) | (0.000) | (0.039) | (0.067) | (0.000) | (0.000) |
| $\beta_3$ | 0.010 | 0.011 | 0.008 | 0.007 | 0.013 | 0.016 | 0.009 | 0.007 |
| | (0.002) | (0.004) | (0.128) | (0.232) | (0.010) | (0.020) | (0.121) | (0.203) |
| $\beta_4$ | 0.007 | 0.007 | 0.007 | 0.007 | 0.007 | 0.007 | 0.007 | 0.007 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_5$ | 0.495 | 0.496 | 0.495 | 0.496 | 0.496 | 0.495 | 0.496 | 0.495 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\alpha_0$ | 0.837 | 0.826 | 0.838 | 0.832 | 0.842 | 0.855 | 0.833 | 0.846 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $Indus_{FF17}{\cdot}Yr\&Firm\ FE$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $N$ | 96,587 | 97,121 | 96,587 | 97,121 | 96,512 | 96,435 | 96,512 | 96,435 |
| $R^2$ | 0.860 | 0.860 | 0.860 | 0.860 | 0.860 | 0.860 | 0.860 | 0.860 |

## Table 3.8: The relation between asset turnover and *OCnet*

This table presents the results from the estimation of the following OLS regression:

$$\frac{SALE_{i,t}}{TA_{i,t-1}} \cdot 100 = \alpha_0 + \beta_1 \cdot \frac{OCnet_{i,t-1}}{TA_{i,t-1}} + \beta_2 \cdot Diver + \beta_3 \cdot \frac{OCnet_{i,t-1}}{TA_{i,t-1}} \cdot Diver + \beta_4 \cdot \frac{1}{TA_{i,t-1}} + \beta_5 \cdot \frac{SALE_{i,t-1}}{TA_{i,t-2}} \cdot 100 + Indus_{FF17} \cdot Yr\&Firm\ FE + \varepsilon_{i,t}$$

where *SALE* is sales and *TA* is total assets. *Diver* is a diversification measure, which represents one of the eight measures. The sample consists of all of Compustat segment data from 1976 to 2014 satisfying the criteria in Table 3.1 and all the variables are as described in the Appendix 2. All dollar values are inflation-adjusted using July 2010 as the base year, and are in billions of dollars. All variables are trimmed at the top and bottom 1%. Residuals are clustered by firm and p-values are in parentheses.

| **Diversification** $_{\text{Measure}}$ | ***U4*** | ***U2*** | ***D·U4*** | ***D·U2*** | ***$H^{-1}4$*** | ***$H^{-1}2$*** | ***$D{\cdot}H^{-1}4$*** | ***$D{\cdot}H^{-1}2$*** |
|---|---|---|---|---|---|---|---|---|
| $\beta_1$ | 0.168 | 0.169 | 0.170 | 0.170 | 0.169 | 0.169 | 0.170 | 0.170 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_2$ | 0.019 | 0.024 | 0.043 | 0.043 | 0.020 | 0.024 | 0.043 | 0.041 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.012) | (0.029) | (0.000) | (0.000) |
| $\beta_3$ | 0.009 | 0.011 | 0.006 | 0.005 | 0.012 | 0.015 | 0.006 | 0.006 |
| | (0.014) | (0.010) | (0.329) | (0.410) | (0.052) | (0.050) | (0.314) | (0.361) |
| $\beta_4$ | 0.007 | 0.007 | 0.007 | 0.007 | 0.007 | 0.007 | 0.007 | 0.007 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_5$ | 0.492 | 0.493 | 0.492 | 0.493 | 0.493 | 0.493 | 0.493 | 0.492 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\alpha_0$ | 0.827 | 0.817 | 0.828 | 0.823 | 0.832 | 0.846 | 0.823 | 0.837 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $Indus_{FF17}{\cdot}Yr\&Firm\ FE$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $N$ | 96,578 | 97,111 | 96,578 | 97,111 | 96,503 | 96,425 | 96,503 | 96,425 |
| $R^2$ | 0.860 | 0.860 | 0.860 | 0.860 | 0.860 | 0.860 | 0.860 | 0.860 |

## Chapter 4. The Transferability of Corporate Social Responsibility

### 4.1 Introduction

In this chapter, I shift focus from organization capital (OC) to another intangible asset – corporate social responsibility (CSR). A general indication of the extent of recent investments made in CSR is provided by a Financial Times article published on October 12, 2014, "U.S. and U.K companies in the Fortune Global 500 spend $15.2bn a year on corporate social responsibility."[38] At the firm level, firms' investments in CSR are increasing in both importance and magnitude (Deng, Kang, and Low, 2013). Many corporations report their CSR activities in their annual reports, on their websites, and publicize through the media.

Given the size and importance of these investments, a natural question is whether corporate reputation, measured using data from the MSCI ESG KLD Stats dataset (KLD), is an asset. According to Deng et al. (2013), there are two contrasting views in the literature about CSR investments. First, there is the stakeholder value maximizing view where investments in CSR have a positive effect on shareholder wealth. Under this view, CSR is an asset and it creates value for shareholders. Second, there is the shareholder expense view where the CSR benefits stakeholders at the expense of shareholders. In this case, CSR is not an asset but is instead a cost to shareholders. While there are many research studies on this topic (see Griffin and Mahon 1997, Margolis and Walsh 2003, Margolis, Elfenbein and Walsh, 2009 for literature reviews), the conclusions therein are mixed. However, Margolis et al. (2009) conclude that, overall, there is a positive but small effect on firm value from investments in CSR.

[38] https://www.ft.com/content/95239a6e-4fe0-11e4-a0a4-00144feab7de

In this study, instead of investigating directly whether CSR creates value for firms, I take a different approach and contribute to this literature by examining whether CSR is an asset that is transferable between firms at some price. To do so, I follow Servaes and Tamaro (2013) by computing a CSR index that is commonly used in this literature (see, e.g., Deng et al., 2013, Cheung, 2016; Amiraslani et al., 2017). As in Chapter 2, I exploit the accounting for M&A to perform this study. Recall that in M&A deals, the bidders record the fair market value of net identifiable tangible assets acquired, identifiable intangible assets acquired, and goodwill. Moreover, goodwill represents the future economic benefit from acquired non-identifiable intangible assets. If CSR is a non-identifiable intangible asset that bidders are paying for, then it should be done through goodwill. If, on the other hand, target CSR represents a liability – in this instance, then it should negatively affect goodwill. Therefore, under the joint hypothesis that CSR is a transferable asset (liability) that has a price (cost), I argue that the value of acquired goodwill – a non-identifiable intangible asset – captures the value of CSR. In short, I use the same methodology used in Chapter 2 and I now control for organization capital. To the best of my knowledge, this is the first paper to show evidence on whether CSR is a transferable asset or liability in the context of M&A.

I first test the hypothesis that the CSR of the target firm is a transferable asset (liability) and has a market price (cost). Since CSR is non-identifiable, it would be natural to use scaled goodwill, which captures the value of non-identifiable assets, as the dependent variable. However, the CSR index consists of components that relate to both identifiable and non-identifiable intangible assets. Therefore, the dependent variable employed should include both identifiable and non-identifiable intangible assets. Thus, I use the four different measures of scaled acquired intangibles used in Chapter 2 as dependent variables. A positive and significant coefficient on the

CSR measure implies that CSR is a transferable asset that has a price, while a negative significant coefficient implies that CSR is a liability that has a cost.

Second, I test the effect of target CSR on bidders' post-acquisition return on assets. A positive relation implies that bidders benefit from their acquired target CSR and confirms that CSR is a transferable asset. A negative relation implies that target CSR is a transferable liability since it adversely affects the bidders' return on assets following the completion of the deal, thereby indicating that CSR is value decreasing in this specific context.

Using a sample of 333 completed U.S. M&A deals from 1991 to 2013, I find a negative relation between the acquired targets' CSR index and scaled intangible assets booked by bidders in same-industry deals. This relation signifies that the higher is the target CSR measure, the lower is the value of scaled intangible assets booked by bidders when acquiring a target. Alternatively, for a given level of book value of total assets, as target CSR increases, less intangible capital is recorded, on average, in M&A transactions. This finding suggests that, in this context, target CSR is value decreasing and is in fact a liability. I additionally find a negative relation between acquired targets' CSR index and bidders' post-acquisition return on assets, further confirming that target CSR does not create value and is thus a liability. Finally, I find that acquired targets' CSR is positively related to changes in bidders' CSR from pre- to post-acquisition. This paper contributes to the CSR literature by showing empirical evidence that in the specific context of M&A, target CSR is a liability to the target firm and an expense to the bidder.[39] However, it is important to note that outside the context of M&A, CSR can be a valuable asset for firms.

[39] This evidence contradicts the finding of a positive relation between targets' socially responsible investments (SRI) and the cross-country announcement effects of M&A in Aktas, de Bodt and Cousin (2011), who conclude that targets' SRI create value for the shareholders in M&A.

The remainder of the paper is organized as follows: I summarize the related literature and develop the hypotheses in the next section. Section 4.3 describes the construction of the dataset and sample. Section 4.4 presents the results and section 4.5 concludes.

