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The Berger-Ofek Diversification Discount Is Just Poor Firm Matching

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ABSTRACT

The widely used measure of diversification value developed by Berger and Ofek (1995) consistently matches large and old diversified firms with small and young focused firms. Since valuation multiples decline with sales and age this approach manufactures a discount. We develop a new measure based on sales and age matching and show that it leads to different and more intuitive conclusions. Using daily returns, we conclude that sales and age matched firms are more than twice as correlated with diversified firms than firms chosen by the Berger and Ofek (1995) methodology and the return-weighted discount is zero. For most firms, the diversification discount is an artifact of the methods used to create it.

Keywords: Diversification Discount, Organizational Structure, Valuation, Matching

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The seminal works of Berger and Ofek (1995) and Lang and Stulz (1994) garnered great 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 focused firms matched by industry classification. This "diversification discount" has been linked to disclosure practices (Bens and Monahan, 2004; Cho, 2015), corporate governance (Hoechle *et al.*, 2012), international diversification (Denis *et al.*, 2002; Creal *et al.*, 2014), allocation of capital to divisions based on social connections (Duchin and Sosyura, 2013), access to external and internal capital (Yan, 2006; Gopalan and Xie, 2011; Matvos and Seru, 2014; Kuppuswamy and Villalonga, 2016), accruals (Demirkan *et al.*, 2012), and firm cost of capital (Hann *et al.*, 2013). The original Berger and Ofek (1995) article has over 1100 citations on Scopus, 887 citations in the Core Collection of Web of Science, and even though published in 1995, has had over 250 Google Scholar citations every year since 2007. We advance a much different interpretation of this value difference: it is simply manufactured by the matching methodology that constructs it.

The value difference which we term the traditional or Berger and Ofek (1995) (hereafter BO 95) excess value measure is calculated as the log-ratio of the market-to-sales ratio of a diversified firm to the sales-weighted average market-to-sales ratios of the median focused firm in the same industry as each segment of the diversified firm. Since market-to-sales ratios decline as sales increase and most focused firms are smaller than diversified firms, the traditional measure generates a discount that is virtually impossible to erase and is related to firm size rather than firm organizational form. Examining the actual matched focused firms, we show in our data (see Table 1) that the BO 95 procedure matches diversified firms to focused firms that are considerably smaller and younger.

The following example clarifies how such a mismatch manufactures a discount. In Fig. 1) we plot the value-to-sales ratios for diversified and focused firms in each percentile of sales. We show that diversified firms are much larger than focused firms, and that value-to-sales ratios decline dramatically as sales increase. Consider a diversified firm with two equal sized

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segments and sales of $400 million. Assume that we calculate its discount by comparing it to two focused firms that are half its size. The market-to-sales ratios for firms in the Compustat universe with sales of approximately $400 million and $200 million are 1.60 and 1.78, respectively, resulting in a calculated discount of 10.7%. This discount results simply from matching firms of different sizes when market-to-sales ratios are decreasing in sales. Put simply, a methodology that consistently matches large diversified firms to portfolios of smaller focused firms manufactures a discount.

Once generated in this way, the diversification discount is remarkably persistent. In a "placebo" test we show that *focused* firms of similar size to diversified firms exhibit nearly identical discounts, and the discount remains the same no matter how we randomize or permute industry assignments. The discount is unchanged if we redefine industries and segments as in Fama and French (1997) or as in Hoberg and Phillips (2016). The discount is unchanged if we match at the 4-digit, 3-digit, or 2-digit levels of SIC codes, and we show there is a discount generated for diversified firms which the BO 95 methodology actually treats as focused.[1] Controls for endogeneity do not appear to remove the diversification discount either. In a replication of Villalonga (2004b) with a much larger sample, we show the diversification discount is left nearly unchanged by difference-in-difference propensity score matching methods.

Our solution follows much of the corporate finance literature by simply matching on characteristics (and later, very broad industry classifications) at the firm level rather than the segment level. We construct a new excess-value measure (hence, the strata-matched excess value measure) by matching diversified firms to "locally-close" (with respect to sales and age) median focused firms and calculating the log-ratio of values. Our new measure suggests that diversification earns a premium, consistent with over 75% of the S&P 500 being diversified and high market values for diversified firms such as Apple and Amazon. Like Kuppuswamy and Villalonga (2016), we find that diversification increased in value during the financial crisis. By extending their analysis back in time however, we show that the traditional measure peaks (i.e., the value of diversification is highest) in 1999–2000 during a period flush with external financing; by contrast, our measure

[1]These are firms with segments in industries with few focused firms and thus the BO 95 methodology matches them at a coarser industry classification. If all the segments of the diversified firm are in the same coarser industry grouping, it is then matched to only one focused firm. Section 5 provides more detail.

reaches its minimum (i.e., the value of diversification is lowest) during this period.

The traditional BO 95 excess value measure and our new strata-matched excess value measure represent nearly orthogonal views on value-relevant characteristics. The BO 95 measure matches narrowly on segment industry and ignores sales and age, whereas our strata-matched measure matches closely on sales and age and ignores segment-level industry. [2] We use daily return covariances to "break the tie" and evaluate which measure is most appropriate for each diversified firm. We then calculate return-weighted excess value measures using weights obtained from decomposing daily return correlations of diversified firms into the portion related to their BO 95 imputed firm portfolios and the portion related to sales- and age-matched portfolios. For almost all firms and especially for large firms, the sales- and age-matched portfolios dominate (similar to the result for β in (Levi and Welch, 2017)), and our return-weighted excess value measure shows that overall focused and diversified firms have very similar values.

Our results have important consequences. Foremost, they imply that the vast research explaining the diversification discount is most likely explaining something else. The explanation that endogeneity biases are responsible for the discount must also be reconsidered given that the discount remains in an updated sample using propensity-score matched difference-in-difference estimates. We show that the traditional method for assessing the value effects of organizational form leads to substantial biases, and we advance a much simpler measure that has intuitive appeal. Paradoxically, we show that segment-level industry classifications are not strongly related to value for diversified firms, and that virtually any permutation or re-definition of industry still leads to a discount using the traditional construction methodology. We are also the first to use daily return covariances to assess the quality of the BO 95 excess value measure and show that it is dominated by our characteristic-matched measure. Last, our results contribute to an emerging literature questioning the importance of industry classifications in the presence of other firm characteristics (see for instance, Levi and Welch (2017) and Asness *et al.* (2014)).

Our paper is closest to a small but very important existing literature on the construction of the excess value measure itself. Both Bevelander

[2] In robustness tests we also show our results are unchanged when our strata-matched measure incorporates broad firm-level industry classifications.

(2002) and Borghesi *et al.* (2007) attempt to incorporate size and age into the measure construction itself, but still are hampered by a reliance on narrow industry classification at the segment level that we show is unwarranted. Custódio (2014) and Mansi and Reeb (2002) focus on measurement discrepancies of goodwill and debt, but still seek to explain the traditionally constructed measure. We are the first to show that the reliance of matching on industry in calculating firm excess value has the unintended consequence of mis-matching on value relevant characteristics that results in a diversification discount. More importantly, we show that matching on value relevant characteristics erases the discount in a comprehensive sample covering more than 30 years.

Our study complements work by Maksimovic and Phillips (2002), Maksimovic and Phillips (2008), Hoberg *et al.* (2014), Khanna and Tice (2001), and Tate and Yang (2015) who show that diversified firms appear to be behaving optimally.[3] Even though these studies still match on industry, they focus on examining actual firm behavior rather than calculating firm excess value to determine if diversified firms behaving efficiently. Nevertheless, our results suggest that the diversified organizational form is not destroying value on average. Our new measure and return-weighting methodology also present a new opportunity to evaluate for *which* firms diversification is efficient.

Section 1 describes our data and calculation of variables, emphasizing some important properties of the traditional construction of the excess value measure. Section 2 details the problems and biases of the existing measure, provides an economic 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 3 details the construction of our new measure and examines the differences and economic consequences of using one measure versus the other. Section 4 uses daily return covariances to weight two competing measures and suggests that sales and age are more relevant value characteristics than industry for most diversified firms. Section 5 examines in detail various definitions of industry and under what conditions and whether industry mis-matching confounds our new measure. Section 6 addresses the potential alternative explanation of selection and provides a replication of Villalonga (2004b), and Section 7 concludes.

[3] See also Maksimovic and Phillips (2013) for a survey of the literature documenting that diversified firms appear to behave efficiently.

1 Data and Sample Construction

1.1 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 1977–2016 and return and market value data from the CRSP monthly returns files. Unlike most studies of the diversification discount, we calculate enterprise value using fiscal year end shares outstanding and prices from CRSP rather than relying on those reported from Compustat, although the traditional discount we calculate is virtually identical to previous studies. Firm annual return, volatility, and market value variables are calculated at the fiscal year end dates from Compustat using monthly CRSP stock return data. In addition, our return-weighted measures use CRSP daily return data from 1977–2016. Firm-years are dropped from the sample according to the BO 95 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 sales. 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 *et al.* (2010).[4] By creating a comparable sample over a 39-year period, it allows for a more comprehensive analysis of the discount and its construction than prior papers.[5] Post SFAS 131, many firms allocate large amounts of assets to a "corporate" segment with zero sales and are allowed latitude to somewhat arbitrarily re-allocate assets across segments, thus rendering asset multipliers incomparable and much more endogenously determined. As such, we only use sales multipliers throughout the paper.

We utilize a number of different classifications and definitions of industries. We use both TNIC and FIC industry classifications derived from the textual analysis in Hoberg and Phillips (2016) and obtained from their

[4] 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).

[5] We exploit the length of our time series in Section 3.4.

data library.[6] Throughout most of the paper, we define diversified firms as firms with more than one business segment in different four-digit SIC codes following the segment aggregation procedure. However, changing the definition of industry will also reclassify firms between focused and diversified, and we address this issue and its consequences in Section 5. We re-organize SIC codes into 10, 30, and 49 industry classifications based on Fama and French (1997). These definitions are available at both the segment and firm level, and allow us to explore the extent to which Fama-French industry classifications change both the number of diversified firms and the measurement of diversified firm excess value.

