Does Diversification Cause the "Diversification Discount"?

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Using recent econometric developments about causal inference, I examine whether diversification destroys value. I estimate the value effect of diversification by matching diversifying and single-segment firms on their propensity score—the predicted values from a probit model of the propensity to diversify. I also use Heckman's (1979) two-stage estimator for comparison purposes. I find that on average, diversification does not destroy value. This finding is robust to the choice of estimator, sample, measures of excess value, and specification.

The diversification discount has been the subject of an active debate in corporate finance during the past few years.[1] At the heart of the debate is the question of whether diversification destroys value. Many studies have replicated Lang and Stulz (1994) and Berger and Ofek's (1995) finding that diversified firms trade at a discount relative to single-segment firms. Yet, there is disagreement as to whether this finding can be interpreted as evidence of value destruction.

This article examines this issue by using recent econometric techniques for causal inference. I argue that assessing whether diversification creates or destroys value is a particular case of the "treatment effects" literature that seeks to establish causation from non-experimental data. I use three different treatment effects estimators to address the diversification question and I compare their performance in this setting: the matching estimators of Dehejia and Wahba (1999, 2001) and Abadie and Imbens (2002), and Heckman's (1979) two-stage method. Heckman's method is well known, and has already been applied to the diversification context by Campa and Kedia (2002).[2] The two matching estimators are based on propensity scores (i.e., the predicted values from a probit model of the decision to diversify). I use the scores to select a matched sample of control observations that are comparable to diversifying firms not just in size and industry, but also in a wider range of characteristics in which the two groups differ.

All three methods result in the disappearance of the diversification discount as such. This finding is consistent with the evidence in Campa and Kedia (2002), Graham, Lemmon, and Wolf

[1]The current state of the debate is reflected in Villalonga's (2003a) research roundtable discussion.

[2]This article is a substantially revised version of my 1999 working paper, which was developed independently and simultaneously to Campa and Kedia (2002).

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(2002), and most event studies of diversifying acquisitions (Schipper and Thompson, 1983; Hubbard and Palia, 1999; Matsusaka, 1993; and Hyland and Diltz, 2002). My results support the conclusion that on average, diversification does not destroy value. Although the size of the estimates varies, the insignificance of the effect is robust to the method, subsample, measure of excess value, and specification I use.

The article is organized as follows. Section I explains the problem of causal inference as it applies to the diversification discount, and introduces the three treatment effect estimators used in this article. Section II describes the sample and excess value measures. Section III reports preliminary analyses. Section IV reports the main results. Section V concludes.

I. Causal Inference and the Diversification Discount

The estimation of diversification's effect on firm value is an example of the general statistical problem of estimating treatment effects in observational studies. The problem is that the simple average difference in outcomes between treatment and control groups is only an unbiased estimate of the treatment effect when units are randomly assigned to the treatment. However, in contexts such as diversification and managerial decision-making, where experimental data are unavailable, assignment is non-random.

Absent experimental data, there are two ways to infer causality. One is to take advantage of "natural experiments" if and when they exist—discrete shocks outside the control of the individual or firm that randomly assign individuals or firms to the "treatment." One example of this in corporate finance is Lamont's (1997) analysis of oil firms' investment behavior following the 1986 oil price decrease. To my knowledge, no similar natural experiment is available to study diversification's effect on firm value.[3] The second avenue, which is feasible in the diversification context and is the one followed in this article, is to use one or more of the statistical techniques available for estimating treatment effects with nonexperimental data.

Using standard notation in causal inference theory, each firm has two possible outcomes or values, Y_{i1} if it diversifies, Y_{i0} if it does not diversify. Using D_i to denote a diversification indicator that equals one for diversified firms and zero for single-segment firms, $E(Y_{i1} \mid D_i = 1)$ denotes the average value of diversified firms, and $E(Y_{i0} \mid D_i = 0)$ the average value of single-segment firms. The parameter of interest $\tau |_{D=1}$ is the effect of diversification on the value of the diversified firms (i.e., the difference between the value of the average diversified firm and the value its segments would have had if they had operated as stand-alone segments):

$$\tau |_{D=1} = E(Y_{i1} \mid D_i = 1) - E(Y_{i0} \mid D_i = 1). \tag{1}$$

[3]Lamont and Polk (2002) attempt to overcome this problem by simulating the following "natural experiment." They define "diversity" as the within-firm dispersion in some industry characteristic such as investment (capital expenditures) or cash flow, and use diversity as a proxy for diversification. Changes in diversity reflect both endogenous changes in the segment structure of the individual firm and exogenous changes in industry characteristics. They compute the exogenous component of changes in diversity between time $t-1$ and time t by measuring the level of diversity the firm would have had at time t if it had maintained the segment structure it had at $t-1$. They then examine the impact of these exogenous changes in diversity on firm value, which turns out to be negative. Based on their assumption that diversity measures diversification, they argue that "the contribution of [their] paper is to show the causal effect of diversification: diversification destroys value" (p. 53). However, Villalonga (2003b) tests explicitly for the assumption that diversity measures diversification and finds that Lamont and Polk's exogenous changes in diversity are in fact *negatively* and insignificantly related to changes in diversification. Hence, while Lamont and Polk's "natural experiment" is valid to answer the question of whether diversity destroys value, it cannot be used to answer the question of whether diversification destroys value.

This difference is generally known as the average treatment effect on the treated (ATT).

Since $E(Y_{i0} \mid D_i = 1)$ is unobservable, what can be computed instead of Equation (1) is the difference in average value between diversified and single-segment firms:

$$\tau^e = E(Y_{i1} \mid D_i = 1) - E(Y_{i0} \mid D_i = 0). \tag{2}$$

The problem, then, is that unless $E(Y_{i0} \mid D_i = 1) = E(Y_{i0} \mid D_i = 0)$, as it occurs under random assignment, Equation (2) is a biased estimator of Equation (1) due to self-selection.

Using standard notation in sample selection models, there are two equations in this context: a value equation:

$$Y_i = \alpha + \delta D_i + \beta X_i + \varepsilon_i, \tag{3}$$

where Y_i is firm value and D_i is a diversification indicator, as in Equations (1) and (2), X_i is a vector of variables characterizing firm i, and ε_i is an error term; and a selection equation modeling a firm's propensity to diversify:

$$D^*_i = \gamma Z_i + \eta_i, \tag{4}$$

where, D^*_i is a latent variable that is observed as $D_i = 1$ if $D^*_i > 0$ or as $D_i = 0$ otherwise, Z_i is a vector of variables that affect a firm's probability to diversify, and η_i is an error term.

The selection bias in an OLS estimate of β arises due to the correlation between D^*_i and ε_i. This correlation may be attributable to one or both of two possible sources of selection bias (Heckman and Robb, 1985, 1986): selection on observables, i.e., when some of the regressors in the diversification equation are not included as regressors in the value equation; and selection on unobservables, when the error terms of the two equations are correlated.

Two broad classes of estimators allow the econometrician to reduce and possibly eliminate sample selection bias and identify the ATT in a non-experimental context: Heckman's (1979) two-stage model, and the method of matching. Each of the two focuses on one of the two sources of selection bias and relies on different assumptions to identify the ATT.

Heckman's model eliminates the bias due to selection on unobservables and relies on exclusion restrictions for the identification of the ATT. That is, for the effect to be identified, there must be at least one variable in Z_i that is not included in X_i, as in a general instrumental variables setup. In addition, Heckman's original model assumes joint normality in the distribution of the error terms, although this assumption can be relaxed (Lee, 1983). Since details on Heckman's procedure can be found in any econometrics textbook, or in Campa and Kedia (2002) as applied to diversification, I omit them in this article.