## 4.2 Research Background and Hypothesis Development

### 4.2.1 Corporate Social Responsibility

Given the magnitude of investments made in CSR, one would expect that these investments would have a positive impact on firm value. Indeed, in their theoretical model, Fatemi, Fooladi, and Tehranian (2015) find that CSR creates value. Empirically, Jiao (2010) finds a positive association between stakeholder welfare score and Tobin's Q. Tsoutsoura (2004) finds that CSR measures are positively related to return on assets, return on equity, and return on sales. In their review of the CSR literature on firm value creation, Griffin and Mahon (1997) find that the relations are positive, negative, or inconclusive, though they also note some methodological inconsistencies. Of the 127 studies reviewed by Margolis and Walsh (2003), 109 use CSR as the independent variable and 54 (7) of these find a positive (negative) relation with financial performance. A later review by Margolis, Elfenbein, and Walsh (2009) finds that the overall CSR-firm value effect is positive but small.

Other researchers have studied the relation between CSR and firm value under specific conditions. For example, Servaes and Tamayo (2013) find the positive association between CSR and firm value applies to firms with high customer awareness (as proxied by advertising intensity). Lins, Servaes and Tamayo (2017) find that, during the recent financial crisis, high CSR firms had higher stock returns when compared to low CSR firms. This result implies that investments in CSR are more beneficial when they are most needed. El Ghoul et al. (2011) study the relation between

CSR and equity financing and find that high CSR firms benefit from cheaper equity financing. Amiraslani et al. (2017) examine the relation between debt financing and CSR. They find that while high CSR firms do not benefit from debt financing under normal conditions, in difficult economic times, these firms are able to raise more debt at lower cost and of longer maturity. Goss and Roberts (2011) apply principal component analysis to CSR data and find that bank loans are more expensive for firms with more negative CSR.

Some studies more related to that in this chapter have linked CSR to M&A. For instance, Deng et al. (2013) study whether CSR creates value for bidders in M&A deals and find that high CSR bidders have higher announcement returns, realize positive long-term stock returns, and have larger increases in post-acquisition long-term operating performance, among others. Thus, in their study, high CSR bidders make better acquisitions than low CSR bidders. These findings support the view that CSR has a positive effect on shareholder wealth. Aktas et al. (2011) find that socially responsible investing (SRI) by target firms is positively associated with the cumulative abnormal return around acquisition announcement. Using CSR as a proxy for cultural similarity, Bereskin et al. (2018) find that firms with similar CSR scores exhibit superior performance following merger completion.

**4.2.2 Hypothesis Development and Variable Definition**

In order to investigate whether CSR is a transferable asset (liability) that has a price (cost) and that bidders acquire CSR in an M&A, I compute a CSR index, following Servaes and Tamaro (2013), using the CSR rating data from the MSCI ESG KLD Stats dataset (KLD). The KLD dataset contains yearly CSR ratings of large public firms and has been used by Jiao (2010), Goss and Roberts (2011), Deng et al. (2013), Servaes and Tamayo (2013), Cheung (2016), Amiraslani et al. (2017), Lins et al. (2017) and Prakash et al. (2017), among others. KLD evaluates companies on

13 categories, seven of which are related to social performance. Each category is associated with strength (positive) and concern (negative) indicators. Following Servaes and Tamayo (2013) and Amiraslani et al. (2017), I consider the following five categories: community, diversity, employment, environment, and human rights. I do not consider the corporate governance and product categories because these are not considered as being related to CSR. For instance, Servaes and Tamayo (2013) argue that the product category focuses on product quality and thus including this category in the CSR measure results in firms of high product quality being considered as high CSR firms. They also reason that corporate governance is a tool for shareholders to reward and control managers while CSR deals with stakeholders and social objectives other than shareholders.

To create the CSR index, for each of the five categories, I sum the number of strengths (concerns) for each firm year. Then, for each of the five categories, I divide the aggregate number of strengths (concerns) by the maximum possible number of strengths (concerns) in that year. Doing so provides a scaled strengths (concerns) number for each of the five categories for each firm year. Next, for each category, I subtract the scaled concerns number from the scaled strengths number, resulting in five indices, each ranging from -1 to +1, for each firm year. Finally, I aggregate the five indices for each firm year to obtain the *CSR index*. The *CSR index* ranges from -5 to +5. Similar measures are used by Deng et al. (2013), Amiraslani et al. (2017), Cheung (2016), and Lins et al. (2017), among others.

Since this *CSR index* consists of components that relate to both identifiable and non-identifiable intangible assets, the measure of acquired intangible assets employed should include identifiable intangible assets in addition to goodwill (*GDWL*). I therefore use the following four acquired intangibles measures: *AcqIntan1, AcqIntan2, AcqIntan3,* and *GDWL* as described in Chapter 2 and Appendix 2. Since the methodology and majority of variables used in this chapter are identical to those used earlier in Chapter 2, to avoid undue repetition, I do not again discuss the full details here.

My first hypothesis is as follows:

*H1: CSR is an asset (liability) that has a price (cost).*

I use the following deal-level regression to test the above hypothesis:

$$\frac{Y_{B,T,t}}{TA_{T,t-1}} = \alpha_0 + \beta_1 CSR\ index_{T,t-1} + \beta_2 CSR\ index_{B,t-1} + \beta_3 \frac{OC_{T,t-1}}{TA_{T,t-1}} + \beta_4 CASH + \beta_5 CAR_B + \beta_6 PREMIUM + Yr\ FE + \varepsilon_{B,T,t} \quad (4.1)$$

where $Y$ is *AcqIntan1, AcqIntan2, AcqIntan3,* or *GDWL*. The subscript $B$ is for the bidder, $T$ is for the target, and time $t$ is the fiscal year during which the transaction was completed. The dependent variable is *Scaled AcqIntan1, Scaled AcqIntan2, Scaled AcqIntan3, or Scaled GDWL* and the variable of interest is $CSR\ index_{T,t-1}$. *Yr FE* are year fixed effects. *CSR Index* is as described above and all other variables are as described earlier in Chapter 2 and in Appendix 2. In the regression analysis, standard errors are clustered by industry.[40] If target CSR is an asset (liability), I expect the coefficient estimate of the variable of interest, $CSR\ index_{T,t-1}$, to be positive (negative) and capture the price (cost) associated with a change in the target *CSR index* by 1 unit holding target total assets constant.

My second hypothesis addresses an alternative approach to investigating whether CSR is transferable by examining the relation between target CSR and bidders' future ROA. My second hypothesis is thus:

*H2: There is a positive (negative) relation between acquired targets' CSR and bidders' future operating returns if target CSR is a transferable asset (liability).*

[40] Since *CSR* has a strong industry effect, I follow Petersen (2009) and cluster standard errors at the industry level.

I use regression analysis with ROA as the dependent variable and acquired target CSR as the variable of interest to study this relation as follows:

$$\frac{OIBDP_{B,t+1}}{TA_{B,t}} \cdot 100 = \alpha_0 + \beta_1 CSR\ index_{T,t-1} + \beta_2 CSR\ index_{B,t} + \beta_3 \frac{OC_{T,t-1}}{TA_{B,t}} + \beta_4 \frac{1}{TA_{B,t}} + \beta_5 \frac{OIBDP_{B,t}}{TA_{B,t-1}+TA_{T,t-1}} \cdot 100 + Yr\ FE + \varepsilon_{B,t+1} \tag{4.2}$$

where *OIBDP* is the operating income before depreciation, *CSR Index* is the CSR measure as described above and all other variables are as described earlier in Chapter 2 and in Appendix 2. The dependent variable is bidders' *ROA* and the variable of interest is the target CSR, $CSR\ Index_{T,t-1}$.[41] Note that *OIBDP* at time *t* is reported by the bidder but includes operating income for both target and bidder. To address this issue, I scale this operating income using the total assets of both bidder and target firms at time *t-1*.

If acquired target CSR is a transferable asset (liability), I expect the coefficient estimate of $CSR\ index_{T,t-1}$ to be positive (negative), implying that acquired target CSR is positively (negatively) associated with post-acquisition operating income. Additionally of note, $\beta_1$ in Eqs. (4.1) and (4.2) are independent of each other and thus they need not be similar. For instance, it is possible that bidders do pay for CSR in M&A deals, meaning CSR has a price and $\beta_1$ is positive in Eq. (4.1), but this CSR is not transferable and $\beta_1$ is not significant in Eq. (4.2).

Lastly, I study the impact of target CSR on bidder CSR in both the acquisition completion year and the subsequent year. My third hypothesis is:

*H3: There is a positive relation between acquired targets' CSR and bidders' future CSR if the former is added to the latter at the completion of the acquisition.*

[41] I drop observations where *ROA* and *lagged_ROA* are not within 100%.

I use regression analysis with the change in bidders' CSR as the dependent variable and acquired targets' CSR as the variable of interest to study this relation as follows:

$$CSR\ index_{B,t} - CSR\ index_{B,t-1} = \alpha_0 + \beta_1 CSR\ index_{T,t-1} + \beta_2 TA_{T,t-1} + \beta_3 TA_{B,t-1} + Yr\ FE + \varepsilon_{B,T,t} \quad (4.3)$$

$$CSR\ index_{B,t+1} - CSR\ index_{B,t-1} = \alpha_0 + \beta_1 CSR\ index_{T,t-1} + \beta_2 TA_{T,t-1} + \beta_3 TA_{B,t-1} + Yr\ FE + \varepsilon_{B,T,t} \quad (4.4)$$

where *CSR index* is the CSR measure as described above and all other variables are as described earlier and in Appendix 2. I expect the coefficient estimate of $CSR\ index_{T,t-1}$ to be positive, implying that acquired targets' CSR is added to bidders' CSR.

