Manufactured Diversification Discount*

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Abstract

The commonly used measure to assess whether corporate diversification adds or subtracts value manufactures a discount by focusing solely on error-prone and irrelevant industry matching to the exclusion of sales and age. When using the traditional methodology, older and larger diversified firms are consistently matched to younger and smaller focused firms. Since size and age have been shown to be value relevant characteristics, this matching results in a "diversification discount." We demonstrate myriad problems with the existing measure and create a new measure that matches on value-relevant characteristics. Using this measure, we conclude that there is no discount to diversification.

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1. Introduction

The seminal works of Berger and Ofek (1995) and Lang and Stulz (1994) garnered substantial attention after showing that the value of a firm that is diversified into multiple business segments is less than the value of a portfolio of similar focused firms. This difference, dubbed the "diversification discount", has been the focus of two vast and distinct strands of research that set out to explain the discount. The first explains the loss of value as a function of various inefficiencies attributable to the diversified corporate form (inefficient internal capital markets, for instance) whereas the second focuses on unobservable factors that are correlated with the decision to diversify (lower value firms are more likely to diversify).[1] While both strands of the literature differ on the cause of the discount, they agree that diversified firms are worth less than portfolios of focused firms and by extension there is an aggregate economic loss to the economy.

We advance a different explanation: the diversification discount is manufactured by the matching methodology used to construct it. To support our explanation we show that industry matching is a less than ideal metric to create otherwise similar samples of diversified and focused firms to compare in the traditional chop-shop approach. We also provide evidence that neglecting to match on value-relevant characteristics creates a distinct bias in the measure. Furthermore, controlling for selection (as in Villalonga (2004b)) does not remove the diversification discount in extended samples with greater statistical power. Given these issues we create a new measure which eliminates the diversification discount.

The excess value measure used in Berger and Ofek (1995) to determine a firms relative value is the log-ratio of the market-to-sales ratio of a diversified firm to the weighted average

[1]Primary examples of the first type of research are Shin and Stulz (1998) and Rajan, Servaes, and Zingales (2000) and key examples of the endogeneity explanation are Campa and Kedia (2002) and Villalonga (2004b). A much more detailed discussion of the vast literature and our contribution follows in subsequent sections.

market-to-sales ratios of the median focused firm in each segment of the diversified firm. We show that this procedure, (the "chop-shop" methodology), is flawed in two distinct dimensions.

First, we provide evidence contrary to the assumption that industry matching is reliable in this context. Namely, market-to-sales ratios are not stable even across adjacent four-digit SIC codes. Thus, a firm's choice of reporting has a significant effect on its relative value. Interestingly, random (as well as various permutations of) assignments of industry for segments always generate a similar discount which demonstrates that the exclusive emphasis on industry in the original chop-shop excess value construction may have been misplaced.

We are not the first to point out the substantial difficulties in assigning firm segments to industry classifications. Villalonga (2004a) takes a different approach by using the business information tracking series rather than SIC codes taken from Compustat segment data to indicate industry, and her results show a diversification premium. Hoberg and Phillips (2013) find that their text-based measure of industry classification is better than conventional measures as an indicator of the true level of competition between firms and of related firm characteristics, such as profitability. Our contribution is to show that industry matching is not only problematic, but is also not as important as other value relevant characteristics when assessing firm value in this context.

Second, we show that the portfolio of benchmark focused firms that results from matching solely on the (reported) industry of the diversified segments is substantially different with respect to important value-relevant characteristics. Specifically, we provide evidence that older and larger diversified firms are matched consistently to younger and smaller focused firms, and it is this biased matching—not corporate form—that results in a diversification discount. In Section 3.3 we discuss how these results are consistent with microeconomic models that result in an inverse relationship between market-to-sales ratios and sales that does not depend on corporate organizational form. In other words, it is firm size and age which is driving the discount rather than firm organizational form.

Another indication that the traditional chop-shop measure neglects to match on factors that affect firm value is the significant observed cross-sectional dispersion. Much of the diversification discount is concentrated in small market-value firms while larger diversified firms tend to trade at a premium. An immediate consequence is that the value-weighted excess value for diversified firms differs dramatically from the standard equal-weighted excess value. In fact, compared to the standard equal-weighted discount of 11% first documented by Berger and Ofek (1995), value-weighting diversified firms' excess values results in a premium of 23%. Berger and Ofek (1995) extrapolate their equal weighted firm excess value measure calculated using the traditional industry-based chop-shop approach and suggest that an 11% diversification discount translates to an aggregate annual economic loss of $200 billion. However, when firms are value weighted instead, diversification results in an aggregate economic gain of $473 billion per year. We pursue this calculation primarily to make a point: ignoring value-relevant characteristics in favor of solely industry matching creates serious, predictable distortions and interpretation problems.

We thus abandon the traditional chop-shop approach in favor of a novel non-parametric direct matching technique that creates neighborhoods of locally comparable firms across important observable value characteristics (firm size and firm age) while also controlling broadly for industry and year.[2] We match on firm age and size as these variables have been shown to affect firm valuation multiples in the microeconomics and asset pricing literature in a manner that does not depend on corporate form. Using our novel non-parametric matching technique, the difference between the values of diversified and focused firms does not show

[2] In doing so we join a growing group of similar papers that seek to understand valuation differences by controlling for multiple valuation relevant dimensions. For instance, Edmans, Goldstein, and Jiang (2012) identify a strong effect for prices on takeover activity once they add firm-specific value dimensions to simple industry controls just as we do here, albeit in a much different context.

a discount to being a diversified firm. Furthermore, in the spirit of Berger and Ofek (1995) and Lang and Stulz (1994) we create a "strata-matched" discount measure equal to the log-ratio of the diversified firm market-to-sales ratio to the median "locally close" focused firm's market-to-sales ratio. Replicating the classic Berger and Ofek (1995) regressions with our new measure results in insignificance for the diversification dummy.

In our tests, we assume that firm age, and firm size are the value relevant characteristics (as has been suggested theoretically) and that older firms and larger firms tend to diversify. One concern is that diversified firms are mechanically larger than focused firms since they are the combination of two or more firms. In other words, the direction of the causality is reversed where the portion of firm size caused by the diversification decision is driving the results.[3] To rule out this possibility, we run a falsification test where we replace each diversified firm with a focused firm of similar size as a "placebo diversified firm" using a variant of the chop-shop approach where focused firm matches for each division are matched by size to the segment size of the diversified firm. When using placebo focused firms in place of diversified firms we find a discount which is not significantly different from the traditional diversification discount. Hence, we conclude that firm size is not endogenously correlated with diversification in a manner which affects firm value.

Showing a lack of a diversification discount has been done before, but our results cast doubt on those findings and provide an alternative explanation. Villalonga (2004b) and Campa and Kedia (2002) erase the diversification discount by using propensity score matching and instrumental variables to control for characteristics of firms that choose to diversify. Their use of the excess value measure as the outcome variable for comparison is problematic given our results indicating that the construction of the excess value measure, not endo-

[3]It does not make sense to examine situations where the causality of firm age is reversed since a firm does not really control its age. In other words, it makes sense to think of older firms diversifying. It does not make sense to think of corporate diversification causing a change in firm age.

geneity, may be driving the spurious relationship with value. We therefore replicate the methodology in Villalonga (2004b) and show that her results (the disappearance of a diversification discount) are not robust to a longer sample period with more statistical power. Specifically, a statistically significant diversification discount returns using her methodology and a longer sample period.

More generally our paper revisits major themes that have developed in the diversification literature since the seminal research of Berger and Ofek (1995) and Lang and Stulz (1994) found a discount to corporate diversification. Once the discount became evident researchers took the next step to explain why. Classic papers in this vein of the literature argue that the complex diversified form leads to inefficient investment (Shin and Stulz (1998), Rajan, Servaes, and Zingales (2000), Scharfstein and Stein (2000), Lamont and Polk (2002), Dittmar and Shivdasani (2003), and Ozbas and Scharfstein (2010)), that diversified firms tend to acquire poorly run firms (Graham, Lemmon, and Wolf (2002)), or that diversified firms have poor governance (Hoechle, Schmid, Walter, and Yermack (2012) and Denis, Denis, and Sarin (1997)).

Recent literature (for instance, Duchin and Sosyura (2013)) continues to assume that a discount in the Berger and Ofek (1995) excess value measure reflects destruction of corporate value and seeks to explain this value loss.[4] We step back to the original contention that a discount exists and find that the discount is simply the outcome of comparing firms that are drastically different with respect to value-relevant characteristics.

Our results have important consequences. First, they imply that research explaining the diversification discount is probably explaining something else. Particularly, we show that controlling for endogeneity using the methodology of prior papers in the literature is insuf-

[4] In Appendix A we provide a more detailed review of current papers that employ the Berger and Ofek (1995) measure or a similarly constructed chop-shop measure either as a dependent variable they are trying to explain or as a control variable in various finance theses.

ficient to remove the discount in an updated sample. Second, we document problematic biases in the commonly used chop-shop method. Third, we show that using value-weighted excess values leads to a substantial aggregate premium for diversified firms, suggesting a total economic value gain for corporate diversified not a loss as previously argued. Lastly, we employ a novel nonparametric methodology to construct a new measure of relative values using focused firms that are locally close to the diversified firms on value-relevant characteristics. Using this new measure (which we term strata-matched to distinguish it from industry-matched) the difference in value across diversified and focused firms is statistically insignificant.

The paper proceeds as follows. Section 2 describes our data and calculation of variables, emphasizing some important properties of the traditional construction of the excess value measure. Section 3 details the problems and biases of the existing measure, provides a motivation for our new measure, and reports the results from a "falsification" test to determine whether the discount is due to corporate form or size. Section 4 addresses the potential alternative explanation of selection and provides a replication of Villalonga (2004b). Also, Section 4 presents a novel nonparametric matching technique used to assess valuation differences between diversified and focused firms, details a new measure of excess value that incorporates the matched firm results, examines the measure in regression models similar to Berger and Ofek (1995), and provides evidence that the discount is erased using the new measure. Section 5 concludes.

2. Data and Sample Construction

2.1. Data Sources and Diversification Indicator

Our empirical analysis begins with merged data from the segment- and firm-level Compustat Industrial Annual files for the period 1977–2012 and return and market value data from the CRSP monthly returns files. Firm annual return, volatility, and market value variables are calculated at the fiscal year end dates from Compustat using the monthly CRSP stock return data. Firm-years are dropped from the sample according to the Berger and Ofek (1995) requirements that firms have no segments in the financial services industry (SIC 6000-6999), total firm sales are above $20 million, and aggregated firm segment sales are within 1% of firm-level data. We also remove regulated utilities (SIC 4900-4941) and firms that do not report sales and four-digit SIC codes for all of their segments. To address the complexities introduced by the new segment reporting rule Financial Accounting Standards Board (1997) (also known as SFAS 131) and to deal with the problem of pseudo-conglomerates (as in Sanzhar (2006)), we perform the aggregation procedure detailed in Hund, Monk, and Tice (2010) and forgo the use of segment asset data.[5] Diversified firms are identified as firms with more than one business segment following the segment aggregation procedure.

2.2. Variable definitions

The diversification premium or discount is calculated at the firm level by following the procedures in Berger and Ofek (1995). We calculate excess value (EV) as the log-ratio of

[5]Effectively this procedure combines sales from multiple segments reported in the same four-digit SIC code into one segment, and then re-classifies as focused those firms whose segments are all within the same four-digit SIC code. For more details, see Berger and Hann (2003). Post SFAS 131 many firms allocate large amounts of assets to a "corporate" segment with zero sales and somewhat arbitrarily re-allocate assets across segments, thus rendering asset multipliers virtually incomparable.

total capital to the imputed value for the firm. The imputed value for the firm is calculated by multiplying the median ratio of total capital to sales for focused firms in a segment's industry by the segment's reported sales and then summing over the number of segments in the firm. Specifically, excess value is:

$$Imp(V) = \sum_{i=1}^{n} Sales_i * (\frac{V}{Sales})_{mf})$$

$$EV = \ln(V/Imp(V))$$

where $Imp(V)$ is the imputed value, V is the firm total capitalization (market value of equity plus book value of debt), $Sales_i$ is sales reported for segment i, and the subscript mf indicates that the value is for the median focused firm in the same industry as segment i, and n is the number of segments in the firm. The matched segment median value comes from the finest SIC code level (two-, three-, or four-digit) with at least five focused firms. Firms with excess values greater than or equal to zero are designated as "premium" firms, and firms with excess values less than zero are designated as "discount" firms.

