Economic Significance in Corporate Finance

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Abstract

Reporting the economic significance of findings in corporate finance has become increasingly common, but a review of the literature reveals shortcomings in typical reporting practices. Researchers can more effectively communicate the practical importance of findings by using standard measures of economic significance scaled by the standard deviation of the dependent variable, by providing all statistics necessary to calculate economic significance, and by providing benchmarks by which to evaluate the magnitude of economic significance. To support these objectives, I show why measures scaled by the standard deviation are preferable, and I provide benchmarks based on hundreds of established findings from the literature. (*JEL* C18, C52, G30)

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Over the years, researchers in various scientific disciplines have cautioned against an overreliance on statistical significance when assessing the importance of empirical results.[1] Researchers in empirical corporate finance have responded to this message, increasing their focus on the economic significance of empirical findings in addition to statistical significance. In a survey of the literature, I study 604 papers published in three top finance journals between 2000 and 2018 that report 954 regressions in which the dependent variable is one of the most common corporate finance outcomes studied: profitability, firm value, leverage, investment, payouts, or cash holdings. Regressions in these categories were increasingly common over this period: I find eight such regressions in papers published in 2000, but 89 in papers published in 2018. In my survey, I find that the practice of reporting economic significance has increased over time. Between 2000 and 2004, 44% of the papers in the sample discussed the economic significance of results, whereas between 2016 and 2018, 85% of papers did so. However, even as researchers have given greater priority to reporting economic significance, my survey of the literature also shows that standard reporting practices are not as effective at evaluating economic significance as they could be. In this paper, I document and evaluate how economic significance calculations are typically performed and interpreted in the literature, with the goal of identifying easily implementable improvements that could increase our understanding of the practical importance of findings in corporate finance.

In empirical corporate finance research, as in other fields, a standard framework is regularly employed for evaluating economic significance. The standard framework consists of reporting how much a dependent variable changes for a given change in an explanatory variable, based on an estimated regression coefficient. For example, in discussing their finding that firms that employ a higher share of skilled labor (measured by a labor skill index, *LSI*) hold more precautionary cash, Ghaly, Dang, and Stathopoulos (2017) state, "The impact

[1]See Boring (1919), Arrow (1960), Morrison and Henkel (1969), Carver (1978), Leamer (1978), Mayer (1980), Cohen (1994), McCloskey and Ziliak (1996), Ioannidis and Doucouliagos (2013), Kim and Ji (2015), Wasserstein (2016), Harvey (2017), Amrhein, Greenland, and McShane (2019), and McShane et al. (2019).

of *LSI* on cash holdings is economically significant: A one standard deviation increase in the index is associated with an increase in the cash-to-assets ratio of 4.2 percentage points, which translates to a 21.2% increase in the cash ratio relative to the sample mean." An important step toward understanding the economic significance of a result is that calculations such as these be carried out and interpreted in a credible, reliable, and informative manner. However, my survey of the literature points to three primary challenges hindering an effective assessment of economic significance.

The first challenge is that the majority of measures of economic significance used in the literature lack several desirable properties. Over 56% of the papers in my sample measure economic significance by scaling the resultant change in the dependent variable by the sample mean of the dependent variable. Measuring economic significance as a percentage of the mean of the dependent variable is problematic for several reasons. First, although measures scaled by the mean are robust to multiplicative transformations of the underlying data, they can be inflated from additive transformations of the dependent variable, such as industry adjustment. Second, measures scaled by the mean often produce high estimates of economic significance for irrelevant independent variables. Third, measures scaled by the mean are susceptible to specification searching, meaning that a researcher could usually find some combination of methods that results in a high estimate of economic significance. Fourth, measures scaled by the mean are not resistant to outliers. Finally, measures scaled by the mean are not robust when the dependent variable includes negative values, such as when the dependent variable is profitability. I demonstrate weaknesses of measures scaled by the mean using simulated regressions of common outcome variables (from Compustat data from 1963 to 2018) on randomly generated explanatory variables.

A simple way to address the problems associated with measures scaled by the mean is to use measures of economic significance scaled by the standard deviation of the dependent variable, which display a number of desirable properties. I show that measures scaled by the standard deviation are robust to multiplicative and additive transformations of the underlying data. In my simulations, measures scaled by the standard deviation never produce spuriously large estimates of economic significance for irrelevant variables. Measures scaled by the standard deviation are also resistant to specification searching, resistant to outliers, and robust to negative dependent variables. Despite the fact that they have these desirable properties, measures of economic significance scaled by the standard deviation are used in only 10% of the papers in my sample.

The second challenge is that papers usually fail to provide the statistics necessary to evaluate economic significance. This is problematic because, as I document in my sample of papers, researchers use many different measures of economic significance, and this lack of standardization makes it difficult to put economic significance in context. The lack of standardization can be overcome if readers can independently calculate measures of economic significance from summary statistics reported in the paper. However, I find that the majority of papers do not provide the summary statistics necessary for independent calculation of the most common measures of economic significance. For example, calculating one standard measure—the change in the dependent variable, as a percentage of its standard deviation, associated with a one-standard-deviation change in the explanatory variable—requires only the regression coefficient and the standard deviations of the explanatory variable and the dependent variable. But in my sample, I find that this information is provided only 33% of the time.

The third challenge is that authors usually provide no benchmarks with which to compare their measure of economic significance. I find that fewer than 13% of the papers in the sample compare the economic significance of their key variables to findings published in other papers or to that of commonly used covariates. When no benchmarks are provided for context, it is difficult for readers to judge how large the reported effects are. To help address this challenge, I establish two sets of benchmarks against which the economic significance of empirical findings can be compared. The first set of benchmarks comes from the economic significance of key findings published in three top finance journals. In my sample of 954 regressions, I calculate standardized measures of economic significance for the key explanatory variables in all papers that provide the necessary information to do so. Although comparisons of economic significance across variables should be made with caution, these statistics can help researchers evaluate how the economic significance of their findings compares to that of published findings in top journals. Detailed lists of the estimated economic significance of hundreds of proposed determinants of corporate finance outcomes are provided in the appendix as a reference. The second set of benchmarks is calculated from the economic significance of standard control variables that are routinely included in corporate finance regressions.

In summary, my analysis points to a few straightforward recommendations for improving the practice of reporting economic significance. Researchers should employ measures of economic significance that are scaled by the standard deviation of the dependent variable rather than the mean of the dependent variable. Researchers should provide the necessary statistics that allow for calculation of standard measures of economic significance. In addition, researchers should provide benchmarks that put measures of significance in context. Many of the conclusions that are drawn from the analysis apply equally well to regressions with other dependent variables, as discussed below. Another context in which these concepts are relevant is in placebo tests, pre-trend tests, and other tests of model assumptions, in which it is common for a lack of statistical significance to be interpreted as evidence that a model assumption holds. But recent literature has emphasized the importance of evaluating the magnitude of coefficients in these tests rather than just statistical significance (see Freyaldenhoven, Hansen, and Shapiro 2019; Bilinski and Hatfield 2019; Kahn-Lang and Lang 2020; Roth 2022).

Even when the recommendations in this paper are followed carefully, more work is typically required to completely evaluate the economic significance of a result. Calculating correct measures and providing informative benchmarks effectively communicates *relative* economic significance better than *absolute* economic significance. Fully understanding the real-world impact of findings often requires additional analysis that is highly dependent on the specific economic setting in question. In other words, getting the calculations right and interpreting them properly—the focus of this paper—is just a first step. As Ziliak and McCloskey (2008) put it, "Real science asks you to make real scientific judgments and real scientific arguments within a community of other scientists. It asks you to be quantitatively persuasive, not to be irrelevantly mechanical." Ultimately, truly evaluating economic significance is not as formulaic as evaluating statistical significance, but carefully doing so is essential for understanding the importance of findings in corporate finance.

1. Current Practice

To better understand how economic significance is currently treated in the corporate finance literature, I survey papers from top finance journals. Regressions in empirical corporate finance study a wide variety of dependent variables, so to put some structure on my survey I limit my analysis to six of the most common categories of regressions: those for which the dependent variable is profitability, firm value, leverage, investment, payouts, or cash holdings.

1.1 Sample of corporate finance regressions

I study all regressions in the six common categories reported in the *Journal of Finance*, *Journal of Financial Economics*, and *Review of Financial Studies* from 2000 to 2018. Table 1 reports the number of regressions reported in each of the six categories by year. In these statistics, a category of regression (e.g., a leverage regression) is counted only once in any given paper, regardless of how many different specifications or robustness checks the paper reports. Table 1 shows that these types of regressions became much more prevalent over this period. In 2000 only eight regressions were reported from all six categories combined, but over 80 per year were reported in 2017 and 2018. The total number of regressions in the sample from all categories is 954, which come from 604 different papers (many papers report regressions from multiple categories).