1.2 Variable definitions

The traditional diversification premium or discount is calculated at the firm level by following the procedures in BO 95, pg. 60. We calculate excess value (EV) as the log-ratio of total capital to the imputed value for the firm at the end of each fiscal year. 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

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

$$EV = \ln(V/Imp(V)) \tag{2}$$

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, 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.

[6] Where we use TNIC and FIC industry classification data, our sample is restricted 1996-2015, which is the latest version of the data available at the authors' data library as of this draft. It is also important to note that these data can not be used to identify individual segment industries.

One important point about the BO 95 excess value measure should be emphasized. It is the log-ratio of the subject firm's market-to-sales ratio over the sales-weighted average market-to-sales ratio of the median focused firm in each segment industry in which the firm operates. Therefore, the 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. Since market-to-sales ratios vary consistently along other dimensions than industry (as documented in Section 2) the diversification discount devolves into a statement about those confounding dimensions rather than one about corporate form.

Because firm age is an important value-relevant characteristic for market-to-sales values (see Pástor and Veronesi, 2003), we carefully consider how age is defined. 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 *et al.* (2010). For the 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, and *Capx/Sales* is the capital expenditures of the firm over sales. *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.

2 Economic Motivation

Diversified firms tend to be larger and older; focused firms tend to be smaller and younger. Value-to-sales ratios are declining in sales and age; newer smaller firms tend to have higher valuation metrics and older bigger firms tend to have lower. These facts together conspire to manufacture a diversification discount using the construction methodology in BO 95.

Simply put, the discount is driven by the size and age difference between the diversified firm (numerator) and its matched portfolio of focused firms (denominator).

Figure 1 provides deeper insight into the empirical differences between diversified and focused firms and how these differences are related to the valuation metric (value-to-sales). It depicts the mean value-to-sales ratio for each percentile of firm 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 "bubbles" in Figure 1. From low to high percentiles of sales, average value-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.

This pattern is consistent with many underlying models of firm fundamentals, though it is beyond our scope to differentiate among these. Most simply, if firms exploit growth options as they age and grow larger, models such as Berk *et al.* (1999) generate higher market-to-sales ratios for younger, smaller firms than older, larger firms. 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. Chang and Yu (2004) link the evolution of a firm's discount or premium to changing uncertainty about the firm and its divisions' informational environment at a microstructure level.

Of particular note is the learning model of Pástor and Veronesi (2003), which predicts that firms with higher uncertainty about their growth rates (younger and smaller firms) 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 *et al.* (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 that 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). Our choice of sales and age as value-relevant characteristics is in part motivated by their high correlation with growth-rate uncertainty.[7] An economic interpretation of our results is the diversification discount is driven by differences in growth-rate uncertainty (as in Hund *et al.*, 2010), and after controlling for that uncertainty the discount disappears.

The construction method of BO 95 amounts to selecting a diversified firm and pairing it with a portfolio of focused firms, matched solely to segment industry. We show in Section 2.1 that on average, diversified firms are matched with focused firms that are 15 times smaller, which in the context of Figure 1 amounts to consistently picking diversified firms from the lower right and matching them with focused firms from the upper left. Indeed, most of the diversified sample is above the 60% percentile of the unconditional sales distribution.

Figure 2 adds age matching to the previous plot (specfically it is a plot of the mean residuals from a regression of market-to-sales on age across sales percentiles). It shows that controlling for age removes much of the distance between diversified and focused firms, especially so above the 60th percentile of the unconditional distribution where most of the diversified firms in our sample are located. This suggests that an excess value measure based on sales and age matching might reduce or eliminate all of the discount; we introduce such a measure, the strata-matched excess value measure, in Section 3.1.

An important caveat is in order, however. BO 95 match exclusively on industry whereas we match primarily on sales and age. We are not saying that industry does not drive value, rather that the industry link to value is exceptionally noisy at granular industry classifications and is swamped by the value-relevance of sales and age. Industry is not a value

[7] In earlier versions and robustness tests, we match on additional characteristics correlated with growth-rate uncertainty (levels of profitability and idiosyncratic volatility). Including these extra variables does not change our results or our measure, and in the interest of simplicity and avoiding endogeneity we focus on sales and age.

factor in the models of either Pástor and Veronesi (2003) or Berk *et al.* (1999) (although growth options and/or growth rate uncertainty could vary by broad industry groupings), and several recent papers have noted that industry is not a particularly strong predictor of beta (Levi and Welch, 2017) or betting against beta strategies (Asness *et al.*, 2014). We do not imply that industry has no impact on firm value, but rather that its effects are likely idiosyncratic. Indeed we show in Section 5 that various segment-level industry definitions all generate virtually the same discount using the methodology in BO 95. We also show later in Section 4 that sales- and age-matching generates imputed firm portfolios that are more correlated with diversified firm returns than segment-level industry matching.

2.1 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, we examine the actual median firm matched to each segment of the diversified firms. Surprisingly, in the vast literature surrounding the diversification discount, we have been unable to find papers which examine the characteristics of the matched-set of focused firms, and their differences to the diversified firms with which they are matched.

Column 1 of Table 1 shows the mean and median of the set of focused firms that are selected as matches using the BO 95 algorithm. Since these are selected as the median firm in each industry grouping with at least five focused firms, they are not guaranteed to be representative of the entire focused firm sample in Column 4. Compared with the entire sample of focused firms, the matched firms have slightly more sales, are older and more profitable, and tend to have smaller value-to-sales ratios. Compared to diversified firms on the other hand, the matched firms are less than half as large in sales, are substantially younger, and have much higher return volatility.

Of much more interest is Column 3, which presents the mean and median differences between the diversified firms and the actual imputed firm formed from the Berger and Ofek (1995) procedure. This imputed firm is the sales-weighted average of the median focused firms in each segment-level industry of the diversified firm. The mean difference in sales between diversified firms and their imputed firm is $2.3 billion dollars, and the diversified firm is 13 years older. To aid interpretation we also calculate the ratio of firm sales (age) to imputed firm sales (age) expressed as a percentage. These unreported variables indicate that diversified firms are on the order of 15 times larger with respect to sales and 3.5 times older. Table 1 also presents our estimate of the traditional BO 95 excess value measure, which at 11.5% is virtually identical to past calculations even given the much larger size of our sample.

Diversified firms are older, much larger on all dimensions and have lower return volatility than the focused firms that are matched to them in the BO 95 methodology.[8] Given that market-to-sales ratios decline with sales and age, and that the standard method of calculating the excess value measure consistently matches large, old diversified firms with small, young focused firms, it is clear how a discount is manufactured.

2.2 Falsification Test

We assume that firm age and firm size are the key value relevant characteristics (as has been suggested theoretically); however, older firms and larger firms tend to be diversified. Since diversified firms are mechanically larger than focused firms due to combining firms together it is not clear if firm size or firm diversification is the driving force behind the diversification discount. We perform an experiment to shed light on this. While we term this an "experiment" it essentially shows that the intuition from Figure 1 generalizes across the entire data set. It emphasizes that the primary dimension of variation for market-to-sales ratios is sales and not organizational form.

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 market-to-sales ratios of

[8]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 *et al.* (2010) for more information regarding the link between growth rate uncertainty and firm multiples.

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. Essentially the "fake" excess value is the excess value calculated by swapping a focused firm of similar size with the diversified firm and calculating the discount. 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 2.

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 10.6% 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 15.2%, but this discount is heavily concentrated in very small diversified firms (that have much lower market-to-sales ratios than their focused counterparts). The difference in excess value measures between diversified firms and their placebo counterparts for firms above the median $250 million in sales is not statistically significant. As sales increase, the difference in point estimates narrows and T-statistics for the difference decrease.

3 A New Measure and Its Consequences

The previous section documents that the excess value measure as constructed in BO 95 creates substantial mis-matches with respect to sales and age, and since sales and age are highly correlated with V/S ratios these mis-matches manufacture a discount. Once generated in such a way, the excess value discount to diversification is nearly impossible to remove as we discuss in Section 5. Controlling for age or sales within each narrow industry match reduces the discount as noted by both Bevelander (2002) and Borghesi *et al.* (2007), but ultimately both papers note that preserving the tight industry match for the segments forces adoption of wide ranges for sales and age which is counterproductive. While it would be possible to move to a broader definition of industry (say Fama-French 49 or 2-digit SIC) to improve sales and age matches, doing so results in fewer and fewer diversified firms, and more importantly these diversified firms begin to be matched to a smaller and smaller number of focused median firms. Ultimately an excess value measure is a choice about the weight one places on industry classification versus other value-relevant factors.

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 2, other economic explanations could certainly drive similar patterns in these characteristics.[9] We begin by ignoring industry as a value-relevant characteristic, but then adopt somewhat more nuanced approaches by matching firm-to-firm within industry classifications of varying granularity. We directly address the degree to which industry *does matter* in Section 5.

3.1 Construction of a new measure

There are many ways to match firms. For high dimensions (a large number of value-relevant characteristics), parametric methods such as propensity scoring are more efficient, but for our purposes we adopt a non-parametric method, Coarsened Exact Matching (CEM), that has improved statistical properties and is intuitively simple. CEM is a nonparametric technique developed in Iacus *et al.* (2011b) and Iacus *et al.* (2011a) that ensures common support and bounds on the maximum imbalance between the covariate distributions across groups. In our case, these groups are diversified and focused firms. Iacus *et al.* (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).[10] CEM is shown to dominate existing matching es-

[9]All matching tests are robust to the inclusion of return volatility and profitability as additional covariates, which are additional proxies for measures related to value in Pástor and Veronesi (2003).

[10]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

timators (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 to match well across all of the percentiles of the underlying distribution. As a robustness check, we show in Appendix A that our results hold when using the more common propensity scoring approach to generate matches for our data.

CEM begins by generating a multi-dimensional grid of the covariates to match upon, dividing each variable into multiple bins (potentially of varying widths). As an illustrative example, with only two covariates (sales and age) and splitting by deciles to create bins, this is simply a square divided into 100 smaller squares, with the smallest and youngest firms in the lower left square and the largest and oldest firms in the upper right square. Each square is termed a “strata.” Within each strata, we can compare diversified firms with focused firms, and we discard all squares where there are no diversified firms or focused firms which ensures that all measures calculated have common support. To create our excess value measure for each firm (strata-matched excess value), within each strata we calculate the log-ratio of the value of the subject firm to the value of the median focused firm in the strata. Our measure is similar in spirit and scale to the BO 95 excess value measure, but it is constructed from firms that are “locally close” with respect to sales and age rather than matched on segment-level industry.