By assuming that treatment assignment is a function of observable variables only, matching methods eliminate the bias due to selection on observables. Thus, conditional on the observed variables, assignment can be taken to be random, and one can estimate the unconditional effect as the expectation of the conditional effects over the distribution of the conditioning variables in the treated population:

$$\tau|_{D=1} = E_X\{E(Y_{i1} \mid X_i, D_i = 1) - E(Y_{i0} \mid X_i, D_i = 0) \mid D_i = 1\}. \tag{5}$$

Traditional matching methods estimate the ATT as the difference in average outcomes of the treated and control groups, where the control group is formed matching units based on one or more characteristics. For instance, in corporate finance it is common practice to construct control groups of firms based on size and industry. The measures of excess value developed by Lang and Stulz (1994) and Berger and Ofek (1995) that assess the value effect of diversification implicitly perform this size-and-industry matching function. This practice amounts to assuming that size and industry are the only two characteristics in which diversified and single-segment firms differ. However, studies of the diversification decision show that the two groups of firms also differ in other characteristics.

The problem with the size-and-industry matching approach is that the extent of the selection bias depends on the overlap between the distributions of characteristics for the treatment and control groups. The greater the overlap in all characteristics, the more comparable the groups are, and the smaller the bias (Heckman, Ichimura, and Todd, 1997; Heckman, Ichimura, Smith, and Todd, 1998). Therefore, and given that there are many possible reasons why firms diversify, partial matches based on only one or two characteristics may not yield the most relevant group for comparison. On the other hand, matching on all the characteristics in which diversified and single-segment firms differ is an intractable problem.

The propensity score matching method solves this problem of the "curse of dimensionality." Rosenbaum and Rubin (1983) define the propensity score as the probability of assignment to treatment conditional on a vector of independent variables X_i:

$$p(X_i) \equiv \Pr(D_i = 1 \mid X_i) = E(D_i \mid X_i)\,. \tag{6}$$

The propensity score theorem says that if the treatment assignment can be ignored conditional on X, then it can also be ignored conditional on the propensity score:

$$Y_{i1}, Y_{i0} \perp D_i \mid X_i \Rightarrow Y_{i1}, Y_{i0} \perp D_i \mid p(X_i)\,. \tag{7}$$

The theorem implies that observations with the same propensity score have the same distribution of the full vector of variables X_i. Hence, by matching on the propensity score, the dimensionality of the problem reduces to one, and maximum comparability between treatment and control units is attained. One can then estimate the ATT as the expectation of the conditional effects over the distribution of the propensity score in the treated population:

$$\tau\,|_{D=1} = E_{p(X)}\,\{E(Y_{i1} \mid p(X_i), D_i = 1) - E(Y_{i0} \mid p(X_i), D_i = 0) \mid D_i = 1\} \tag{8}$$

Propensity score matching estimators are increasingly being used in evaluation studies and have been refined in multiple ways in recent years.[4]

The latest evaluations of treatment effects estimators suggest that two propensity score matching estimators generally outperform all others. These include a difference-in-difference estimator such as the one developed by Dehejia and Wahba (1999, 2001), and the bias-corrected estimator of Abadie and Imbens (2002), which is also best implemented as a difference-in-differences estimator. In this article, I use these two estimators to evaluate the causal effect of diversification on firm value. I also use Heckman's (1979) two-stage estimator for comparison purposes.

II. Data

I construct the sample by applying the criteria in Berger and Ofek (1995) to the longest

[4]See Smith and Todd (2000) and Abadie and Imbens (2002) for a more complete review.

possible period for which business segment data are available and comparable.[5] The sample comprises both active and inactive ("research") firms that have data in Compustat company- and segment-level files during 1978–1997. I eliminate firm-years if any of the following conditions hold: missing or non-positive firm assets or market value; sales less than $20 million or missing; missing segment sales or assets for any segment; sum of segment sales not within 1% of the total sales of the firm; any segment with a one-digit SIC code of zero, six (financial), or nine; any segment with less than five single-segment firms in its two-digit SIC code. These criteria yield a total of 60,930 firm-years from 8,937 firms during 1978–1997. Of these, 20,173 firm-years are diversified (multisegment) and 40,757 are single-segment. Thus, the sample is comparable to those in prior studies of the diversification discount.

I use the full sample of firms to construct measures of excess value and replicate earlier cross-sectional results. In addition, my analyses require a longitudinal subsample, which I also construct by following the precedent in earlier studies (Graham et al., 2002 and Hyland and Diltz, 2002). This subsample is described below, before the analyses for which it is used.

I use three different measures of excess value throughout the article. Following Berger and Ofek (1995), I compute excess values based on asset or sales multipliers as the natural logarithm of the ratio of a firm's actual value to its imputed value. A firm's imputed value is the sum of the imputed values of its segments, where a segment's imputed value is equal to the segment's assets (sales) multiplied by the industry median ratio of market value to assets (sales) in its year. Market value refers to the market value of common equity plus the book value of debt and preferred equity. I consider observations with excess values lower than -1.386 or greater than 1.386 as outliers and eliminate them from the statistical analyses.

Following Lang and Stulz (1994), excess values based on industry-adjusted q are the difference between the firm's q and the asset-weighted average of the imputed q's of its segments, where a segment's imputed q is the industry average q. I measure q as the ratio of market value to the book value of assets. I compute industry averages and medians at the most precise SIC level for which there is a minimum of five single-segment firms in the industry-year: 39% at the 4-digit SIC code level, 53% at the 3-digit level, and 8% at the 2-digit level.

III. Preliminary Analyses

As a preliminary step to my main analyses, I verify that the finding of a "diversification discount" as estimated in prior studies also holds for my sample.

A. Cross-Sectional Discount

Table I reports one-stage estimates of diversification's cross-sectional effect on firm value. Following Lang and Stulz (1994) and Berger and Ofek (1995), I estimate this effect as the mean or median difference in excess values between diversified (multisegment) firms and single-segment firms.

My results are in line with those in earlier studies. The mean (median) discount on the full

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[5] After 1997, segment information conforms to a different reporting standard (SFAS131 as opposed to FASB14). Under the new standard, firms do not need to report disaggregated information by line-of-business unless they organize themselves that way for purposes of performance evaluation. As a result, segment data before and after 1997 are not directly comparable. See Berger and Hahn (2003) or Villalonga (2004) for further details.

Table I. Cross-Sectional Effect of Diversification on Firm Value: One-Stage Estimates

The table shows the mean and median differences in excess values between diversified (multisegment) firms and single-segment firms. A firm's excess value based on asset or sales multipliers is the natural logarithm of the ratio of the firm's market value to its imputed value. A firm's imputed value is the sum of the imputed values of its segments, where a segment's imputed value is equal to the segment's assets (sales) multiplied by its industry median ratio of market value to assets (sales) in its year. Market value is the market value of common equity plus the book value of debt and preferred equity. Industry-adjusted q is the difference between the firm's q and the asset-weighted average of the imputed q's of its segments, where a segment's imputed q is the industry average q, and q is measured as the ratio of market value to assets. I compute industry averages at the most precise SIC level for which there is a minimum of five single-segment firms in the industry-year. The sample comprises 60,930 firm-years from 8,937 firms during 1978–1997. The Lang and Stulz subsample "excluding smaller firms" excludes firms with less than $100 million of assets on average and firms with less than two years of data. t-statistics for means and z-statistics from Wilcoxon rank-sum tests for medians appear in parentheses.