The total number of papers published per year in these journals increased over this time period as well, from 181 in 2000 to 299 in 2018. However, Table 1 shows that even when scaling the number of these regressions by the total number of papers, the incidence of regressions from all categories increased by more than a factor of seven, from 0.04 per paper in 2000 to 0.30 per paper in 2018.

1.2 Usage of measures of economic significance

Researchers calculate a variety of measures to assess economic significance, even though the general framework used by researchers to express economic significance is consistent across papers. Researchers typically report that, based on the estimated regression coefficient, a change of some amount in the explanatory variable is associated with a change of some amount in the dependent variable. What differs across papers is the assumed change in the explanatory variable (e.g., a change of one standard deviation in the explanatory variable), and how the resultant change in the dependent variable is measured (e.g., as a percentage of the mean of the dependent variable).

Table 2 reports the frequency with which different measures of economic significance are used in my sample of papers.[2] The statistics in Table 2 are based on 396 papers in the sample of 604 that report a measure of economic significance. Statistics are reported for continuous explanatory variables in rows 1 through 6 (269 cases) and for dummy explanatory variables

[2]Categorizing each paper by the measure of economic significance used involves some subjectivity. If multiple measures are used, I record the measure that seems to be the focus of the paper.

in row 7 (127 cases). Column 2 lists the different assumed changes in the explanatory variable that researchers use. For continuous explanatory variables, these include a one-standard-deviation change, a change from the 25th percentile to the 75th percentile (the interquartile range, IQR), other percentile shifts (e.g., from the 10th to the 90th percentile), a change of one percentage point, and an "other" category that includes an assortment of other assumed changes that do not fit in a standard category. The headings of columns 3 to 8 list the different ways in which the resultant change in the dependent variable is measured. These include expressing the resultant change as a percentage of the mean of the dependent variable, as a percentage of the standard deviation of the dependent variable, as a number of percentage points, as a probability (for dummy dependent variables), and as a percentage (for logged dependent variables).

As an example of interpreting the numbers in Table 2, row 1 in column 3 indicates that, for continuous explanatory variables, 37% of all papers measure economic significance as a one-standard-deviation change in the explanatory variable while measuring the resultant change in the dependent variable as a percentage of its mean.[3] The only other measure used in more than 10% of papers is a one-standard-deviation change in the explanatory variable with the resultant change in the dependent variable expressed as a percentage of its standard deviation (12% usage). The totals in column 9 show that the assumed change in the explanatory variable is one standard deviation in 65% of papers, with the IQR being used in 9% of papers. The totals in row 6 show that the percentage of the mean is used to express the resultant change in the dependent variable in 56% of papers, while the percentage of the standard deviation is used in 12% of papers.

For dummy explanatory variables, the assumed change in the explanatory variable is always a change from zero to one. Row 7 of Table 2 shows that the resultant change in the dependent variable is measured as a percentage of the mean for 57% of dummy explanatory

[3]About 2% of papers use the median rather than the mean, but for simplicity I include both in the same category.

variables and as a percentage of the standard deviation for 6% of dummy explanatory variables. Thus, despite a majority consensus on a measure when using dummy variables, the statistics in Table 2 demonstrate an overall lack of common practice for measuring economic significance.

1.2.1 Definitions of standardized measures.

To facilitate my discussion of economic significance, I define measures of economic significance, focusing on those incorporating the most commonly used assumed changes in the explanatory variable (one standard deviation, IQR, zero to one) and measures for the implied change in the dependent variable (percentage of mean, percentage of standard deviation). I label the measures generally as E^i_j, where i denotes the assumed change in the explanatory variable and j denotes the measure used to express the implied change in the dependent variable.

The first measure of economic significance, which I label $E^s_{\overline{y}}$, is the change in the dependent variable, as a percentage of its mean, associated with a one-standard-deviation change in the explanatory variable, based on the estimated regression coefficient. It is calculated as

$$E^s_{\overline{y}} = \left|\frac{bs_x}{\overline{y}}\right|, \tag{1}$$

where b is the estimated regression coefficient for the explanatory variable, s_x is the sample standard deviation of the explanatory variable, and $\overline{y}$ is the sample mean of the dependent variable. The absolute value of the quantity is taken because economic significance focuses on the magnitude of the effect. As noted in Table 2, $E^s_{\overline{y}}$ is used in 37% of papers. A typical example of $E^s_{\overline{y}}$ can be found in Smith (2016), who states that "the result is economically significant: A one standard deviation change in corruption implies a change equal to 12.29% of mean leverage." In other words, Smith (2016) finds that $E^s_{\overline{y}} = 0.12$.

The second measure of economic significance, E^s_s, is the change in the dependent variable, as a percentage of its standard deviation, associated with a one-standard-deviation change in the explanatory variable. It is calculated as

$$E_s^s = \left|\frac{bs_x}{s_y}\right|, \tag{2}$$

where s_y is the sample standard deviation of the dependent variable. Table 2 shows that E_s^s is used in 12% of papers. E_s^s is commonly known as the standardized coefficient, beta coefficient, or standardized beta coefficient.[4] If the explanatory variable and dependent variable are both standardized (to a mean of zero and standard deviation of one), then E_s^s is simply the absolute value of the regression coefficient.[5] An example of E_s^s can be found in Guiso, Sapienza, and Zingales (2015), who state, "These effects are also economically relevant: a one standard deviation increase in integrity is associated with a 0.19 standard deviation increase in Tobin's *q*." In other words, Guiso, Sapienza, and Zingales (2015) find that $E_s^s = 0.19$.

A third measure of economic significance, $E_{\overline{y}}^{IQR}$, is the change in the dependent variable, as a percentage of its mean, associated with a change in the explanatory variable across its *IQR*. It is calculated as

$$E_{\overline{y}}^{IQR} = \left|\frac{b(p75_x - p25_x)}{\overline{y}}\right|, \tag{3}$$

where $p75_x$ ($p25_x$) is the 75th (25th) percentile of the explanatory variable. Table 2 shows that $E_{\overline{y}}^{IQR}$ is used in 6% of papers. An example of $E_{\overline{y}}^{IQR}$ can be found in Mueller, Ouimet, and Simintzi (2017), who state, "Both effects are economically significant. Moving from the 25th to the 75th percentile of the pay-inequality distribution raises ROA by 1.68 percentage

[4]Despite its wide usage as a measure of relative importance in many fields of study, the standardized coefficient also has been criticized as ineffective or misleading (e.g., King 1986; Greenland et al. 1991; Bring 1994; Sterck 2019).

[5]In the special case of a regression with only one independent variable or orthogonal independent variables, E_s^s is equal to the correlation between the independent variable and the dependent variable and $0 \leq E_s^s \leq 1$. But in the typical case with multiple (correlated) independent variables, E_s^s can be greater than one (Deegan 1978).

points (a 28.6% increase) and Tobin's q by 0.12 (a 9.0% increase)." In other words, based on a mean ROA of 5.88% and a mean Tobin's q of 1.38 (reported elsewhere in the paper), Mueller, Ouimet, and Simintzi (2017) find $E_{\overline{y}}^{IQR} = 0.29$ for profitability and $E_{\overline{y}}^{IQR} = 0.09$ for firm value.

A fourth measure of economic significance, E_s^{IQR}, is the change in the dependent variable, as a percentage of its standard deviation, associated with a change in the explanatory variable across its IQR. It is calculated as

$$E_s^{IQR} = \left| \frac{b(p75_x - p25_x)}{s_y} \right|. \tag{4}$$

I find no examples of E_s^{IQR} in my sample of papers, but I include the definition here for completeness.

The final two measures that I define are for dummy explanatory variables. Dummy variables are commonly used in the literature, accounting for 39% of the key explanatory variables in my sample. One measure used for dummy variables, $E_{\overline{y}}^1$, is the change in the dependent variable, as a percentage of its mean, associated with a change from zero to one in the explanatory variable. It is calculated as

$$E_{\overline{y}}^1 = \left| \frac{b}{\overline{y}} \right|. \tag{5}$$

$E_{\overline{y}}^1$ is used in 57% of articles using dummy explanatory variables. An example of $E_{\overline{y}}^1$ can be found in Custódio and Metzger (2014), who report, "The R&D results using OLS estimates suggest that firms with financial experts tend to spend less in R&D. The estimate is economically significant: compared to the mean, financial expert CEOs spend 25% less in R&D." In other words, Custódio and Metzger (2014) find that $E_{\overline{y}}^1 = 0.25$.