**4.3 Data and Sample Description**

The M&A data used in this chapter is obtained from the Thomson Reuters Securities Data Company (SDC), the accounting data is from Compustat, and stock price data is from the Center for Research in Security Prices (CRSP) database. In the first part of this study, I use deal-level goodwill data, a subset of that used in Chapter 2. I start with a sample of 999 M&A transactions with hand-collected goodwill from 1990 to 2013. The CSR measure is computed using the KLD dataset, and this dataset begins coverage in 1991. From the M&A sample, I am able to identify with certainty target CSR measures for only 333 observations.

In the second part of this chapter, I investigate the relation between the target CSR index and bidders' post-acquisition profitability, ROA. As mentioned in the previous chapter, ROA is measured at the bidder level and, unlike goodwill, cannot be disaggregated to transaction level. Aggregating acquired targets' CSR is problematic when the bidder makes acquisitions of private targets and would thus lead to an error in independent variable problem and violate the zero-conditional mean assumption of OLS, resulting in a biased and inconsistent OLS estimator. I address this issue by using deals where the bidder made only one acquisition in a given fiscal year and the target is a public firm. Doing so results in a sample of 131 observations. To ensure that the ROA of the bidders are not contaminated by other acquisitions, I drop observations where the bidder made any acquisition(s) in the fiscal year following the completion of the deal in question. This removal of confounding events leads to a sample of size of 94 observations in year *t+1*. Table 4.1 provides a summary of the construction of the sample.

## 4.4 Results

### 4.4.1 Summary Statistics

In Panel A1 of Table 4.2, I present the summary statistics of the main variable of interest, the unscaled versions of the booked intangible capital, which are the main dependent variables, along with some reference variables. The summary statistics of the unscaled and reference variables gives the reader a better view of the meaning of the results and provide some statistics about the recorded dollar amount of intangible capital in M&A deals. I present the statistics for the Full sample first, followed by the Cross- and Same-Industry samples, respectively. The Same- (Cross-) Industry sample consists of observations where the bidder and target (do not) share the same two-digit SIC codes.

The targets' *CSR index* (hereafter *CSR*) has a mean (median) of -0.152 (-0.125) while the bidders' *CSR* has a mean (median) of 0.073 (0.000).[42] On average, targets' *CSR* is poor as the negative sign indicates that the concern factors outweigh the strength factors. As well, targets'

[42] The *CSR* can take a minimum of value of -5 and a maximum of +5. However, $CSR_T$ varies between -0.962 and +1, and $CSR_B$ varies between -0.983 and +2.119 in my sample.

*CSR* is significantly lower than bidders' *CSR*. I can conclude that, in this sample, the bidders are more socially responsible than the target firms, on average. Both target and bidder *CSR* indices in this sample are larger in magnitude than those in Deng et al. (2013) and Lins et al. (2017).

In the Full sample, *AcqIntan1*, *AcqIntan2*, *AcqIntan3*, and *GDWL* have means (medians) of \$2.68 (\$1.17), \$2.33 (\$0.97), \$1.76 (\$0.79), and \$1.71 (\$0.77) billion, respectively. These statistics are comparable to those in the two subsamples, and show that, on average, a sizeable dollar amount is being recorded as intangible assets acquired in an M&A deal.[43] Additionally, these statistics are larger in magnitude than those in Panel A1 of Table 2.2 because the current sample uses CSR data that are biased toward larger public U.S. firms. This is confirmed by the average market value of equity (*ME*) and book value of total assets (*TA*) of the targets and bidders, measured at the most recent pre-acquisition fiscal year-end. As expected, the bidders are larger firms than the targets, on average. Moreover, bidders in the Cross-Industry sample are larger than those in the Same-Industry sample.

The summary statistics of the above intangible asset variables scaled by targets' total assets measured at the last fiscal year end prior to the completion of the acquisition are shown in Panel A2. The mean (median) of *Scaled AcqIntan1* is 2.20 (1.51) in the Full sample, indicating that the average amount attributed to intangible assets in a transaction is more than double that of the targets' *TA*. Similarly, the means (medians) of *Scaled AcqIntan2* and *Scaled AcqIntan3* are 1.71 (1.28) and 1.31 (0.91), respectively. The mean (median) of *Scaled GDWL* is 1.29 (0.91) in the Full sample. Thus, the average amount of goodwill recorded in a transaction in this sample is about 129% of the *TA* of the target. Similar statistics are observed in the two subsamples, with the

[43] Note that in 191 observations, the bidder recorded in-process R&D and patents (*AcqIntan1 – AcqIntan2*) with a combined mean of \$0.6 billion. In 263 observations, the bidder recorded advertising-related intangible assets (*AcqIntan2 - AcqIntan3*) with a mean of \$0.6 billion. In 32 observations, the bidder recorded workforce and non-compete agreements (*AcqIntan3 - GDWL*) with a combined mean of \$0.3 billion.

exception of *Scaled AcqIntan2* where the mean is significantly higher in the Cross-Industry than in the Same-Industry sample.

In terms of control variables, the mean (median) of *Scaled OC* is 1.39 (1.11) and about 50% of the deals are financed solely with cash across all samples. Similar statistics are observed in the two subsamples. The mean of $CAR_{B,t}$ is -1.49% for the Full, -2.82% for the Cross-Industry and -0.82% for Same-Industry samples. The average *PREMIUM* that the bidder paid in a transaction in this sample is 42% (41%) in the Full (Same-Industry) sample. These statistics are consistent with Betton et al. (2008).

Recall that in the second part of this chapter, I study the relation between post-acquisition return on assets (*ROA*) and acquired target *CSR*. The mean (median) of post-acquisition *ROA* is 10% (11%) and 12.24% (11.09%) in the Full and Same-Industry samples, respectively. The mean (median) of acquired target *CSR* is -0.175 (-0.138) and bidders' *CSR* is -0.065 (-0.092) in the Full sample. Similar statistics are observed in the Same-Industry sample. The mean (median) of the control variable acquired targets' OC scaled by bidders' total assets in the acquisition completion year is about 0.38 (0.18) in Full and Same-Industry samples.[44]

Lastly, I study the relation between acquired targets' CSR and changes in bidders' *CSR* in the year of and that subsequent to the completion of acquisitions. The mean (median) of the change in bidders *CSR* from the year before to the acquisition completion year, $\Delta CSR_{B,t}$, is 0.01 (0.00) in the Full sample and -0.028 (0.00) in the Same-Industry sample. The mean (median) of the change in bidders' *CSR* from the year before to the year after acquisition completion, $\Delta CSR_{B,t+1}$, is 0.08 (0.00) and 0.03 (0.00) in the Full and Same-Industry samples, respectively.

[44] Since the Cross-Industry sample in this section has too few observations for meaningful inference, I present the corresponding statistics merely for completeness.

Panel B1 of Table 4.2 presents the correlation matrix for the variables used in the first part of this chapter. As expected, the different measures of scaled intangibles have positive and significant correlation coefficients. I find no significant correlation between the different measures of scaled intangible assets and target *CSR*. These correlation coefficients are negative in the Same-Industry sample and mostly positive in the Full sample. All the different measures of acquired scaled intangible assets have positive and significant correlation with the bidders' *CSR*. The correlation coefficients of the control variables are similar to those in Panels B1 and B2 of Table 2.2.

In Panel B2, the correlation between acquired targets' *CSR* and post-acquisition *ROA* is insignificant. Nevertheless, the post-acquisition *ROA* is positively correlated with bidders' *CSR*, a control variable. In Panel B3, acquired targets' *CSR*, is positively correlated with $\Delta CSR_{B,t}$ in the Full sample. From the different correlation matrices, I find that acquired targets' *CSR* has a positive and significant relation with changes in post-acquisition bidders' *CSR*.

**4.4.2 The Price (Cost) of CSR**

I present the results of Eq. (4.1) in Table 4.3, starting with the regression of *Scaled AcqIntan1* on $CSR_T$ on a deal-level basis in the first three columns and end with *Scaled GDWL* as the dependent variable in the last three columns. I start with the aggregate of all acquired intangible assets booked in an M&A transaction, then remove the identifiable intangible assets, and then use the non-identifiable intangible assets, *GDWL*.

First, I find that the coefficient estimates of *CSR index* are negative in all models and all samples, and significant in the Same-Industry sample.[45] The negative coefficient estimate of $CSR_T$ implies that the higher is the targets' *CSR*, the lower is the amount of scaled intangible assets

[45] Note that in the last three models, the difference in the coefficient estimates of *CSR index* between the Cross- and Same-Industry sample are insignificant.

booked by bidders when acquiring the targets. Using *Scaled AcqIntan1* as the dependent variable, an increase in target *CSR* by 1-standard-deviation is associated with a 0.252 decrease in *Scaled AcqIntan1*, on average, in the Same-Industry sample.[46] Since the mean of *Scaled AcqIntan1* is 2, this implies a decrease of 1/8 in *Scaled AcqIntan1* at the mean. Alternatively, for a given level of book value of total assets, as target *CSR* increases, less intangible capital is recorded, on average, in M&A transactions. Using the first model, holding target total assets constant, an increase in target CSR index by 1 unit is associated with a decrease of $708 million of acquired intangible assets, on average, in the Same-Industry sample.