Two important points about the excess value measure should be emphasized. First, the excess value measure is the log-ratio of the firm's market-to-sales ratio over the sales-weighted average market-to-sales ratio of the median focused firm in each industry in which the firm operates. The Berger and Ofek (1995) diversification discount is essentially a statement that on average, diversified firms have lower market-to-sales ratios than the median focused firms that operate in their industries. If market-to-sales ratios vary consistently along other dimensions than industry (as we document in Section 3.2) the diversification discount devolves into a statement about those confounding dimensions rather than one about corporate form. Second, we note that the excess value measure defines a distribution of excess values for both focused and diversified firms. There are substantial numbers of discount and premium focused firms, just as there are substantial numbers of discount and premium diversified firms. We more closely examine this distribution for diversified firms in Section 3.2.

Because firm age is an important value-relevant characteristic for market-to-sales values (see Pástor and Veronesi (2003)), we carefully consider its construction. The age of the firm at IPO has fallen substantially during our sample period so simply using the first appearance in the Compustat database or the listing date severely understates the age of older firms in the sample. This exacerbates the bias in comparing market-to-sales ratios of older firms with younger firms. We define firm age using data containing firm "birth" dates from Jovanovic and Rousseau (2001) that was supplemented by Fink, Fink, Grullon, and Weston (2010). For the few firms remaining without birth dates in these databases, we calculate birth dates using the first listing date in Compustat.

Our other variables are standard accounting and stock return measures. *Profit Margin* is defined as EBITDA over sales, *Earnings* are defined as income before extraordinary items plus deferred taxes and tax credits, and *Sales* are total firm revenues. *Return Volatility* is the standard deviation of the monthly stock returns during the firm's fiscal year, and *Excess Return Volatility* is the standard deviation of the monthly excess stock returns during the firm's fiscal year where excess stock returns are defined as the difference between the firm's stock return and the value-weighted market return for that month.

3. Motivation for a New Measure

3.1. Matching on Industry

As noted earlier, the excess value measure of Berger and Ofek (1995) is the log ratio of market-to-sales ratios of the entire firm to the median focused firms matched in the finest possible industry match for each segment. The preference for matching within four-digit SIC codes creates large discrepancies on dimensions (such as size and age) over which market-to-sales ratios are known to vary predictably (see Pástor and Veronesi (2003)). Since these omitted dimensions are embedded non-linearly in the excess value measure, they cannot be controlled for within a linear regression specification merely by including them as independent variables (as in Borghesi, Houston, and Naranjo (2007)).

As a practical matter, inaccurate classification of industry codes to segments will contaminate the excess value measure, since by construction it is designed to rely exclusively on the accuracy of four-digit SIC classification to match diversified firm segments and focused firms. Indeed, it is the case that Compustat itself is not internally consistent with SIC codes between its Segment and Industrial data files. A cursory comparison of SIC code matches between the Segment and Industrial Compustat files reveals that this is an extremely serious issue. *Focused* firms have different four-digit SIC codes in the two files over 20% of the time; approximately 5% differ at even the three-digit SIC code level. Even more troubling for our purposes, over 34% of diversified firms have different SIC codes in the Industrial Annual file than their maximum sales segment in the Segment files.

In addition, there is ample reason to believe that segment data reported to Compustat is less than perfectly reliable. Financial Accounting Standards Board (1997) gave substantial latitude to corporations to self-report segments in line with their management practice, but at the substantial cost of comparability over time and across firms.[6] Even in the pre-1997 period, Denis, Denis, and Sarin (1997) document frequent arbitrary reporting changes in the number of segments that are unrelated to changes in business operations. Villalonga (2004a) finds that using data from the U.S. census to identify segments rather than data from Compustat results in a premium rather than a discount, a result potentially due to firms strategically manipulating their segment reporting to appear less valuable than a portfolio of single-segment competitors as is shown in Botosan and Stanford (2005).[7]

3.1.1. Variation of adjacent industry market-to-sales ratios

Misclassifications and potential endogenous reporting choices in industry reporting would be of little consequence if industry valuation varied smoothly over nearby SIC classifications along the market-to-sales dimension. In fact, the opposite is true; market-to-sales ratios vary dramatically across adjacent four-digit SIC codes. Table 1 depicts the averages and standard deviations of the market-to-sales ratio of the median focused firm from each four-digit SIC code averaged across years and one-digit SIC codes. While the average of the median firm market-to-sales ratios across all firm-years is 1.445, the standard deviation is 1.267, indicating that within one-digit industries there are exceptionally large differences in market-to-sales ratios of median focused firms at the four-digit SIC code level. More importantly, median focused firms in adjacent four-digit SIC codes have very different market-to-sales ratios.

Table 1 documents the absolute value of the difference in market-to-sales ratio for median focused firms in adjacent four-digit SIC codes, again averaged over one-digit SIC codes and

[6] Among the many sources that document this effect are Berger and Hann (2003) and Sanzhar (2006).

[7] Villalonga (2004a) and Montgomery (1994) document problems with the minimum segment reporting threshold of 10% of total firm sales. In particular, Montgomery (1994) examines the largest firms in the economy (as we do here) and finds that they are far more diversified than reported in the Compustat data. The fact that this additional diversification appears exactly in the set of firms we identify as having the highest premium strengthens the case for aggregate economic benefits to diversification.

years. Market-to-sales ratios of adjacent SIC codes are on average 0.828 different, nearly a 50% discrepancy from the mean level of 1.445. In other words, a firm in one SIC code could potentially alter its diversification discount substantially by selecting an adjacent four-digit SIC code. For instance, in 2011 a firm reporting a segment in 3676 (Electronic Resistors) would be matched against a firm with a market-to-sales ratio of 1.51 whereas a firm reporting a segment in adjacent 3677 (Electronic Coils and Transformers) would be matched with a firm that had more than twice the market-to-sales ratio (3.68). The standard deviation of market-to-sales of adjacent SIC codes is also large, indicating further instability in the relationship between market-to-sales values and four-digit SIC codes.

3.1.2. Excess value with random and shifted industries

We further investigate the effect of industry assignment on excess value by calculating excess values as in Berger and Ofek (1995) after randomizing and shifting the focused firm SIC codes in various ways. Our goal here is slightly different than that of the previous section which focused on the noise that could be created by misclassification or firm reporting choice. Here we wish to emphasize that while for individual firms there is substantial noise in the standard industry classification, segment industry classification as a value characteristic has almost no explanatory power. In other words, focused firm industry is essentially irrelevant for generating a discount. To show this we conduct several simulation and counterfactual tests reported in Table 2.

Panel A of Table 2 reports the results of a simulation that scrambles focused firm SIC codes across varying degrees of granularity. For instance, for the one-digit results, all of the focused firms in SIC codes beginning with 3 are assigned random SIC codes also beginning with 3. For the 2-digit results all of the focused firms in SIC codes beginning with 32 are assigned random SIC codes also beginning with 32, and so on. Excess values are calculated using the common chop-shop methodology of Berger and Ofek (1995) and calculations are repeated 1000 times. In addition, for each simulation a regression of excess value on the diversification dummy and the controls used by Berger and Ofek (1995) is run and the coefficient on the dummy is reported in Panel A. The broad conclusion to draw from the results is that a substantial discount persists regardless of the industry classification of the matched focused firms. In fact, it is virtually impossible to get anything other than a diversification discount by comparing diversified firm segments to median focused firms chosen by industry.

A related test in Panel B of Table 2 provides more evidence to support this claim. To examine a different form of randomizing industry designation we shift focused firm SIC codes either up or down by 1, 10, or 100, respectively. Again, the discount formed after this permutation is *always* around 11% and there is never a significant difference from the original value of the discount created with the actual assigned SIC codes.

Taken together our results cast serious doubts on the efficacy and reliability of constructing an excess-value measure matching segments solely on the dimensions of the finest industry match and year. Section 3.1.1 shows that even if the SIC code of either a diversified firm segment or its focused firm benchmark is misclassified by one at the four-digit SIC code level (i.e., the minimum that an industry can be misclassified), the market-to-sales ratio of either could be biased by over 50%. Furthermore, Section 3.1.2 shows that randomization of focused firm industries always generates a discount.

3.2. Neglecting to Match on Other Characteristics

Previous research uses the equal-weighted excess value to extrapolate an aggregate loss of value due to diversification. For example, Berger and Ofek (1995) on pg. 49 note that "the mean dollar loss per firm during 1986–91 is $235.1 million, implying a total loss in value for the approximately 850 multi-segment sample firms of $200 billion." In this section we show that there are actually aggregate "gains" to diversification if the value-weighted excess value is used, but these benefits (and the aforementioned equal-weighted losses) rely on the fact that excess value has been calculated without controlling for confounding effects of value-relevant characteristics.

Figure 1 shows the effects of size on excess value for diversified firms by charting mean excess values relative to deciles of market value of equity. Because we sort by market value and the Berger and Ofek (1995) excess value measure is the ratio of market-to-sales ratios, the top three deciles of diversified firm market value show a substantial *premium*, not a discount. The largest market value diversified firms are also the ones that (mechanically) generate the highest excess value; in fact the largest diversified firms, with a mean market value of nearly $20 billion, have an 18% premium.[8] In this situation, we argue that using a value-weighted approach provides a better way to analyze the aggregate economic impact of diversified firms, and more generally, using this approach is second-best to creating a measure that accounts for value-relevant characteristics inherently.

Because of skewness in the distribution of market values and the association of higher market values with premiums based on the excess value measure, there is a value-weighted

[8] Even though we aggregate our data to remove duplicate segments and match explicitly to CRSP data, when we restrict our attention to the 1986–1991 period studied by Berger and Ofek (1995), we calculate a mean (median) discount of 9.8% (11.4%) compared to 9.7% (10.6%) in Berger and Ofek (1995) for excess values based on sales multiples. In addition, our discounts are also within 2% of Berger and Ofek (1995) at the 25th and 75th percentiles, and have virtually identical standard deviations. In order to more closely replicate the data in Berger and Ofek (1995), we use a legacy segment file from 1999 and the legacy version of Compustat firm data from 2006 and do not aggregate the data or match to CRSP, and calculate discounts based on both assets and sales multiples. While our sales multiple discounts continue to be virtually identical to those in Berger and Ofek (1995) we calculate a median asset multiple discount of 10.3% vs. their 16.6% discount. Our computed discount is identical to that calculated by Campa and Kedia (2002) when they restrict their sample to the 1986–1991 period, and we note as they do, that the difference is likely due to restatements and additions in the Compustat files. Our sample using legacy data has 4,464 firms (similar to the 4,565 firms in Campa and Kedia (2002)), but significantly more than the 3,659 reported by Berger and Ofek (1995). Using our legacy data files, the equal-weighted average loss to diversification (using sales multiples over the period from 1986–1991) is $196 million per firm, and the value-weighted average gain to diversification is $100 million per firm.

premium for diversified firms. In Table 3 we calculate the average excess value in every year by equal-weighting or value-weighting by total capitalization.[9] The difference is substantial. Whereas the overall discount is 11% when the simple average is formed, the overall value-weighted average is a premium of 23%. Moreover, diversification provides a net gain to the economy in all years but two from 1977 to 2012. Using market value of equity to value-weight excess value results in a net gain in every year, and the overall value-weighted premium increases to 32%.

From these values, we can work out the aggregate excess value in dollars in every year by simply calculating the average value of diversified firms and multiplying that value by the average percentage gain/loss associated with the equal- or value-weighted excess value measure. Averaging the equal-weighted loss across years from 1977 to 2012 leads to a loss of $340 million in value per firm-year, which is similar to the result of $235.1 million that Berger and Ofek (1995) find for a much smaller sample. However, if value-weighted, diversified firms have an average aggregate market value gain of $720 million per year relative to their imputed values. Multiplying this average gain by the average number of diversified firms over our sample period yields a total gain of $473 billion per year.[10] Far from destroying value, diversification has economic benefits of enormous magnitude.