Implementation of CEM requires a choice of bin size. In our contrived example above with deciles formed from the entire population, most diversified firms would be in the upper right and most focused in the lower left, and matches would not be very near with respect to either sales or age. Choosing 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.[11] In all cases we restrict firms to match on year, and we introduce additional industry classifications as exact matches. For

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of covariates, or general nonlinear relationships.

[11] 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.

instance, incorporating an incremental match to be within Fama-French 10 (FF10) industry would result in a separate sales-age strata for each year-FF10 industry pair.

3.2 Matching across percentiles

Table 3 presents our results using CEM to match focused firms to diversified firms using sales and age, controlling for year and various measures of industry. The column labeled “Y” (representing only matching by year) 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 \$327 million more in sales and is 12 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 \$1.53 billion more than focused firms and diversified firms are 31 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.

The other columns of Table 3 present the results of the CEM matching on sales and age for four cases: matching in each year (“Y-SA”); matching within each year and FF10 industry (“YFF10-SA”); matching within each year and FF49 industry (“YFF49-SA”); and matching within each year and 2-digit (“YSICH2-SA”) or 4-digit SIC code (“YSICH4-SA”). The number of firms that are unmatched due to the requirement for common support (i.e., “squares” where there are only focused or diversified firms) is presented as Unmatched. The L1 statistic is a overall measure of scaled imbalance across the distribution developed by Iacus *et al.* (2011a) with perfect balance achieved at zero.

Our first observation is simply the unsurprising result that matching works. Mean differences for all four matched samples fall by orders of magnitude and differences across the entire distribution of sales and age are dramatically reduced. In particular, the matching at the 25th and 75th percentiles is substantially improved. Our next observation is that the new measure we create leads to a diversification premium, both in our non-industry adjusted measure and with any broad or narrow firm industry classification (FF-10, FF-49, and 2- and 4-digit SIC code matching).[12] These

[12]Using Hoberg and Phillips (2016) FIC 100 industries also generates a similar small

diversification premia are significantly different from zero unconditionally, and in the following section we show that including controls yields a measure which is insignificantly different from zero.

3.3 Regressions of competing excess value measures

Table 4 presents a replication of BO 95's main regression specification and versions of that regression where the excess value measure is substituted by two strata-matched excess value measures: one which ignores industry and the other which broadly matches on FF10 industry.[13] Our much larger sample (102,497 from 1977–2016 versus 15,287 from 1986–1991) confirms what many other papers have shown; once constructed, the traditional excess value measure implies a discount of about 11% for diversified firms. 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. Consistent with the results in Table 3, the univariate regression on the strata-matched excess value measure implies a diversification premium. Once firm-level controls are added however, this premium becomes insignificant. Size and age variables in the strata-matched regressions (which are matched on size and age) have significance since they control for within-strata variation. Our primary point is not that there is a premium to diversification, but rather that once matched on value-relevant characteristics, organizational form is not value-destroying.

3.4 Different economic conclusions from different measures

In a recent influential paper, Kuppuswamy and Villalonga (2016) (henceforth KV) use the time series of excess values through the financial crisis of 2007–2009 to show that diversification creates value in the presence of external financing constraints. While KV calculate excess values quarterly (although using annual segment sales values and classifications) and our excess value calculations are annual, we can use their financial crisis "experiment" to broadly investigate the differences between the traditional

premium.

[13]Results using other broad firm-level industry controls, such as the Hoberg and Phillips (2016) based FIC-100, FF-49, and 2- and 1-digit SIC codes are very similar.

and our strata-matched excess value measures. Figure 3 plots annual mean excess value measures over our entire sample period of 1977–2016. Both the B0-95 EV measure and the Y-SA CEM strata EV measure are increasing throughout the crisis and fall after, implying similar conclusions: that the value of diversification increased during a period where external financing was constrained. However, examining the entire sample period leads to dramatically different conclusions. First, the value to diversification implied by the traditional measure reaches its maximum not during the financial crisis, but during the dot-com boom of 1998–2000, a period where external financing was presumably not scarce. Conversely, during the dot-com boom the strata-matched excess value measure reaches its minimum value, possibly due to the high value of growth options attributed to focused firms during that period, and reaches its maximum at the height of the Great Recession. After the dot-com "bust", diversification (as measured by the strata-matched excess value measure) begins to gain in value reflecting the rise in industry concentration as well as the dominance of conglomerates such as Amazon and Apple.

Our broader point is that the traditional excess value measure performs somewhat counterintuitively with respect to external financial constraints. Either the measure is capturing something other than the value of diversification, or external financing was far more constrained in the dot-com boom than during the Great Recession. Our new strata-matched excess value delivers different economic conclusions than the traditional measure and in fact clearly indicates that the value of diversification increases in periods of constrained external finance.

4 Return Covariances and Excess Value

Although the BO 95 measure and the strata-matched measures developed in 3.1 attempt to measure the same thing, the relative value of the conglomerate organizational form, they are different on many dimensions. For example, the BO 95 measure matches narrowly on industry and ignores sales and age whereas the strata-matched measure matches closely on sales and age yet ignores industry. Which drastically different view on value is correct?

4.1 Return-weighted excess value methodology

Both the BO 95 measure and our strata-matched measures use groups of related firms to create an “imputed" or comparable firm which is then matched against the diversified firm value. In this section, we exploit the daily return covariances between these portfolios of related firms and the diversified firm to investigate which measure provides the “closest" match. For each diversified firm-year we form two portfolios: 1) one composed of the 2 to 10 median focused firms that are matched to each segment of the firm using the BO 95 method (BOPORT); and 2) another composed of five sales- and age-matched focused firms (SALEAGEPORT). BOPORT represents exactly the “imputed” firm that BO 95 claim replicates the diversified firm in the absence of frictions such as agency costs and financial constraints, and SALEAGEPORT represents a standardized proxy for a firm matched on characteristics. We calculate the daily returns of these portfolios as

$$BOPORTret_t^{iy} = \sum_{j=1}^{J} w_j^{iy} r_{jt}^{mf} \quad \text{and} \quad SALEAGEPORTret_t^{iy} = \frac{1}{5}\sum_{k=1}^{5} r_{kt}^{sa} \tag{3}$$

where $BOPORTret_t^{iy}$ is the daily return on the portfolio composed of the median focused firms matched to the J segments of diversified firm i in year y (measured from July 1 to June 30) and $SALEAGEPORTret_t^{iy}$ is the daily return on the portfolio composed of the K sales and age nearest-neighbor (based on Mahalanobis distance) focused firms for diversified firm i in year y. Throughout the paper we set K equal to five, but results with K equal to 3 or 7 are extremely similar. w_j^{iy} are segment sales weights in the diversified firm, although nearly identical results obtain when we equally weight the portfolio.

For each diversified firm in every year, we regress the daily returns of the diversified firm on the daily returns of BOPORT and SALEAGEPORT. We constrain the regression coefficients to sum to one and run the regression without a constant, essentially decomposing the return correlation across the two portfolios as shown in Eq. 4

$$DIVret_t^{iy} = \beta_1^{iy} BOPORTret_t^{iy} + \beta_2^{iy} SALEAGEPORTret_t^{iy} + \varepsilon_t \quad \text{with} \quad \beta_1^{iy} + \beta_2^{iy} = 1 \tag{4}$$

This procedure naturally provides coefficients β_1^{iy} and β_2^{iy} that we use as weights to apply to the BO 95 excess value measure and to the excess value measure derived from the log-ratio of the diversified firm's value to the median focused firm value in SALEAGEPORT.[14] We term the resulting measure the "return-weighted excess value measure." Note that if BOPORT is indeed a perfect replica of the firm and investors realize that the diversified firm is merely the sum of its segment firms, then the weight β_1^{iy} derived from the constrained regression will be one and the return-weighted measure will be identically the traditional excess value measure in BO 95. Alternatively, if sales and age are the dominant characteristics for value, the return-weighted measure will recover (approximately) our strata-matched measure.

4.2 Return-weighted excess value results

Table 5 presents the values of the BO 95 excess value measure (BO 95 EV), the sales- and age-matched excess value measure (SalesAge EV), and their respective weights, BO 95-Weight and SalesAge-Weight, by sales deciles of diversified firms. The first key result is that the SALEAGEPORT explains over twice the daily return covariance of diversified firms than the BOPORT does. Put differently, a very small portfolio of close sale and age focused firms tracks the returns of diversified firms far better than a portfolio chosen to be exactly matched with respect to the industries of the diversified firm's segments. The overall SalesAge EV is a 7% premium, which is identical to the value of the strata-matched excess value measure shown in Table 4 showing that restricting our matches to 5 close neighbors leads to similar conclusions as the full strata-matching methodology. At least as measured by daily return covariances, the industry imputed firm is a poor match, with BOPORT explaining only 32.7% of diversified return covariances. Conversely, the characteristic-matched imputed firm does surprisingly well, explaining more than twice as much, or 67.3%. Finally, weighting by daily return covariances, there seems to be virtually no overall difference between the values of focused and diversified firms.

[14]This is not exactly the CEM strata-matched excess value measure since it is derived from just five sale and age-matched firms and not all of the firms in the strata. We do this to be consistent and to provide a fair test with respect to idiosyncratic risk of the portfolios. Some strata may have more than 20 (some close to 50) focused firms whereas the number of firms in the BOPORT must lie strictly between 2 and 10 (the number of diversified firm segments).

An additional surprising result is that sales- and age-matching dominates as the size of the firm increases. This was against our intuition, as larger conglomerates tend to have larger portfolios of segment-matched focused firms and (we thought) were more likely to be managed and analyzed as portfolios of standalone businesses. Larger and older firms seem to trade together regardless of whether they are focused or diversified; for the most important diversified firms in our sample, the portfolio comprised of the imputed BO 95 firms does an especially poor job of describing returns. Simply put, size matters for returns far more than segment-level industry, at least for diversified firms.