				Asset Multiplier		Sales Multiplier		Industry-Adj. *q*	
	Period	Firm-Yrs	Diversified Firm-Yrs	Mean	Med.	Mean	Med.	Mean	Med.
Full Sample	1978–1997	60,930	20,173	-0.123 (-26.39)	-0.117 (-27.86)	-0.095 (-19.62)	-0.105 (-20.21)	-0.199 (-23.31)	-0.099 (-22.97)
Berger and Ofek's Subsample	1986–1991	17,390	5,563	-0.114 (-13.65)	-0.104 (-14.48)	-0.078 (-8.48)	-0.079 (-8.59)	-0.180 (-12.93)	-0.108 (-12.94)
Lang and Stulz's Subsample	1978–1990	35,518	14,152	-0.125 (-21.90)	-0.114 (-23.29)	-0.099 (-16.69)	-0.103 (-17.18)	-0.181 (-23.04)	-0.108 (-24.01)
Lang and Stulz's Subsample Excluding Smaller Firms	1978–1990	17,371	8,260	-0.173 (-23.78)	-0.108 (-23.65)	-0.170 (-21.97)	-0.114 (-21.34)	-0.272 (-24.56)	-0.147 (-27.43)

sample is 12.3% (11.7%) using asset multipliers, and 9.5% (10.5%) using sales multipliers. By way of comparison, Campa and Kedia (2002), whose sample is similar to mine, report median discounts of 11.6% and 10.9% for asset and sales multipliers, respectively. Berger and Ofek find mean (median) discounts of 10.8% (16.2%) and 9.5% (10.6%) for the period 1986–1991 using asset and sales multipliers, respectively. For the same period (1986–1991), my sample yields mean (median) discounts of 11.4% (10.4%) using asset multipliers and 7.8% (7.9%) using sales multipliers. These numbers are lower that Berger and Ofek's, but similar to those reported by Campa and Kedia for the 1986–1991 period (10.3% and 7.6% median discounts). Like Campa and Kedia, I attribute this difference between our results and Berger and Ofek's to changes in the Compustat database that came about between the times we retrieved our data.

The mean (median) discount in terms of industry-adjusted q is 0.2 (0.1). The mean (median) industry-adjusted discount for the period 1978–1990 is 0.18 (0.11), which is consistent with the findings of Lang and Stulz (1994).[6]

B. Longitudinal Discount

A negative average cross-sectional discount is not evidence per se that diversification destroys value. For the discount to be interpreted as evidence of value destruction, diversified firms must have destroyed value by engaging in diversification, or at least be destroying value by staying diversified. If firms are staying diversified, it requires evidence about the benefits of corporate refocusing. In either case, one needs to look at changes in diversification status, which requires me to use a longitudinal approach. In addition to event studies, three diversification discount papers take such an approach: Lang and Stulz (1994) (in the last section of their paper), Graham et al. (2002), and Hyland and Diltz (2002).

As a second preliminary analysis, I assess the longitudinal effect of diversification in my sample as estimated in these three studies. Like them, I focus on those firms that change their diversification status from single-segment to diversified (multisegment). There are two reasons for this selection: first, the diversification discount literature usually defines diversification as a multisegment dummy (or as a dummy for diversifying mergers); and second, Lang and Stulz (1994) and subsequent studies find that the discount is significant between one- and two-segment firms, but not between two-segment firms and firms with larger numbers of segments.

Graham et al. (2002) and Hyland and Diltz (2002) show that the estimates of a diversification discount may be contaminated by reporting changes in Compustat. Therefore, it is important to eliminate these reporting changes from my sample. Using supplementary information from Lexis-Nexis, firms' annual reports, and the appendix in Hyland (1997), I identify 167 segment increases in my sample that are the result of acquisitions or internal growth. I use this subset of diversifying firm-years as well as the 40,757 single-segment firm years in the sample for all longitudinal analyses.

This subsample is comparable to the sample in Hyland and Diltz (2002), which includes 143 segment increases from acquisitions or internal growth during the period 1978–1992. The subsample is also comparable to the samples in Graham et al. (2002) (141 segment increases from acquisitions only for 1978–1996), and Lang and Stulz (1994) (192 segment increases not excluding reporting changes).

Panel A of Table II presents mean and median excess values for the 167 diversifying firms arrayed in event-time, from five years before through five years after the diversification event. Two results are notable. First, there is no evidence that diversifying firms trade at a

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[6]Lang and Stulz (1994) report yearly averages for 1978–1990 that range between 0.27 and 0.73. The average of their estimates (weighted or unweighted) is 0.44 for the entire period. Two reasons might account for the discrepancy between my results and theirs. First, the Lang and Stulz sample is about half the size of mine for the same period. It also comprises only larger firms. (Lang and Stulz show that size alone explains a large part of the diversification discount.) If I too exclude firms with an average of less than $100 million of assets and firms with less than two years of data, the average discount in my 1978–1990 subsample increases by 50% to 0.27.

Second, Lang and Stulz (1994) correct the denominator of q so as to capture the replacement cost of assets. In contrast, I use the book value of assets. Lang and Stulz report multivariate regression estimates of the discount using market-to-book ratios and adjusted and unadjusted Tobin's q (Table 7 in their paper). The averages of their yearly estimates are 0.42 for unadjusted q, 0.37 for adjusted q, and 0.14 for (unadjusted) market-to-book. These figures seem to indicate that although q and market-to-book generally exhibit a very high correlation, market-to-book yields a diversification discount almost three times lower in the same sample. These two reasons can also explain why Lang and Stulz's estimates are approximately twice as large as Berger and Ofek's for their asset multiplier measure, which is also based on market-to-book ratios.

Table II. Longitudinal Effect of Diversification on Firm Value: One-Stage Estimates

Diversifying firms are firms that increase their number of segments from one to two or more as a result of acquisitions or internal growth. A firm's excess value based on asset or sales multipliers is the natural logarithm of the ratio of the firm's market value to its imputed value. A firm's imputed value is the sum of the imputed values of its segments, where a segment's imputed value is equal to the segment's assets (sales) multiplied by its industry median ratio of market value to assets (sales) in its year. Market value is the market value of common equity plus the book value of debt and preferred equity. Industry-adjusted q is the difference between the firm's q and the asset-weighted average of the imputed q's of its segments, where a segment's imputed q is the industry average q, and q is measured as the ratio of market value to assets. I compute industry averages at the most precise SIC level for which there is a minimum of five single-segment firms in the industry-year. The full sample comprises 60,930 firm-years from 8,937 firms during 1978–1997. The subsample in Panel A includes 167 diversifying firm-years plus the 40,757 single-segment firm-years in the full sample, which I use to compute excess values. The subsample in Panels B through D includes the 150 diversifying firms with data from one year before until one year after diversification, plus the 24,539 single-segment firm-years with data on the same firm for the previous year and the subsequent year. t-statistics for means and z-statistics from Wilcoxon rank-sum tests for medians appear in parentheses.