In the next model, a 1-standard-deviation increase in target *CSR* is associated with a decrease of 0.116 in *Scaled AcqIntan2*, on average, in the Same-Industry sample. In the last two models, a 1-standard-deviation increase in target *CSR* is associated with a decrease of 0.103 in either dependent variable, on average, in the Same-Industry sample. Since both of these variables have the same mean, this implies a decrease of 0.09 at their respective mean. Alternatively, holding target total assets constant, an increase in target CSR index by 1 unit is associated with a decrease of $290 million of booked goodwill, on average, in the Same-Industry sample. These results imply that target CSR is a liability to the target firms in this M&A context because of the negative relation between recorded intangible assets and target *CSR*. These results are consistent with the observations from the correlation matrix.

Second, the coefficient estimates of $CSR\ index_{B,t}$ are positive and significant in two out of three samples when using *Scaled AcqIntan1* as dependent variable. These results imply that the higher is the bidders' *CSR*, the more scaled intangible assets they record in an acquisition. As expected, the coefficient estimate of *Scaled OC* is positive in all samples and significant in the Full

[46] The standard deviation of target *CSR* is 0.356.

and Same-Industry samples in all models. The coefficient estimates of the control variables are similar to those in Table 2.3 of Chapter 2. The coefficient estimate of *CASH* is positive in all samples but not always significant. The coefficient estimate of $CAR_B$, is negative in all samples and significant mostly in the Full and Same-Industry samples. These results imply that there is a negative relation between bidder's stock price reaction and the amount of scaled intangible assets booked in a transaction. The coefficient estimate of *PREMIUM*, $\beta_5$, is positive and significant in all samples. The negative coefficient of $CAR_B$ and the positive coefficient of *PREMIUM* can be interpreted as a proxy for managerial hubris, a component of goodwill (Roll, 1986).

The magnitude of the coefficient estimates of $CSR_T$ in the different models suggests that acquired targets' *CSR* is related to the identifiable as well as the unidentifiable intangible assets. From this table, I can make two conclusions: first, acquired targets' CSR reduces the amount of intangible assets recorded in M&A deals, suggesting that target CSR is a liability. Note that while target CSR can be a valuable asset to the target, in this specific context, it is a liability from the bidder's perspective. Second, there is the puzzling result that bidders' CSR is positively associated with the amount of intangible assets that they book in M&A deals.

It should be noted that the dependent variables in Eq. (4.1) are censored from below since recorded intangible assets do not take negative values in this sample. As a result, the Tobit model is more appropriate than the traditional OLS regression. In untabulated results, I find that the Tobit model produces results that are quite comparable to those using the OLS regressions and, thus, for ease of exposition, I present only the output from the OLS regressions.[47,48]

[47] The results of the Tobit model are available upon request.
[48] Due to the small sample size, these models do not include industry fixed effects. When using industry fixed effects, the p-values increase to about 0.15 in the Same-Industry sample but the sign of the coefficient of the variable of interest does not change and its magnitude is comparable to those presented. Note that the presence of fixed effects potentially removes significant valuable variation in the data (see Gormley and Matsa, 2014).

In the next section, I analyze the relation between the bidders' post-acquisition ROA and acquired targets' CSR using deals where the bidders' sole acquisition in a fiscal year is a public target. Before doing so, however, I verify whether the results just described hold similarly for bidders who made a single public acquisition in a fiscal year. Ex ante, there is no reason to expect the results to be different for this subsample. I replicate Tables 4.3 using this subsample and show the results in Tables 4.4.[49]

In Table 4.4, I find that the coefficient estimates of $CSR_T$ are negative and significant in all models using the Same-Industry sample, except when using *Scaled AcqIntan1* as the dependent variable. Where significant, the coefficient estimates of $CSR_T$ are also of the same magnitude, indicating that an increase in target CSR index by 1-standard-deviation is associated with a decrease of 0.235, on average, in *Scaled AcqIntan2, Scaled AcqIntan3, or Scaled GDWL* in the Same-Industry sample.[50] Alternatively, for a given level of book value of total assets, an increase in target CSR by 1 unit is associated with an average decrease of $656 million in booked goodwill.

The coefficient estimate of $\beta_2$ is still positive and significant. The coefficient estimate of *Scaled OC* is positive and significant the Sample-Industry sample. The coefficient estimate of *CASH* and *PREMIUM* are insignificant. The coefficient estimate of $CAR_B$ is still negative, and insignificant in the Same-Industry sample in the last two models. The takeaway from this table is that in Same-Industry deals, targets' CSR is negatively associated with booked intangible capital in acquisitions, thereby implying that target CSR is a liability and not creating value for the bidder.

[49] I do not report the results for the Cross-Industry sample since this sample is limited to only 25 observations.
[50] The standard deviation of target CSR is 0.361 in this subsample.

### 4.4.3 ROA and CSR

I present the results of Eq. (4.2) in Table 4.5. In the first column, I present the results for the Full sample and the Same-Industry sample in the second column. None of the CSR variables has significant coefficient estimates in the Full sample. In the Same-Industry sample, the coefficient estimate of acquired targets' *CSR* is negative and significant, implying that acquired target CSR is negatively associated with post-acquisition ROA. A 1-standard-deviation increase in acquired target CSR is associated with a decrease of 1.16 percentage points in post-acquisition *ROA*. Since the mean of post-acquisition *ROA* is 12.24%, the impact of 1-standard deviation increase in acquired targets CSR leads to an approximate 9.5% reduction in ROA. I also find that the coefficient estimates of bidders' CSR are positive but not significant.

The results from this table are consistent with the results in Tables 4.3 and 4.4 since these results further imply that acquired targets' CSR is a liability in the context of M&A as it is negatively associated with both booked intangible assets in M&A deals and with post-acquisition ROA.[51] Targets' CSR does not appear to create value for the bidders in this specific setting.

### 4.4.4 Changes in Post-Acquisition Bidders' CSR

I present the results of Eqs. (4.3) and (4.4) in Table 4.6. I find that the coefficient estimates of $CSR_T$ are positive and significant in all specifications except in the Full sample for $\Delta CSR_{B,t+1}$. These results imply that acquired target CSR is positively associated with the change in bidders' CSR index pre- to post-acquisition completion. For instance, a 1-standard deviation increase in acquired target CSR is associated with an increase of 0.09 and 0.10, on average, in $\Delta CSR_{B,t}$ and $\Delta CSR_{B,t+1}$, respectively, in the Same-Industry sample. These results are consistent with the

[51] Similar to the approach in Chapter 2, I also estimate the regressions of both sales growth and asset turnover as the dependent variable and acquired targets' CSR as the variable of interest. I find a negative relation between the target CSR and the two other variables. However, these coefficient estimates are statistically insignificant. Thus, I do not report them.

observations made in the correlation matrix in Panel B3 of Table 4.2. The results in this subsection are not surprising, since post-acquisition, bidders would be associated not only with their own CSR but also that of their target firms.

### 4.5 Concluding Remarks

In this chapter, I explore whether the CSR of target firms is transferrable in mergers and acquisitions. Overall, I find that acquired targets' CSR has a negative association with both the booked scaled intangible capital in M&A deals and bidders' post-acquisition ROA. The former finding is consistent with target CSR lowering net acquired intangible assets, and the latter indicates that target CSR is not creating value for bidders. Taken together, these results suggest that acquired targets' CSR is a liability, in this specific instance, and provide some evidence in contrast to the findings of studies in the literature that document CSR as a valuable asset. I also find the puzzling positive association between bidders' CSR and booked scaled intangible capital. Furthermore, I find acquired targets' CSR is positively related to bidders' changes in CSR following the completion of the acquisitions.

**Table 4.1: Sample construction**

| Selection Criteria | No. of transactions |
|---|---|
| Completed acquisitions by U.S public acquirers[52] (1990-2013) | 87,297 |
| Matched acquirers' *PERMNO* and *GVKEY* | 63,878 |
| Public targets | 6,814 |
| U.S targets | 5,571 |
| Exclude transactions in: | |
| Financial sector (SIC 6000-6999) | 3,331 |
| Public utilities (SIC 4900-4999) | |
| SDC transaction value greater than $1m (July 2010 dollars) | 3,093 |
| Acquirers' ownership of targets: | |
| Prior to the announcement date: less than 50% | 2,409 |
| After the completion: 100% | |
| Matched targets' *PERMNO* and *GVKEY* | 1,986 |
| Transaction value greater than 1% of bidder's market value of equity 11 days prior to announcement date | 1,804 |
| Target's delisting code in CRSP is in the 200s | 1,768 |
| Transactions with hand-collected goodwill | 999 |
| Observations with target CSR Index | 333 |

| Subsample for productivity test | |
|---|---|
| Single transaction in a fiscal year | 131 |
| Excluding confounding events in year *t+1* | 94 |

[52] Excluding repurchases and self-tenders.