We perform the same analysis shown in Table 3 using the sample of focused firms. In results reported in Appendix B, we show that focused firms have a value-weighted premium in every year. The value-weighted premium for focused firms is greater than for diversified

[9]We focus our attention on total capitalization as the market value for comparability to Berger and Ofek (1995), though our results are robust to using market value of equity as the measure of market value. In Table 3 we calculate these values by applying the contemporaneous market value with the calculated discount to emphasize the economic value of the result. Using the beginning of the period market value as a weight does not materially affect our results, nor does using only the market value of equity instead of the total capitalization of the firm.

[10]In constant 2009 dollars (using the PCE Index to account for inflation), the average aggregate market value gain per diversified firm is $826 million and the aggregate total gain is $608 billion per year. Including financial firms strengthens the result, leading to larger value-weighted gains.

firms in most years, but when the dollar loss/gain calculation is considered, diversified firms still show a larger gain relative to the gain for focused firms due to their much larger market values. This is an additional difficulty with calculating the aggregate economic gain or loss from the traditional measure of excess value; skewness in the distribution of market values generates economic gains relative to the median focused firms for both focused and diversified firms. In Section 4.2, we create a measure that allows for more robust comparison between diversified and focused firms by first matching them based on value-relevant characteristics.

3.3. Economic Motivation

Yet another problem with using the chop-shop approach in this context is revealed in two empirical facts: there is a strong negative relationship between market-to-sales ratios and sales, and diversified firms are much larger than focused firms with respect to sales. Regardless of the underlying economic process that could generate these facts (and we discuss several plausible candidates below), the consequences of employing the chop-shop methodology in such an environment manufactures a diversification discount.

Consider a randomly chosen firm with sales of $400 million and assume that we calculate its discount by comparing it to two segments that are half its size.[11] The market-to-sales ratios associated with average firms of $400 and $200 million are 1.6 and 1.78, which results in a calculated discount of 10.7%. Essentially any firm matched on average with firms to the left of it in sales percentiles will result in a discount; since an overwhelmingly large percentage of diversified firms are in the right half of the distribution of sales, matching to focused firms without properly controlling for size manufactures a discount. Berger and Ofek

[11] We show in our data (see Table 4) that on average in the entire dataset the Berger and Ofek (1995) procedure matches diversified firms to focused firms that are 15 times smaller.

(1995) control for size in a linear fashion after construction of their excess value measure, but this does not control for size properly as it is embedded nonlinearly in the excess value.

Figure 2 provides deeper insight into the empirical differences between diversified and focused firms and how these differences are related to the valuation metric (market-to-sales). It depicts the mean market-to-sales ratio for each percentile of sales for the entire sample and for diversified and focused firm subsamples. More precisely, we form the percentile breakpoints each year using the entire sample and calculate averages over all of the years in our sample. Importantly this results in different numbers of diversified and focused firms in each percentile, a fact that is represented by the size of the symbols in Figure 2. From low to high percentiles of sales, average market-to-sales ratios for focused firms decrease from more than 2.0 to approximately 1.3. For diversified firms, the relationship is present, but less pronounced. Put differently, the market value of each unit of sales declines as sales increases. There is also a clear indication that focused firms tend to be much smaller than diversified firms, and critically, this relationship is non-linear. Section 3.4 provides more support for the difference in sales, among other value-relevant characteristics.

This pattern is consistent with several underlying models of firm fundamentals, though it is beyond our scope to differentiate among these. Rather, this discussion serves to motivate that such a pattern results directly from plausible underlying economic processes. Investment-based models such as Xing and Xing (2008) and Zhang (2005) both show that investment growth rates are negatively correlated with future equity returns, consistent with stochastic discount rate q-theory. Growth firms have much higher investment growth rates than value firms; higher investment is the result of low future discount rates which imply high current market values (and subsequent lower equity returns). In fact, the close relationship between book value of assets and sales combined with q-theory is consistent with the market-to-sales ratio pattern we highlight here. Dynamic models of firm and investor evolution will also reproduce this inverse relationship. If firms exploit growth options as they age and grow larger, models based on Berk, Green, and Naik (1999) will generate higher market-to-sales ratios for younger, smaller firms than older, larger firms.

The learning model of Pástor and Veronesi (2003) predicts that firms with higher uncertainty about their growth rates will have higher market-to-book ratios and that both uncertainty and market-to-book ratios will decline through time as firms grow and age. Hund, Monk, and Tice (2010) show that many empirical facts about diversification (a discount in levels, larger changes in firm excess value for diversified firms, higher idiosyncratic volatility for focused firms, and discounts which co-vary with the business cycle) can be explained by interpreting the diversification discount as matching firms with low uncertainty about growth rates (diversified firms) with firms with high uncertainty about growth rates (focused firms).

Figure 2 also indicates that a diversification discount might exist in small diversified firms. Average market-to-sales for small diversified firms appears to be much less than average market-to-sales for small focused firms. Any such discount would represent a small economic magnitude, however, since over half of the diversified firms are above the 65th percentile of the unconditional distribution. Diversified firms in general also have lower market-to-sales ratios in almost all percentiles, suggesting that even among sales-matched firms a slight discount could exist. While we examine this issue in great statistical detail in Section 4, Figure 3 is a plot of the mean residuals from a regression of market-to-sales on age across sales percentiles that shows controlling for age removes much of the distance between diversified and focused firms, especially so above the 60th percentile of the unconditional distribution.

3.4. Summary Statistics

The intuition of the preceding section is conditional on substantial differences existing between diversified and focused firms, certainly with regard to sales and age, but also along other confounding value dimensions. To solidify our argument that the chop-shop methodology leads to mechanical discounts, we show that the actual median firm matched to each segment of the diversified firm consistently falls along one of the value-relevant dimensions. Table 4 presents the differences in both the unconditional and the chop-shop matched samples.

Table 4 shows the dramatic difference between focused and diversified firms. Diversified firms have over twice the market value, assets, and sales of focused firms and are nearly twice as old. Diversified firms are more profitable and have significantly lower return volatility as should be expected from more mature, larger firms. Median values are substantially lower than the means for the market values and accounting measures, pointing out the severe skewness in these distributions whose consequences we have discussed in Section 3.2.

The differences in the unconditional focused and diversified distributions dramatically understates the differences between diversified firms and their actual industry-level median focused firm matches. Diversified firms are approximately twice as large as benchmark firms (e.g., sales of \$2.489 billion vs. \$1.341 billion) and 50% older (Age of 44.9 vs. 29.5). To further understand the differences between firms and their benchmark firms we create Sales Match % (Age Match %) as the ratio of firm sales (age) to benchmark sales (age) weighted by the proportion of firm sales in the subject firm, summed over all subject firm segments, and expressed as a percentage. These variables indicate that diversified firms are on the order of 15 times larger (1,522%) with respect to sales and almost 3.5 times older (342%).

Diversified firms are older, much larger on all dimensions, and more profitable than focused firms and even more so than the firms matched to them in the Berger and Ofek (1995) methodology.[12] Given that market-to-sales ratios decline with sales and age, and that the standard chop-shop method of calculating the excess value measure consistently matches large, old diversified firms with small, young focused firms, it is easy to see how a discount is manufactured.

3.5. Falsification Test

We assume that firm age, and firm size are the key value relevant characteristics (as has been suggested theoretically) and that older firms and larger firms tend to diversify. One concern is that diversified firms are mechanically larger than focused firms since they are the combination of two or more firms. In other words, the direction of the causality is reversed where the portion of firm size caused by the diversification decision is driving the results. To rule out this possibility we perform the following experiment.[13] First, we perform a firm-level match for each year by matching (with replacement) each diversified firm with the focused firm closest to it in sales during that year. Next, we perform a segment-level match for each year by matching each *segment* of the diversified firm with a focused *firm* by sales within year. From the segment-level match we calculate an excess value measure as the log-ratio of the market-to-sales ratio of the diversified firm divided by the sales-weighted average of the

[12] Together, these facts support the hypothesis that diversified firms may have lower uncertainty about their growth rates, and potentially, lower market-to-sales ratios than focused firms for reasons that are entirely consistent with value maximizing behavior in an older, more mature firm. (See Pástor and Veronesi (2003) and Hund, Monk, and Tice (2010) for more information regarding the link between growth rate uncertainty and firm multiples.)

[13] While we term this an "experiment" it essentially shows that the intuition from Figure 2 generalizes across the entire data set. It also emphasizes that the primary dimension of variation for market-to-sales ratios is sales and not organizational form. We turn to a much more formal and robust comparison of characteristic matched firms in Section 4.

market-to-sales ratios of the focused firm matches to the segments of the diversified firm. We call this the "real" excess value.

We then create a placebo value (which we call the "fake" excess value) by recomputing the excess value measure after substituting the market-to-sales ratio of the focused firm-level match to the diversified firm. To generate confidence intervals for the difference in excess values between the "real" and "fake" excess values we use a bootstrapping procedure with 500 replications and block resampling (to preserve the panel-data structure and additionally preserving the balance between focused and diversified firms). The results are presented in Table 5.

The most immediate conclusion from this experiment is intuitive: calculating a measure by comparing "big" firm market-to-sales ratios with the average of several smaller firm market-to-sales ratios leads to a discount regardless of organizational form. The focused firm "fake" discount is 11.1% implying in the traditional interpretation that these firms are value-destroying. Diversified firms seem to destroy even more value with a calculated "real" discount of 15.4%, but this discount is heavily concentrated in very small diversified firms (that have much lower market-to-sales ratios than their focused counterparts). Calculating the difference in excess value measures between diversified firms and their placebo counterparts for firms above the median $250 million in sales shows no statistical difference in the discount. As sales increase, the difference in point estimates narrows and t-statistics for the difference decrease.

Age is the other value relevant firm characteristic proposed by theory. As with firm size, reverse causality needs to be considered. However, it does not make sense to examine situations where the causality of firm age is reversed since a firm does not really control its age. In other words, it makes sense to think of older firms diversifying. It does not make sense to think of corporate diversification causing a change in firm age.

Focused and diversified firms differ substantially across characteristics that are strongly associated with value and this variation is consistent with rational value-maximizing models of the firm. The standard methodology for calculating the diversification discount matches solely on industry and preserves substantial bias along important dimensions, most essentially by matching large firms with small firms.

4. Matching Estimators of the Diversification Discount

Previous sections have documented the biases that are a direct consequence of employing the chop-shop methodology to construct the excess value measure. Not only are industry classifications fraught with measurement error (and potential endogeneity), picking median focused firms in each SIC classification results in matches that generate a discount regardless of whether the firm is diversified *or* focused. Controlling for age or sales within each narrow industry match reduces the discount as noted by both Bevelander (2002) and Borghesi, Houston, and Naranjo (2007), but ultimately both papers note that preserving the tight industry match for the segments forces adoption of wide ranges for age which is counterproductive.

We adopt a different approach to the problem. Rather than preserving problematic matches for each segment, we compare the values of focused and diversified firms directly, controlling for characteristics. We choose characteristics (sales and age) that are correlated with growth rate uncertainty as in Pástor and Veronesi (2003) as a guide, yet as noted in Section 3.3 other economic explanations could certainly drive similar patterns in these characteristics. Furthermore, if the diversified corporate form is systematically destroying firm value via agency costs, empire building, or inefficient cross-subsidization, then the difference between the market values of focused and diversified firms should be magnified by matching on age and sales. Large and old focused firms should be worth far more than their diversified counterparts. But if the measured discount is purely an artifact of comparing firms with different ages and levels of sales, then the difference between market values of focused and diversified firms should disappear when we match on these covariates.[14]

The results described in the sections below show clearly that the diversification discount disappears once value-relevant characteristics are addressed. We focus our discussion on

[14] All matching tests are robust to the inclusion of return volatility as an additional covariate, which is a proxy for measures related to value in Pástor and Veronesi (2003).

a non-parametric matching paradigm called coarsened exact matching due to its favorable properties in this context and provide similar results from a robustness test using parametric propensity score matching in Appendix C.[15]

4.1. Consideration of Selection

In this section, we examine whether our alternative explanation for the diversification discount is necessary. Results in Villalonga (2004b) already suggest that the decision to diversify is not associated with value destruction once observable differences are controlled for via propensity score matching. However, there is a critical difference between her approach and ours; she first constructs the excess value measure as in Berger and Ofek (1995) and then attempts to explain the discount formed by that methodology whereas we show that the Berger and Ofek (1995) methodology manufactures a discount that is difficult to remove once constructed. We reconcile the findings in Villalonga (2004b) with ours by showing that in an extended sample with more statistical power, propensity scoring difference-in-differences methods still result in a significant diversification discount.