The other measure, E_s^1, is the change in the dependent variable, as a percentage of its standard deviation, associated with a change from zero to one in the explanatory variable.

It is calculated as

$$E_s^1 = \left|\frac{b}{s_y}\right|. \tag{6}$$

E_s^1 is used in 6% of papers using dummy explanatory variables. An example of E_s^1 can be found in Li and Srinivasan (2011), who state, "The coefficient on FDIR is 0.30 (t-statistic=3.34), implying that Tobin's q of founder-director firms is 0.30 higher than that of nonfounder firms. This magnitude is economically significant compared with the standard deviation (of 1.87)." In other words, Li and Srinivasan (2011) find that $E_s^1 = 0.16$ (0.30/1.87).

1.3 Statistics on current practice

Table 3 reports other statistics on how economic significance is reported in the literature. Panel A of Table 3 reports the time trend in the percentage of papers that include discussions of the economic significance of reported results. This percentage rose steadily during the sample period, from 44% in the 2000–2004 period to 85% in the 2016–2018 period.

Although published papers frequently do not report typical measures of economic significance, readers of the article may be able to calculate the measures themselves using the regression coefficients and summary statistics reported in the paper. However, Panel B of Table 3 shows that the required information is usually not provided. Panel B reports the percentage of regressions in published papers for which are reported the necessary summary statistics to calculate the standardized measures. Panel B shows that $E_{\overline{y}}^s$ can be independently calculated for only 36% of the regressions, E_s^s for 33% of the regressions, $E_{\overline{y}}^{IQR}$ for 15% of the regressions, and E_s^{IQR} for 14% of the regressions. Among regressions with dummy explanatory variables, $E_{\overline{y}}^1$ can be calculated 60% of the time and E_s^1 38% of the time.

Panel C of Table 3 reports whether papers in the sample use benchmarks for measures of economic significance. Two types of benchmarks can provide context for the importance of the variable being tested. The first type of benchmark compares the economic significance of the key explanatory variable to the economic significance of key explanatory variables in other papers. An example of this type of benchmark can be found in Coles, Daniel, and Naveen (2008), who state, "the coefficient of -0.110 for board size (β_1) indicates that if board size increases by one, Q decreases by 0.6%. In contrast, Yermack (1996) reports that when board size doubles, Q decreases by 1%." The second type of benchmark compares the economic significance of the key explanatory variable to the economic significance of other variables in the same regression model, typically control variables that are standard in the literature. An example of this type of benchmark comes from Almazan et al. (2010), who state, "In relative terms, the cluster effect (i.e., 4.4 and 3.6 percentage points) is similar to a one-standard deviation change in other determinants of leverage. For instance, a one-standard deviation change in Sales, EBITDA/TA, and Market to Book, respectively, produces a change in net market leverage of 3.5, 4.8, and 4.4 percentage points." I find that neither of these types of benchmarks is used frequently in the literature. Fewer than 4% of papers use benchmarks from other articles, and only 9% use benchmarks based on control variables. The remaining 88% of papers do not use any benchmarks to evaluate economic significance.

Finally, panel D of Table 3 reports, for those papers discussing economic significance, the percentage of papers that claim that their key results are economically significant. In addition to the most commonly used phrase, "economically significant," authors make claims about their results with phrases such as "economically large," "economically meaningful," "economically relevant," or "economically important." I find that 92% of papers claim that their key results are economically significant, less than 2% say that their key results are not economically significant, and 7% report some measure of economic significance without passing judgment on whether or not the results are economically significant.[6] The large

[6]Categorizing the papers according to their economic significance claims requires some subjective judgment, but I attempt to characterize the claims made concerning the central results studied in the paper. In some cases, papers claim economic significance of central results, while stating that some ancillary results are not economically significant.

percentage of published papers claiming economic significance is perhaps not surprising if we expect the review process to weed out papers lacking practical importance, but claims of economic significance can be problematic for two reasons. First, authors frequently do not offer a justification for claims of economic significance. Second, absolute declarations of economic significance disregard the fact that economic significance is necessarily a relative concept. Unlike statistical significance, which has established thresholds for what is considered significant, economic significance has no such established standards. Of course, standard thresholds for statistical significance (e.g., p-values of .01, .05, or .10) have themselves been criticized as arbitrary and detrimental to empirical research.[7] Recent efforts have looked to curtail absolute declarations of statistical significance, such as journals like the *American Economic Review* forbidding the use of asterisks to indicate levels of significance. Analogously, the literature might benefit from fewer absolute declarations of economic significance, with greater focus on providing sufficient information for readers to judge the importance of results.

2. Properties of Economic Significance Measures

I now discuss properties of the measures of economic significance defined above. My focus is on the properties of measures scaled by the mean of the dependent variable compared to measures scaled by the standard deviation of the dependent variable. The discussions for three of the properties below (scale independence, origin independence, robustness with negative variables) are based on theoretical arguments that apply equally well to regressions with any dependent variable. The discussion for the other three properties (absence of spurious estimates, resistance to specification searching, resistance to outliers) are based on empirical arguments from simulated regressions employing the six common dependent

[7]See Gelman and Stern (2006), Stigler (2008), Nuzzo (2014), Amrhein, Greenland, and McShane (2019), Ioannidis (2019), McShane et al. (2019), Wasserstein, Schirm, and Lazar (2019), and Abadie (2020).

variables. These findings may well apply to other dependent variables, but the simulations cannot speak to the degree to which the results carry over to other settings.

2.1 Scale independence

I first consider whether the measures of economic significance are scale independent; that is, whether they are unchanged by multiplicative transformations of the underlying data. This is an important property because measures of economic significance ideally should not change if researchers change the unit of measurement of the data or scale data up or down for presentation purposes. I find that measures scaled by the standard deviation are scale independent with respect to multiplicative transformations of either the independent variable (x) or dependent variable (y), so that for any constants c_1 and c_2,

$$E_s^s(c_1 x, c_2 y) = E_s^s(x, y), \tag{7}$$

$$E_s^{IQR}(c_1 x, c_2 y) = E_s^{IQR}(x, y), \tag{8}$$

$$E_s^1(x, c_2 y) = E_s^1(x, y). \tag{9}$$

Measures scaled by the mean are also scale independent with respect to x and y, such that

$$E_{\overline{y}}^s(c_1 x, c_2 y) = E_{\overline{y}}^s(x, y), \tag{10}$$

$$E_{\overline{y}}^{IQR}(c_1 x, c_2 y) = E_{\overline{y}}^{IQR}(x, y), \tag{11}$$

$$E_{\overline{y}}^1(x, c_2 y) = E_{\overline{y}}^1(x, y). \tag{12}$$

2.2 Origin independence

Next, I consider whether the measures of economic significance are independent of change of origin; that is, whether they are unchanged by additive transformations of the underlying data. This property is important because in empirical corporate finance, researchers sometimes add constants to or subtract constants from the underlying data—for example, when variables are industry adjusted—but transformations such as these ideally should not affect the economic significance of the results. I find that measures scaled by the standard deviation are unchanged from additive transformations of x or y, that is,

$$E_s^s(x + c_1, y + c_2) = E_s^s(x, y), \tag{13}$$

$$E_s^{IQR}(x + c_1, y + c_2) = E_s^{IQR}(x, y), \tag{14}$$

$$E_s^1(x, y + c_2) = E_s^1(x, y). \tag{15}$$

In contrast, measures scaled by the mean are not independent of change of origin. Specifically,

$$E_{\overline{y}}^s(x + c_1, y + c_2) = \left|\frac{bs_x}{\overline{y} + c_2}\right|, \tag{16}$$

$$E_{\overline{y}}^{IQR}(x + c_1, y + c_2) = \left|\frac{b(p75x - p25x)}{\overline{y} + c_2}\right|, \tag{17}$$

$$E_{\overline{y}}^1(x, y + c_2) = \left|\frac{b}{\overline{y} + c_2}\right|. \tag{18}$$

The last three equations show that when a positive constant is added to the dependent variable, measures of economic significance scaled by the mean are deflated, and when a positive constant is subtracted from the dependent variable, measures scaled by the mean are inflated. So, for example, in the case of industry adjustment, a positive constant is typically subtracted from the dependent variable (within each industry grouping), resulting in inflated measures of economic significance. Another problematic example is when the dependent variable is standardized, in which case the constant (c_2) that is subtracted from the dependent variable is $\overline{y}$, and $E^s_{\overline{y}}, E^{IQR}_{\overline{y}}$, and $E^1_{\overline{y}}$ are all undefined.[8]

2.3 Absence of spurious estimates

Next, I consider whether the various measures produce spuriously large estimates of economic significance. This property is important in order to avoid attributing significance to an explanatory variable that has no important relation with the dependent variable. I test for this property by performing regressions with randomly generated independent variables and calculating the economic significance of these variables for common dependent variables taken from Compustat data. Ideally, the economic significance of randomly generated independent variables should be negligible, or close to zero. Because the independent variables are constructed to be irrelevant in the simulations, large estimates of economic significance for any particular measure calls into question the reliability of that measure.