Panel A. Excess Values for Diversifying Firms Before and After the Diversification Decision (N = 167)

	Diversified Firm-Yrs	Asset Multiplier		Sales Multiplier		Industry-Adjusted q	
		Mean	Median	Mean	Median	Mean	Median
EV_{-5}	85	0.069	2E-16	-0.036	0	0.133	-0.112
EV_{-4}	94	0.055	8E-03	-0.033	0	0.022	-0.160*
EV_{-3}	117	0.037	0	-0.012	-0.014	0.083	-0.160
EV_{-2}	127	0.056	3E-04	-0.004	0.001	0.054	-0.124
EV_{-1}	150	0.034	0	0.047	0.036	0.149	-0.130
EV_{0}	167	-0.076*	-0.162**	0.024	-0.028	-0.174***	-0.302***
EV_{1}	153	-0.098**	-0.120***	0.011	-0.024	-0.188***	-0.220***
EV_{2}	138	-0.076*	-0.106**	-0.022	0.011	-0.213***	-0.267***
EV_{3}	123	-0.124**	-0.169***	-0.037	-0.038	-0.201**	-0.311***
EV_{4}	102	-0.069	-0.139	-0.085	-0.103	-0.199***	-0.233***
EV_{5}	92	-0.094*	-0.025	0.003	0.033	-0.278***	-0.233***

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

discount prior to diversifying. Sometimes they trade at a discount, but sometimes they trade at a premium, depending on the measure of excess value and on whether I focus on means or medians. None of the prediversification discounts or premiums is significantly different from zero. Second, when I use asset multipliers or industry-adjusted q, a significant discount appears in the diversification year and in the five subsequent years. I find no significant discount when I use sales multipliers, and no clear pattern of increase or decrease in the post-diversification discount for any measure of excess value. Both of these results are consistent with Graham et al.'s (2002) findings. In contrast, Hyland and Diltz (2002) find no significant discount on assets or EBIT multipliers for the five years subsequent to the diversification event, and a significant premium on sales multipliers.

In Panel B of Table II, I test for the significance of these changes, and report tests statistics

Table II. Longitudinal Effect of Diversification on Firm Value: One-Stage Estimates (*Continued*)

Panel B. Mean Change in Excess Values for Diversifying Firms (N = 150)

	Asset Multiplier		Sales Multiplier		Industry-Adjusted q	
EV^d_{-1}	0.034	(0.79)	0.047	(0.88)	0.149	(1.22)
EV^d_1	-0.098	(-2.39)***	0.012	(0.25)	-0.188	(-3.08)***
$EV^d_1 - EV^d_{-1}$	-0.132	(-4.38)	-0.035	(-0.96)	-0.337	(-3.19)***

Panel C. Mean Change in Excess Values for Single-Segment Firms (N = 24,539)

	Asset Multiplier		Sales Multiplier		Industry-Adjusted q	
EV^{ss}_{-1}	0.030	(9.96)***	0.016	(4.64)***	0.022	(3.89)***
EV^{ss}_1	-0.034	(-11.67)***	-0.049	(-14.62)***	-0.110	(-19.76)***
$EV^{ss}_1 - EV^{ss}_{-1}$	-0.063	(-23.35)***	-0.065	(-22.70)***	-0.132	(-25.07)***

Panel D. Mean Difference in the Change in Excess Values between Diversifying Firms and Single-Segment Firms

	Asset Multiplier		Sales Multiplier		Industry-Adjusted q	
$(EV^d_1 - EV^d_{-1}) - (EV^{ss}_1 - EV^{ss}_{-1})$	-0.069	(-1.67)*	0.029	(0.73)	-0.205	(-2.78)***

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

for within-firm changes in the average discount between the year before and the year after diversification. I adopt the $(t-1, t+1)$ timing convention for measuring the change in excess values to follow the precedent in Graham et al. (2002) and also to avoid losing observations as I move away from the diversification year. The increase in the discount is statistically significant for the two asset-based measures of excess value, but not for sales multipliers.

I also provide a more formal test of the longitudinal effect of diversification on firm value by looking at the differences in the change in excess values between diversifying firms and all the single-segment firms in the sample. These "difference-in-differences" estimates are more like the cross-sectional estimates in Table I, in that they are mean differences between the two groups of firms.[7] The use of difference-in-differences estimators is also common practice in the evaluation of treatments and training programs, as discussed in Section I. Panel C of Table II shows the changes in excess values from one year to two years later for single-segment firms (analogous to the information reported for diversifying firms in Panel B). Panel D reports the difference-in-differences. As with the simple changes in excess values for diversifying firms, the difference-in-differences discount is statistically significant for industry-adjusted q and for asset multipliers, although only marginally so (10% level) for the latter. The estimate using sales multipliers is a premium, but insignificant.

IV. Main Results

None of the estimates so far reported in this article take into account the fact that

[7]In the full sample, the median excess value of single-segment firms based on asset or sales multipliers is zero by construction, as is the mean industry-adjusted q. Therefore, some of the cross-sectional estimates of Table I are equivalent to the mean or median excess value for diversified firms only, and thus comparable to the simple change estimates of Panel B of Table II.

diversification is endogenous. In Section I, I explain from an econometric standpoint why the endogeneity of diversification precludes the interpretation of the discount as evidence of value destruction. In contrast to the common interpretation that value destruction explains the discount, several theories consistent with value maximization can also account for the finding of a discount (Zuckerman, 1999; Bernardo and Chowdry, 2002; Maksimovic and Phillips, 2002; Burch, Nanda, and Narayanan, 2003; and Gomes and Livdan, 2004). To differentiate between the two sets of explanations, one needs to control for the endogeneity of diversification.

I use three different estimators of the average treatment effect on the treated (ATT) to evaluate diversification's causal effect on firm value: those of Dehejia and Wahba (1991, 2001), Abadie and Imbens (2002), and Heckman (1979). The estimators differ in their assumptions and estimation approach, but they all share the underlying two-stage model of Equations (3) and (4). The first stage in any of the three approaches requires estimating a firm's propensity to diversify as a discrete choice model, such as a probit regression. The second stage uses information from the first to estimate the ATT.

A. Propensity to Diversify

To ensure greater robustness, I implement all three estimators as difference-in-differences estimators. Thus, I estimate the probit model on the same longitudinal subsample I use to compute the one-stage difference-in-differences estimates reported in Table II. The subsample includes the 150 diversifying firms with data from one year before until one year after diversification, plus the 24,539 single-segment firm-years with data on the same firm for the previous year and the subsequent year. The proportion of diversifying events in the sample is similar to that in Colak and Whited's (2003) study of the ATT of refocusing (107 spinoffs or 139 divestitures, and 16,048 control observations).

One caveat to the interpretation of the probit results is that because of the overwhelming proportion of zeroes in the sample relative to the ones, the t-statistics may be overstated. This problem, which is common in discrete choice model applications, is sometimes addressed through state-based sampling (Manski and McFadden, 1981), i.e. using only a random sample of the zeroes (e.g., one percent) to estimate the model. In my sample, I find that using state-based sampling generates coefficients that are very different from those I obtain using the full sample of zeroes. For this reason, and to avoid contaminating the treatment effect estimates, which are ultimately the object of interest in this article, I use the full sample of diversifying and single-segment firms to estimate the propensity to diversify. I also note that in the second stage of the ATT estimation, the propensity score method discards part of the control observations (as many as 30%), those that are not comparable to diversifying firms in their propensity to diversify.

I model a firm's propensity to diversify as a function of the characteristics of the firm, its industry, and its macroeconomic environment at the time of diversification. I focus on the firm's first decision to diversify, because it is the most appropriate point in time for evaluating treatment effects. In that respect, my model is most directly comparable to Hyland and Diltz's (2002). In contrast, Campa and Kedia (2002) estimate the (cross-sectional) probability of a firm to be diversified. Earlier strategy and industrial organization studies such as Montgomery and Hariharan (1991) or Silverman (1999) model the propensity of firms to increase their level of diversification, regardless of whether they are already diversified or not.