Villalonga (2004b) studies a group of firms that change their form from single to multiple segments (termed *diversifying* firms) and compares the change in their excess value (measured as in Berger and Ofek (1995)) from time t-1 to t+1 to the change in excess value for all focused firms from time t-1 to t+1 during the period from 1978–1997. We replicate her methodology (using the sales-weighted excess value measure) over both the 1978–1997 time period and using the full 1977–2013 period utilized in the rest of our paper. Table 6 presents our results as well as coefficients and statistics from Villalonga (2004b) to facilitate comparison.

[15] An excellent summary of matching estimators that discusses both propensity scores and coarsened exact matching can be found in Stuart (2010).

Exactly replicating the results in Villalonga (2004b) is difficult for several reasons. First, the 150 diversifying firms in her sample are hand-selected based on Hyland (1997) and Hyland and Diltz (2002), as well as examination of Lexis-Nexis news articles to represent true examples of diversification and remove the effects of reporting changes on the analysis. Here we include all firms who first transition from one segment to multiple segments during this period and thus we have 387 diversifying firms instead of the 150 in Villalonga (2004b).[16] We conjecture that including firms that are not "true" diversifying firms should, if anything, bias our results towards not finding a discount in both the shorter and full samples, and indeed, our coefficients on the change in excess value are much smaller than those in Villalonga (2004b) in similar time periods. Secondly, because of the comparability problems with asset weights created by Financial Accounting Standards Board (1997) discussed earlier, we focus exclusively on sales-weighted excess values.

Nevertheless, our samples over similar time periods seem to be broadly comparable. The top two panels of Table 6 show summary statistics and calculated excess values for our sample of diversifying and focused firms in both the period from 1978–1997 and the full sample, as well as reprinting values from Villalonga (2004b) to facilitate comparison. Compared to the Villalonga (2004b) sample the mean and median discounts are virtually identical, and even though we have two and a half times more diversifying firms (387 vs. 150), a comparison of asset size, profitability, and capital expenditures reveals few meaningful differences. The only substantial difference is in the lagged industry adjusted q, but we use a sales-weighted measure due to aforementioned problems with asset weights from allocation to segments while Villalonga (2004b) uses an asset-weighted measure. Our focused samples have extremely similar summary statistics and nearly the same number of firms.

[16] We attempted several screens to try to identify pure "reporting" changes in our data. Requiring the firm to not change its number of segments after the initial diversifying event for three, four, or five years, performing the aggregation procedure for pseudo-conglomerates described in Section 2, or requiring the firm to be focused in all years up until the diversifying event did not change any of our results significantly.

The bottom panel of Table 6 presents the results of applying the difference-in-difference propensity score treatment effects model of Villalonga (2004b) and OLS to both the 1978–1997 time period and our full sample.[17] In all cases, the dependent variable is the change in excess value (sales-weighted) from t-1 to t+1 for diversifying (firms that change their form for the first time) and all focused firms with data. As in Villalonga (2004b) we compute two models: a reduced model that includes controls for ln(assets), EBIT/Sales, CAPX/Sales, lagged industry-adjusted q, and lagged industry q and an enhanced model. Our enhanced model (as in Villalonga (2004b)) adds dummies for S&P Index inclusion, major exchange, foreign incorporation and dividend payment status as well as controls for firm age and R&D intensity. Unlike Villalonga (2004b), we do not include institutional and insider ownership controls (both of which have near zero marginal effects), and we estimate the model with individual year effects rather than macro control variables.[18]

Like Villalonga (2004b), we find an insignificant causal effect on diversification in the OLS estimates for the reduced model, but (perhaps reflecting the dilutive effect from the lack of hand-selecting firms with diversifying news as discussed earlier) our point estimate for the change in excess value for diversifying firms is much lower. In the extended model, the OLS coefficient in Villalonga (2004b) is significant but is based only on the 109 diversifying firms left in her sample. Our OLS estimates in the extended model are very similar to those of the reduced model for the 1978–1997 time period, which is likely related to the fact that fewer firms are dropped in our extended model (because we omit ownership variables).

We then use the reduced (extended) models to estimate propensity scores for the 387 (380) diversifying firms via a probit regression using those firms and the 25,746 (25,554)

[17]We again present the relevant coefficient estimates from Villalonga (2004b) to facilitate comparison.

[18]We have experimented with inclusion of various macro controls, but their effect on estimates compared to year fixed effects is negligible.

focused firms.[19] We then implement the Abadie and Imbens (2002) matching estimator, but we calculate our standard errors using the updated procedure in Abadie and Imbens (2011). As in Villalonga (2004b) we do not find causal evidence for diversification destroying firm value in the period from 1978–1997.[20]

We then extend our sample significantly to incorporate the entire period from 1977–2013, still using the same methodology. Our longer time period approximately doubles the number of focused and diversifying firms in our sample; we now have 689 (681) in the reduced (extended) models as compared to the 150 (109) diversifying firms in Villalonga (2004b). We find a significant discount to diversifying in the OLS reduced and enhanced models (as in Villalonga (2004b)) but now the difference-in-difference propensity score matching methods of Abadie and Imbens (2002) no longer render that discount statistically insignificant. Indeed, we find that the act of diversifying decreases the calculated excess value measure by 7.8% in the reduced and 6.6% in the extended model. Applying causal treatment effects estimators (as in Villalonga (2004b)) to the standard excess value measure does *not* remove the diversification discount in the full sample.

We are not asserting that diversification destroys firm value because of these results, however. To the contrary, we perform this exercise to draw the subtle but important distinction between true economic value destruction and changes in the excess value measure. Firms' excess value measures *do* change signficantly when firms add segments, but this decline in relative value of the excess value measure as calculated by Berger and Ofek (1995) is due to faulty comparisons embedded in the measure itself. As we discuss in much greater detail in the next section, the diversification "discount" is more about construction than selection.

[19] This contrasts with the 150 (109) diversifying firm observations in the Villalonga (2004b) original paper over the same time period.

[20] Note that in the original Villalonga (2004b) paper, it is the enhanced model that generates a significant coefficient in the OLS model and an insignificant coefficient (t-stat of 1.60) in the average effect of the treatment on the treated, and this is precisely where concerns about the power of the test should be the largest.

4.2. Coarsened Exact Matching Estimators

Common criticisms of propensity score methods are that they are prone to model misspecification in the propensity score estimation and that they are focused on achieving optimal average balance among the covariates and not balance over their entire distributions (including ensuring correct common support). Coarsened Exact Matching (CEM) is a non-parametric technique developed in Iacus, King, and Porro (2011b) and Iacus, King, and Porro (2011a) that ensures common support and bounds on the maximum imbalance between the covariate distributions across groups, diversified and focused firms in our case. Iacus, King, and Porro (2011b) show that CEM estimators belong to a class of matching methods, termed Monotonic Imbalance Bounding, that generalizes and extends the class of existing matching estimators (which includes more commonly used methods such as propensity scoring based on probit or logit models, or nearest neighbor and Mahalanobis distance matching).[21] CEM can be shown to dominate existing matching estimators (such as propensity score matching or weighting) in reducing imbalance and avoiding dependence on model specification even in data that is expressly generated to favor common matching methods. In our data, especially since sales is highly skewed, it becomes even more important to use non-parametric methods which better match higher moments and empirical quantiles.[22] As a robustness check, we show in Appendix C that our results hold when using the more common propensity scoring approach to generate matches for our data.

Essentially, CEM generates a multi-dimensional grid of the covariates to match upon, dividing each variable into multiple bins (potentially of varying widths). The intersection of the "top" bin (for example) of all covariates forms a strata, or local area associated with

[21]This class is the Equal Percent Bias Reducing class introduced in Rubin (1976), which is based on reducing only the mean covariate imbalances, and not other moments, interactions of covariates, or general nonlinear relationships.

[22]In a completely unrelated context, Duygan-Bump, Parkinson, Rosengren, Suarez, and Willen (2013) use CEM to match money market funds with and without holdings of auction-backed commercial paper.

the highest values of all covariates. All possible intersections of the bins are computed and this forms the total set of strata for the matching procedure. Once formed, all diversified firm observations in a particular strata are matched with the focused firms in each strata and the weighted averages on the outcome variable (in this case, the market value of the firm) constitute the "treatment" effect. Any strata with no focused or no diversified firms is discarded (along with the firm observations in them) ensuring that the matching is only on the common support of the distributions.[23]

Implementation of CEM estimators involves a choice of "bin" size; too wide a bin size results in inefficient matching, whereas too narrow of a "bin" may result in discarding too many observations. For our data we use a simple rule based on the range of the data for age and an optimization-based rule to select bins for the highly skewed and multi-modal sales distribution.[24]

Table 7 presents our results using CEM to match focused firms to diversified firms using sales and age to examine the effects of diversification status on firm value. The column labeled "Unmatched" shows that the mismatch between focused and diversified firms on sales and age is persistent not just for the mean values, but all along the quartiles of each distribution. For example, the median diversified firm has $222 million more in sales and is 14 years older than its match from focused firms. The importance of using methods such as CEM rather than moment-based propensity scoring methods are apparent by observing the skewness in the sales and age distributions, where at the 75th percentile sales in diversified firms are a billion more than focused firms and diversified firms are 33 years older. Also apparent is the extreme skewness of the sales distribution where the difference in mean is above the difference at the 75th percentile.

[23] Details on the statistical properties of the estimators, including the bounds on error and model dependence, are available in Iacus, King, and Porro (2011b).

[24] Specifically, we use Sturges' rule for the smoothly distributed age distribution and the methods developed for multi-modal and skewed data in Shimazaki and Shinomoto (2007) for the sales variable distribution.

The other columns of Table 7 present the results of the CEM matching procedure for three cases: treating each firm-year observation as independent ("Matched"); matching separately for each year ("MatchedYr"); and matching separately within each one-digit SIC code industry and year ("MatchedYrInd"). The "Matched" case, in which firms can be matched across years, is only accurate under unrealistic stationarity conditions and is primarily presented as a benchmark to compare the accuracy of the matching algorithm in a more realistic yearly context. Despite aforementioned problems with industry designation, we include "MatchedYrInd" to check robustness to including a broad industry control (one-digit SIC code) and as a benchmark to the chop-shop approach, which controls for industry integrally.

Our first observation is simply the unsurprising result that matching works. Mean differences for all three matched samples fall by orders of magnitude and differences across the entire distribution of sales and age are dramatically reduced. Most importantly, our main result (apparent heuristically from the falsification test and Figure 2) is confirmed in a full-fledged experimental design: once matched on value-relevant characteristics, focused and diversified firms have statistically indistinguishable market values as shown in the "Treatment" row of Table 7.[25] Balanced fairly well across the mean and all of the quartiles of the covariates, diversified and focused firm values are statistically indistinguishable.

4.3. Alternative Excess-Value Measures and Quality of Matching

Results using matched estimators (both parametric and non-parametric) suggest that much of the traditionally measured diversification discount is due to predictable variation in value-

[25]These results are robust to many different alterations such as using market values of equity as the measure of value, using equity values derived from both CRSP data and Compustat data in the calculation of value, using historical SIC codes or the Hoberg and Phillips (2013) industry designations to determine industry matches.

relevant characteristics that are missed when matching is done solely within segment industry. In this section, we construct a simple alternative measure of excess value based on CEM that controls for size and age, and show that given this measure, there is no significant value difference between focused and diversified firms.