We perform several robustness tests (unreported) to confirm these results. Table 5 presents results for all 34,408 diversified firm-years for which we can obtain a full set of daily returns. Restricting the sample further to the firms with BO 95 excess values between +/-1.386 (as in BO 95) generates a 2% overall return-weighted excess value premium with most of the difference accounted for by the excess values and not the weights. Equal-weighting the BOPORT and changing the number of firms from five to three or seven in the SALEAGEPORT makes little difference. We also run unconstrained regressions (with a constant) for each of BOPORT, SALEAGEPORT and both together. In the individual regressions, BOPORT has a mean R^2 of 5.9% while the mean R^2 for SALEAGEPORT is 42% higher at 8.4%. And in the combined unconstrained regressions the coefficient on SALEAGEPORT is nearly twice that of BOPORT, 0.294 versus 0.152.

Our results indicate that segment-level industry matching does a poor job of producing an "imputed" firm that closely tracks diversified firm returns. This does not mean that industry is unrelated to market-to-sales ratios or is not relevant in explaining corporate decisions. Indeed, Section 5.2 notes that broad industry categories have substantially different market-to-sales ratios, and in the following section we address whether mis-matching on this industry variation influences our results.

5 Wait, How Can Industry Not Matter?

5.1 Matching on Industry

As a practical matter, inaccurate classification of industry codes to segments will contaminate the BO 95 excess value measure, since by construction it is designed to rely exclusively on the accuracy of four-digit SIC code 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.[15] Even in the period before 1997, Denis *et al.* (1997) document frequent arbitrary reporting changes in the number of segments that are unrelated to changes in business operations. Villalonga (2004a) finds a diversification premium using data from the Business Information Tracking Series (BITS) census database to define diversification as multiple establishments rather than using the business segments from Compustat to indicate diversification.[16] Her sample finds a large degree of establishment-level diversification in US firms (80% of firms are diversified using her definition) and this unobserved establishment diversification in firms classified by Compustat as focused further highlights the problems with segment-level industry matches. It also emphasizes a point we exploit below: that changing the definition of industry also redefines which firms are diversified and which are focused.

5.2 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

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

[16] 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.

smoothly over nearby SIC classifications along the market-to-sales dimension. In fact, the opposite is true; market-to-sales ratios vary drastically across adjacent four-digit SIC codes. For example, within one-digit SIC code 3 (Manufacturing) the median (at the four-digit level) focused firm has an average value-to-sales ratio of 1.1. Yet the average difference for value-to-sales ratios between adjacent four-digit SIC code median firms is 0.7, and that difference has a standard deviation of 0.837.

For the entire sample, median focused firm value-to-sales ratios of adjacent SIC codes are on average 0.896 different, over a 50% discrepancy from their mean level of 1.520. 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).

5.3 Excess value with random and shifted industries

We further investigate the effect of industry assignment on excess value by calculating excess values as in BO 95 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 6.

Panel A of Table 6 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 methodology of BO 95 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 BO 95 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 6 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 5.2 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, this section shows that randomization of focused firm industries always generates a discount.

5.4 Alternate industry classifications and excess values

Whereas randomizing industries as in Section 5.3 abstracts from the economic intuition that industries are different with respect to factors that may impact valuation, this section uses three novel definitions of industry to examine more directly the potential impact of industry on excess values. However, the result is the same: there is always a diversification discount regardless of how industries are defined or classified. These results are shown in Tables 7 and 8.

First, we reconstruct excess values using the translation of segment-level SIC codes to segment-level industry codes based on Fama and French (1997). Using the segment-level Fama-French industries at the 10, 30, and 49-industry levels, we reconstruct the focused-firm median benchmarks for each industry level with five focused firms in each industry. A large advantage of the Fama-French industry classifications, and one which we are the first to exploit, is that they are regroupings of four-digit SIC codes, which makes them applicable to the segment level SIC codes. Thus not only do the firm level classifications change, the definition of diversified firms changes as their segments are allocated to "sensible" industry groupings of varying granularity. The excess value (EV) is the log ratio of the subject firm total capitalization to the segment sales-weighted total capitalization of the median benchmark(s) from the industry (industries) in which the subject firm operates, which is identical to the approach in BO 95.[17] Other excess measures are the difference between the subject firm measure (such as Sales) and the sales-weighted median benchmark measure. Columns two, four, and six of Table 7 show a diversification discount of 7.6%, 8.4%, and 6.67% for the 10-, 30-, and 49-industry measures, respectively. Also, the mismatch between diversified firms and their focused benchmarks shows that diversified firms are approximately $1 billion larger with respect to sales and about 10 years older.

Second, we use the Hoberg and Phillips (2016) firm-level textual network industry classifications (TNIC) created from textual analysis of product descriptions in firm 10K filings. To construct TNIC, each year pairs of firms are scored by the relatedness of the common words used in their product descriptions. A threshold score is then set to create an industry coarseness that is equal to the coarseness of three-digit SIC codes, meaning that two randomly chosen firms are equally likely to be in the same classification. The classification is not necessarily transitive, and industry categories are not fixed over time as is the case with SIC codes, Fama-French industries, NAICS, and others.

To examine the effects of the TNIC classification on excess values we create two excess value measures. The first is the log ratio of the subject firm total capitalization to the median total capitalization taken from all of the focused competitor firms within the subject firm's classification. The only difference for the second measure is that it takes the median total capitalization from the 10 focused firms with the highest relatedness scores to the subject firm. A firm is considered "focused" if it has only one business segment at the four-digit SIC code level. Other excess measures are simply the difference between the subject firm measure and the median benchmark firm measure. Here again, Table 7 shows that a diversification discount

[17]Unlike BO 95 we do not broaden the industry classification to the finest industry level in which there are five focused firms.

remains and mismatches on sales and age are similar to other models.

The method employed by BO 95 takes the median benchmark firm value from the finest SIC code level (four-, three-, or two-digit) in which there are five focused firms. Throughout the paper and in the column titled "FINE" in Table 8, we employ the same method for comparability. However, in the following analysis we examine the effects of changing the definition of industry and diversification itself by creating separate excess value measures at each level of fineness rather than allowing it to change. Specifically, each year for one-, two-, three-, and four-digit segment level SIC codes we force the focused median benchmark to come from the same code at the same level as the subject segment. Since we keep the requirement of at least five focused firms within an industry classification, this results in fewer observations at finer levels of industry classification. Moreover, we change the definition of what it means to be diversified to indicate that a firm has more than one segment at each respective level of fineness. That means, for example, that a firm with segments in SIC 3676 and 3677 would be diversified at the four-digit level, but focused at three-digit level. All other calculations of excess value are as they are in BO 95.

Yet again, a diversification discount remains as indicated in Table 8, and it is present at all levels of fineness. The mismatches between diversified firms and their median focused competitor are also apparent in sales and age, although the age mismatch for the one-digit model (column labeled "SIND1") for diversified firms is only 3.46 years on average. Interestingly, the diversification discount at the two-digit level is slightly lower than the one at the four-digit level, which is contrary to finding in BO 95 that unrelated diversification suffers a larger discount.

Lastly, an interesting artifact of the BO 95 methodology is that it is internally inconsistent with respect to diversification classification. Specifically, firms are defined as diversified at the four-digit SIC level, but if there are too few firms (less than five) the industry "fineness" backs up a level. For some firms in related but sparse industries, this results in all segments of the firm being matched to the same focused firm, which is identical to focused firm treatment. Echoing the result that pseudoconglomerates (firms with multiple segments in the same 4-digit classifications) also have a discount in Sanzhar (2006), we find that these 1378 pseudo-treatment conglomerate observations also have a median 7.7% discount.

5.5 Mis-matching on industry in the new measure

Since we criticize the traditional BO 95 measure for manufacturing mismatches on sales and age, it is only fair to be concerned that our new strata-matched measure is generated by mis-matching on industry. In particular, since diversified firms tend to be larger and older than most focused firms, the focused firms they will be matched to might be in more mature industries (for instance retail) and have consequently low value-to-sales ratios on average. Matching a diversified firm that is 51% retail and 49% technology with a large retail focused firm may create a premium through industry mis-matching, even if we match directly in our strata to the largest segment industry.[18] We have discussed above (Section 5.2) the noisiness of value-to-sales ratios at the 3- and 4-digit level, but it is certainly true that there is significant variation in these ratios across broad industry groupings (Retail is lower on average than Business Services, for example.), and thus this mis-matching could generate at least a portion of the premium we find, if not all of it.[19]

We can use the two-digit SIC code matched version of our strata-matched excess value measure and the related/unrelated segment variables from BO 95 to investigate the magnitude of this bias. We separately calculate the two-digit matched measure for diversified firms with only related segments (i.e. those firms where all of their segments are in the same 2-digit SIC code) and for firms that have at least one unrelated segment. Unconditionally, this measure generates a premium of 5.5%. For diversified firms with all of their segments correctly matched within a two-digit SIC code (60% of the sample), the premium is 3.98% and for those firms with at least one unrelated segment (40% of the sample), the premium is 10.29%. We conclude that while at least some of the premium we find in our excess measure is due to industry mis-matching, our main conclusion that focused and diversified firms are similar in value is unlikely to be reversed by it.

We further investigate the degree to which industry matching is related to the size of the excess value premium we find. For our main measure, which matches only on year, size and age, it is certainly possible that all of our premium firms are matched to low value-to-sales industries (such as

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[18] We are grateful to an anonymous referee for suggesting this possibility.

[19] As shown in Table 3, the strata-matched measure is robust to different industry classification schemes, but industry matching at the firm level could still leave some segment industries mis-matched.

retail) and that all of our discount firms are matched to high value-to-sales industries. Figure 4 presents a mosaic plot of the FF-49 industry distribution for the focused firms matched to diversified firms in each decile of our strata-matched measure. The height of each stacked area within a decile category represents the proportion of focused firms in that particular FF-49 industry. It is immediately apparent that the distribution of focused firms for discount and premium excess value firms is remarkably similar, in fact it has little variation across all of the deciles.