Estimates of economic significance also could be influenced by different methodological decisions made by researchers performing regressions. Studies in empirical corporate finance employ a wide variety of different methodologies (Mitton 2022). Therefore, as part of the simulations, I also run regressions using alternative methods of sample selection, variable transformation, and model specification. This allows me to assess the degree to which methodological decisions alter estimates of the various measures of economic significance.

2.3.1 Data and summary statistics.

The data set for the simulations includes over 400,000 firm-year observations from Compustat between 1963 and 2018, although the number of available observations varies for dif-

[8] The relations presented in Sections 2.1 and 2.2 are verified in the appendix.

ferent variables.[9] Not all studies use Compustat data, but in my sample of papers Compustat is used 77% of the time, so the data are representative of much of the published literature.

I refer to my sample of papers in the literature for guidance on making methodological decisions for the simulations. One important methodological issue is to determine the appropriate proxy for each dependent variable, because researchers use many different proxies to represent a firm's profitability, value, leverage, investment, payouts, or cash holdings. To make this determination, I survey the 954 regressions in my sample, and alternately use the two proxies that are employed most frequently in the literature in each category of regression. Another important issue is to determine which control variables to include in each category of regression, given that the set of control variables is not standardized in the literature. To make this determination, I document the usage of control variables in the 954 regressions in my sample. In my tests I use, at a minimum, all control variables that are employed at least 50% of the time in the literature. From Compustat I obtain data on the two most common dependent variables in each category of regression, the three most common size controls used in the literature, and two other common control variables, asset tangibility and firm age. Table A1 in the appendix defines the variables, and Table A2 in the appendix gives the summary statistics.

2.3.2 Regression specification.

I regress the common dependent variables on randomly generated variables using different combinations of methods. Clearly an infinite number of methodological combinations are possible, so to structure the analysis I focus on six binary methodological decisions related to decisions researchers in empirical corporate finance routinely make:[10]

[9]To avoid back-filling bias, I exclude observations prior to 1963 and require that a firm appear in the data set for 2 years before including it in the sample.

[10]Usage rates for control variables, dependent variables, and size controls, as well as data on the prevalence of financial firm exclusion, lagging variables, treating outliers, and other methodological decisions are documented in Mitton (2022).

1. Include all industries or exclude financial firms (SIC codes 6000–6999).

2. Use the most common proxy for the dependent variable or use the second most common proxy. (Table A1 in the appendix lists the two most common proxies for each category of regression.)

3. Use the most common size control (log of total assets) or use the second most common size control (log of market value for profitability and payout regressions; log of sales for all other categories).

4. Lag the explanatory variable or not.

5. Winsorize outliers at the 1st and 99th percentiles or retain outliers.

6. Use the most commonly used control variables (usage rate of 50% or higher in the literature), or also add the next most commonly used control variable.[11]

For a given category of regression (e.g., with profitability as the dependent variable), I randomly generate an independent variable and perform regressions of the following form:

$$y_{ijt} = \alpha + \beta x_{ijt} + \mathbf{z}'_{ijt}\boldsymbol{\phi} + \gamma_j + \delta_t + \varepsilon_{ijt}, \qquad (19)$$

where y_{ijt} is one of the dependent variables from Compustat (such as profitability) for firm i of industry j in year t, x_{ijt} is the randomly generated hypothesized determinant of y, and $\mathbf{z}_{ijt}$ is the set of firm-level control variables. The term γ_j represents a set of industry fixed effects (at the two-digit SIC level) and the term δ_t represents a set of year fixed effects. I also report specifications in which the industry fixed effects are replaced with firm fixed effects, γ_i. The coefficient of interest in the regression is β, and our particular interest is in how the economic significance of β changes when using different methods.

I randomly generate normally distributed explanatory variables by randomly selecting a mean between 10 and 100 and randomly selecting a standard deviation between 1 and

[11]Table 5 lists the control variables with usage rates above 25%. Additionally, firm age (23% usage) is the next most commonly used control variable in value regressions.

10. I also create dummy explanatory variables by generating a uniform random variable on the interval (0,1) and creating an indicator that equals one if an observation is above a randomly selected cutoff on the interval (0,1) and zero otherwise. For each explanatory variable generated, I perform a separate regression for each possible combination of the six methodological decisions listed above—a total of 64 regressions for each explanatory variable. I repeat this procedure for 100 randomly generated explanatory variables for each type of explanatory variable and each category of regression. I perform all regressions twice, once with industry fixed effects and once with firm fixed effects.

2.3.3 Simulation results.

Figure 1 displays histograms of the measures of economic significance calculated from the regressions of the six outcome variables on randomly generated explanatory variables.[12] Panel A compares $E_{\overline{y}}^{s}$ with E_{s}^{s} for normally distributed explanatory variables; panel B compares $E_{\overline{y}}^{IQR}$ with E_{s}^{IQR} for normally distributed explanatory variables; and panel C compares $E_{\overline{y}}^{1}$ with E_{s}^{1} for dummy explanatory variables. Each panel of Figure 1 is based on measures of economic significance from 76,800 regressions (6 categories of regressions, 100 explanatory variables, 64 methodological combinations, 2 types of fixed effects). Panel A of Figure 1 shows that E_{s}^{s} is always small in the simulated regressions. Across all categories of dependent variables, E_{s}^{s} is never greater than 0.01, meaning that in all cases, a one-standard-deviation change in a randomly generated explanatory variable is associated with no more than a change of one 100th of a standard deviation of the dependent variable. Panel A shows that, by comparison, $E_{\overline{y}}^{s}$ can often be high in the simulated regressions. Over 40% of the measures of $E_{\overline{y}}^{s}$ are greater than 0.01, and although most of the measures are less than 0.10, $E_{\overline{y}}^{s}$ reaches as high as 1.59. For comparison, as reported in the next section, the median $E_{\overline{y}}^{s}$ for published findings in my sample of papers ranges from 0.07 (for leverage regressions) to 0.18

[12] I combine results from all six categories of regressions into a single figure, but the patterns demonstrated are fairly similar in each individual category.

(for cash regressions). Thus, many of the randomly generated measures of economic significance would be high in comparison to the economic significance of established results from the literature. Panel B of Figure 1 shows a similar pattern for E_s^{IQR} and $E_{\overline{y}}^{IQR}$. Across all dependent variables, E_s^{IQR} is never greater than 0.01. Meanwhile, over 40% of the measures of $E_{\overline{y}}^{IQR}$ are greater than 0.01, with a maximum $E_{\overline{y}}^{IQR}$ of 2.13.

Panel C of Figure 1 reports results for randomly generated dummy explanatory variables. Although E_s^1 is occasionally higher than 0.01, its upper range is far below the upper range of values for $E_{\overline{y}}^1$. Once again, panel B shows that scaling economic significance by the mean can sometimes result in very high estimates of economic significance for randomly generated variables, with the maximum value of $E_{\overline{y}}^1$ reaching 10.77. Overall, Figure 1 shows that, at least for the methodological decisions modeled in these simulations, E_s^s, E_s^{IQR}, and E_s^1 are more reliable than $E_{\overline{y}}^s$, $E_{\overline{y}}^{IQR}$, and $E_{\overline{y}}^1$. Measures of economic significance scaled by the standard deviation behave as they should—they always show negligible economic significance for randomly generated variables.