We begin by using the coarsened exact matching (CEM) technology from the previous section; that is, we form strata each year based on sales and age holding years constant, and then drop all strata that do not include both a diversified and a focused firm to ensure common support for the distribution. Within each strata firms are locally "close" on these matched value characteristics, which suggests a natural measure of excess value in the spirit of Berger and Ofek (1995). We select the median focused firm within each strata as our benchmark, and form an excess value measure by taking the log-ratio of the value of each firm in the strata divided by the value of the median focused firm in that strata.[26]

Table 8 presents summary statistics about the differences between firms and their median benchmark comparison firms for both constructions of the excess value measure (we call the traditional Berger and Ofek measure "industry-matched" and our new CEM based measure "strata-matched"). For the strata-matched measure, this is the difference between each firm and the median focused firm in each strata. For the industry matched (traditional) measure of excess value, this is the difference between each firm and the imputed benchmark firm formed from the sales-weighted SIC code matched segments.

[26] To ensure direct comparability between the new measure and the traditional one we also trimmed excess values less than -1.386 and greater than 1.386 as in Berger and Ofek (1995). There is slightly more noise in the new strata-matched measure than the traditional one, so we experimented with various trimming schemes either dropping observations as detailed above or winsorizing at various percentiles (1%, 2%, 5%, and 10%). Our results are robust to all of the various trimming schemes, so we use the simplest one used previously by Berger and Ofek (1995) in this analysis. Even though sales within each strata are very close by construction, we also replicate our results by using the log-ratio of each firm's market-to-sales ratios rather than just the ratio of market values.

The traditional measure does a terrible job of balancing across value-relevant characteristics, whereas the strata-matched version is very close in both mean and median differences. Consistently, the traditional industry-matched excess value measure shows a 12.1% equally weighted median discount for diversified firms. However, once the key value characteristics of sales and age are matched within strata, diversified firms show a 8.09% median premium. Using industry as a basis for constructing benchmark firms and ignoring all other value-relevant characteristics results in the traditional discount; using only two value-relevant characteristics suggested by asset pricing models such as Pástor and Veronesi (2003) results in a premium for diversified firms in our univariate tests. We thus conclude that the diversification discount discussed and theoretically addressed so extensively in the prior literature is an artifact of using a biased benchmark firm for comparison.

Finally, Table 9 shows the results from various regression models using the industry-matched excess value and the strata-matched excess value as separate dependent variables. All of the models with the industry-matched excess value as the dependent variable show a discount, and the discount is not ameliorated by the addition of control variables similar to those used in Berger and Ofek (1995) [size (ln(assets)), profitability (EBITDA/sales), and investment intensity (capital expenditures/sales)] or the addition of controls for variables we use to match firms (sales and age). Our results are very consistent with the regressions from Berger and Ofek (1995) using their excess value measure.

However, when we use the strata-matched excess value measure, we show no diversification discount once characteristics are directly controlled for in the measure itself and other controls are included. This emphasizes the need to correctly construct the excess value measure in the first place; simply adding controls for value-relevant characteristics is not enough to mitigate the biases created by nonlinearly compounding such characteristics into the dependent variable.

The results using our new excess value measure further support one of our main points: the traditional construction of the diversification discount ignores important determinants of value and is thus biased towards finding value destruction. Using a different measure constructed to properly control for characteristics known to covary with value leads to the conclusion that at the firm level there is no diversification discount.

5. Conclusion

Since the seminal paper of Berger and Ofek (1995), many studies have been done to examine why diversified firms are worth less than an imputed firm value derived from median industry matched focused firm market-to-sales ratios. In this paper we show that this difference is manufactured simply from two facts: matching large, old diversified firms to small, young focused firms in conjunction with market-to-sales ratios that decline with sales and age. As a consequence, the literature that seeks to explain the discount either by inefficiencies associated with corporate form or by endogeneity is likely explaining something else altogether. Indeed, if agency and inefficient internal capital markets are primarily driving the discount, then correctly matching large, old diversified firms (where these problems should be most noticeable) to large, old focused firms should magnify the discount rather than erasing it.

We also show that industry matching at the segment level is fraught with errors and is at best close to random assignment of industry in its effects on the excess value measure. Controlling for industry in the measure of excess value to the exclusion of size and age essentially compares apples to oranges. We note that the size discrepancy between focused and diversified firms also creates a premium in large diversified firms that are very important to the overall size of the market; rather than an aggregate loss to the economy, diversification (even traditionally measured) generates value-weighted gains. While it is commonly asserted that controlling for biases generated by selection is an explanation for the diversification discount, we show that this effect has more to do with a lack of statistical power than with endogenous selection.

We employ a novel non-parametric matching technique to control for value-relevant characteristics (suggested by, but not necessarily exclusively caused by growth rate uncertainty as motivated by Pástor and Veronesi (2003) and Hund, Monk, and Tice (2010)). Once we control for sales and age at the firm level, we show that there is no diversification discount. In addition, we create an alternative measure of excess value based on our matching algorithms, and show that this measure is not related to corporate form in regressions based on the Berger and Ofek (1995) methodology that is prevalent in the diversification literature.

It may be fruitful to now explore the potential dimensions and contexts along which the conglomerate form affects value, such as advantages in labor markets (as in Tate and Yang (2014)), alleviating credit constraints (as in Dimitrov and Tice (2006)), compensation for better performance during economic crises (as in Kuppuswamy, Serafeim, and Villalonga (2012)), or higher product differentiation (as in Hoberg and Phillips (2012)). Most interestingly, understanding the determinants of value in large and old diversified firms should shed much more light on the drivers of value creation or destruction in the entire economy. We leave this for further research.

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Tables

Table 1: Within Industry Variation in Market-to-Sales

This table reports the summary statistics of the market-to-sales ratio of the median focused firm in every four-digit SIC code over the period 1977–2012 contained in our sample. Market-to-sales is calculated as the ratio of total capital (market value of end-of-fiscal year equity plus book value of debt) to total sales. The summary statistics are for the market-to-sales ratio of the median focused firm averaged over one-digit SIC codes and years. The statistics for adjacent differences are calculated using the absolute value of the difference in median market-to-sales ratios across adjacent (ascending) four-digit SIC codes, averaged across one-digit SIC codes and years.

	Summary Statistics			Adjacent Differences (4-digit)			
SIC 1-Digit	N	Mean	Std Dev.	N	Mean	Median	Std Dev.
0	8	2.604	1.854	40	2.191	2.202	1.816
1	36	1.707	1.704	544	0.994	0.588	1.164
2	36	1.044	1.024	3,779	0.760	0.445	1.061
3	36	1.066	0.798	5,114	0.678	0.438	0.819
4	36	2.044	1.668	761	1.511	1.042	1.563
5	36	0.614	0.540	2,576	0.473	0.280	0.588
7	36	1.682	1.424	1,392	1.397	0.828	1.634
8	36	1.701	1.577	721	1.494	0.862	1.855
Average		1.445	1.267		0.828	0.510	1.019

Table 2: Excess Value Measures Generated By Random Industry Assignment

This table reports results on excess value measures resulting from various randomization schemes for focused industry SIC (Standard Industrial Classification) codes. Panel A shows the mean and median excess value measures of diversified firms calculated using the methodology in Berger and Ofek (1995) and the coefficient on the diversification dummy in a regression of excess value on the natural logarithm of total assets, capital expenditures-to-sales, profitability, and leverage, as in Berger and Ofek (1995). The "1-digit" results assign focused firms randomly to SIC codes within the industry defined by the first digit of their SIC code (that is, a focused firm with SIC code 3699 could be assigned any code between 3000–3999), and the "2-digit" and "3-digit" results follow a similar pattern. Diversified firms retain their actual segment industry classification. The randomization is repeated 1000 times and the range between the 5th and 95th percentiles of the generated distribution is reported below the estimate in parentheses. Panel B reports the results of a similar exercise in which excess value measures of diversified firms are computed as in Berger and Ofek (1995), but focused firm SIC codes are shifted up or down by 1, 10, or 100 before the calculation. The difference up and difference down are calculated as the difference from the actual to the shifted estimates and standard errors are reported beneath the estimates.

Panel A

Randomize within:	Mean	Median	Coefficient
1-digit	-0.144	-0.172	-0.147
	(0.015)	(0.015)	(0.015)
2-digit	-0.121	-0.134	-0.141
	(0.010)	(0.010)	(0.010)
3-digit	-0.108	-0.120	-0.133
	(0.005)	(0.005)	(0.005)

Panel B

Shift by:	Excess Value	Up	Down	Difference Up	Difference Down
1	-0.110	-0.108	-0.110	0.001	0.002
	(0.562)	(0.561)	(0.561)	(0.129)	(0.068)
10	-0.110	-0.111	-0.110	0.001	0.000
	(0.562)	(0.563)	(0.562)	(0.077)	(0.029)
100	-0.110	-0.111	-0.110	0.000	-0.001
	(0.562)	(0.565)	(0.563)	(0.088)	(0.065)

Table 3: Weighted Excess Value Averages by Year

This table presents results for the excess value (EV) as computed in Berger and Ofek (1995) for diversified firms averaged by year. The Weighted Mean EV super-column represents the mean excess value weighted equally ("Equal"), by market value of equity ("MVE"), and by total capitalization ("V"). MVE is the firm fiscal year end market value of equity in millions from CRSP. Total capitalization of the firm is calculated as MVE plus the book value of debt in millions. $\overline{V}$ represents mean total capitalization. Weighted Loss/Gain is computed as the Equal- (V-) weighted mean EV multiplied by the mean capitalization of the firm, $\overline{V}$. The percentage of diversified firms with an excess value measure greater than or equal to zero in a particular year is provided in the %Prem column. All dollar values are nominal.

		Weighted Mean EV				Weighted Loss/Gain		
Year	N	Equal	MVE	V	$\overline{V}$	Equal	V	%Prem
1977	854	-0.073	0.319	0.218	432	-32	94	42
1978	977	-0.086	0.193	0.123	422	-36	52	41
1979	967	-0.123	0.094	0.027	488	-60	13	38
1980	914	-0.123	0.109	0.037	600	-74	22	38
1981	896	-0.143	0.154	0.071	589	-84	42	39
1982	861	-0.172	0.101	0.037	640	-110	24	37
1983	825	-0.186	0.004	-0.032	793	-148	-26	33
1984	810	-0.149	0.036	-0.002	791	-118	-2	38
1985	794	-0.138	0.103	0.054	990	-136	54	37
1986	719	-0.096	0.179	0.131	1,258	-121	165	41
1987	664	-0.075	0.256	0.177	1,346	-100	238	44
1988	647	-0.098	0.188	0.091	1,349	-133	123	40
1989	594	-0.095	0.366	0.254	1,648	-157	418	44
1990	569	-0.096	0.428	0.300	1,720	-164	516	43
1991	574	-0.127	0.416	0.263	2,142	-271	563	40
1992	596	-0.099	0.335	0.203	2,099	-207	426	43
1993	591	-0.102	0.208	0.085	2,184	-224	186	44
1994	616	-0.134	0.210	0.102	2,001	-269	203	40
1995	610	-0.122	0.291	0.220	2,191	-267	483	42
1996	600	-0.084	0.307	0.243	2,758	-231	669	46
1997	569	-0.096	0.404	0.348	3,531	-340	1,230	44
1998	917	-0.022	0.738	0.574	3,523	-79	2,023	48
1999	1,013	-0.054	0.530	0.462	4,196	-226	1,940	47
2000	928	-0.090	0.451	0.356	3,932	-352	1,398	44
2001	844	-0.120	0.341	0.237	4,408	-527	1,046	42
2002	815	-0.075	0.404	0.287	3,748	-281	1,076	46
2003	755	-0.149	0.319	0.230	5,236	-781	1,206	41
2004	739	-0.149	0.327	0.217	5,684	-846	1,232	41
2005	712	-0.140	0.241	0.171	5,460	-762	936	41
2006	699	-0.147	0.199	0.110	6,646	-976	730	39
2007	638	-0.098	0.242	0.178	7,278	-715	1,294	42
2008	651	-0.060	0.337	0.259	4,934	-298	1,280	47
2009	657	-0.110	0.214	0.141	5,999	-659	846	44
2010	633	-0.103	0.282	0.211	7,225	-747	1,522	45
2011	631	-0.092	0.309	0.232	7,922	-725	1,842	43
2012	613	-0.156	0.321	0.248	9,987	-1,553	2,479	39
Average		-0.110	0.321	0.234	3,083	-340	720	42

Table 4: Summary Statistics by Diversification Status

This table presents summary statistics for industry-year matched firms, focused firms, and diversified firms from 1977–2012. The IY-Matched column reports the statistics for the industry-year matched focused benchmark firms according to the algorithm in Berger and Ofek (1995). Using the Compustat segment file, firms are categorized into focused (one business segment) and diversified (greater than one business segment). MVE is the firm fiscal year-end market value of equity from CRSP. V is the total capitalization of the firm calculated as MVE plus the book value of debt. Sales ($M), Assets ($M), EBITDA ($M), and Profit Margin (EBITDA/Sales) are from Compustat data. Age is firm age calculated using data and methods from Jovanovic and Rousseau (2001). Sales Match (%) and Age Match (%) indicate the average percentage difference between a firm type and its match, weighted by sales for diversified firms. Return Volatility and Excess Return Volatility are calculated respectively as the standard deviation of monthly returns and monthly returns net of the market index from CRSP data. Median values are in brackets below mean values.