To test whether these decile industry distributions are in fact statistically the same, we turn to a novel test and decomposition from the ecology and biodiversity literature. Following the development in Jost (2007) and Tuomisto (2010), we calculate the numbers-equivalent Shannon entropy for each distribution. Given p_i as the proportion of firms in one of S industries (in our particular case of the FF-49, $S = 49$), the numbers-equivalent Shannon entropy is

$$D = exp\left(-\sum_{i=1}^{S} p_i lnp_i\right) \tag{5}$$

A loose interpretation of D is the "effective" number of industries in the distribution; for example for $D = 20$, the diversity of sample is the same as that produced by a distribution with 20 industries with the same number of firms in each.[20] Table 9 presents the Shannon entropies for each excess value decile. To assess their statistical significance, we calculate standard errors by bootstrapping the distribution of diversified firms and recomputing the excess value deciles and Shannon entropies for 500 replications. It is clear from this calculation that each decile matched-focused firm distribution is statistically indistinguishable from each other.

Finally, a useful property of the Shannon Entorpy measure we use here is that it permits an intuitive bivariate comparative measure, the Horn (1966) Overlap index. For any 2 distributions their combined distribution can be decomposed into a common component (alpha) and a idiosyncratic component (beta).[21] The Shannon beta D_i^{β} for decile i can then be

[20]Diversity measures based on proportions are pervasive in virtually all social sciences, and the Shannon entropy we calculate here is closely related to Herfindahl and Gini-Simpson indices. It can be easily shown that Gini and Herfindahl type indices are more sensitive to categories with large proportions whereas the Shannon versions are more balanced.

[21]Of special note here is that the definitions of these in the standard ecology literature are exactly the opposite of what a financial economist would expect.

re-expressed as an overlap proportion, $Horn_i$ which represents the proportion of industry distribution shared between the two decile distributions. Formally,

$$D_i^{\beta} = \frac{D^{i+j}}{D^i} \quad \text{and} \quad Horn_i = \frac{(ln2 - lnD_i^{\beta})}{ln2} \tag{6}$$

Table 9 shows that with respect to the largest premium decile, the minimum degree of overlap for industry distributions is still over 97.9%, confirming the visual inspection of Figure 4. High strata excess value firms are matched to virtually identical distributions of focused firms as low strata excess value firms.

6 Could It Be Endogeneity? Replication of Villalonga (2004b)

In this section, we examine whether our alternative explanation for the diversification discount is even 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 BO 95 and then attempts to explain the discount formed by that methodology whereas we show that the BO 95 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 BO 95) 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 1977–2016 period utilized in the rest of our paper. Table 10 presents our results as well as coefficients and statistics from Villalonga (2004b) to facilitate comparison.

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 to 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).[22] 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 10 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 (373 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.

The bottom panel of Table 10 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.[23] 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

[22] 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 1, or requiring the firm to be focused in all years up until the diversifying event did not change any of our results significantly.

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

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.[24]

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 373 (372) diversifying firms via a probit regression using those firms and the 24,754 (24,681) focused firms. We then implement the matching estimator and accompanying standard errors using the 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.[25]

We then extend our sample significantly to incorporate the entire period from 1977–2016, still using the same methodology. Our longer time period approximately doubles the number of focused and diversifying firms in our sample; we now have 672 (671) in the reduced (extended) models as compared to the 150 (109) diversifying firms in Villalonga (2004b). We

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

[25]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-statistic 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.

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 (2011) no longer render that discount statistically insignificant. Indeed, we find that the act of diversifying decreases the calculated excess value measure by 10.0% in the reduced model and 10.2% 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 significantly when firms add segments, but this decline in relative value of the excess value measure as calculated by BO 95 is due to faulty comparisons embedded in the measure itself. The diversification "discount" is more about construction than selection.

7 Conclusion

A vast literature and industry has been built upon the conclusion in Berger and Ofek (1995) that diversified firms are consistently worth less than the sum of their parts. We show that this conclusion 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 create a simple new measure based on sales- and age-matching which leads to different conclusions regarding the value of diversification during periods of external financing constraints. We are the first to use daily return covariances to show that our measure (which relies on characteristics and ignores industry) is preferred to the Berger and Ofek (1995) measure (which ignores characteristics and relies on industry) by nearly a 2-to-1 margin, and that a return-weighted measure leads to the conclusion that on average, matched diversified and focused firms have similar values.

We extensively investigate the surprising conclusion that granular industry classifications are not strongly associated with value, permuting and randomizing industries to show that the methodology in Berger and Ofek (1995) results in a discount regardless of how industry is defined. We further redefine industry and diversification status as in Fama and French (1997) and in Hoberg and Phillips (2016) and show that these alternative industry classifications do not resolve the mismatching on characteristics that manufacture the diversification discount. We also replicate Villalonga (2004b) using our much more comprehensive sample of diversifying firms, and show that endogeneity is not an explanation for the diversification discount. The discount is an artifact of its construction, not selection.

Our results suggest that much of what we know about the value of the conglomerate organizational form should be re-examined, and that research should focus much more upon which diversified firms create value and how they do so.

A Propensity Score Matching Estimators

Throughout the paper, we use coarsened exact matching (CEM) to provide locally-close matches for diversified firms. In this appendix we show that more traditional parametric matching based on propensity scores delivers similar conclusions on diversified firm value. 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.

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.[26] Importantly we do not use propensity scoring

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

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 such as sales and age using a probit specification, and compute the propensity score as the predicted value of the regression. 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 in our extended specification. 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.[27]

Table A1 presents the results of the propensity score matching procedure for five cases: matching diversified firms within years on sales and age ("Y-SA"); within years using an extended probit model ("Y-Extended"); within years and one-digit SIC code industry on sales and age ("YSIC1-SA"); within years and the same 100-level industry code as in Hoberg and Phillips (2016) on sales and age ("YHP100-SA"); and within years and the same FF-49 industry on sales and age ("YFF49-SA"). Of the five models, 3 produce statistically significant premiums and 2 produce statistically insignificant discounts. The "Y-SA" case, matches well across sales and age (although not as well as the extended model). The "Y-Extended" model supplements sales and age in the probit model with additional controls including profit margin, cash balances, leverage, excess return volatility, and dummies for major exchange inclusion and dividend payment. It produces a statistically insignificant diversification discount. The other three models enforce matching within industry groups of varying granularity. The most granular uses the 100-level text-based industry codes as provided in Hoberg and Phillips (2016) 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 least granular, matching within 1-digit SIC codes each year also leads to the conclusion that focused and diversified firms have similar values. Overall, the results do not support a diversification discount. If anything, there is some evidence of a diversification premium. Using a completely different (semi-parametric) matching

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

method, we do not find evidence supporting a diversification discount, confirming the earlier results generated by non-parametric strata-matching method based on CEM.

Table A1: Diversification Effects on Value Using Propensity Score Matching

	Y-SA	Y-Extended	YSIC1-SA	YHP100-SA	YFF49-SA
V					
Focused	3,914	4,568	4,441	4,498	3,292
Diversified	4,361	4,363	4,375	7,150	4,284
Difference	-447	205	66	-2,652	-992
Std Err	137	137	142	275	124
p-value	0.001	0.134	0.641	0.000	0.000
Sales					
Focused	2,929	3,243	2,688	2,308	2,307
Diversified	3,699	3,695	3,709	4,308	3,709
p-value	0.000	0.000	0.000	0.000	0.000
Age					
Focused	43.9	44.1	44.4	43.3	41.2
Diversified	43.0	43.0	43.0	45.0	42.5
p-value	0.001	0.000	0.000	0.001	0.000
Observations (Average Within-group)					
Focused	1,896	1,872	406	48	72
Diversified	982	974	241	28	40

Description: 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 within years on sales and age ("Y-SA"); within years using an extended probit model ("Y-Extended"); within years and one-digit SIC code industry on sales and age ("YSIC1-SA"); within years and the same 100-level industry code as in Hoberg and Phillips (2016) on sales and age ("YHP100-SA"); and within years and the same FF-49 industry on sales and age ("YFF49-SA"). Sales (in millions) is computed from Compustat, Age is calculated using methods and data from Jovanovic and Rousseau (2001). Data span the years 1977–2016.

Interpretation: Using propensity score matching with various covariates, there is no evidence of a statistically significant diversification discount (i.e., a positive difference between the value of Focused firms compared to Diversified firms).

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Table 1: Summary Statistics Using BO 95-Matching

	BO 95-Match Firms	Diversified Firms	Excess Measure	Focused Firms
Sales	1,583	3,700	2,298	1,334
	[213]	[504]	[93.8]	[186]
Age	29.8	43	13.1	25.7
	[19]	[29]	[5.45]	[16]
Profit Margin	.116	.119	.00399	.0951
	[.105]	[.111]	[.00299]	[.105]
Return Volatility	.134	.122	-.00748	.144
	[.116]	[.104]	[-.0131]	[.124]
V/Sales	1.27	1.32		2.13
	[.877]	[.812]		[1.06]
EV			-.115	
			[-.105]	
Observations	11,530	38,047	36,296	76,680

Description: This table presents summary statistics from 1977–2016. The BO 95-Match column reports the statistics for median firms in industry groupings with 5 or more focused firms. Diversified and Focused Firms are all firms with more than one and exactly one segments reported in the Compustat segment file at the 4-digit SIC code. The Excess Measure column reports differences between the diversified firm characteristic value and the value for the imputed firm formed using the BO 95 methodology. Sales ($M) and Profit Margin (EBITDA/Sales) are from Compustat data. Age is firm age in years calculated using data and methods from Jovanovic and Rousseau (2001). Return Volatility is calculated as the standard deviation of monthly returns from CRSP data. V is the total capitalization of the firm calculated as market value of equity plus the book value of debt. EV is the log ratio of the diversified firm V to the sales-weighted imputed firm V as in BO 95 except that outliers ($-1.386 < EV < 1.386$) are not removed. Median values are in brackets below mean values.

Interpretation: The BO 95 algorithm consistently matches smaller and younger focused firms to larger and older diversified firms.

Table 2: Falsification Test of Excess Value

	"Real" EV	"Fake" EV	Difference		
	Mean	Mean	Mean	σ	T-stat
Full Sample	-0.152	-0.106	-0.046	0.011	-4.104
Sales >250	-0.127	-0.100	-0.028	0.015	-1.873
Sales >500	-0.118	-0.100	-0.018	0.017	-1.067
Sales >750	-0.113	-0.093	-0.020	0.019	-1.087
Sales >1000	-0.106	-0.091	-0.015	0.020	-0.726

Description: 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) for the period 1977–2016. The diversified firm and all segments of that firm are matched (with replacement) to the focused firm with the most similar sales. 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 (σ) and T-statistics for the difference.