2.4 Resistance to specification searching

The next property I consider is whether the measures of economic significance are susceptible to specification searching; that is, whether they are susceptible to changes in magnitude when different methodologies are chosen. Resistance to specification searching is a desirable property because it limits the possibility of methodologies being selectively chosen to make results appear more important. The results already presented in Figure 1 suggest that measures of economic significance scaled by the mean are more susceptible to specification searching than measures scaled by the standard deviation, because combinations of accepted methods can produce high values of $E_{\overline{y}}^s, E_{\overline{y}}^{IQR}$, and $E_{\overline{y}}^1$. What is not observable in Figure 1 is the *percentage* of randomly generated variables that are susceptible to specification searching. In other words, it is not clear from Figure 1 whether the high values observed for $E_{\overline{y}}^{s}, E_{\overline{y}}^{IQR}$, and $E_{\overline{y}}^{1}$ come from a small percentage of randomly generated variables that produce high values for many methodological combinations, or if they come from a large percentage of randomly generated variables, each of which produces high values for a small number of methodological combinations. To demonstrate how frequently randomly generated variables can, through specification searching, be shown to have high levels of economic significance, I return to the simulated regressions from the previous section. For each randomly generated variable in the simulations, I consider the *maximum* economic significance that is generated across all 64 methodological specifications tested for each variable. A high maximum economic significance for a particular variable suggests that the variable is susceptible to specification searching; that is, some combination of methodological decisions produces a high estimate of economic significance for that variable. A low maximum economic significance for a particular variable suggests that the variable is not susceptible to specification searching.

Figure 2 shows the distribution of maximum economic significance, comparing measures of economic significance scaled by the mean to measures scaled by the standard deviation. Panel A compares E_{s}^{s} to $E_{\overline{y}}^{s}$; panel B compares E_{s}^{IQR} to $E_{\overline{y}}^{IQR}$; and panel C compares E_{s}^{1} to $E_{\overline{y}}^{1}$. The lines in the charts display the complementary cumulative distribution of maximum economic significance across all tested explanatory variables, with each chart representing results for 1,200 randomly generated variables (6 categories of regressions, 100 explanatory variables, 2 types of fixed effects). In other words, each point in the charts shows the percentage of explanatory variables that have maximum economic significance greater than the level indicated. For example, panel A shows that over 50% of randomly generated variables have a maximum $E_{\overline{y}}^{s}$ of over 0.20. This means that, for roughly half of randomly generated variables, some methodological combination would allow researchers to report an $E_{\overline{y}}^{s}$ of 0.20 or more. Panel A shows further that for about 20% of randomly generated variables, some methodological combination would allow reporting of an $E_{\overline{y}}^{s}$ of 0.40 or more.

By contrast, Panel A confirms that E_s^s never reaches a high level in the simulations; the maximum E_s^s is always less than 0.01.

Panels B and C of Figure 2 show similar patterns for E_s^{IQR} compared to $E_{\overline{y}}^{IQR}$, and for E_s^1 compared to $E_{\overline{y}}^1$. Randomly generated variables can often be shown to have high levels of economic significance when measures of economic significance are scaled by the mean. For example, panel B shows that for over 60% of explanatory variables, some methodological combination allows reporting of $E_{\overline{y}}^{IQR}$ of over 0.20. Panel C shows that for over 80% of explanatory variables, some methodological combination allows reporting of $E_{\overline{y}}^1$ of over 0.20. In short, measures of economic significance scaled by the mean are usually susceptible to specification searching, whereas measures scaled by the standard deviation are not. In this regard, measures of economic significance scaled by the standard deviation are also superior to measures of statistical significance (i.e., t-statistics or p-values), which are highly susceptible to specification searching (see Mitton 2022).

2.5 Resistance to outliers

The next property I consider is whether the measures of economic significance are resistant to outliers. I propose that a robust measure of economic significance should not be highly sensitive to whether or not outliers are treated. I find that measures of economic significance scaled by the mean are highly sensitive to outliers, and that measures scaled by the standard deviation are highly resistant to outliers. Returning to the results of the simulations described above, I calculate the difference in the measures of economic significance induced by outlier treatment in each of the iterations of the simulations. Across 38,400 pairs of regressions (one with outliers treated, one with outliers untreated), the average absolute value of the difference in $E_{\overline{y}}^s$ is 0.08, in $E_{\overline{y}}^{IQR}$ it is 0.11, and in $E_{\overline{y}}^1$ it is 0.21. Thus, for all measures of significance scaled by the mean, outlier treatment has a very large effect on whether or not a result would be considered economically significant. In contrast, measures scaled by the standard deviation change very little when outliers are treated. The average absolute value of the difference in E_s^s is 0.001, for E_s^{IQR} it is 0.001, and for E_s^1 it is 0.003.

Some intuition for why measures scaled by the mean are more sensitive to outliers than measures scaled by the standard deviation can be found in the formulas for $E_{\overline{y}}^s$ and E_s^s (Equations (1) and (2)). Both formulas have the same numerator (bs_x), but the denominator for $E_{\overline{y}}^s$ is $\overline{y}$ and the denominator for E_s^s is s_y. Estimates of b tend to be of greater magnitude when outliers are retained rather than winsorized, but this effect is offset for E_s^s, because s_y also tends to be of greater magnitude when outliers are retained. The same offsetting effect does not occur with $\overline{y}$ in the denominator of $E_{\overline{y}}^s$. Consequently, the vast majority of high values of $E_{\overline{y}}^s$ produced by the simulations occur when outliers are not winsorized. Winsorizing outliers at the 1st and 99th percentiles appears to largely eliminate the risk of spuriously high measures of economic significance. So a possible way to mitigate specification searching could be to always treat outliers. However, I find that in over 40% of the papers in my sample, outliers are not treated in any way (see Mitton 2022). Furthermore, in some studies it may not be appropriate to treat outliers, given the nature of the data or the theory being tested. Thus, a better alternative is to use measures of economic significance scaled by the standard deviation, which are robust to outliers.

2.6 Robustness with negative dependent variables

A final property I consider is whether the measures of economic significance appropriately reflect the importance of a result when the dependent variable can be negative. Measures scaled by the mean are problematic in this regard, because the mean of the dependent variable (the denominator of each of these measures) can be arbitrarily small when the range of the dependent variable includes negative values. In my simulations, this is a problem only for the profitability regressions, because the other categories of regressions have dependent variables that are strictly non-negative. But in practice, the problem occurs frequently, because even strictly positive dependent variables can take on negative values if the dependent variable is transformed, for example, by taking first differences or by logging a ratio dependent variable. In the sample of papers I study, about 47% of the regressions are potentially susceptible to this problem. As an example from the literature, in showing that bank holding companies with stronger risk management have higher profitability, Ellul and Yerramilli (2013) report, "These results are economically significant: the coefficient of 0.006 on RMI_{t-1} in column (1) indicates that a one-standard-deviation increase in RMI is associated with a 15.82% increase in ROA (relative to the sample mean ROA of 1.07%)." This calculation is not incorrect, *per se*, but since negative values of ROA can produce a mean ROA that is arbitrarily close to zero, $\overline{y}$ is not an effective scaling parameter, and the resultant magnitude of economic significance could be misleading. Measures of economic significance scaled by the standard deviation (E_s^s, E_s^{IQR}, and E_s^1) do not suffer from this same weakness because negative values of the dependent variable do not arbitrarily reduce the magnitude of the standard deviation. Of course, the standard deviation also could be too small to allow for meaningful measures of economic significance, but this is a rare occurrence, at least in the sample of papers I study.

3. Benchmarks for Economic Significance

The importance of an empirical result can be evaluated more easily when the size of the effect is placed in the context of other results reported in the literature. I establish benchmarks for economic significance based on results for key explanatory variables reported in top finance journals and for standard control variables. Comparisons of economic significance across variables should be made with caution. For example, if the distributions of two variables are highly dissimilar, then their economic significance estimates may not be directly comparable (Willett, Singer, and Martin 1998; Greenland et al. 1991; Lu and Westfall 2019).

Additionally, collinearity among predictor variables (Grömping 2007; Sterck 2019) and the presence of interaction terms (Friedrich 1982) can make interpretation of economic significance more difficult. Despite these complications, benchmarks can go a long way toward helping researchers communicate the practical importance of their findings.

3.1 Benchmarks from existing literature

One way the economic significance of a key explanatory variable can be put in context is to compare it to the economic significance of existing findings from the literature. Making these comparisons can be difficult because measures of economic significance are not standardized across papers in the literature. To provide benchmarks of economic significance from published findings, I calculate standard measures of economic significance for the key explanatory variables in my sample of regressions from the existing literature. I am only able to calculate these measures for papers that report the necessary summary statistics to make the calculations, and as noted in Table 3, the majority of papers do not report all the statistics necessary. Among the continuous explanatory variables I am able to calculate E_s^s in 182 cases, and among the dummy explanatory variables I am able to calculate E_s^1 in 134 cases. I also provide statistics on $E_{\overline{y}}^s$ and $E_{\overline{y}}^1$, for 201 cases in which $E_{\overline{y}}^s$ can be calculated, and for 210 cases in which $E_{\overline{y}}^1$ can be calculated. I do not attempt to calculate $E_{\overline{y}}^{IQR}$ or E_s^{IQR} because of the infrequency with which papers report the IQR. Papers that study only financial firms are excluded from these statistics.