**Table 4.2: Summary statistics and correlation coefficients**

The sample consists of 333 completed M&A deals from 1990 to 2013 satisfying the criteria in Table 4.1 and all the variables are as described in Appendix 2. Same- (Cross-) Industry are observations where the bidder and the target (do not) share the same two-digit SIC codes. All dollar values are inflation-adjusted using July 2010 as the base year, and are in billions of dollars. All the variables are trimmed at the top and bottom 1%. Panel A1 shows the summary statistics of some reference and unscaled variables. Panel A2 shows the summary statistics of the other variables used in this study. Panel B1 to B3 show the pairwise correlation of the variables. Superscripts x, y, and z represent the statistical significance at the 1, 5, and 10% levels, respectively. Superscripts a, b, and c represent the statistical significance at the 1, 5, and 10% levels, respectively, between the Cross- and Same-Industry.

*Panel A1: Summary Statistics of Reference & Unscaled Variables*

| | **Full** | | | **Cross-Industry** | | | **Same-Industry** | | |
|---|---|---|---|---|---|---|---|---|---|
| Variables | N | Mean | Median | N | Mean | Median | N | Mean | Median |
| $CSR_{T-1}$ | 329 | -0.152 | -0.125 | 113 | -0.144 | -0.075 | 216 | -0.156 | -0.155 |
| $CSR_{B-1}$ | 305 | 0.073 | 0.000 | 101 | 0.173 | 0.107 | 204 | $0.023^{b}$ | 0.000 |
| *AcqIntan1* | 327 | 2.681 | 1.174 | 113 | 2.289 | 1.398 | 214 | 2.888 | 0.989 |
| *AcqIntan2* | 326 | 2.333 | 0.969 | 112 | 2.007 | 1.200 | 214 | 2.505 | 0.884 |
| *AcqIntan3* | 326 | 1.757 | 0.790 | 112 | 1.570 | 0.979 | 214 | 1.855 | 0.728 |
| *GDWL* | 330 | 1.710 | 0.769 | 113 | 1.482 | 0.978 | 217 | 1.828 | 0.670 |
| $ME_{T,t-1}$ | 321 | 2.661 | 0.932 | 108 | 2.780 | 0.944 | 213 | 2.600 | 0.906 |
| $ME_{B,t-1}$ | 320 | 23.436 | 5.339 | 106 | 32.384 | 12.190 | 214 | $19.003^{a}$ | 4.141 |
| $TA_{T,t-1}$ | 321 | 2.385 | 0.706 | 108 | 2.628 | 0.681 | 213 | 2.262 | 0.745 |
| $TA_{B,t-1}$ | 319 | 17.768 | 4.772 | 105 | 22.715 | 10.430 | 214 | $15.340^{b}$ | 3.590 |

*Panel A2: Summary Statistics of Variables used in this chapter*

| | Full | | | Cross-Industry | | | Same-Industry | | |
|---|---|---|---|---|---|---|---|---|---|
| **Variables** | N | Mean | Median | N | Mean | Median | N | Mean | Median |
| ***Dependent Variable related to the acquisition of CSR*** | | | | | | | | | |
| *Scaled AcqIntan1* | 322 | 2.204 | 1.507 | 107 | 2.414 | 1.663 | 215 | 2.099 | 1.336 |
| *Scaled AcqIntan2* | 321 | 1.713 | 1.277 | 107 | 1.932 | 1.553 | 214 | $1.603^{b}$ | 1.101 |
| *Scaled AcqIntan3* | 321 | 1.307 | 0.912 | 106 | 1.472 | 1.150 | 215 | 1.225 | 0.837 |
| *Scaled GDWL* | 325 | 1.285 | 0.903 | 108 | 1.434 | 1.094 | 217 | 1.210 | 0.836 |
| **Control Variables** | | | | | | | | | |
| *Scaled OC* | 302 | 1.391 | 1.110 | 88 | 1.420 | 1.045 | 214 | 1.380 | 1.125 |
| *CASH* | 333 | 0.465 | 0.000 | 114 | 0.482 | 0.000 | 219 | 0.457 | 0.000 |
| $CAR_B$ | 323 | $-1.491^{x}$ | -0.990 | 109 | $-2.816^{x}$ | -1.899 | 214 | $-0.816^{zb}$ | -0.594 |
| *PREMIUM* | 327 | $42.278^{x}$ | 37.751 | 111 | $43.933^{x}$ | 35.240 | 216 | $41.427^{x}$ | 38.379 |
| ***Variable related to the productivity of acquired of CSR*** | | | | | | | | | |
| $ROA_{t+1}$ | 94 | $10.302^{x}$ | 10.919 | 24 | 4.650 | 10.486 | 70 | $12.239^{xb}$ | 11.089 |
| $CSR_{T,t-1}$ | 94 | -0.175 | -0.138 | 24 | -0.122 | -0.104 | 70 | -0.193 | -0.155 |
| $CSR_{B,t}$ | 88 | -0.065 | -0.092 | 21 | 0.157 | 0.098 | 67 | -0.134 | -0.2 |
| $OC_{T,t-1}/TA_{B,t}$ | 94 | 0.381 | 0.181 | 24 | 0.409 | 0.164 | 70 | 0.372 | 0.186 |
| ***Variable related to Bidders post-acquisition CSR*** | | | | | | | | | |
| $\Delta\ CSR_{B,\ t}$ | 87 | 0.010 | 0.000 | 21 | 0.130 | 0.000 | 66 | -0.028 | 0.000 |
| $\Delta\ CSR_{B,\ t+1}$ | 86 | 0.078 | 0.000 | 21 | 0.242 | 0.042 | 65 | 0.025 | 0.000 |

*Panel B1: Pairwise Pearson Correlation Coefficients for variables related to the acquisition of CSR*

| | | | SAME-INDUSTRY | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| | 1 | *Scaled AcqIntan1* | 1 | $0.851^{x}$ | $0.851^{x}$ | $0.852^{x}$ | -0.052 | $0.236^{x}$ | $0.181^{x}$ | $0.189^{x}$ | -0.102 | $0.247^{x}$ |
| | 2 | *Scaled AcqIntan2* | $0.830^{x}$ | 1 | $0.953^{x}$ | $0.954^{x}$ | -0.033 | $0.208^{x}$ | $0.196^{x}$ | $0.181^{x}$ | -0.102 | $0.204^{x}$ |
| F | 3 | *Scaled AcqIntan3* | $0.836^{x}$ | $0.952^{x}$ | 1 | $0.999^{x}$ | -0.041 | $0.180^{y}$ | $0.136^{y}$ | $0.139^{y}$ | -0.095 | $0.209^{x}$ |
| U | 4 | *Scaled GDWL* | $0.836^{x}$ | $0.952^{x}$ | $0.999^{x}$ | 1 | -0.042 | $0.189^{x}$ | $0.141^{y}$ | $0.144^{y}$ | -0.090 | $0.210^{x}$ |
| L | 5 | $CSR_T$ | -0.012 | 0.017 | 0.012 | 0.008 | 1 | $0.205^{x}$ | 0.080 | -0.046 | -0.108 | -0.112 |
| L | 6 | $CSR_B$ | $0.239^{x}$ | $0.207^{x}$ | $0.188^{x}$ | $0.195^{x}$ | $0.230^{x}$ | 1 | 0.088 | $0.198^{x}$ | -0.025 | $0.155^{y}$ |
| | 7 | *Scaled OC* | $0.212^{x}$ | $0.223^{x}$ | $0.179^{x}$ | $0.191^{x}$ | $0.107^{z}$ | 0.087 | 1 | $0.193^{x}$ | 0.105 | 0.098 |
| | 8 | *CASH* | $0.211^{x}$ | $0.186^{x}$ | $0.162^{x}$ | $0.173^{x}$ | -0.026 | $0.264^{x}$ | $0.189^{x}$ | 1 | $0.194^{x}$ | $0.126^{y}$ |
| | 9 | $CAR_B$ | -0.040 | -0.034 | -0.047 | -0.037 | $-0.102^{z}$ | -0.026 | 0.073 | $0.229^{x}$ | 1 | 0.098 |
| | 10 | *PREMIUM* | $0.157^{x}$ | 0.089 | $0.113^{y}$ | $0.120^{y}$ | -0.062 | $0.188^{x}$ | $0.170^{x}$ | $0.132^{y}$ | 0.077 | 1 |

*Panel B2: Pairwise Pearson Correlation Coefficients for variables related to ROA*

| | | | SAME-INDUSTRY | | | |
|---|---|---|---|---|---|---|
| | | | 1 | 2 | 3 | 4 |
| *F* | 1 | *ROA* | 1 | 0.046 | $0.305^{y}$ | 0.075 |
| *U* | 2 | $CSR_{T,t-1}$ | -0.021 | 1 | 0.048 | $0.320^{x}$ |
| *L* | 3 | $CSR_{B,t}$ | $0.267^{y}$ | 0.148 | 1 | -0.086 |
| *L* | 4 | $OC_{T,t-1}/TA_{B,t}$ | -0.011 | $0.233^{y}$ | -0.033 | 1 |

*Panel B3: Pairwise Pearson Correlation Coefficients for variables related to post acquisition CSR*

| | | | SAME-INDUSTRY | | |
|---|---|---|---|---|---|
| *F* | | | 1 | 2 | 3 |
| *U* | 1 | $\Delta\ CSR_{B,\ t}$ | 1 | $0.646^{x}$ | 0.184 |
| *L* | 2 | $\Delta\ CSR_{B,\ t+1}$ | $0.595^{x}$ | 1 | 0.041 |
| *L* | 3 | $CSR_{T,t-1}$ | $0.211^{z}$ | -0.012 | 1 |