Interpretation: A discount is present even if a focused firm is swapped into the excess value calculation in the place of a diversified firm. Moreover, the "fake" discount is similar to the "real" discount for a diversified firm except for very small firms.

Table 3: Matching Using Coarsened Exact Matching

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Y	Y-SA	YFF10-SA	YFF49-SA	YSICH4-SA	YSICH2-SA
EVcem	.	0.073***	0.061***	0.048***	0.045***	0.055***
Sales Imbalance						
mean	2,396	249	257	254	222	262
25%	61	38	31	28	21	29
50%	327	203	154	129	101	135
75%	1,530	779	617	521	413	537
L1	0.214	0.133	0.127	0.127	0.123	0.132
Age Imbalance						
mean	16.7	0.3	0.3	0.3	0.5	0.4
25%	5.0	0.0	0.0	1.0	0.0	1.0
50%	12.0	1.0	1.0	1.0	1.0	1.0
75%	31.0	0.0	0.0	0.0	0.0	1.0
L1	0.213	0.035	0.038	0.042	0.053	0.044
Overall Model						
N_Focused	84,309	83,544	81,184	76,553	51,716	73,419
N_Diversified	39,540	37,902	35,339	32,436	24,600	32,341
L1	0.396	0.434	0.614	0.706	0.656	0.688
Unmatched						
N_Focused	0	765	3,125	7,756	32,593	10,890
N_Diversified	0	1,638	4,201	7,104	14,940	7,199

Description: This table provides measures of the valuation difference and accompanying covariate imbalances between diversified firms and focused firms using the coarsened exact matching algorithm from Iacus *et al.* (2011a) for data from 1977–2016. The valuation difference is the mean of the strata-matched excess values (EVcem) for diversified firms. EVcem is 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 covariates indicated in the column headings, where firms are matched exactly by fiscal year "Y," Fama-French industry "FF10" or "FF49," and historical SIC Code "SICH4" or "SICH2," and and are matched within bins for sales and age "SA." For imbalance calculations, diversified firms are compared against all focused firms within their coarsened strata, with weights computed proportionally within the strata where strata are defined using the bin selection algorithm in Shimazaki and Shinomoto (2007). Firms not in the common support and with extreme values are dropped to correspond with BO 95. Sales ($M) is from Compustat, and Age (in years) is calculated using methods and data from Jovanovic and Rousseau (2001). Table entries for sales and age imbalances 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).

Interpretation: Once firms are matched according to sales and age, there is a diversification premium. Matching firms based on year, sales, and age results in considerable mitigation of imbalance while preserving observations relative to adding industry as an additional covariate.

Table 4: Regressions of Excess Value Measures on Firm Characteristics

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	BO 95			Y-SA		YFF10-SA	
Diversification Dummy	-0.076***	-0.107***	-0.090***	0.078***	-0.002	0.102***	-0.019
	(0.009)	(0.009)	(0.009)	(0.014)	(0.013)	(0.016)	(0.013)
ln(Assets)		0.043***	0.259***		0.249***		0.299***
		(0.003)	(0.007)		(0.010)		(0.009)
Capx/Sales		0.224***	-0.039***		0.104***		-0.030*
		(0.017)	(0.013)		(0.024)		(0.017)
Profit Margin		0.167***	0.157***		0.179***		0.083***
		(0.020)	(0.016)		(0.022)		(0.016)
Age			0.001***		-0.002***		0.001***
			(0.000)		(0.000)		(0.000)
ln(Sales)			-0.246***		-0.062***		0.046***
			(0.008)		(0.010)		(0.010)
Constant	-0.001	-0.276***	-0.086***	-0.005	-0.987***	-0.027***	-1.858***
	(0.005)	(0.014)	(0.016)	(0.008)	(0.028)	(0.009)	(0.023)
R-squared	0.004	0.044	0.101	0.002	0.174	0.004	0.319
Observations	103,473	102,497	102,497	70,492	69,806	64,568	63,936

Description: This table reports results for the regression of BO 95 excess values and coarsened exact matching (CEM) excess value measures on firm characteristics. BO 95 excess values are constructed as in BO 95. CEM 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 year, sales, and age (Y-SA) or year, Fama-French 10-industry designation, sales, and age (YFF10-SA). Firms not in the common support and with extreme values are dropped to correspond with BO 95. The Diversification Dummy equals one if a firm has more than one business segment at the four-digit SIC code level 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.

Interpretation: The diversification discount is present in all models using the BO 95 methodology while it is not present in any of the models using coarsened exact matching.

Table 5: Return-weighted Measures of Excess Value (All firms)

Sales Decile	N	Sales	BO 95-Weight	BO 95 EV	SalesAge-Weight	SalesAge EV	Return-weight EV
1	3,458	32	0.461	-0.229	0.539	-0.446	-0.379
2	3,437	68	0.409	-0.196	0.591	-0.212	-0.228
3	3,445	125	0.390	-0.144	0.610	-0.090	-0.133
4	3,436	215	0.364	-0.116	0.636	0.058	-0.023
5	3,439	360	0.344	-0.116	0.656	0.145	0.016
6	3,443	610	0.315	-0.061	0.685	0.154	0.052
7	3,444	1,103	0.291	-0.067	0.709	0.168	0.100
8	3,437	2,001	0.276	-0.011	0.724	0.296	0.198
9	3,445	4,259	0.240	-0.045	0.760	0.298	0.190
10	3,424	14,282	0.211	-0.117	0.789	0.227	0.155
Total	34,408	531	0.327	-0.107	0.673	0.070	0.001

Description: This table reports daily return covariance weighted measures of diversification excess value by sales decile for diversified firms from 1978–2016. Sales deciles are formed using the sales of the diversified firms, and the median sales of each decile is presented in the "Sales" column. BO 95- and SalesAge-Weight are the median by decile of coefficients from constrained regressions of daily returns of diversified firms on the returns of their BO 95-matched firms portfolio and the returns of a 5-firm sales- and age-matched portfolio for each diversified firm-year, respectively. Daily portfolio returns are calculated from July to June and matched for the fiscal year end for each diversified firm. BO 95 EV is the excess value measure from BO 95. SalesAge EV is the log difference of the diversified firm total capitalization and the total capitalization of the median sales- and age-matched portfolio firms. Return-weights are calculated as the firm-year by firm-year weighted average of return coefficients and excess values. Totals are averages over the deciles, except for N, which is the total number of diversified firms in the sample. The diversified firm sample is restricted to firms meeting the criteria in BO 95.

Interpretation: The sales-age weighted portfolio explains over twice the daily return covariance of diversified firms as the BO 95-matched imputed firm does. Also, the explanatory power of the sales- and age-matching increases with the size of the firm.

Table 6: Excess Value Measures Generated By Random Industry Assignment

Panel A: Randomization of SIC Codes			
	Randomize within		
	1-digit	2-digit	3-digit
Mean Excess Value	-0.151	-0.125	-0.107
	[0.006]	[0.004]	[0.002]
Median Excess Value	-0.179	-0.138	-0.118
	[0.007]	[0.004]	[0.002]
Diversification Dummy	-0.160	-0.149	-0.137
	[0.006]	[0.004]	[0.002]
Panel B: Shifting of SIC Codes			
	Shift by		
	1	10	100
Excess Value	-0.107	-0.109	-0.109
	[0.0031]	[0.0032]	[0.0031]
EV Up-shift	-0.110	-0.110	-0.109
	[0.0031]	[0.0032]	[0.0031]
EV Down-shift	-0.110	-0.108	-0.107
	[0.0032]	[0.0032]	[0.0031]
Difference Up	0.003	0.002	0.000
	[0.0008]	[0.0004]	[0.0004]
Difference Down	0.003	-0.001	-0.002
	[0.0004]	[0.0002]	[0.0004]

Description: This table reports excess value measures resulting from various randomization schemes for focused industry SIC codes. Panel A shows the mean and median excess value measures of diversified firms calculated using the methodology in BO 95 and the coefficient on the diversification dummy in a regression of excess value on log of total assets, capital expenditures-to-sales, profitability, and leverage, as in BO 95. The interquartile range is reported below the estimate in brackets. 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 reported segment industry classification. The randomization is repeated 1000 times. Panel B reports the results of a similar exercise in which focused firm SIC codes are shifted up or down by 1, 10, or 100 before the calculation of excess values. The difference up and difference down are calculated as the difference from the non-shifted to the shifted estimates and standard errors are reported beneath the estimates in brackets.

Interpretation: The BO 95 excess value measure results in a diversification discount even with random industry assignment.

Table 7: Summary Statistics using Alternate Classifications of Segment and Firm Industry

Excess Measures	FFINDS10		FFINDS30		FFINDS49		HPall		HPtop10	
	Foc	Div	Foc	Div	Foc	Div	Foc	Div	Foc	Div
EV	.0178	-.0756	.015	-.0838	.0152	-.0666	-.0383	-.108	-.0552	-.124
	[.013]	[-.0785]	[.00851]	[-.0943]	[.00367]	[-.0708]	[-.0383]	[-.103]	[-.0559]	[-.117]
Excess Sales	-50.7	1,222	-548	1,138	-843	1,098	-129	2,588	-.946	2,618
	[-31]	[1.1]	[-22.7]	[16.7]	[-37.6]	[18.7]	[-46.6]	[126]	[-50]	[118]
Excess Age	-1.91	11.5	-4.24	9.72	-2.75	11.4	-.276	12.3	.557	11.9
	[-3]	[3.62]	[-3.5]	[3.18]	[-2]	[4.81]	[-1]	[6]	[-.5]	[6]
Excess Return Volatility	.0055	-.00673	.00178	-.0121	.00232	-.00885	.000986	-.00902	-.000251	-.00971
	[.0000609]	[-.0114]	[-.00186]	[-.0168]	[0]	[-.0131]	[-.0028]	[-.0105]	[-.00412]	[-.0111]
Excess Profit Margin	.0081	.00739	.0112	.0109	.00271	.00803	-.00225	.00985	.00887	.00687
	[0]	[-.00284]	[.00438]	[.00193]	[.000457]	[.00191]	[.000523]	[-.000866]	[.00487]	[-.00228]
Excess V	308	2,237	.372	2,155	-335	2,246	-91.4	4,378	198	4,526
	[-26.2]	[1.5]	[-19.1]	[6.49]	[-31.7]	[8.9]	[-71.2]	[116]	[-88.9]	[92]
Observations	81,216	20,999	76,015	25,836	75,248	27,073	33,603	14,648	28,275	10,860

Description: This table reports means [medians] for excess measures calculated for focused (Foc) and diversified (Div) firms according to different segment-level and firm-level industry classifications. EV is the log-ratio of firm value-to-sales over the sales-weighted median focused firm value-to-sales as in BO 95, but the median benchmark firms come from industry classifications as indicated in the column headings. Other "Excess" measures are calculated as the difference between the firm characteristic and its sales-weighted median benchmark. FFINDS10, FFINDS30, FFINDS49 indicate segment-level Fama-French industries at the 10-, 30-, or 49-industry levels that are translated from segment-level SIC codes. HPall (HPtop10) indicate textual network firm-level industry classification created using all (top 10 scored) competitors from the data developed in Hoberg and Phillips (2016) and Hoberg and Phillips (2017). Extreme values for EV are trimmed ($-1.386 < EV < 1.386$). Data to calculate Sales, Profit Margin (EBITDA/Sales), and V (total capitalization) are from Compustat. Age is calculated using methods and data from Jovanovic and Rousseau (2001), and Return Volatility is the standard deviation of monthly returns.