The firm characteristics I use in my model are firm size (log of total assets); profitability (EBIT/sales); investment (CAPX/sales); and dummies that indicate whether the firm belongs to a major S&P index (industrial or transportation); whether it is listed on a major exchange (NYSE, AMEX, or Nasdaq); whether the firm is incorporated abroad; and whether it paid dividends. I also examine the percentage of outstanding common stock owned by institutions; the percentage of outstanding common stock owned by insiders; the ratio of R&D to assets; and the logarithm of firm age, proxied by the number of years listed in CRSP. The industry characteristics I use are the industry q in the prior year, the fraction of firms in the industry that are diversified, and the fraction of industry sales accounted for by diversified firms. I consider the macroeconomic characteristics of GDP growth, the number of months that the economy was in recession during the year, the number of merger or acquisition announcements in the year, and the annual dollar value of announced mergers and acquisitions. I also include prediversification performance (broken down into industry q and the firm's industry-adjusted q), to account for the potential reverse causality in the diversification-value relation.

I obtain the data for these variables from several sources: Securities Data Corporation (SDC) for merger activity, Compact Disclosure for insider ownership, Spectrum for institutional ownership, CRSP for firm age, NBER for GDP growth and business cycles, and Compustat for all other variables.

Table III reports probit estimates from five different models of firms' propensity to diversify. Model (1) comprises only the Berger and Ofek (1995) control variables (logarithm of assets, EBIT/sales, and CAPX/sales) and the measures of pre-diversification performance. Model (2) includes the same variables that Campa and Kedia (2002) have in their probit model, although I do not include lagged or squared values of any variables as they do. Model (3) is the most complete specification, and includes all of the variables described above. Model (4) excludes from Model (3) the variables with the largest amount of missing data: insiders, R&D/Assets, and the logarithm of firm age.

The pseudo-R^2's are in the 0.03–0.19 range. This goodness-of-fit is in line with the pseudo-R^2's of 0.08–0.09 reported in Hyland and Diltz (2002) and the likelihood ratio index of 0.08 reported in Campa and Kedia (2002). The number of observations on which I estimate each model ranges between 24,689 for Model (1) and 3,418 for Model (3). This large variation highlights the trade-off between the number of variables used in the model and the number of observations available to estimate the model with those variables. The amount of missing data is due to the fact that some data sources have a much more limited coverage than Compustat (e.g., Compact Disclosure), and/or some variables have a large amount of missing data in their original sources (e.g., R&D in Compustat).

The results of the probit regressions are sensitive to the specification used, which is not surprising given the variation in sample size. For instance, the pre-diversification industry-adjusted q coefficient is positive and significant in Models (1) and (4). After controlling for characteristics that are not included in the univariate regressions of Table II, my results suggest that the diversifying firms in those subsamples were trading at a premium. In Table II, the mean industry-adjusted q in the year prior to diversification is also a premium (0.149), but it is not statistically significant. The coefficient is not significant in Model (3). In contrast, industry q is negative and significant in Models (1) and (3), but not in Model (4). Size has a positive and significant effect in the propensity of firms to diversify for three out of the four models, but profitability has the opposite effect.

Institutions and dividends paid are significant in Model (3) but not in Model (4). Insiders and log of age are not significant in Model (3), and R&D/Assets is significant only at the 10% level. Because these three variables are the ones with the greatest amount of missing data and are not (or not highly) significant, I omit them from Model (4). The two proxies for the attractiveness of the industry to diversified firms have either positive or insignificant

Table III. Propensity to Diversify

This table reports probit estimates from four different models of firms' propensity to diversify. The dependent variable is one for firm years in which the number of segments increased from one to two or more as a result of acquisitions or internal growth, zero for single-segment years. The subsample in this table includes all firm-years with excess values available for years $t + 1$ and $t - 1$ and non-missing data in year t for any of the variables listed. M.E. are marginal effects. t-statistics appear in parentheses.

	Model (1)		Model (2)		Model (3)		Model (4)	
	Coef.	M.E.	Coef.	M.E.	Coef.	M.E.	Coef.	M.E.
Firm Characteristics								
Log of Assets	0.132	0.002	0.226	0.002	0.101	2E-4	0.223	0.002
	(6.64)		(8.50)		(0.98)		(6.37)	
EBIT/Sales	-1.163	-0.014	-1.820	-0.015	0.497	7E-4	-1.910	-0.015
	(-2.63)		(-3.88)		(0.23)		(-3.19)	
CAPX/Sales	-0.145	-0.002	-0.025	-2E-4	-5.608	-0.008	-0.133	-0.001
	(-0.68)		(-0.14)		(-1.70)		(-0.47)	
S&P Index			-0.100	-7E-4	-0.180	-2E-4	-0.196	-0.001
			(-0.86)		(-0.49)		(-1.40)	
Major Exchange			-0.049	-4E-4	-0.315	-7E-4	-0.070	-6E-4
			(-0.59)		(-1.21)		(-0.66)	
Foreign incorporation			-0.202	-0.001	-0.031	-4E-5	-0.283	-0.002
			(-1.22)		(-0.07)		(-1.24)	
Industry-adjusted q in prior year	0.079	0.001			-0.100	-2E-4	0.108	9E-4
	(2.82)				(-0.63)		(3.45)	
Dividends Paid					0.474	8E-4	0.026	2E-4
					(2.01)		(0.28)	
Institutions					-0.014	-2E-5	-0.002	-1E-5
					(-2.44)		(-0.67)	
Insiders					-0.004	-5E-6		
					(-0.56)			
R&D/Assets					2.301	0.003		
					(1.80)			
Log of Age (years listed on CRSP)					3E-4	5E-7		
					(0.03)			
Industry Characteristics								
Industry q in prior year	-0.092	-0.001			-0.372	-6E-4	0.058	5E-4
	(-1.65)				(-1.49)		(0.81)	
Fraction of firms in industry that are diversified			1.098	0.009	-0.483	-7E-4	0.943	0.008
			(4.12)		(-0.67)		(2.97)	
Fraction of industry sales from diversified firms			0.440	0.004	0.745	0.001	0.236	0.002
			(2.12)		(1.53)		(0.98)	

coefficients, which is consistent with the findings in Campa and Kedia (2002). However, neither the S&P nor the major exchange indicators are significant, GDP growth and the business cycle are significant (while they are not in Campa and Kedia), and the number and volume of mergers in the year takes different signs depending on the specification. Altogether, the comparison between my results and Campa and Kedia's suggests that the variables that

Table III. Propensity to Diversify (*Continued*)

	Model (1)		Model (2)		Model (3)		Model (4)	
	Coef.	M.E.	Coef.	M.E.	Coef.	M.E.	Coef.	M.E.
Macroeconomic Characteristics								
GDP Growth			0.059	5E-4	-0.102	-2E-4	0.073	6E-4
			(2.25)		(-0.64)		(2.30)	
No. of recession months in year			0.243	0.002	2.684	0.004	0.474	0.004
			(0.96)		(2.20)		(1.59)	
Number of Mergers in Year			-1E-4	-1E-6	0.002	3E-6	-1E-4	-8E-7
			(-2.16)		(2.14)		(-1.21)	
Dollar Volume of Mergers in Year			7E-7	5E-9	-9E-6	-1E-8	3E-7	2E-9
			(1.00)		(-2.22)		(0.33)	
Constant	-3.075		-4.444		-5.407		-4.343	
	(-22.9)		(-18.7)		(-3.26)		(-14.5)	
No. of Observations	24,689		22,527		3,418		17,094	
Log Likelihood	-743.1		-688.0		-91.3		-463.1	
Pseudo-R^2	0.03		0.12		0.19		0.10	

affect a firm's propensity to diversify for the first time are not necessarily the same that affect its probability to be diversified in the cross-section.

B. Diversification's Causal Effect on Firm Value

I use the probit Models (1) and (4) from Table III to compute propensity scores—the predicted values from the models—and estimate the ATT. I refer to these two models as "the reduced model" and "the extended model," respectively. I do not use the more extended Model (3) because of the significant loss of observations it entails.