	IY-Matched	Focused	Diversified
Sales	1,341	1,129	2,489
	[197]	[172]	[392]
Sales Match (%)	100	509	1,522
	[100]	[91.2]	[224]
Age	29.5	26.5	44.9
	[19]	[17]	[31]
Age Match (%)	100	202	342
	[100]	[100]	[168]
Assets	1,269	1,163	2,705
	[167]	[158]	[336]
atmatchdiffpc	99.9	569	1,882
	[100]	[90]	[230]
MVE	985	1,137	2,369
	[123]	[134]	[209]
V	1,365	1,468	3,087
	[186]	[190]	[331]
V/Sales	1.22	1.67	1.16
	[.868]	[1]	[.792]
EBITDA	174	165	381
	[20.3]	[17.7]	[41.8]
Profit Margin	.114	.112	.119
	[.105]	[.106]	[.11]
Return Volatility	.137	.142	.122
	[.119]	[.124]	[.105]
Excess Return Volatility	.127	.133	.111
	[.11]	[.114]	[.0934]
Observations	7,170	60,265	26,427

Table 5: Bootstrapped Excess Value

This table presents the results from a falsification test that swaps sales-matched focused firms for diversified firms in the calculation of excess value (EV). The diversified firm and all segments of that firm are matched (with replacement) to the focused firm with the most similar sales and the excess value ("Real" EV) is calculated as the log-ratio of the market-to-sales of the diversified firm to the sales-weighted average market-to-sales ratio of the matched focused firm segment level matches. "Fake" EV is then calculated by swapping the sales-matched focused firm for the diversified firm in the calculation. Difference is the difference between these quantities. The entire data set is then block-resampled and the calculation is repeated 500 times to generate standard errors and t-statistics for the difference.

	"Real" EV	"Fake" EV	Difference		
	Mean	Mean	Mean	σ	t-stat
Full Sample	-0.154	-0.111	-0.042	0.013	-3.266
Sales >250	-0.121	-0.102	-0.019	0.017	-1.072
Sales >500	-0.113	-0.102	-0.011	0.020	-0.529
Sales >750	-0.106	-0.091	-0.015	0.023	-0.658
Sales >1000	-0.100	-0.090	-0.010	0.025	-0.387

Table 6: Replication of Villalonga (2004b)

The following table presents results from Villalonga (2004b) alongside those from a replication of it using the same time period of 1978–1997 and using a longer time period of 1997–2013. Column headings labeled "Villalonga" are taken directly from the original paper. Panel A reports summary statistics for the mean and median of the sales-weighted excess value of diversified and focused firms, where "diversified" ("focused") means firms with more than one (one) business segment. Panel B reports various statistics for the sample of diversifying firms (i.e., firms that are focused in year t-1, become diversified in year t, and remain diversified in year t+1) and focused firms after propensity score matching using the reduced model of Villalonga (2004b). Panel C reports the effects of diversifying on the change in excess value from t-1 to t+1 using two methods: a one-stage OLS regression and a two-stage propensity score matching that results in the average treatment effect on the treated.

Panel A: Summary Statistics (Comparable to Villalonga (2004b), Table 1)

	Diversified			Focused		
	Villalonga	1978–1997	1977–2013	Villalonga	1978–1997	1977–2013
Mean EV	-0.095	-0.096	-0.096	.	-0.004	-0.003
Median EV	-0.105	-0.099	-0.100	.	0.000	0.000
N (firm-years)	20,173	17,832	23,837	40,757[a]	39,612	66,959

Panel B: Matched Sample (Comparable to Villalonga (2004b), Table 4)

	Diversifying			Focused, [t-1 to t+1]		
	Villalonga	1978–1997	1977–2013	Villalonga	1978–1997	1977–2013
N (firm-years)	150	387	689	23,691	25,746	41,303
ln(Assets)	5.87	5.23	5.53	5.16	5.05	5.37
EBIT/Sales	0.87[b]	0.07	0.06	0.09	0.08	0.07
CAPX/Sales	0.14	0.12	0.10	0.09	0.09	0.10
Ind. Adj. q in prior year	0.20	-0.06	-0.13	0.04	-0.04	-0.06
Ind q in prior year	1.23	1.23	1.43	1.30	1.33	1.48

Panel C: Treatment Effects (Comparable to Villalonga (2004b), Table 5)

	Reduced Model			Extended Model		
	Villalonga	1978–1997	1977–2013	Villalonga	1978–1997	1977–2013
OLS	-0.073	-0.037	-0.082	-0.139	-0.035	-0.076
t-stat	-1.48	-1.53	-4.13	-2.34	-1.43	-3.78
Avg Treatment on Treated	-0.027	-0.026	-0.078	-0.103	-0.027	-0.066
z-stat[c]	-0.48	-1.04	-3.66	-1.60	-1.22	-3.27
N Diversifying (firm-years)	150	387	689	109	380	681
N Focused (firm-years)	23,691	25,746	41,303	12,043	25,554	41,093

[a] This total is deduced using the total firm-years of 60,930 provided.

[b] Probable typographical error in the original paper. This value is 0.09 for diversifying firms using the sample for the extended model.

[c] We implement the same matching estimator as the original paper, but calculate standard errors using an updated procedure from Abadie and Imbens (2011).

Table 7: Diversification Effects on Value Using Coarsened Exact Matching

This table reports sample average treatment effects on value for diversified firms compared to focused firms (labeled "Treatment") and the matching statistics for given covariates. Value is measured as the total capitalization of the firm in millions calculated as the firm fiscal year-end market value of equity from CRSP plus the book value of debt. Titled columns indicate the level of matching of diversified firms to focused firms: "Unmatched" indicates no matching; "Matched" indicates matched results on sales and age; "MatchedYr" indicates matched results on sales, age, and year; and "MatchedYrInd" indicates matched results on sales, age, year, and one-digit SIC code industry. Sales (in millions) is computed from Compustat, and Age is calculated using methods and data from Jovanovic and Rousseau (2001). Diversified firms are matched with focused firms using the coarsened exact matching algorithm from Iacus, King, and Porro (2011a) for data from 1977–2012. Diversified firms are compared against all focused firms within their coarsened strata, with weights computed proportionally within the strata and strata defined using the bin selection algorithm in Shimazaki and Shinomoto (2007). Table entries for sales and age reflect differences between diversified and focused firms at the means and the 25th (25%), 50th (50%), and 75th (75%) percentiles. The L1 statistic is a measure of overall imbalance with perfect balance (complete separation) indicated by a value of zero (one). Asterisks indicate the statistical significance of the coefficient: *** for 10%, ** for 5%, and * for 1%.

	Unmatched	Matched	MatchedYr	MatchedYrInd
Treatment	1,531.8***	-60.1	-59.3	-54.0
Sales Differences				
mean	1,508	179	209	232
25%	45	25	28	29
50%	222	131	131	127
75%	1,128	621	604	517
L1	0.184	0.098	0.116	0.127
Age Differences				
mean	17.8	0.3	0.3	0.3
25%	6.0	0.0	0.0	0.0
50%	14.0	0.0	0.0	0.0
75%	33.0	0.0	0.0	0.0
L1	0.232	0.037	0.033	0.033
Overall Model				
N_Focused	65,780	65,673	65,013	63,358
N_Diversified	28,329	28,183	27,244	25,611
L1	0.277	0.181	0.433	0.626

Table 8: Summary Statistics on Alternate Measures of Excess Value

This table reports summary statistics on the average difference between firms and their median matched firm with the simple average presented above the median value for each variable. For the Industry-Matched columns, the values represent the distance between the firm and the imputed firm constructed from the median focused firm in each four-digit (or three-digit, depending on whether five focused firms exist at the four-digit level) using sales weights and matching on segment industry codes and year as in Berger and Ofek (1995). For focused firms, this will represent simply the distance between each focused firm and the median focused firm in each industry classification. For the Strata-Matched columns, the values represent the distance between the firm and the median focused firm within each strata formed from coarsened exact matching on sales and age, holding years constant. Extreme values for both excess value measures are trimmed (where the excess value measure is below -1.386 or above 1.386). The Strata-Matched excess value measure also has common support; that is, the measure is not computed for strata where there are not both focused and diversified firms. Excess Value is calculated as the log of firm total capitalization (V) over the imputed value taken from matched focused firms. Data to calculate V, Sales, and Profit Margin (PM=EBITDA/Sales) are taken from Compustat. Age is calculated using methods and data from Jovanovic and Rousseau (2001), and Volatility is the standard deviation of monthly returns.

	Industry-Matched		Strata-Matched	
	Focused	Diversified	Focused	Diversified
EV	-.00646	-.11	-.0116	.0553
	[0]	[-.121]	[0]	[.0809]
V-med(V)	76.7	1,866	174	149
	[-8]	[27.5]	[0]	[12.7]
Sales-med(Sales)	-53.9	1,324	56.9	137
	[-8.7]	[53.6]	[-7.78]	[20]
Age-med(Age)	-.0545	14.5	-.284	-.0603
	[0]	[6.55]	[0]	[0]
Volatility-med(Volatility)	-.00223	-.0112	-.00967	-.00956
	[-.000525]	[-.0164]	[-.0065]	[-.00805]
PM-med(PM)	.00409	.00545	.00495	.00485
	[0]	[.000927]	[0]	[.000371]
Observations	60,268	26,426	41,879	16,848

Table 9: Regressions of Excess Value Measures on Firm Characteristics

This table reports results for the regression of Industry-Matched and Strata-Matched excess value measures on firm characteristics. Industry-matched excess values are constructed as in Berger and Ofek (1995). Strata-matched excess values are constructed as the log-ratio of the total capitalization of each firm to the median focused firm within each strata formed by coarsened exact matching on sales, age, and year. Firms not in the common support and with extreme values are dropped to correspond with Berger and Ofek (1995). The Diversification Dummy equals one if a firm has more than one business segment in the Compustat Segment database. Assets, sales, capital expenditures (Capx), and Profit Margin (EBITDA/sales) are computed from Compustat. Age is calculated using methods and data from Jovanovic and Rousseau (2001). Standard errors that are clustered at the firm level are in parentheses below the coefficients. Asterisks indicate the statistical significance of the coefficient: * for 10%, ** for 5%, and *** for 1%.