Interpretation: The BO 95 excess value measure results in a diversification discount using segment-level Fama-French classification and firm-level classification as developed in Hoberg and Phillips (2016) and Hoberg and Phillips (2017). Diversified firms are consistently larger and older than their matched focused firms.

Table 8: Summary Statistics using Alternate Levels of Industry

Excess Measures	SIND1		SIND2		SIND3		SIND4		FINE	
	Foc	Div	Foc	Div	Foc	Div	Foc	Div	Foc	Div
EV	.0218	-.0956	.0167	-.0776	.00983	-.0875	.00125	-.115	-.000941	-.0904
	[.0144]	[-.108]	[.00316]	[-.0861]	[0]	[-.0988]	[0]	[-.128]	[0]	[-.0987]
Excess Sales	-232	1,514	-326	1,492	-157	1,436	-113	1,632	-64	1,794
	[-75.8]	[-34.1]	[-35.7]	[8.98]	[-18.4]	[5.06]	[-11.6]	[-.0605]	[-3.83]	[75.2]
Excess Age	-7.1	3.46	-3.93	10.1	-2.32	9.24	-1.33	8.09	-.918	13.4
	[-3]	[-.217]	[-2]	[3.55]	[-1]	[3.29]	[-1]	[2.78]	[0]	[5.51]
Excess Return Volatility	.00702	-.00438	.00584	-.0093	.00317	-.00651	.000941	-.0111	.00122	-.0103
	[.00343]	[-.011]	[.00102]	[-.0148]	[0]	[-.0124]	[0]	[-.0159]	[0]	[-.0151]
Excess Profit Margin	-.00349	-.000716	-.0025	.00414	.00695	.0128	-.00636	.0179	-.00361	.00529
	[-.00247]	[-.00686]	[0]	[-.00181]	[.00109]	[.00519]	[0]	[.00631]	[0]	[.00172]
Excess V	-252	2,178	182	2,409	299	2,797	-3.74	3,510	62.5	2,716
	[-61.6]	[-31.1]	[-28.3]	[.401]	[-16.8]	[-.761]	[-12.4]	[-15.5]	[-2.95]	[42]
Observations	83,780	18,421	75,224	25,703	62,624	13,392	48,404	5,976	70,096	32,028

Description: This table reports means [medians] for excess measures calculated for focused (Foc) and diversified (Div) firms according to different levels of segment industry. EV is the log-ratio of firm value-to-sales over the sales-weighted median focused firm value-to-sales as in BO 95, but the median benchmark firms come from industry levels as indicated in the column headings. Other "Excess" measures are calculated as the difference between the firm characteristic and its sales-weighted median benchmark. SIND1, SIND2, SIND3, and SIND4 indicate that benchmark focused firms are in the same 1, 2, 3, or 4-digit segment-level SIC-code industry, respectively, as the segments of the subject firm. Focused is defined as having one segment at each industry level. FINE indicates that the benchmark focused firm median is taken from the finest level of segment-level SIC-code that has at least five focused (at the four-digit SIC code level) firms. Excess Value (EV) is calculated as the log of firm total capitalization (V) over the imputed value taken from matched focused firms as in BO 95. Extreme values for EV are trimmed ($-1.386 < EV < 1.386$). Data to calculate V, Sales, and Profit Margin (EBITDA/Sales) are from Compustat. Age is calculated using methods and data from Jovanovic and Rousseau (2001), and Return Volatility is the standard deviation of monthly returns.

Interpretation: The BO 95 excess value measure results in a diversification discount using alternate levels segment industry based upon SIC codes. Diversified firms are consistently larger and older than their matched focused firms.

Table 9: Industry Distribution Diversity by CEM Excess Value Decile

CEM EV Decile	N	CEM EV	Shannon Diversity	s.e.(Shannon Div.)	Horn Overlap
1	2309	-1.193	28.224	0.410	0.979
2	2308	-0.854	28.069	0.436	0.979
3	2309	-0.552	27.966	0.412	0.987
4	2308	-0.275	29.012	0.424	0.990
5	2309	-0.019	28.308	0.432	0.988
6	2308	0.223	28.191	0.449	0.990
7	2309	0.460	28.511	0.453	0.991
8	2308	0.714	28.533	0.418	0.990
9	2309	0.968	28.239	0.427	0.994
10	2308	1.240	27.771	0.429	.
Total	23085	0.071	28.618	.	.

Description: This table reports industry distribution diversity measures by CEM excess value decile. Diversified firms are sorted into deciles by CEM excess value and the Fama-French 49-industry distribution of the focused firms that are matched to diversified firms in that decile is calculated. The table reports the "effective number" Shannon True Diversity score for each decile and for the entire population. Standard errors are calculated by bootstrapping the diversified firm population, recomputing deciles and the consequent Shannon True Diversity. The Horn Overlap measure is calculated as in Jost (2007) with the largest excess value decile serving as the benchmark and can be interpreted as the proportion of "shared" industries between the two deciles.

Interpretation: High strata excess value firms are matched to virtually identical distributions of focused firms as low excess value firms. The CEM EV measure does not suffer from mis-matching on industry.

Table 10: Replication of Villalonga (2004b)

Panel A: Summary Statistics (Comparable to Villalonga (2004b), Table 1)						
	Diversified			Focused		
	Villalonga	1978–1997	1977–2016	Villalonga	1978–1997	1977–2016
Mean EV	-0.095	-0.107	-0.115	.	-0.006	-0.007
Median EV	-0.105	-0.113	-0.119	.	0.000	0.000
N(firm-years)	20,173	17,045	23,155	40,757[a]	37,871	66,655

Panel B: Matched Sample (Comparable to Villalonga (2004b), Table 4)						
	Diversifying			Focused, [t-1 to t+1]		
	Villalonga	1978–1997	1977–2016	Villalonga	1978–1997	1977–2016
N (firm-years)	150	373	672	23,691	24,754	41,532
ln(Assets)	5.87	5.21	5.57	5.16	5.06	5.46
EBIT/Sales	0.09[b]	0.07	0.06	0.09	0.08	0.07
CAPX/Sales	0.14	0.11	0.10	0.09	0.09	0.11
Ind. Adj. q in prior year	0.20	-0.05	-0.12	0.04	-0.04	-0.06
Ind q in prior year	1.23	1.22	1.42	1.30	1.34	1.53

Panel C: Treatment Effects (Comparable to Villalonga (2004b), Table 5)						
	Reduced Model			Extended Model		
	Villalonga	1978–1997	1977–2016	Villalonga	1978–1997	1977–2016
OLS	-0.073	-0.032	-0.102	-0.139	-0.035	-0.091
t-stat	-1.48	-1.23	-4.95	-2.34	-1.36	-4.41
Avg Treatment on Treated	-0.027	-0.042	-0.100	-0.103	-0.042	-0.102
z-stat[c]	-0.48	-1.50	-4.47	-1.60	-1.48	-4.66
N Diversifying (firm-years)	150	373	672	109	372	671
N Focused (firm-years)	23,691	24,754	41,532	12,043	24,681	41,441

[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, but is shown as 0.87 in the original paper.
[c] We implement the same matching estimator as the original paper, but calculate standard errors using an updated procedure from Abadie and Imbens (2011).

Description: 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 1977–2016. 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 at the four-digit SIC code level. 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 procedure that results in the average treatment effect on the treated.

Interpretation: The diversification discount persists even after controlling for endogeneity as in Villalonga (2004b).

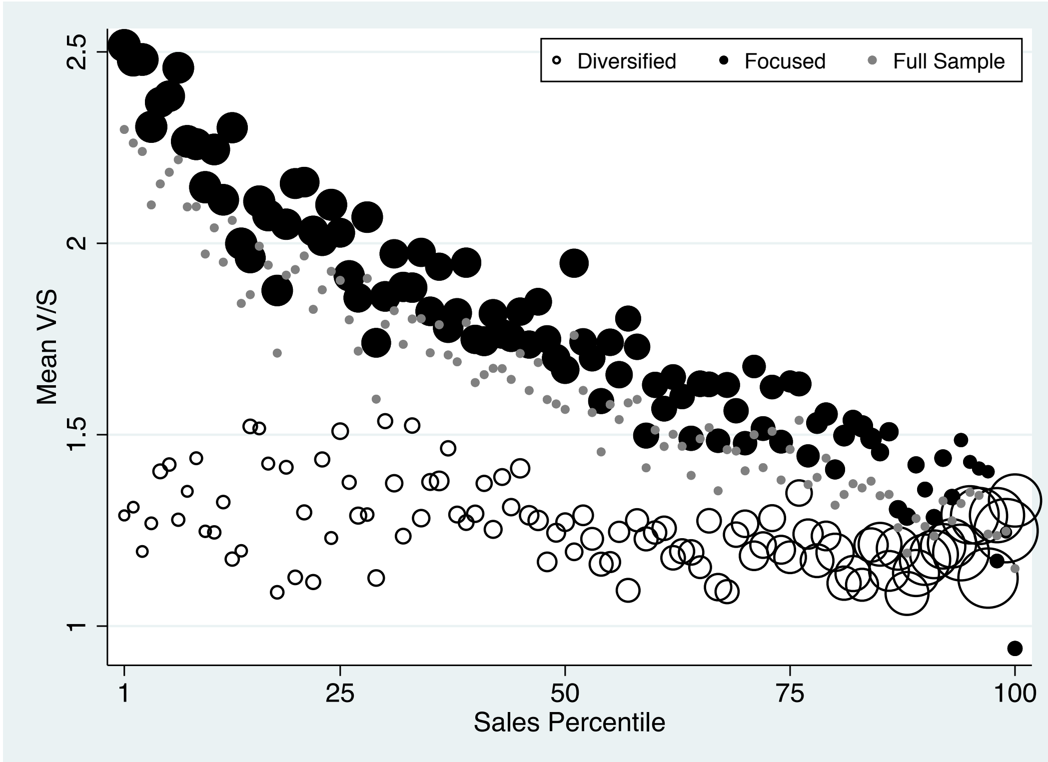

Figure 1: Value-to-Sales by Sales Percentile

Description: This figure presents the average total capitalization-to-sales ratios over the period 1977–2016 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.