## Table 4.3: The price of acquired target CSR

This table presents the results from the estimation of the following OLS regression:

$$\frac{Y_{B,T,t}}{TA_{T,t-1}} = \alpha_0 + \beta_1 CSR\ index_{T,t-1} + \beta_2 CSR\ index_{B,t-1} + \beta_3 \frac{OC_{T,t-1}}{TA_{T,t-1}} + \beta_4 CASH + \beta_5 CAR_B + \beta_6 PREMIUM + Yr\ FE + \varepsilon_{B,T,t}$$

where *Y = AcqIntan1, AcqIntan2, AcqIntan3, GDWL*. *AcqIntan1* is transacted goodwill plus all other acquired intangible assets. *AcqIntan2* is *AcqIntan1* less both in-process R&D and patents. *AcqIntan3* is transacted goodwill plus work force and non-compete agreements. *GDWL* is the transacted goodwill. *TA* is book value of total assets. The sample consists of 333 completed M&A deals from 1990 to 2013 satisfying the criteria in Table 4.1 and all the variables are as described in Appendix 2. Same- (Cross-) Industry are observations where the bidder and the target (do not) share the same two-digit SIC codes. All dollar values are inflation-adjusted using July 2010 as the base year. All the variables are trimmed at the top and bottom 1%. Residuals are clustered by the target Fama-French 17-Industry classification and p-values are in parentheses.

| **Model** | ***Scaled AcqIntan1*** | | | ***Scaled AcqIntan2*** | | | ***Scaled AcqIntan3*** | | | ***Scaled GDWL*** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Full | Cross-Industry | Same-Industry | Full | Cross-Industry | Same-Industry | Full | Cross-Industry | Same-Industry | Full | Cross-Industry | Same-Industry |
| $\beta_1$ | -0.513 | -0.075 | -0.708 | -0.277 | -0.231 | -0.327 | -0.207 | -0.127 | -0.291 | -0.215 | -0.178 | -0.290 |
| | (0.225) | (0.885) | (0.088) | (0.100) | (0.686) | (0.064) | (0.111) | (0.711) | (0.045) | (0.094) | (0.636) | (0.046) |
| $\beta_2$ | 0.750 | 0.760 | 0.712 | 0.542 | 0.889 | 0.358 | 0.403 | 0.617 | 0.259 | 0.408 | 0.633 | 0.265 |
| | (0.036) | (0.000) | (0.123) | (0.000) | (0.000) | (0.016) | (0.000) | (0.000) | (0.027) | (0.001) | (0.000) | (0.031) |
| $\beta_3$ | 0.288 | 0.256 | 0.321 | 0.206 | 0.223 | 0.216 | 0.130 | 0.123 | 0.145 | 0.132 | 0.139 | 0.142 |
| | (0.012) | (0.184) | (0.031) | (0.042) | (0.231) | (0.027) | (0.094) | (0.453) | (0.067) | (0.096) | (0.415) | (0.071) |
| $\beta_4$ | 0.453 | 0.427 | 0.633 | 0.324 | 0.420 | 0.366 | 0.210 | 0.377 | 0.210 | 0.216 | 0.405 | 0.210 |
| | (0.002) | (0.230) | (0.000) | (0.078) | (0.191) | (0.056) | (0.137) | (0.115) | (0.206) | (0.145) | (0.073) | (0.209) |
| $\beta_5$ | -0.054 | -0.016 | -0.080 | -0.031 | -0.004 | -0.046 | -0.024 | -0.002 | -0.036 | -0.023 | -0.002 | -0.034 |
| | (0.027) | (0.522) | (0.003) | (0.136) | (0.859) | (0.008) | (0.071) | (0.885) | (0.002) | (0.100) | (0.931) | (0.006) |
| $\beta_6$ | 0.016 | 0.010 | 0.020 | 0.008 | 0.012 | 0.010 | 0.008 | 0.010 | 0.010 | 0.008 | 0.010 | 0.009 |
| | (0.018) | (0.014) | (0.058) | (0.080) | (0.013) | (0.097) | (0.031) | (0.010) | (0.059) | (0.035) | (0.011) | (0.065) |
| $\alpha_0$ | -1.040 | -0.253 | 0.493 | -0.200 | 1.228 | 0.868 | -0.131 | -0.255 | 0.880 | -0.124 | -0.340 | 0.880 |
| | (0.210) | (0.698) | (0.469) | (0.559) | (0.082) | (0.022) | (0.630) | (0.669) | (0.008) | (0.649) | (0.605) | (0.008) |
| *Yr FE* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *N* | 260 | 73 | 187 | 260 | 72 | 187 | 260 | 73 | 187 | 262 | 73 | 189 |
| $R^2$ | 0.190 | 0.264 | 0.251 | 0.180 | 0.289 | 0.247 | 0.178 | 0.288 | 0.226 | 0.182 | 0.289 | 0.229 |

**Table 4.4: The price of acquired target CSR for firms that made single transaction in a fiscal year**

This table present the results from the estimation of the following OLS regression:

$$\frac{Y_{B,T,t}}{TA_{T,t-1}} = \alpha_0 + \beta_1 CSR\ index_{T,t-1} + \beta_2 CSR\ index_{B,t-1} + \beta_3 \frac{OC_{T,t-1}}{TA_{T,t-1}} + \beta_4 CASH + \beta_5 CAR_B + \beta_6 PREMIUM + Yr\ FE + \varepsilon_{B,T,t}$$

where *Y* = *AcqIntan1, AcqIntan2, AcqIntan3, GDWL*. *AcqIntan1* is transacted goodwill plus all other acquired intangible assets. *AcqIntan2* is *AcqIntan1* less both in-process R&D and patents. *AcqIntan3* is transacted goodwill plus work force and non-compete agreements. *GDWL* is the transacted goodwill. *TA* is book value of total assets. The sample consists of 131 completed M&A deals from 1990 to 2013 satisfying the criteria in Table 4.1 and all the variables are as described in Appendix 2. Same- (Cross-) Industry are observations where the bidder and the target (do not) share the same two-digit SIC codes. All dollar values are inflation-adjusted using July 2010 as the base year. All the variables are trimmed at the top and bottom 1%. Residuals are clustered by the target Fama-French 17-Industry classification and p-values are in parentheses.

| **Model** | ***Scaled AcqIntan1*** | | ***Scaled AcqIntan2*** | | ***Scaled AcqIntan3*** | | ***Scaled GDWL*** | |
|---|---|---|---|---|---|---|---|---|
| | Full | Same-Industry | Full | Same-Industry | Full | Same-Industry | Full | Same-Industry |
| $\beta_1$ | -0.488 | -1.153 | -0.185 | -0.646 | -0.189 | -0.654 | -0.189 | -0.656 |
| | (0.541) | (0.174) | (0.640) | (0.057) | (0.612) | (0.085) | (0.614) | (0.086) |
| $\beta_2$ | 1.255 | 1.276 | 0.734 | 0.700 | 0.605 | 0.589 | 0.604 | 0.589 |
| | (0.008) | (0.031) | (0.000) | (0.001) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_3$ | 0.273 | 0.522 | 0.188 | 0.388 | 0.156 | 0.327 | 0.156 | 0.327 |
| | (0.277) | (0.086) | (0.233) | (0.027) | (0.267) | (0.080) | (0.268) | (0.081) |
| $\beta_4$ | 0.270 | -0.035 | 0.308 | -0.082 | 0.155 | -0.197 | 0.155 | -0.198 |
| | (0.297) | (0.905) | (0.158) | (0.759) | (0.406) | (0.501) | (0.409) | (0.503) |
| $\beta_5$ | -0.038 | -0.075 | -0.032 | -0.061 | -0.025 | -0.050 | -0.025 | -0.050 |
| | (0.022) | (0.059) | (0.016) | (0.041) | (0.010) | (0.110) | (0.010) | (0.112) |
| $\beta_6$ | 0.000 | 0.005 | 0.003 | 0.004 | 0.004 | 0.005 | 0.004 | 0.005 |
| | (0.950) | (0.474) | (0.552) | (0.520) | (0.435) | (0.411) | (0.441) | (0.415) |
| $\alpha_0$ | 0.000 | -0.254 | -0.044 | -0.033 | 0.069 | 0.063 | 0.069 | 0.063 |
| | (0.999) | (0.732) | (0.918) | (0.941) | (0.851) | (0.881) | (0.851) | (0.882) |
| *Yr FE* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *N* | 102 | 77 | 102 | 77 | 102 | 77 | 103 | 78 |
| $R^2$ | 0.203 | 0.312 | 0.201 | 0.297 | 0.192 | 0.277 | 0.198 | 0.283 |

## Table 4.5: Target CSR and profitability in the 1st fiscal year post-acquisition

This table presents the results from the estimation of the following OLS regressions:

$$\frac{OIBDP_{B,t+1}}{TA_{B,t}} \cdot 100 = \alpha_0 + \beta_1 CSR\ index_{T,t-1} + \beta_2 CSR\ index_{B,t} + \beta_3 \frac{OC_{T,t-1}}{TA_{B,t}} + \beta_4 \frac{1}{TA_{B,t}} + \beta_5 \frac{OIBDP_{B,t}}{TA_{B,t-1} + TA_{T,t-1}} \cdot 100 + Yr\ FE + \varepsilon_{B,t+1}$$