The three ATT estimators use different information from the first-stage probit. I follow Dehejia and Wahba (1999, 2001), whose estimator uses the propensity scores as an input for the following algorithm: 1) Separating treatment and control groups (diversifying and single-segment firms) and sorting observations within each group from lowest to highest scores; 2) Discarding all single-segment firms with an estimated propensity score lower (higher) than the minimum (maximum) of the propensity score for diversified firms. The purpose of this step is to restrict the subsequent ATT analysis to the region of common support, i.e., to eliminate from the control group all firms to which diversified firms are not comparable to begin with; 3) Stratifying all firms into blocks defined by quantiles (e.g., quintiles) of the propensity score distribution for diversified firms. (Using quantiles of the score distribution for diversified firms provides a convenient starting point for the definition of the blocks, as a minimum number of firms is allocated to each block by construction. However, the blocks are typically redefined at a later stage); and 4) Performing balancing tests for each pre-diversification variable, as well as for the propensity score. These are t-tests of differences in means between the diversified and specialized firms within each block.

The next step in the algorithm is conditional on the outcome of the balancing tests. If all blocks are well balanced (i.e., the t-statistics not significant) for most variables, the algorithm ends. However, if a block is not well balanced, I divide the block into finer blocks and re-evaluate. If most blocks are not well balanced, I modify the probit model (on the complete sample) and re-evaluate. These steps ensure that even though both groups of firms are different in a number of characteristics, they are comparable within the blocks defined.

My final step is to estimate the ATT as the weighted average of the within-block mean differences in value between diversified and single-segment firms. Because exclusion restrictions are not required for identification here, all variables I use as regressors in the probit models are also used as regression controls in the estimation of these differences. I calculate the variance by adding up the within-block variances multiplied by the square of the weight of the block.

Abadie and Imbens's (2002) estimator is also based on propensity score matching and obtains the ATT as an average of the within-match regression-adjusted differences. However, it differs from Dehejia and Wahba's (1999, 2001) in three fundamental ways. First, instead of matching by blocks, I match each diversifying firm with four single-segment firms. I use four such firms because Abadie and Imbens find in their simulations that four matches performs well in terms of mean-squared error. Second, the matching is done with replacement, which Abadie and Imbens show reduces asymptotic bias. (Matching with replacement implies that single-segment firms may be used more than once in the matching process, which introduces nonindependence in the disturbances. Abadie and Imbens's procedure for computing standard errors corrects for this non-independence.) The final ATT estimate includes an additional bias correction term, which is explained in their paper in further detail.

Heckman's (1979) estimator uses the first-stage probit model to estimate the inverse Mills ratio that accounts for the correlation between the error terms of Equations (3) and (4). The inverse Mills ratio then enters Equation (3) as an additional regressor to recover the ATT from the parameter δ. Because Heckman's method requires exclusion restrictions for identification, I include as controls in the value equation the same variables as Campa and Kedia (2002) (firm size, profitability, investment, and the S&P index), as well as lagged industry q.

The two probit specifications reported in Table III meet the balancing property required in the Dehejia-Wahba algorithm. That is, for each specification there is an optimal number of blocks that ensures that within each block, there are no significant differences between the diversifying and single-segment firms in either the propensity score or in any of its component variables. The final number of blocks is nine for the reduced model, ten for the extended model. (These are no longer quantiles, e.g. deciles, because the final blocks differ in size).

Table IV provides summary statistics from the Dehejia-Wahba propensity score matching process in my sample. Panel A shows how propensity scores are distributed among diversifying and single-segment firms, and how the common support region is defined (the region is bounded between the minimum and maximum propensity score for diversifying firms). Panel B reports mean characteristics for diversifying and single-segment firms for each variable entering the propensity score. I report summary statistics separately for single-segment firms in the common support, and firms out of the common support.

As expected, the single-segment firms out of the common support are less comparable to the diversifying firms than are those within the common support. The difference in comparability is notorious for some variables. For instance, the mean industry-adjusted q is 0.2 for diversifying firms, and 0.01 for single-segment firms, and this difference is significant at the 1% level. The breakdown of the single-segment firms shows that most of this difference is attributable to the single-segment firms out of the common support region, which have a mean of -0.07 in the extended model. The mean for the common support single-segment firms in that model is 0.09 and is statistically indistinguishable from the diversifying group's mean. A similar result occurs for industry q in both the reduced and the extended models and for the S&P indicator and GDP growth.

For other variables, the difference in means between diversifying and single-segment

Table IV. Propensity Score Matching: Summary Statistics

This table reports summary statistics from the propensity score matching process. *Propensity scores* are the predicted probabilities of diversification from the first-stage probit models. Panel A shows how propensity scores are distributed among diversifying and single-segment firms. The Common Support region is bounded between the minimum and maximum propensity score for diversifying firms. Panel B reports the means of the independent variables used to estimate each probit model.

	Reduced Model				Extended Model			
		Single-Segment Firms				Single-Segment Firms		
	Diversifying Firms	All	In Common Support	Out of Common Support	Diversifying Firms	All	In Common Support	Out of Common Support
Panel A. Propensity Score Distribution								
Mean	7E-3	5E-3***	5E-3***	1E-3***	0.017	5E-3***	6E-3***	1E-3***
Median	6E-3	4E-3***	4E-3***	1E-3***	1E-2	3E-3***	4E-3***	6E-4***
Minimum	1E-3	1E-4	1E-3	1E-4	3E-4	3E-6	1E-3	3E-6
Maximum	0.055	0.126	0.048	0.126	0.134	0.242	0.055	0.242
Panel B. Mean Firm Characteristics								
Firm Characteristics								
Log of Assets	5.87	5.00***	5.16***	4.62***	5.87	5.00***	5.45***	4.75***
EBIT/Sales	0.87	0.91	0.09	0.09	0.09	0.09	0.09	0.09
CAPX/Sales	0.14	0.09***	0.09***	0.09***	0.14	0.09***	0.09***	0.09***
S&P Index					0.13	0.09*	0.11	0.06***
Major Exchange					0.72	0.69	0.74	0.65*
Foreign Incorporation					0.05	0.05	0.03	0.06
Industry-adjusted q in prior year	0.20	0.01**	0.04*	-1.03***	0.20	0.01***	0.09	-0.07***
Dividends Paid					0.64	0.48***	0.56***	0.40***
Institutions					31.4	32.4	31.9	33.5

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

Table IV. Propensity Score Matching: Summary Statistics (*Continued*)

	Reduced Model				Extended Model			
		Single-Segment Firms				Single-Segment Firms		
	Diversifying Firms	All	In Common Support	Out of Common Support	Diversifying Firms	All	In Common Support	Out of Common Support
Panel B. Mean Firm Characteristics								
Industry Characteristics								
Industry q in prior year	1.23	1.36**	1.30	2.79***	1.23	1.36***	1.30	1.41***
Fraction of firms in industry that are diversified					0.64	0.45***	0.51***	0.39***
Fraction of industry sales from diversified firms					0.66	0.46***	0.53***	0.40***
Macroeconomic Characteristics								
GDP Growth					3.27	2.95**	3.16	2.73***
No. of recession months in year					0.12	0.11	0.10	0.12
Number of mergers in year					1,529	1,940***	1,917***	1,967***
Dollar volume of mergers in year					123.2	151.3***	148.9***	154.3***
No. of Observations	150	24,539	23,691	848	109	16,985	12,043	4,942

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

firms is typically smaller within the common support that out of it, but the differences are statistically significant. This result is not surprising, given that Table IV does not separate the common support into the blocks used to perform the matching in the Dehejia-Wahba algorithm. Within those blocks, the differences are statistically insignificant. In other words, if all the differences between the common support single-segment firms and the diversifying firms reported in Table IV were insignificant, there would be no need to stratify the observations into blocks; the elimination of the out-of-support firms would be sufficient to ensure the comparability between treatment and control units.