One complication in compiling these statistics is that most papers report multiple regression specifications for the same key explanatory variable, each of which can give differing values for economic significance. For example, a specification with few or no control variables might result in a higher estimate of economic significance than a specification with many control variables. Although some subjectivity is unavoidable, I report values that correspond to what appears to be a representative baseline specification in each paper, including the control variables that the authors appear to consider the most essential. In general, when making comparisons across papers, attention should be given to the control variables included in each paper as well as other differences among specifications.

Panel A of Table 4 reports summary statistics for estimates of E_s^s for reported findings in the literature. Again, these are usually *not* the measures of economic significance reported in the papers; they are the measures that would have been reported had the authors reported E_s^s. Panel A reports statistics for each of the six categories of regressions. For example, for profitability regressions, panel A shows that the median E_s^s in the published papers is 0.07, meaning that for half the papers in the literature, a one-standard-deviation change in the key explanatory variable is associated with a change of no more than seven 100ths of a standard deviation of profitability. At the extremes, the lowest E_s^s in the literature is 0.001, and the highest E_s^s is 0.36. The pattern for the other five dependent variables is similar to that for profitability. The economic significance of the majority of published findings is below 0.10, with median values for E_s^s ranging from 0.04 (for payouts) to 0.11 (for cash).

Panel B of Table 4 reports summary statistics for estimates of E_s^1 in published papers with dummy explanatory variables. The figures reported are similar to those in panel A, but comparing the medians from panel B to panel A shows that values for E_s^1 tend to be somewhat higher than values for E_s^s.[13] The figures reported for the measures of economic significance that are scaled by the mean of the dependent variable (panels C and D) tend to be higher than their counterparts in panels A and B, although the figures reported in panels C and D are potentially subject to the weaknesses of measures scaled by the mean, as discussed above.

For reference purposes, Tables A3 through A8 in the appendix report the economic

[13] A change from zero to one in a dummy explanatory variable is equivalent to a change of at least two standard deviations. (A dummy variable with mean p has a standard deviation of $\sqrt{p(1-p)}$, which is at most 0.5.) So it is not surprising that E_s^1 tends to be higher than E_s^s, which measures a change of only one standard deviation in the explanatory variable. Gelman (2008) recommends rescaling continuous variables by two standard deviations so that standardized coefficients of continuous and dummy variables are on a comparable scale.

significance of the key explanatory variables in each of the papers included in the statistics in panels A and B of Table 4. The statistics reported in Table 4 and the appendix can provide researchers with context of how the economic significance of a key explanatory variable they are studying compares with the economic significance of other key findings reported in papers published in top journals. Researchers studying other dependent variables can find similar benchmarks in the literature if the outcome of interest has been studied previously. If the outcome of interest has not been studied previously, then the economic significance of theoretically motivated control variables can be used for benchmarking, as discussed below.

3.2 Control variable benchmarks

Many standard control variables are included in regression models because they have been accepted in the literature as important determinants of the dependent variable. Thus, another way to provide context for the importance of a key explanatory variable is to compare its economic significance to the economic significance of standard control variables. In this section I report measures of economic significance for the most commonly used control variables in each category of regression. To measure the economic significance of the control variables I perform regressions as in Equation (19), except that no randomly generated explanatory variable is included. The data for the regressions come from Compustat for the years 1963 to 2018. I select the most commonly used proxy for the dependent variable in each category, and I test all control variables that are used at least 25% of the time in the literature.[14]

Table 5 reports the results of these tests. Column 2 reports the most commonly used proxy in the literature for each category of regression. Column 3 reports the most commonly used control variables in each category of regression, and column 4 reports the frequency

[14]Regarding the other methodological decisions mentioned in Section 2.3.2, in these tests I retain financial firms, use log(total assets) as the size control, do not lag the independent variables, and winsorize variables at the 1st and 99th percentiles.

with which each control variable is used. In all six categories, firm size is the most frequently used control variable. Reflecting the somewhat circular nature of empirical corporate finance, the other most commonly used control variables in each category are themselves standard dependent variables in the literature. The one exception is asset tangibility, which is used as a control variable in 52% of leverage regressions.

Column 5 of Table 5 reports E^s_s for each of the control variables when the regressions include industry fixed effects. All measures of economic significance for the control variables in column 5 are between 0.00 and 0.60. The largest effect in column 5 is for profitability in value regressions; the magnitude indicates that, based on the estimated regression coefficient from Equation (19), a one-standard-deviation change in profitability is associated with a change equal to six-tenths of a standard deviation of firm value. Column 6 reports analogous results for $E^s_{\bar{y}}$, although some of the results in column 6 are spuriously inflated (particularly for profitability). Columns 7 and 8 report E^s_s and $E^s_{\bar{y}}$ for each of the control variables when the regressions include firm fixed effects. In most cases, the estimated magnitudes are not greatly different from the estimates using industry fixed effects.

In comparing the economic significance of a key explanatory variable to that of standard control variables, researchers can calculate their own estimates of economic significance based on their own regression results. Calculating the economic significance of control variables from the same regression is often preferable, because then the economic significance of the key explanatory variable and control variables are both calculated based on the exact same dependent variable and sample. Additionally, the estimates in Table 5 are not directly applicable to regressions with dependent variables other than the six documented, but the economic significance of theoretically motivated control variables from the same regression can serve as benchmarks for regressions with any dependent variable. Nevertheless, for common dependent variables, the measures reported in Table 5 can serve as a reference when a study does not provide calculations of economic significance for control variables.

As a caveat, it is important to remember that the economic significance of some control variables may reflect the cumulative effect of many endogenous forces. For example, the economic significance of profitability for leverage is relatively large (between 0.28 and 0.44 in Table 5), but the literature has debated multiple factors that could contribute to the observed relation between profitability and leverage. Consequently, this level of economic significance is not necessarily a reasonable benchmark for a single, well-identified causal effect of another variable on leverage.

4. Conclusion

A movement within the scientific community seeks to change the way that researchers assess the importance of empirical results. A recent article in *Nature* calling for "the entire concept of statistical significance to be abandoned" has been signed by 854 scientists from 52 countries (Amrhein, Greenland, and McShane 2019). The article advocates for increased thoughtfulness in the way results are reported and interpreted. A number of recommendations have been advanced for how to improve the interpretation of empirical results,[15] but one key recommendation is to put greater focus on the practical importance of findings. This paper offers some simple guidelines toward improving the way in which economic significance is reported and discussed in the literature. These recommendations include using measures of economic significance scaled by the standard deviation, providing sufficient information to allow readers to judge economic significance, and providing benchmarks for putting economic significance in context. Although this paper focuses on six common dependent variables, these recommendations apply in other contexts as well: at least some of the desirable properties of measures scaled by the standard deviation hold for all dependent variables, providing sufficient information is a common-sense recommendation for all

[15] See McCloskey and Ziliak (1996), Ioannidis (2005, 2008), Ellis (2010), Harvey (2017), Leek et al. (2017), Christensen and Miguel (2018), Abadie (2020), and Sterck (2019).

dependent variables, and using benchmarks is helpful for all dependent variables. In sum, by following the recommendations in this paper and by giving greater attention to evaluating the economic significance of empirical results, we can increase our understanding of the importance of findings in corporate finance research.

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Appendix

In this appendix, I verify the relations presented in Sections 2.1 and 2.2 regarding the scale and origin independence of measures of economic significance (Equations (7) to (18)).

A.1 Scale Independence

For any constant c, the following relations are well known:

$$\overline{cy} = c\overline{y}, \tag{A1}$$

$$s_{cx} = |c|\, s_x. \tag{A2}$$

Additionally, for an independent variable x and a dependent variable y, the estimated slope coefficient from a regression of y on x scales up (down) when y (x) is multiplied by a constant. Thus, if $b(x, y)$ is the estimated slope coefficient of a regression of y on x, and c_1 and c_2 are constants, then

$$b(c_1x, c_2y) = \frac{c_2}{c_1} b(x, y). \tag{A3}$$

From these relations, it follows that,

$$E_s^s(c_1x, c_2y) = \left|\frac{b(c_1x, c_2y)s_{c_1x}}{s_{c_2y}}\right| = \left|\frac{\frac{c_2}{c_1}b(x, y)\,|c_1|\,s_x}{|c_2|\,s_y}\right| = \left|\frac{b(x, y)s_x}{s_y}\right| = E_s^s(x, y), \tag{A4}$$

$$E_s^1(x, c_2y) = \left|\frac{b(x, c_2y)}{s_{c_2y}}\right| = \left|\frac{c_2b(x, y)}{c_2s_y}\right| = \left|\frac{b(x, y)}{s_y}\right| = E_s^1(x, y). \tag{A5}$$

These equations verify the scale independence of E_s^s and E_s^1. The scale independence of $E_{\overline{y}}^s$ follows from the same logic as in Equation (A4). Given that $IQR(cx) = cIQR(x)$ and $IQR(x+c) = IQR(x)$, the scale independence of E_s^{IQR} and $E_{\overline{y}}^{IQR}$ also follows from the same logic. The scale independence of $E_{\overline{y}}^1$ follows from the same logic as in Equation (A5).