	Industry-Matched EV			Strata-Matched EV		
Diversification Dummy	-0.104***	-0.130***	-0.112***	0.067***	-0.008	0.023
	(0.010)	(0.010)	(0.010)	(0.015)	(0.014)	(0.015)
ln(Assets)		0.044***	0.271***		0.192***	0.266***
		(0.003)	(0.008)		(0.006)	(0.011)
Capx/Sales		0.238***	-0.065***		0.238***	0.130***
		(0.016)	(0.016)		(0.022)	(0.022)
Profit Margin		0.251***	0.221***		0.255***	0.269***
		(0.027)	(0.022)		(0.033)	(0.033)
Age			0.000*			-0.002***
			(0.000)			(0.000)
ln(Sales)			-0.255***			-0.063***
			(0.009)			(0.011)
Constant	-0.006	-0.290***	-0.096***	-0.011	-1.070***	-1.054***
	(0.006)	(0.015)	(0.017)	(0.008)	(0.029)	(0.031)
R-squared	0.007	0.051	0.107	0.002	0.180	0.192
Observations	86,994	86,112	86,031	58,911	58,265	58,206

Figures

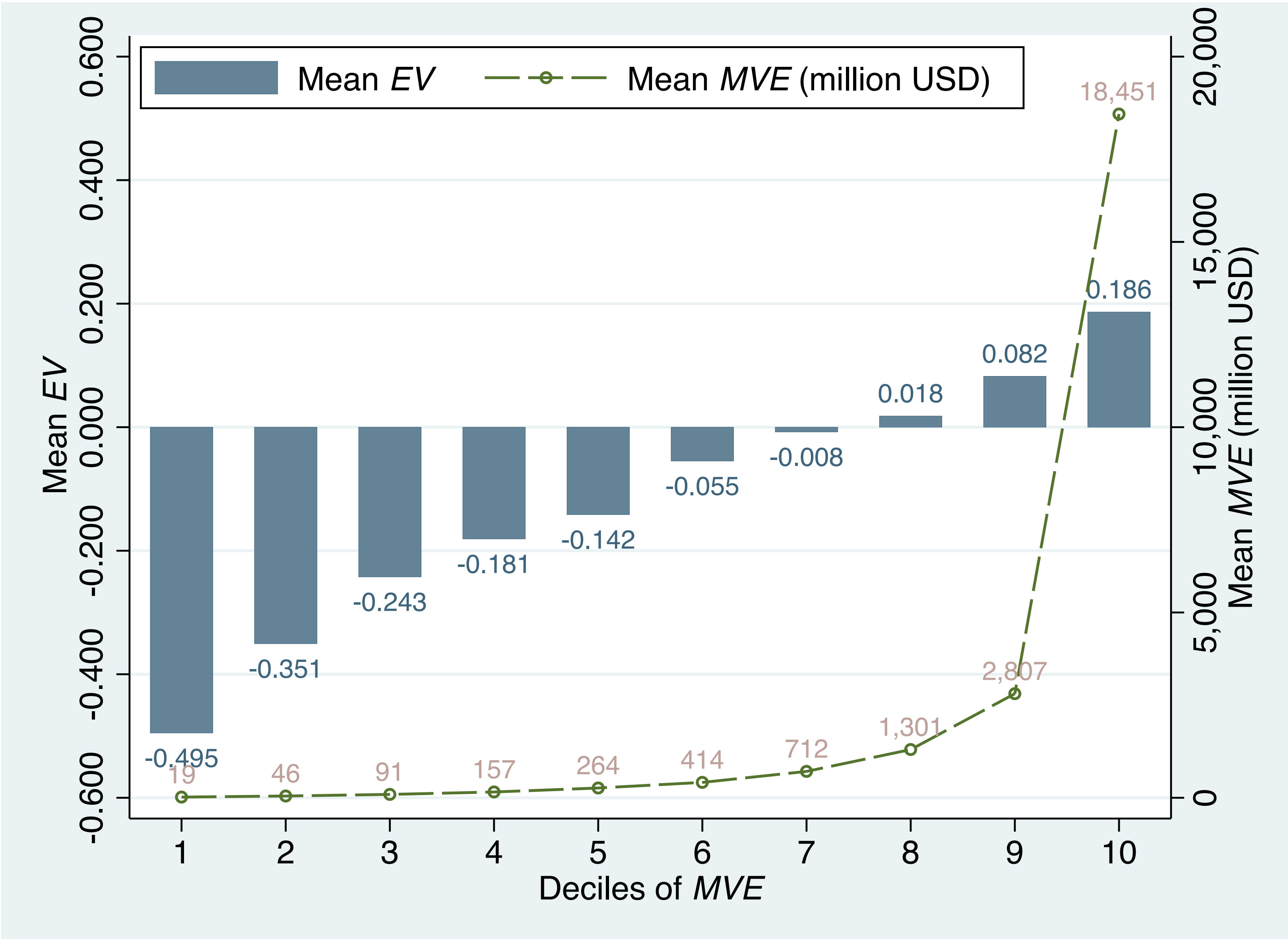

Figure 1: **Mean Excess Value and Market Value of Equity by Decile.** This figure presents the mean excess values for diversified firms computed as in Berger and Ofek (1995) for deciles of market value of equity (MVE) at the beginning of each year for the period between 1977–2012. The right-hand axis presents the mean market value of equity for the firms in each decile for the same period.

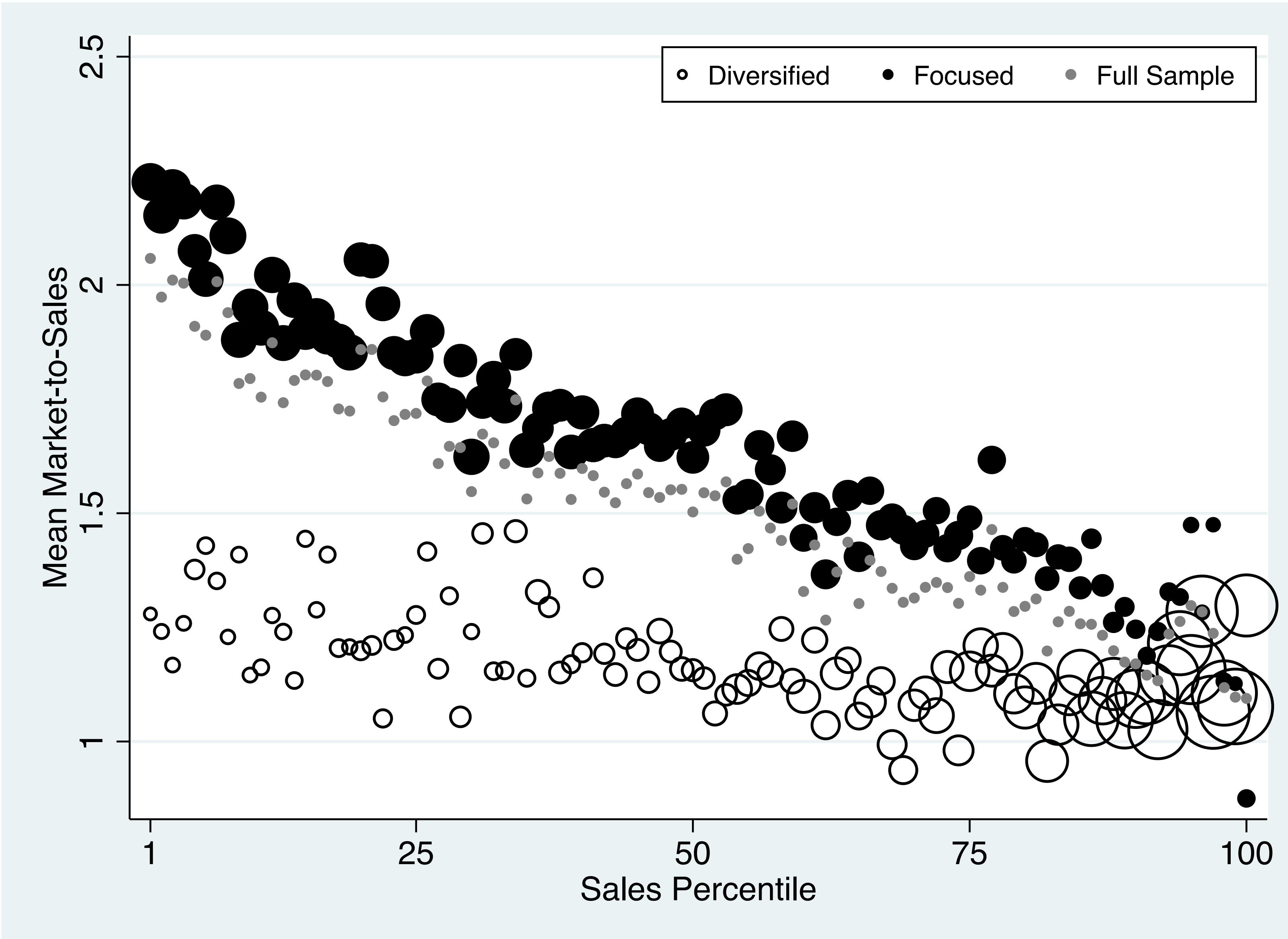

Figure 2: **Market-to-Sales by Sales Percentile.** This figure presents the average total capitalization-to-sales ratios over the period 1977–2012 for diversified firms, focused firms, and all firms across sales percentiles that are calculated by sorting firms each year into percentiles by lagged sales using the unconditional distribution of all firms. Averages are computed for each percentile across years for the different subsamples. The size of the each bubble reflects the degree by with the proportion of firms in each sales percentile exceeds the expectation of the distribution from the unconditional (full) sample.

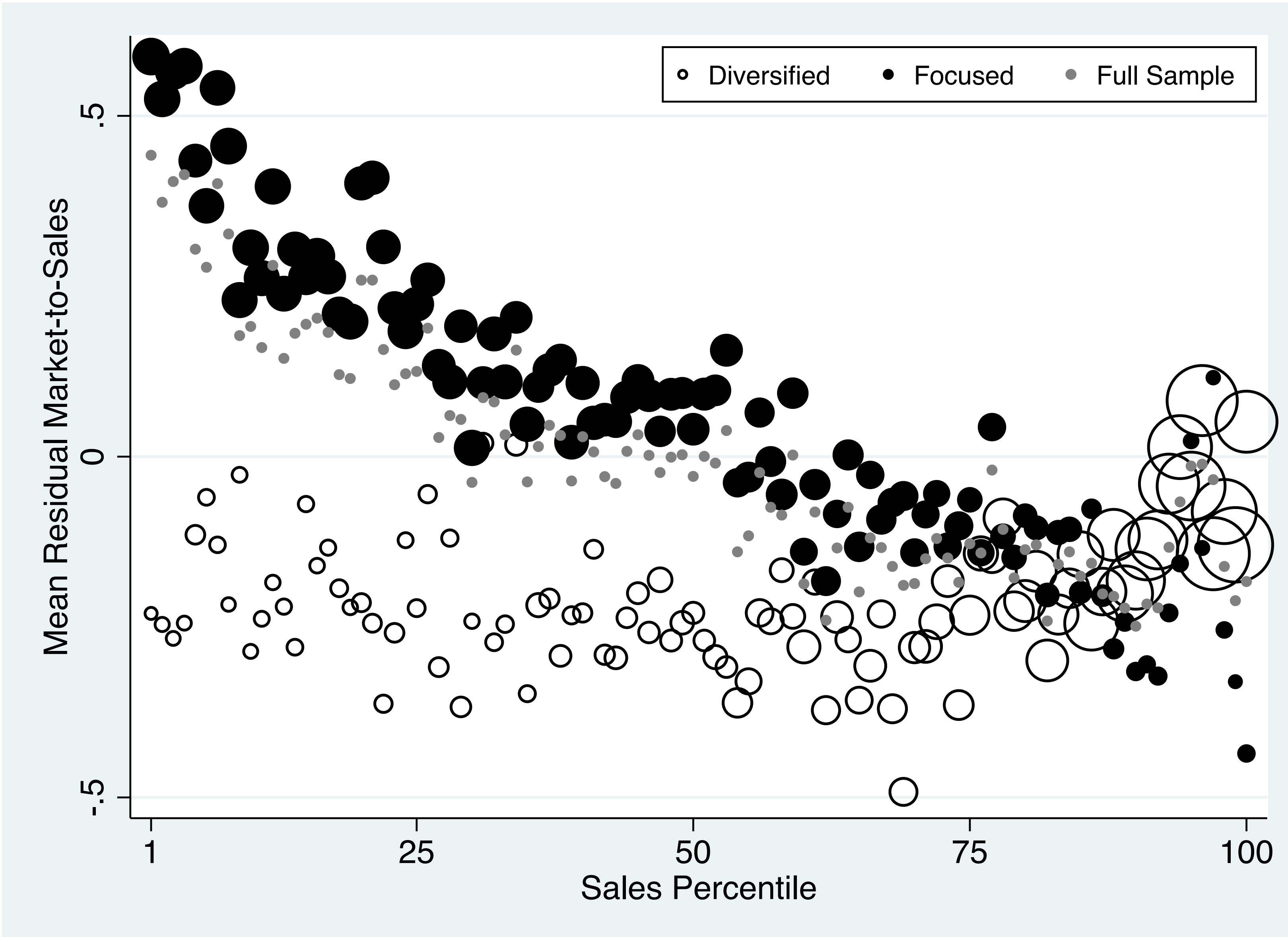

Figure 3: **Market-to-Sales Residuals by Sales Percentile.** This figure shows mean residuals from yearly cross-sectional regressions of total capitalization-to-sales on a constant and age by sales percentiles for focused, diversified, and a combined sample of firms. Each year from 1977–2012 firms are sorted into percentiles by sales using the unconditional distribution of all firms and mean residuals are computed for each percentile across years for the different subsamples. The size of the each bubble reflects the degree by with the proportion of firms in each sales percentile exceeds the expectation of the distribution from the unconditional (full) sample.