*OIBDP* is operating income before depreciation and *TA* is total assets. The sample consists of 94 completed M&A deals from 1990 to 2013 satisfying the criteria in Table 4.1. All the variables are as described in Appendix 2. Same-Industry are observations where the bidder and the target share the same two-digit SIC codes. All dollar values are inflation-adjusted using July 2010 as the base year and are in billions of dollars. All variables are trimmed at the top and bottom 1%. Residuals are clustered by the target Fama-French 17-Industry classification and p-values are in parentheses.

| **Model** | ***ROA*$_{t+1}$** | |
|---|---|---|
| | Full | Same-Industry |
| $\beta_1$ | 1.212 | -2.765 |
| | (0.699) | (0.009) |
| $\beta_2$ | 2.019 | 2.163 |
| | (0.382) | (0.287) |
| $\beta_3$ | 1.094 | 4.462 |
| | (0.555) | (0.012) |
| $\beta_4$ | 0.147 | -1.366 |
| | (0.884) | (0.114) |
| $B_5$ | 0.406 | 0.584 |
| | (0.027) | (0.000) |
| $\alpha_0$ | 7.127 | 2.466 |
| | (0.068) | (0.051) |
| *Yr FE* | Yes | Yes |
| *N* | 86 | 65 |
| $R^2$ | 0.481 | 0.743 |

## Table 4.6: The effect of target CSR on bidders' CSR following acquisition

This table presents the results from the estimation of the following OLS regressions:

$$CSR\ index_{B,t} - CSR\ index_{B,t-1} = \alpha_0 + \beta_1 CSR\ index_{T,t-1} + \beta_2 TA_{T,t-1} + \beta_3 TA_{B,t-1} + Yr\ FE + \varepsilon_{B,T,t}$$

$$CSR\ index_{B,t+1} - CSR\ index_{B,t-1} = \alpha_0 + \beta_1 CSR\ index_{T,t-1} + \beta_2 TA_{T,t-1} + \beta_3 TA_{B,t-1} + Yr\ FE + \varepsilon_{B,T,t}$$

where $CSR_B$ is the CSR index for the bidder. The sample consists of 94 completed M&A deals from 1990 to 2013 satisfying the criteria in Table 4.1. All the variables are as described in Appendix 2. Same-Industry are observations where the bidder and the target share the same two-digit SIC codes. All dollar values are inflation-adjusted using July 2010 as the base year and are in billions of dollars. All variables are trimmed at the top and bottom 1%. Residuals are clustered by the target Fama-French 17-Industry classification and p-values are in parentheses.

| **Model** | $\Delta CSR_{B,t}$ | | $\Delta CSR_{B,t+1}$ | |
|---|---|---|---|---|
| | Full | Same-Industry | Full | Same-Industry |
| $\beta_1$ | 0.220 | 0.236 | 0.164 | 0.287 |
| | (0.003) | (0.023) | (0.199) | (0.031) |
| $\beta_2$ | 0.002 | 0.006 | -0.005 | 0.011 |
| | (0.652) | (0.065) | (0.524) | (0.077) |
| $\beta_3$ | -0.003 | -0.002 | 0.003 | -0.008 |
| | (0.130) | (0.365) | (0.560) | (0.039) |
| $\alpha_0$ | 0.091 | 0.078 | 0.046 | 0.122 |
| | (0.004) | (0.068) | (0.443) | (0.016) |
| *Yr FE* | Yes | Yes | Yes | Yes |
| *N* | 84 | 64 | 83 | 63 |
| $R^2$ | 0.379 | 0.383 | 0.310 | 0.467 |

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## Appendix 1. Econometric Appendix

In this section, I show the econometric rationale for hand-collecting goodwill from annual reports. The econometric approach is based on the *Measurement Error in an Explanatory Variable* in Chapter Nine of Wooldridge (2003). Please refer to Wooldridge (2003) for further details about measurement error in an explanatory variable.

One of the objectives of this paper is to study whether bidders pay for target OC in M&A deals. I do this by regressing the goodwill paid to targets' shareholders on acquired targets' OC (both of which are scaled by total assets) and including control variables. Goodwill, an item on the balance sheet, is available from the Compustat database. Since goodwill is reported once per year, I compute the change in goodwill from one fiscal year to the subsequent fiscal year to determine the flow of goodwill. This change in goodwill represents the aggregate goodwill, net of impairment, acquired by the bidder in that fiscal year. If I add impairment (also available on Compustat) back to the change in goodwill, I obtain the gross aggregate goodwill acquired. I use the term aggregate since bidders may make multiple acquisitions in a fiscal year. Thus, the gross aggregate change in goodwill is the sum of all acquired goodwill during that fiscal year. For each bidder, I can use the following regression, ignoring scaling and the control variables for simplicity, to perform this study:

$$\Delta GDWL_{B,t} = \alpha_0 + \beta_1 \cdot Agg\_OC_{B,t} + \varepsilon_{B,t} \tag{A1}$$

where $\Delta GDWL_{B,t}$ is the gross aggregate change in goodwill for bidder *B*, in the fiscal year *t*. Since the dependent variable is an aggregated variable, I should aggregate the OC of all targets acquired by the bidder in that particular fiscal year. Hence, $Agg\_OC_{B,t}$ is the sum of all acquired targets' OC by bidder *B* during that fiscal year *t*.

$$Agg\_OC_{B,t} = \sum_{T=1}^{n} OC_{T,t-1} \tag{A2}$$

In the above equation, $OC_{T,t-1}$ is the OC of target $T$ prior to the acquisition made by bidder $B$ in year $t$. I can assume that A1 satisfies the traditional Gauss-Markov assumptions, meaning that OLS produces unbiased and consistent estimators. $OC_{T,t-1}$ can be from a public target ($OC_{T,public}$) or a private target ($OC_{T,private}$), and $Agg\_OC_{B,t}$ can be any combination of $OC_{T,public,t-1}$ and $OC_{T,private,t-1}$. Thus, A2 can be written as:

$$Agg\_OC_{B,t} = \sum_{T\geq 0}^{n} OC_{T,public,t-1} + \sum_{T\geq 0}^{n} OC_{T,private,t-1} \tag{A3}$$

While I can compute the OC of public targets, I cannot do so for private targets since the data is not publicly available. As a result, I cannot compute $Agg\_OC_{B,t}$ because I cannot compute $OC_{T,private}$. Substituting A3 into A1 generates the following:

$$\Delta GDWL_{B,t} = \alpha_0 + \beta_1 \cdot \left[\sum_{T\geq 0}^{n} OC_{T,public,t-1} + \sum_{T\geq 0}^{n} OC_{T,private,t-1}\right] + \varepsilon_{B,t} \tag{A4}$$

A4 is equivalent to:

$$\Delta GDWL_{B,t} = \alpha_0 + \beta_1 \cdot \left[\sum_{T\geq 0}^{n} OC_{j,public,t-1}\right] + u_{B,t} \tag{A5}$$

$$\text{where } u_{B,t} = \beta_1 \cdot \left[\sum_{T\geq 0}^{n} OC_{T,private,t-1}\right] + \varepsilon_{b,t} \tag{A6}$$

If I use A5 instead of A1, there will be an error in independent variable issue whenever a bidder makes acquisitions of private targets. The error would result from using only the observed portion of the independent variable ($\sum_{T\geq 0}^{n} OC_{T,public,t-1}$) and excluding the unobserved portion of the independent variable ($\sum_{T\geq 0}^{n} OC_{T,private,t-1}$). Usually, in the case of error in independent variable, the assumption is that the expected value of the difference between the observed independent variable and the unobserved independent variable is zero. In the current situation, this difference is $\sum_{T\geq 0}^{n} OC_{T,private,t-1}$ and cannot be assumed to be zero since public bidders do acquire private targets and private targets do have OC.

Earlier, I assumed that $\varepsilon_{B,t}$ satisfies the zero-mean condition assumption of OLS. However, I cannot make the same assumption for $u_{B,t}$, since I do not know the correlation between $\sum_{T\geq 0}^{n} OC_{T,public,t-1}$ and $\sum_{T\geq 0}^{n} OC_{T,private,t-1}$. Based on the above arguments, the expected value of $u_B$ conditional on the independent variable is:

$$\mathrm{E}[u_B|\textstyle\sum_{T\geq 0}^{n} OC_{T,public,t-1}] = \mathrm{E}[(\varepsilon_B + \sum_{T\geq 0}^{n} OC_{T,private,t-1})|\sum_{T\geq 0}^{n} OC_{T,public,t-1}] \qquad \text{(A7)}$$

Since E[$\varepsilon$] = 0 and it satisfies the zero-conditional mean assumption, A7 becomes:

$$\mathrm{E}[\textstyle\sum_{T\geq 0}^{n} OC_{T,private,t-1}|\sum_{T\geq 0}^{n} OC_{T,public,t-1}] \neq 0 \qquad \text{(A8)}$$

This is a violation of the zero-conditional mean assumption, meaning the estimated $\beta_1$ from A5 is a biased estimator of $\beta_1$ from A1. Moreover, if I use A5, I can show that the estimated coefficient is not equal the true coefficient as follows:

$$\hat{\beta}_1 = \beta_1 + \beta_1 \cdot \frac{Covariance(\sum_{T\geq 0}^{n} OC_{T,public,t-1} + \sum_{T\geq 0}^{n} OC_{T,private,t-1})}{Variance(\sum_{T\geq 0}^{n} OC_{T,public,t-1})} \qquad \text{(A9)}$$

where $\hat{\beta}_1$is the estimated coefficient from A5 and $\beta_1$ is the true coefficient from A1. Therefore, using A5 leads to a biased and inconsistent OLS estimator. I can also show that the variance of $u$ is larger than the variance of $\varepsilon$.