A.2 Origin Independence

The following relations are well known:

$$\overline{y+c} = \overline{y} + c, \tag{A6}$$

$$s_{x+c} = s_x. \tag{A7}$$

Additionally, the estimated slope coefficient from a regression of y on x is unaffected by additive transformations of either x or y, so that

$$b(x+c_1, y+c_2) = b(x,y). \tag{A8}$$

From these relations, it follows that,

$$E_s^s(x+c_1, y+c_2) = \left|\frac{b(x+c_1, y+c_2)s_{x+c_1}}{s_{y+c_2}}\right| = \left|\frac{b(x,y)s_x}{s_y}\right| = E_s^s(x,y), \tag{A9}$$

$$E_s^1(x, y+c_2) = \left|\frac{b(x, y+c_2)}{s_{y+c_2}}\right| = \left|\frac{b(x,y)}{s_y}\right| = E_s^1(x,y). \tag{A10}$$

These equations verify the origin independence of E_s^s and E_s^1. The origin independence of E_s^{IQR} follows from the same logic as in Equation (A9). Measures of economic significance scaled by the mean are not independent of origin, as shown below:

$$E_{\overline{y}}^s(x+c_1, y+c_2) = \left|\frac{b(x+c_1, y+c_2)s_{x+c_1}}{\overline{y+c_2}}\right| = \left|\frac{b(x,y)s_x}{\overline{y}+c_2}\right| \neq E_{\overline{y}}^s(x,y), \tag{A11}$$

$$E_{\overline{y}}^1(x, y+c_2) = \left|\frac{b(x, y+c_2)}{\overline{y+c_2}}\right| = \left|\frac{b(x,y)}{\overline{y}+c_2}\right| \neq E_{\overline{y}}^1(x,y). \tag{A12}$$

The lack of origin independence of $E_{\overline{y}}^{IQR}$ follows from the same logic as in Equation (A11).

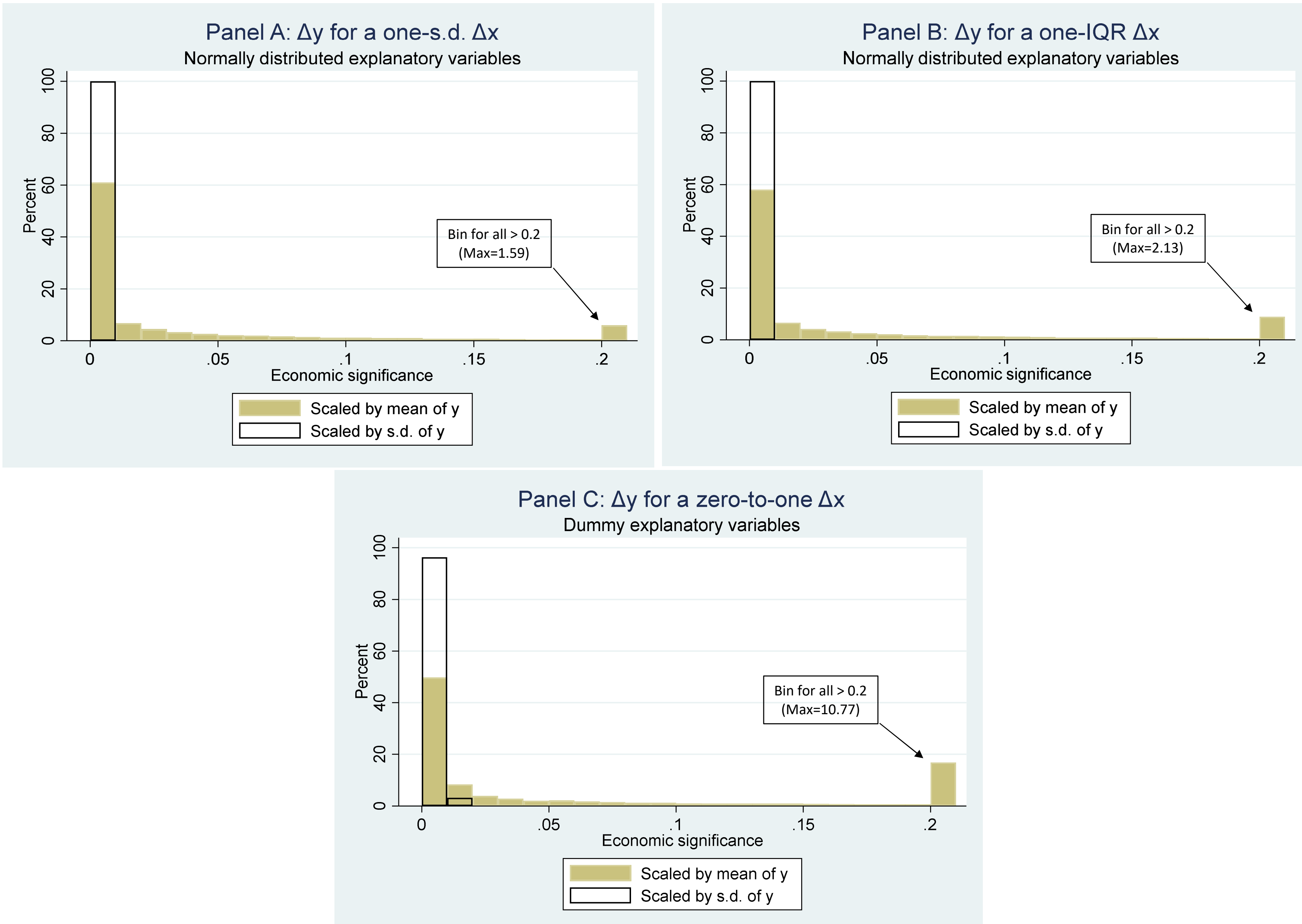

Figure 1

Economic significance of randomly generated explanatory variables

Histograms of the economic significance of randomly generated explanatory variables in regressions of profitability, firm value, leverage, investment, payouts, and cash holdings. Each panel combines results from all six categories of regressions, and for each category, 100 explanatory variables are tested with all possible combinations of six binary methodological decisions in both industry-fixed-effects regressions and firm-fixed-effects regressions, resulting in a total of 76,800 regressions represented in each panel. For definitions of the measures of economic significance, see Section 1.2.1. All data other than randomly generated explanatory variables come from the Compustat database for the years 1963 to 2018. Each regression includes year fixed effects.