Table V reports the ATT difference-in-differences estimates of diversification's effect on firm value that I obtain from the three estimators. The two propensity score matching methods discard the control observations that are out of the common support region. These are only a small fraction of the candidate control observations in the case of the reduced model (848 out of 24,539, or 3.5%), but they are a large fraction in the case of the extended model (4,942 out of 16,985, or 29%). The Dehejia-Wahba estimator uses all the common support observations (divided into blocks) to match all the diversifying firms. The Abadie-Imbens estimator uses only four control firms to match each diversifying firms, i.e., 600 control firms for the reduced model and 436 for the extended model. I also apply the Heckman estimator to the region of common support to show how much of the difference in results between the Heckman estimator and the matching estimates is due to the support, and how much is due to sheer estimation technique. The table shows the different number of observations on which the final ATT estimates are computed under each method.

The last two rows of the table report one-stage difference-in-differences estimates for both the full and common support. These are analogous to the estimates reported in the last panel of Table II, but because they are based on multivariate regressions and estimated on the same subsamples as the two-stage ATT estimates, they are a more relevant benchmark. For the reduced model, which I estimate on the same sample as the estimates in Table II, the benchmark OLS estimates on either the full or the common support are -0.06 for asset multipliers, -0.07 for sales multipliers, and -0.28 for industry-adjusted q. The univariate regression estimates reported in Table II are -0.07, 0.03, and -0.2, respectively. This result shows that a simple regression adjustment in most cases makes the discount larger, not smaller. The difference-in-differences discount for the reduced model is only significant for industry-adjusted q. This lack of statistical significance makes the two-stage analysis on sales and asset multipliers less interesting a priori, although, as the simple regression adjustment shows, it is not clear in which direction the results may go. On the other hand, for the extended model, which I estimate with a subset of the observations, the discount is significant—and much higher—for all three measures of excess value: -0.1 for asset multipliers, -0.14 for sales multipliers, and -0.41 for industry-adjusted q.

The first four rows of Table V show the main result of this paper: All of the two-stage estimates of the ATT for diversifying firms are statistically insignificant. When I use any of the three econometric estimators to control for the selection bias, the diversification discount as such disappears. This finding shows that on average, diversification does not destroy value. The result is consistent with the evidence in Campa and Kedia (2002), Graham et al. (2002), and event studies—although the latter do not control for selection bias.

Table V also shows that although the sign (insignificance) of the effect is robust, the size of the estimates varies depending on which method, subsample, excess value measure, and specification I use. Although not reported here, the results are also robust when I use a logit instead of a probit model of diversification. The variation across measures of excess value and subsample is not surprising, given that the one-stage estimates exhibit a similar variation.

Table V. Diversification's Effect on Firm Value: Average Treatment Effect on the Treated

This table reports one- and two-stage estimates of the "average treatment effect on the treated" for diversifying firms using several difference-in-differences estimators. The treatment indicator is one for firm-years in which the number of segments increases from one to two or more as a result of acquisitions or internal growth, zero for single-segment years. The outcome variable is the change in excess value from year $t-1$ to year $t+1$ for three different measures of excess value. The first stage in the two-stage models is one of two probit models of the propensity to diversify. The reduced probit model's independent variables are the diversification dummy, log of assets, EBIT/Sales, CAPX/Sales, lagged industry-adjusted q, and lagged industry q. The extended probit model includes all of the variables in the reduced model as well as institutional ownership, the fraction of firms in the industry that are diversified, the fraction of industry sales accounted for by diversified firms, GDP growth, the number of recession months in the year, the number and dollar value of mergers in the year, and dummies that indicate whether the firm belongs to a major S&P index; whether it is listed on a major exchange; whether the firm is incorporated abroad; and whether it paid dividends. The second-stage models for the matching estimators are multivariate regressions of the change in excess value on the treatment indicator and all independent variables included in the propensity equation. The OLS and the second-stage regression in Heckman's models include the following control variables: log of assets, EBIT/Sales, CAPX/Sales, lagged industry q, and the S&P index dummy. The subsample in this table includes all diversifying or single-segment firm-years with excess values available for years $t+1$ and $t-1$ and non-missing data for year t on any of the variables included in each model. t-statistics appear in parentheses.

	Reduced Model				Extended Model			
	Asset Multiplier	Sales Multiplier	Industry-Adjusted q	N	Asset Multiplier	Sales Multiplier	Industry-Adjusted q	N
Dehejia & Wahba matching estimator	-0.017 (-0.51)	-0.035 (-0.67)	-0.117 (-1.25)	23,841	-0.062 (-1.43)	-0.121 (-1.54)	-0.250 (-1.46)	12,152
Abadie & Imbens matching estimator	-0.010 (-0.28)	-0.027 (-0.48)	-0.055 (-1.28)	750	-0.045 (-1.07)	-0.103 (-1.60)	-0.056 (-0.63)	545
Heckman two-stage method	-0.037 (-0.88)	-0.050 (-1.08)	-0.141 (-1.48)	24,689	-0.074 (-1.42)	-0.120 (-1.52)	-0.203 (-1.49)	17,094
Heckman method on common support	-0.024 (-0.59)	-0.041 (-0.86)	-0.133 (-1.26)	23,841	-0.073 (-1.42)	-0.118 (-1.47)	-0.198 (-1.37)	12,152
OLS regression	-0.060 (-1.41)	-0.073 (-1.48)	-0.281 (-3.32)	24,689	-0.102 (-1.97)	-0.139 (-2.34)	-0.411 (-3.84)	17,094
OLS regression on common support	-0.061 (-1.42)	-0.074 (-1.50)	-0.284 (-3.35)	23,841	-0.100 (-1.97)	-0.137 (-2.35)	-0.409 (-3.98)	12,152

The comparison between the OLS and Heckman estimates on the full and common support shows that the differences in results between those estimates and those produced by propensity score matching are almost entirely attributable to differences in estimation technique, not in the support itself.

C. Comparing Treatment Effect Estimators in the Context of Diversification

A frequent critique to the studies that champion propensity score matching estimators over Heckman's (1979) estimator is that they are based on a specific dataset, and it is not clear whether the results generalize to other data (see, e.g. Heckman et al. 1998). In particular, one may be skeptical about how applicable these results are to the study of corporate decisions such as diversification, and their effect on firm value.

A careful analysis of the assumptions required for any of the three estimators suggests that none of the assumptions is very realistic in the context of the diversification discount. On the one hand, consider selection on observables, which is the central assumption underlying all matching estimators. Although Table III shows fairly rich specifications of the propensity to diversify, it would be difficult to argue that no other variable affects this decision. In fact, earlier studies of diversification (e.g. Montgomery and Hariharan, 1991; and Silverman, 1999) show that the characteristics of the target industry also matter. Graham et al. (2002) show that the characteristics of the target firm in diversifying acquisitions influence not only the diversification decision, but also its effect on firm value. The stringency of this assumption is mitigated by the use of a difference-in-differences estimator that allows for time-invariant unobservable differences between diversifying and single-segment firms. Nevertheless, the assumption is still a strong one.