Interpretation: The value-to-sales ratio is decreasing in sales. Most diversified firms are in the far right of the sales distribution while most focused firms are in the far left.

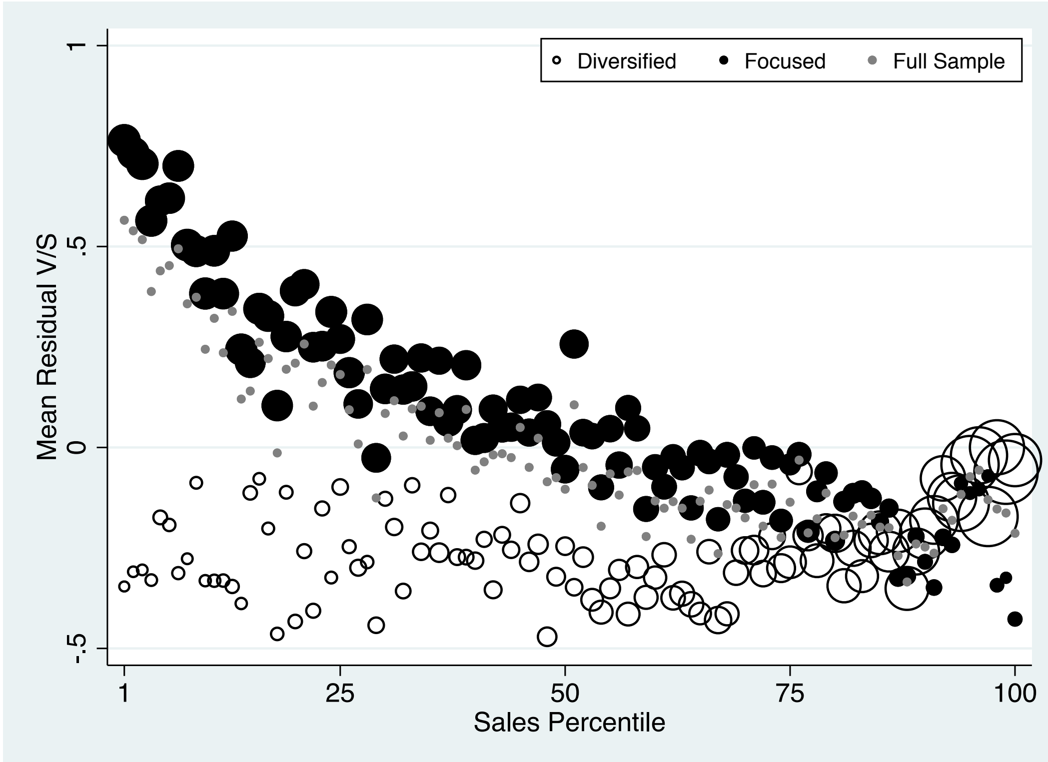

Figure 2: Value-to-Sales Residuals by Sales Percentile

Description: 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 1977–2016 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.

Interpretation: Controlling for age removes much of the distance between valuations of diversified and focused firms.

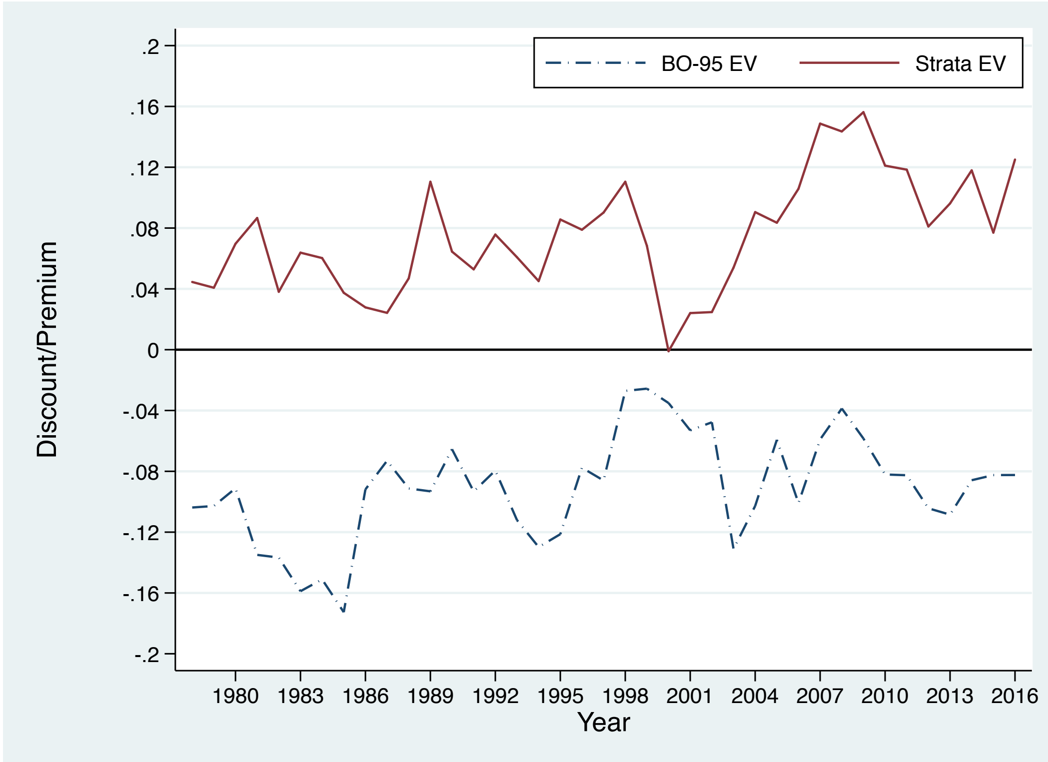

Figure 3: CEM Y-SA versus BO 95 EV Measures Over Time

Description: This figure graphs the cross-sectional mean standard excess value measure from BO 95 versus the cross-sectional mean strata-matched excess value measure developed in the paper by year over the entire sample period, 1977–2016.

Interpretation: Over time, the strata-matched excess value leads to different results and interpretations of the relative value of diversification versus the BO 95 measure.

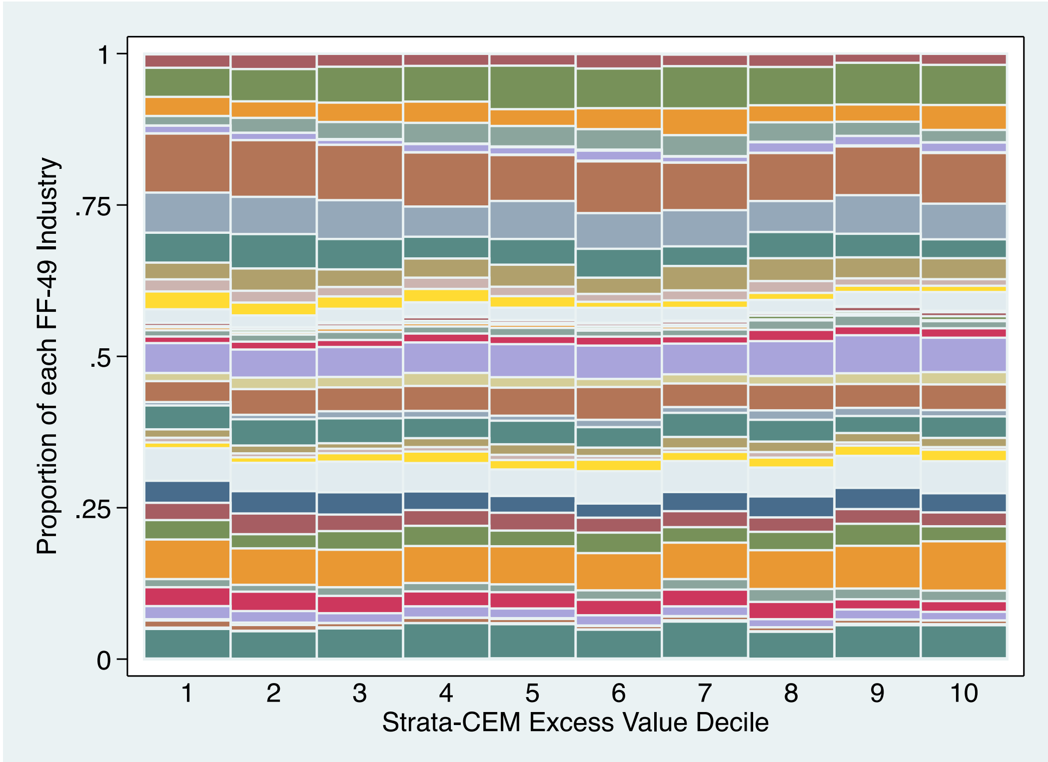

Figure 4: Industry Distributions of Matched Focused Firms

Description: This figure plots the Fama French 49 industry distribution of the focused firms matched to each diversified firm in the strata-EV measure procedure, by increasing deciles of the strata-EV discount/premium. The height of the each color within each bar represents the proportion of a particular FF49 industry represented by the matched focused firm in each decile.

Interpretation: Focused-firm industries are fairly evenly distributed across all of the deciles of the strata-EV measure.