One way of solving this issue is to use observations where the bidder made only public acquisition(s) in any particular fiscal year. Doing so eliminates the unobserved portion of the independent variable. Alternatively, I can limit the sample to observations where the bidder made only one acquisition in a fiscal year and this target is a public company, thereby enabling me to use deal-level regressions instead of bidder-level regressions. While doing so leads to a smaller sample, it also leads to a more meaningful coefficient of OC in the regression for the following reasons: (1) it preserves the variation in the data since I can use all the data points from each transaction and I do not have to aggregate OC, and (2) it allows for differentiation between within-industry and cross-industry transactions. A third approach to solve the error-in-independent variable problem is to use deal-level regressions and hand-collect the amount of goodwill paid by the bidder for each public target from the annual report. Under this scenario, the dependent variable is the goodwill paid to the target shareholders and the variable of interest is the OC of that particular target. This third approach is superior relative to the other two methods and thus is the approach employed in this study.

## Appendix 2. Variable Definitions

All dollar values are inflation-adjusted using July 2010 as the base year, and are in billions of dollars. All variables are trimmed at the top and bottom 1%. Subscript *B* is for the bidder, *T* is for the target, and time *t* is the fiscal year during which the transaction was completed. *t-1* is the fiscal year prior to the completion of the transaction, *t+1* is the fiscal year following the completion of the transaction, and *t+2* is the second fiscal year following the completion of the transaction.

| Variable | Definition | Data Source(s) |
|---|---|---|
| $AcqIntan1_{B,T,t}$ | Acquired goodwill ($GDWL_{B,T,t}$) plus all acquired intangibles assets recorded in the M&A deal such as other intangibles, in-process R&D, work force, trademark, etc. | Hand-collected from annual reports |
| $AcqIntan2_{B,T,t}$ | $AcqIntan1_{B,T,t}$ less both in-process R&D and patents. *AcqIntan2* is acquired intangible assets not related to R&D expenses. | Hand-collected from annual reports |
| $AcqIntan3_{B,T,t}$ | Acquired goodwill ($GDWL_{B,T,t}$) plus work force and non-compete agreements. *AcqIntan3* is acquired intangibles assets related to human capital. | Hand-collected from annual reports |
| $Asset\ Turnover_{B,t}$ | $SALE_{B,t}/TA_{B,t-1}$ | Compustat (*Sale, AT*) |
| $CAR_B$ | Cumulative announcement abnormal return (*CAR*) of the bidder, in percentage, for the three days around the acquisition announcement date. The market model is use to estimate the abnormal stock return. The equally-weighted CRSP market return is used to estimate alpha and beta of the market model. | CRSP and SDC |
| *CASH* | A dummy variable which takes the value of 1 for 100% cash-financed deals and 0 otherwise. | SDC |
| *CSR index* | The CSR index is made using data from the following five categories: community, diversity, employment, environment, and human rights. For each category, I aggregate the number of strengths (concerns) then I divide the aggregated number by the maximum possible number of strengths (concerns). Next, I subtract the scaled concerns number from the scaled strengths number and this results in five indices. The CSR index is the sum of each of the five indices. | KLD dataset |
| $D{\cdot}H^{-1}4$ | A dummy variable which takes the value of 0 when $H^{-1}4$ is zero and 1 otherwise (diversified). | Compustat Segment Data |
| $D{\cdot}H^{-1}2$ | A dummy variable which takes the value of 0 when $H^{-1}2$ is zero and 1 otherwise (diversified). | Compustat Segment Data |

| | | |
|---|---|---|
| *D·U4* | A dummy variable which takes the value of 1 when the number of unique four-digit SIC code segments reported is more than one (*U4>0*) and zero otherwise. | Compustat Segment Data |
| *D·U2* | A dummy variable which takes the value of 1 when the number of unique two-digit SIC code segments reported is more than one (*U2>0*) and zero otherwise. | Compustat Segment Data |
| $GDWL_{B,T,t}$ | Goodwill paid and recorded by bidder *B* to acquire target *T* for the deal completed in year *t* as per the bidder's annual report. | Hand-collected from annual reports |
| $H^{-1}4$ | The reciprocal of the ratio of segment sales based Herfindahl minus one, except that segment sales are first aggregated into four-digit SIC code and therefore each segment sales represents a unique four-digit SIC code industry. When $H^{-1}4$ is zero, the firm reported sales are from a single four-digit SIC code industry and is therefore non-diversifying. As $H^{-1}4$ increases, the firm becomes more diversifying and has sales in multiple four-digit SIC code industry. | Compustat Segment Data |
| $H^{-1}2$ | The reciprocal of the ratio of segment sales based Herfindahl minus one, except that segment sales are first aggregated into two-digit SIC code and therefore each segment represents a unique two-digit SIC code industry. When $H^{-1}2$ is zero, the firm reported sales are from a single two-digit SIC code industry and is considered non-diversifying. As $H^{-1}2$ increases, the firm becomes more diversifying and has sales in multiple two-digit SIC code industry. | Compustat Segment Data |
| $Indus_{FF17}$ *& Yr FE* | Fama-French 17-Industry classification and year fixed effects (FE). | Kenneth French Data Library and CRSP |
| $Indus_{FF17}$*·Yr &firm FE* | Fama-French 17-Industry classification by year and firm fixed effects (FE). | Kenneth French Data Library and CRSP |
| *ME* | Market value of equity at the end of fiscal year: *CSHO*prcc_f* | CRSP (CSHO, prcc_f) |
| $OC_{B(T),t}$ | $OC_{B(T),t} = (1 - Depr_{OC})OC_{B(T),t-1} + \frac{SG\&A_{B(T),t}}{cpi_t}$ and $OC_{B(T),0} = \frac{SG\&A_{B(T),1}}{g+Depr_{OC}}$, where $SG\&A_{B(T),t=1}$ is the firm's first positive SG&A expenses. $Depr_{oc}$ is OC depreciation rate set to 15%, and *g* is the average real growth rate set to 10% following Eisfeldt and Papanikolaou (2013). | Compustat (*XSGA*)*;* *CPI* from Federal Reserve Bank of St Louis website |

| | | |
|---|---|---|
| $OCnet_{T,t}$ | Same as $OC_{T,t}$ above except that I replace $SG\&A_{T,t}$ by $SG\&A_{T,t} - R\&D_{T,t} - Advertising_{T,t}$. | Compustat (*XSGA, XRD, XAD*); *CPI* from Federal Reserve Bank of St Louis website |
| *OIBDP* | Operating income before depreciation | Compustat (*OIBDP*) |
| *PREMIUM* | [(Initial offer price/target stock price 60 days prior to announcement) - 1]×100 | SDC and CRSP |
| $ROA_{B,t}$ | $(OIBDP_{B,t}/TA_{B,t-1})\times 100$ | Compustat (OIBDP, AT) |
| *Sale* | Sales | Compustat (SALE) |
| $Sales\ Growth_{B(T),t}$ | $[(Sale_{B(T),t} - Sale_{B(T),t-1})/Sale_{B(T),t-1}]\times 100$ | Compustat (SALE) |
| *Scaled GDWL* | $GDWL_{B,T,t}/TA_{T,t-1}$ | |
| *Scaled AcqIntan1* | $AcqIntan1_{B,T,t}/TA_{T,t-1}$ | |
| *Scaled AcqIntan2* | $AcqIntan2_{B,T,t}/TA_{T,t-1}$ | |
| *Scaled AcqIntan3* | $AcqIntan3_{B,T,t}/TA_{T,t-1}$ | |
| *Scaled OC* | $OC_{T,t-1}/TA_{T,t-1}$ | |
| *Scaled Bidder OC* | $OC_{B,t-1}/TA_{B,t-1}$ | |
| *Scaled OCnet* | $OCnet_{T,t-1}/TA_{T,t-1}$ | |
| *SG&A* | Selling, general, and administrative expenses | Compustat (*XSGA*) |
| *TA* | Book value of total assets | Compustat (*AT*) |
| *U4* | The number of unique four-digit SIC code segments reported minus one. When *U4* is zero, the firm operates in a single four-digit SIC code industry and is defined as non-diversified. When *U4* is zero the firm can still operates multiple segments but all the segments are in the same four-digit SIC code industry. | Compustat Segment Data |
| *U2* | The number of unique two-digit SIC code segments reported minus one. When *U2* is zero, the firm operates in a unique two-digit SIC code industry and is defined as non-diversified. When *U2* is zero the firm can still operates in multiple segments but all the segments are in the same two-digit SIC code industry. | Compustat Segment Data |