On the other hand, the exclusion restrictions required to identify a Heckman model also seem unrealistic. Following Campa and Kedia (2002), I use as instruments some of the variables included in the propensity model. Table VI reports results from a regression of changes in excess value on these variables and the other propensity determinants considered in this article. The results show that all of these variables also affect excess value in at least one of its measures. Also, to the extent that corporate finance and investment decisions are a function of expected value, all variables that affect value should also be included in the propensity equation. Therefore, although one only needs to find one variable that affects the propensity to diversify and does not also affect firm value, in practice it may be difficult to find such a variable.

Lalonde (1986) and subsequent studies (Heckman et al. 1997, 1998; Dehejia and Wahba, 1999, 2001; and Smith and Todd, 2000) take advantage of training programs that were run as experiments to compare different evaluation estimators against an experimental benchmark. Because I cannot perform a similar exercise in the context of diversification due to the lack of an experimental benchmark, I use simulations to compare the performance of the three estimators in this setting.

For each propensity model, I simulate 1,000 diversifying firms by aggregating pairs of single-segment firms from the region of common support described in Table IV. I combine each single-segment firm with the single-segment firm that is closest to it in its propensity score but has a different SIC code. The 1,000 diversifying firms are randomly drawn from among the pairs. I form the diversifying firm's characteristics as an asset-weighted average of the characteristics of the two single-segment firms, except for the sales-based variables (sales multiplier excess value, EBIT/Sales, and CAPX/Sales). I construct these variables as a sales-weighted average. I also construct the dummies to take on a value of one for the simulated firm if they are positive for any of the single-segment firms that are part of it. By construction, the simulated conglomerates have no value either created or destroyed. As in the analysis on true diversifying firms, the control group includes all single-segment firm-years for the Heckman and OLS estimates, and the common support only for all other estimators.

Table VII shows the results of the simulation. The two matching estimators perform well in that they always yield estimates that are not significantly different from zero. In contrast, Heckman's method and the OLS estimates yield a statistically significant discount in some cases, such as those for the extended model using sales multipliers or industry-adjusted q. This finding suggests that propensity score matching may be a more appropriate approach

Table VI. Multivariate Regression of Change in Excess Value on Propensity Score Determinants

In this table, the dependent variable is the change in excess value from year $t-1$ to year $t+1$ for three different measures of excess value. The full sample comprises 60,930 firm-years from 8,937 firms during 1978–1997. I use all 40,757 single-segment firm-years in the sample to compute excess values. The subsample in this table includes the 22,334 diversifying or single-segment firm-years with excess values available for years $t+1$ and $t-1$ and non-missing data for year t on any of the variables listed. Diversifying firms are firms that increase their number of segments from one to two or more as a result of acquisitions or internal growth.

	Asset Multiplier		Sales Multiplier		Industry-Adjusted q	
	Coef.	***t*-stat.**	**Coef.**	***t*-stat.**	**Coef.**	***t*-stat.**
Firm Characteristics						
Log of Assets	-0.020	(-8.59)	-0.025	(-8.74)	-0.060	(-14.1)
EBIT/Sales	0.737	(18.6)	0.892	(18.7)	1.830	(25.9)
CAPX/Sales	-0.074	(-4.44)	-0.046	(-2.31)	-0.133	(-4.45)
S&P Index	0.104	(11.5)	0.101	(9.28)	0.242	(14.9)
Major Exchange	0.080	(11.6)	0.084	(10.0)	0.127	(10.2)
Foreign Incorporation	0.002	(0.17)	0.008	(0.46)	0.041	(1.64)
Industry-adjusted q in prior year	-0.185	(-59.3)	-0.164	(-43.9)	-0.506	(-91.1)
Dividends Paid	0.033	(5.36)	0.055	(7.50)	0.065	(5.91)
Institutions	2E-4	(1.23)	0.001	(3.33)	0.001	(5.44)
Industry Characteristics						
Industry q in prior year	0.014	(0.68)	-0.015	(-0.62)	-0.014	(-0.38)
Fraction of firms in industry that are diversified	0.018	(1.16)	0.061	(3.31)	0.005	(0.20)
Fraction of industry sales from diversified firms	-0.021	(-4.37)	-0.019	(-3.34)	-0.117	(-13.7)
Macroeconomic Characteristics						
GDP Growth	0.002	(0.93)	0.006	(2.16)	-0.002	(-0.52)
No. of recession months in year	-0.016	(-0.81)	-0.002	(-0.08)	-0.085	(-2.41)
No. of mergers in year	-2E-5	(-3.45)	-5E-6	(-0.75)	-4E-5	(-4.56)
Dollar volume of mergers in year	2E-7	(3.47)	-8E-8	(-1.3)	3E-7	(3.08)
Constant	-0.102	(-5.83)	-0.152	(-7.25)	0.056	(1.78)
R^2	0.15			0.09	0.28	

than Heckman's selection model to assess the causal effect of diversification on firm value. At the very least, the three methods provide complementary evidence about this question.

V. Conclusion

This article shows that diversification, on average, does not destroy value. I bring recent developments in causal inference to bear on the diversification question. I use three different treatment effects estimators: the matching estimators of Dehejia and Wahba (1999, 2001) and

Table VII. Average Treatment Effect on the Treated for Simulated Diversifying Firms

This table reports one- and two-stage difference-in-differences estimates of the "average treatment effect on the treated" for simulated diversifying firms. For each propensity model, I simulate 1,000 diversifying firms by aggregating pairs of single-segment firms from the region of Common Support. I randomly select each single-segment firm and combine it with the single-segment firm that is closest to it in its propensity score but has a different SIC code. I construct the simulated firm characteristics as a weighted average of the characteristics of the two single-segment firms. The control group includes all single-segment firm-years for the Heckman and OLS estimates, and the common support only for all other estimators. The number of control observations is 24,539 for the reduced model and 16,985 for the extended model.

	Reduced Model			Extended Model		
	Asset Multiplier	Sales Multiplier	Industry-Adjusted *q*	Asset Multiplier	Sales Multiplier	Industry-Adjusted *q*
Dehejia & Wahba matching estimator	0.015	0.013	0.041	-0.003	-0.022	-0.010
	(1.21)	(0.78)	(1.42)	(-0.27)	(-1.33)	(-0.36)
Abadie & Imbens matching estimator	0.003	0.007	-0.039	-0.010	-0.026	-0.035
	(0.18)	(0.39)	(-1.33)	(-0.78)	(-1.62)	(-1.47)
Heckman two-stage method	-0.005	-0.003	-0.015	-0.022	-0.042	-0.050
	(-0.31)	(-0.17)	(-0.51)	(-1.38)	(-2.28)	(-1.49)
Heckman method on common support	-0.006	-0.002	-0.009	0.030	0.037	-0.048
	(-0.35)	(-0.13)	(-0.32)	(-1.93)	(-2.68)	(-1.53)
OLS regression	0.006	0.006	0.013	-0.017	-0.034	-0.047
	(0.33)	(0.31)	(0.41)	(-1.08)	(-1.82)	(-1.40)
OLS regression on common support	0.014	0.014	0.043	-0.013	-0.032	-0.023
	(0.83)	(0.74)	(1.32)	(-0.83)	(-1.83)	(-0.73)

Abadie and Imbens (2002), and Heckman's (1979) two-stage method. The three estimators yield different estimates of the effect of diversification on firm value. However, the effect is invariably insignificant across all estimates. That is, none of these techniques produce results that imply that corporate diversification destroys value.

I evaluate the specific applicability of these methods to the diversification context, and more generally to the field of corporate finance. I acknowledge the limitation that none of the assumptions on which the different methods rely is likely to be fully supported by corporate data. Nevertheless, the fact that all methods render insignificant the OLS effect confirms the importance of correcting for sample selection biases to the extent that it is possible.■

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