Appendix A Prominence of the Chop-shop Method

We provide the following appendix to indicate the prominence of the empirical method of imputing a value for a firm by combining benchmark (firm) values for divisions, and then comparing the imputed value to the actual value of the firm. The term "chop-shop" has been used in reference to this approach due to its similarity to the business of separating a useful item (e.g., an automobile) into parts (e.g., windows, brake lights, and alternators) to be sold. Of course, the goal of a chop-shop is to sell the parts for more than the value of the whole. One goal of using the associated empirical method in assessing firm value is the same: to determine whether the parts are worth more than the whole.

Berger and Ofek (1995) and Lang and Stulz (1994) use the chop-shop approach to assess the value of corporate diversification. These papers show that the "excess value," which equals the log ratio of the subject firm value to imputed value, is negative on average for diversified firms. In other words, the whole is worth less than its parts, which in this context is called a "diversification discount." The following section provides a number of recent citations and details that use the methods of these papers or similar methods. This review is by no means exhaustive.

- Duchin and Sosyura (2013) examine the impacts of social connections between divisional managers and CEOs on excess value. A similar chop-shop method is used to calculate a relative investment efficiency variable that uses focused firms' Tobin's Q as a benchmark as in Rajan, Servaes, and Zingales (2000).

- To analyze whether diversified firms have a lower cost of capital than focused firms Hann, Ogneva, and Ozbas (2013) create "excess cost of capital," which is whole firm cost of capital relative to an implied cost of capital using focused firms' cost of capital as the benchmark.

- Though Hoberg and Phillips (2013) take a novel approach to the problem of assigning firms to industries, many of their tests utilize traditional chop-shop methods to create their new measure of excess value. Much of the explanatory power shown for their measure in the context of valuation appears to derive from the model in which firms are first matched according to accounting characteristics.

- Kuppuswamy, Serafeim, and Villalonga (2012) analyze the effects of institutional factors on excess value.

- Schneider and Spalt (2014) show that the conglomerates comprised of segments with high expected skewness tend to have substantially low excess values and CEOs overinvest in such high skewness segments consistent with a "long shot bias."

- To examine bond yield differences between diversified and focused firms Franco, Urcan, and Vasvari (2013) calculate an "excess yield" using a chop-shop approach.

- Hoechle, Schmid, Walter, and Yermack (2012) examine the effects of corporate governance on excess value.

- Mitton (2012) creates and examines a measure of "excess productivity" by comparing the productivity of conglomerates to an imputed value taken from single segment firms.

- Khorana, Shivdasani, Stendevad, and Sanzhar (2011) show that a diversification discount exists in most regions of the world.

- Subramaniam, Tang, Yue, and Zhou (2011) use the chop-shop approach to create a measure of industry-adjusted cash holdings.

- In a robustness test of their findings on agency cost motivations for aggregation in financial reporting, Bens, Berger, and Monahan (2011) bifurcate their sample into discount and premium firms according to the chop-shop method.

Appendix B Weighted EV by Year—Focused Firms

This table presents results for the excess value (EV) as computed in Berger and Ofek (1995) for focused firms averaged by year. The Weighted Mean EV super-column represents the mean excess value weighted equally ("Equal"), by market value of equity ("MVE"), and by total capitalization ("V"). Market value of equity is the firm fiscal year end market value of equity in millions from CRSP. Total capitalization of the firm is calculated as MVE plus the book value of debt in millions. $\overline{V}$ represents mean total capitalization. Weighted Loss/Gain is computed as the Equal- (V-) weighted mean EV multiplied by the mean capitalization of the firm, $\overline{V}$. The percentage of focused firms with an excess value measure greater than or equal to zero in a particular year is provided in the %Prem column. All dollar values are nominal.

		Weighted Mean EV				Weighted Loss/Gain		
Year	N	Equal	MVE	V	$\overline{V}$	Equal	V	%Prem
1977	725	0.014	0.303	0.222	363	5	81	42
1978	976	0.000	0.236	0.146	326	0	48	41
1979	980	-0.014	0.178	0.111	337	-5	37	38
1980	956	-0.001	0.124	0.057	370	-0	21	38
1981	986	0.006	0.156	0.076	392	2	30	39
1982	1,066	-0.021	0.267	0.167	475	-10	80	37
1983	1,132	-0.019	0.194	0.119	543	-10	65	33
1984	1,263	0.019	0.289	0.204	435	8	89	38
1985	1,356	0.015	0.224	0.145	580	8	84	37
1986	1,379	-0.004	0.211	0.144	618	-3	89	41
1987	1,573	-0.003	0.249	0.154	600	-2	92	44
1988	1,685	-0.011	0.272	0.179	584	-6	104	40
1989	1,651	-0.000	0.319	0.232	700	-0	162	44
1990	1,643	0.000	0.475	0.347	684	0	237	43
1991	1,656	-0.022	0.422	0.320	824	-18	264	40
1992	1,810	-0.004	0.402	0.312	864	-4	269	43
1993	2,057	-0.002	0.352	0.256	907	-2	233	44
1994	2,375	0.006	0.363	0.290	892	5	259	40
1995	2,558	-0.006	0.312	0.230	1,136	-7	262	42
1996	2,793	-0.010	0.369	0.281	1,275	-13	358	46
1997	3,012	-0.024	0.316	0.249	1,505	-37	375	44
1998	2,373	-0.015	0.427	0.361	1,050	-16	379	48
1999	1,991	-0.048	0.496	0.415	1,481	-72	615	47
2000	1,902	-0.037	0.529	0.461	1,840	-68	847	44
2001	1,893	0.009	0.384	0.339	1,845	16	625	42
2002	1,860	0.001	0.449	0.381	1,589	2	605	46
2003	1,823	0.010	0.336	0.288	2,142	21	618	41
2004	1,800	0.002	0.338	0.288	2,203	5	634	41
2005	1,791	0.003	0.370	0.326	2,497	7	814	41
2006	1,805	-0.023	0.281	0.239	2,684	-62	642	39
2007	1,749	-0.017	0.312	0.272	3,146	-54	855	42
2008	1,665	-0.000	0.374	0.307	2,287	-0	703	47
2009	1,616	0.001	0.289	0.233	2,744	2	639	44
2010	1,596	0.012	0.274	0.234	3,194	37	749	45
2011	1,551	0.010	0.310	0.240	3,428	33	822	43
2012	1,455	0.003	0.279	0.207	3,864	11	800	39
Average		-0.006	0.342	0.277	1,478	-9	409	42

Appendix C Propensity Score Matching Estimators

This table reports sample average treatment effects on value, V, in the row titled "Difference" along with the standard error and p-value of the effect after propensity score matching of diversified firms to focused firms based on Sales and Age. Mean values for matching variables for diversified firms and focused firm matches are presented with the p-value of the test of the statistical significance of the differences between the mean values. V is the total capitalization of the firm in millions calculated as the firm fiscal year-end market value of equity from CRSP plus the book value of debt. Diversified firms are matched with focused firms using propensity scores from probit regressions. Diversified firms are compared against their three closest matched neighbors with respect to the generated propensity score. Separate columns contain results from matching diversified firms on sales and age using no additional constraints ("Matched"); constraining matches to be within the same year ("MatchedYr"); within the same one-digit SIC code industry and year ("MatchedYrInd"); and within the same 100-level industry code as in Hoberg and Phillips (2013) and year ("MatchedYrIndHP"). Sales (in millions) is computed from Compustat, Age is calculated using methods and data from Jovanovic and Rousseau (2001). Data span the years 1977–2012.

	Matched	MatchedYr	MatchedYrInd	MatchedYrIndHP
V				
Focused	2,487	2,500	2,749	3,318
Diversified	2,704	2,704	2,707	4,800
Difference	-217	-204	42	-1,481
Std Err	99	103	117	278
p-value	0.029	0.048	0.718	0.000
Sales				
Focused	2,295	2,079	1,813	1,741
Diversified	2,329	2,329	2,332	2,861
p-value	0.672	0.001	0.000	0.000
Age				
Focused	43.9	44.2	44.5	42.2
Diversified	43.9	43.9	43.9	44.0
p-value	0.950	0.405	0.075	0.006
Observations (Average Within-group)				
Focused	60,365	1,787	412	48
Diversified	26,265	815	226	25

Propensity score matching provides a method for controlling confounding characteristics in an observational, rather than experimental, context. Specifically, to isolate the effect of organizational form on firm value we must control for variables such as sales and age that are correlated with firm value and organizational form. These variables jointly proxy for the uncertainty of growth rates that is shown to be correlated with firm valuation measures in the model of Pástor and Veronesi (2003). Hund, Monk, and Tice (2010) show that many empirical facts associated with diversification can be explained by interpreting the diversification discount as a difference in uncertainty of growth rates between diversified and focused firms. If diversified firms have lower growth rate uncertainty than focused firms, then it is critical to control for this difference in assessing the effects of organizational form on firm value.

Models using propensity score methods to control for endogeneity in the diversification decision have been used previously, most notably in Villalonga (2004b) and Çolak (2010). Both of these papers model the decision to diversify on a restricted sample of firms that are moving from focused status to diversified status.[27] Importantly we do not use propensity scoring in this context, rather we use propensity scores as a parametric balancing metric to summarize multiple dimensions of potentially confounding covariates.

To estimate propensity scores, we regress diversification status on firm characteristics of sales and age using a probit specification, and compute the propensity score as the predicted value of the regression.[28] We then match each diversified firm to the closest three neighboring focused firms based on their estimated propensity scores, and form the weighted average of their total capitalization (equity market value plus book value of debt) to compare to the matched diversified firm.[29]

Table C presents the results of the propensity score matching procedure for four cases: treating each firm-year observation as independent ("Matched"); matching separately for each year ("MatchedYr"); matching separately within each one-digit SIC code industry and year ("MatchedYrInd"); and matching separately within each 100-level industry code as in

[27]Çolak (2010) also considers the decision to spin-off, or re-focus as a function of endogenous firm characteristics.

[28]Our results do not depend on the particular form of the propensity score regression; they hold whether we compute propensity scores using a logit or as the odds ratio, or whether we include additional variables such as profit margin.

[29]Using five neighbors or a slightly different matching criterion does not alter our results.

Hoberg and Phillips (2013) and year ("MatchedYrIndHP"). Three out of four models produce a diversification premium and all three are statistically significant at traditional levels. The "Matched" case, in which firms can be matched across years, is only accurate under unrealistic stationarity conditions and is primarily presented as a benchmark to compare the accuracy of the matching algorithm in a more realistic yearly context. Simply matching on the two characteristics substantially improves the average discrepancy between diversified and focused firms as compared to the unmatched sample presented in Table 4. The "MatchedYr" model results in a slight diversification premium that is statistically significant at the 5% level, though a significant difference remains in the matched covariate Sales. In the "MatchedYrIndHP" column we use the 100-level text-based industry codes as provided in Hoberg and Phillips (2013) as the industry control. This model further worsens the match on sales and age, decreases the sample size, and results in a statistically significant diversification premium. The results support no diversification discount or even a diversification premium. They do not support a diversification discount. Using a completely different (parametric) matching method, we do not find evidence supporting a diversification discount, confirming the earlier results generated by CEM.