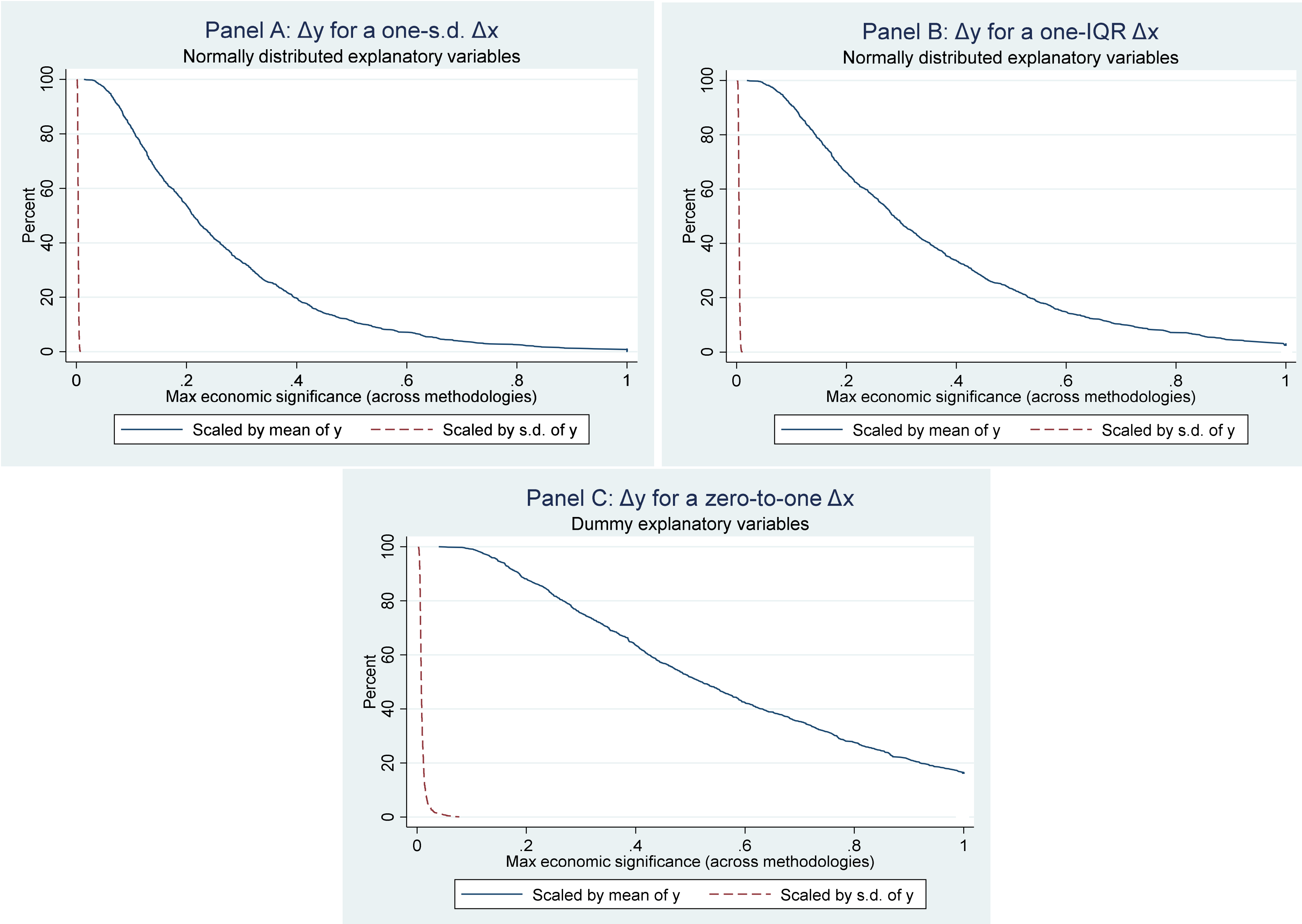

Figure 2
Economic significance with specification searching
Complementary cumulative distributions of the maximum economic significance that could be reported for randomly generated explanatory variables when a researcher has discretion over methodological decisions. Each explanatory variable is tested using all combinations of six binary methodological decisions, and the maximum economic significance for each variable is represented in the figure. Each panel combines results from six categories of regressions, and for each category, 100 explanatory variables are tested in both industry and firm fixed effects regressions, resulting in a total of 1,200 variables represented in each panel. For definitions of the measures of economic significance, see Section 1.2.1. All data other than randomly generated explanatory variables come from the Compustat database for the years 1963 to 2018. Each regression includes year fixed effects.

Table 1
Corporate finance regressions in top finance journals

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	All years
Profitability	2	2	1	6	3	4	8	10	8	11	17	21	15	16	16	14	14	18	21	207
Value	2	4	12	6	3	3	6	8	9	17	11	15	12	9	12	8	6	13	10	166
Leverage	0	2	3	7	4	4	9	8	9	13	16	9	16	18	17	17	24	12	21	209
Investment	1	0	1	2	1	2	5	11	12	10	14	10	17	13	14	18	14	24	22	191
Payout	3	3	2	0	0	3	6	2	7	8	2	9	7	7	7	8	7	6	7	94
Cash	0	1	0	0	1	0	1	4	1	9	7	4	5	9	9	9	11	8	8	87
Total	8	12	19	21	12	16	35	43	46	68	67	68	72	72	75	74	76	81	89	954
All papers published	181	176	200	191	202	205	216	246	258	317	290	302	279	303	266	278	285	294	299	4788
Total/all papers	0.04	0.07	0.10	0.11	0.06	0.08	0.16	0.17	0.18	0.21	0.23	0.23	0.26	0.24	0.28	0.27	0.27	0.28	0.30	0.20

The table reports the number of corporate finance regressions (of the categories shown) reported in papers in the *Journal of Finance, Journal of Financial Economics,* and *Review of Financial Studies,* by year. Multiple regressions of the same category in a given paper are counted as one regression. Also reported are the number of papers in the three journals and the total number of regressions scaled by the number of papers, by year.

Table 2
Measures of economic significance used in empirical corporate finance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
			Units for the resultant change in dependent variable (denominator)						
	Type of explanatory variable	Assumed change in explanatory variable (numerator)	Percentage of the mean	Percentage of the standard deviation	Percentage points	Probability (dummy dependent variable)	Percentage (logged dependent variable)	Other	Total
(1)	Continuous	One standard deviation	37	12	7	2	0	7	65
(2)		Interquartile range	6	0	1	1	0	2	9
(3)		Other percentile shifts	3	0	0	0	0	0	4
(4)		One percentage point	0	0	1	0	0	0	2
(5)		Other	10	0	3	1	1	4	19
(6)		Total (for continuous)	56	12	13	4	1	13	100
(7)	Dummy	Zero to one	57	6	9	0	6	22	100

The table reports percentages of papers using various measures of economic significance in the *Journal of Finance, Journal of Financial Economics,* and *Review of Financial Studies* between 2000 and 2018. The statistics are based on 396 papers that report a measure of economic significance out of the 604 papers in the sample. Column 2 lists the change in the explanatory variable assumed in the calculation of economic significance. Columns 3 to 8 report the percentage usage of each assumed change, categorized by how the resultant change in the dependent variable is expressed. Statistics are reported for continuous explanatory variables in rows 1 to 6 (269 cases) and for dummy explanatory variables in row 7 (127 cases).

Table 3
Current practice of reporting of economic significance

A: Percentage of papers discussing economic significance (by years)	
2000–2004	44
2005–2008	65
2009–2012	66
2013–2015	75
2016–2018	85
B: Reported summary statistics allow for calculation (among all papers, %)	
Continuous explanatory variables:	
$E_{\bar{y}}^{s}$	36
E_{s}^{s}	33
$E_{\bar{y}}^{IQR}$	15
E_{s}^{IQR}	14
Dummy explanatory variables:	
$E_{\bar{y}}^{1}$	60
E_{s}^{1}	38
C: Benchmarks of economic significance used (among papers discussing economic significance, %)	
Benchmarks from other papers	4
Benchmarks from standard control variables	9
No benchmarks	88
D: Claims regarding key results (among papers discussing economic significance, %)	
Economically significant	92
Not economically significant	2
No claim	7

The table reports statistics on the reporting of economic significance in the *Journal of Finance, Journal of Financial Economics,* and *Review of Financial Studies* between 2000 and 2018. The statistics are based on a sample of 604 papers containing corporate finance regressions. For definitions of the measures of economic significance, see Section 1.2.1.

Table 4
Economic significance of reported findings in the literature

(1) Category	(2) Min	(3) 10th pctile	(4) 25th pctile	(5) Median	(6) 75th pctile	(7) 90th pctile	(8) Max	(9) N
A: E_s^s (continuous explanatory variables)								
Profitability	0.00	0.02	0.04	0.07	0.14	0.28	0.36	35
Value	0.01	0.02	0.05	0.08	0.20	0.30	0.95	36
Leverage	0.00	0.01	0.03	0.06	0.13	0.23	0.62	43
Investment	0.00	0.02	0.04	0.09	0.14	0.29	0.49	39
Payouts	0.00	0.00	0.01	0.04	0.12	0.27	0.32	18
Cash	0.02	0.03	0.03	0.11	0.28	0.46	0.56	11
All	0.00	0.02	0.03	0.07	0.14	0.28	0.95	182
B: E_s^1 (dummy explanatory variables)								
Profitability	0.01	0.01	0.02	0.15	0.24	0.27	0.70	23
Value	0.01	0.04	0.06	0.16	0.25	0.34	0.40	19
Leverage	0.01	0.02	0.05	0.10	0.22	0.35	0.70	32
Investment	0.00	0.01	0.04	0.08	0.12	0.27	0.45	29
Payouts	0.00	0.01	0.03	0.16	0.20	0.60	0.99	15
Cash	0.02	0.02	0.06	0.10	0.16	0.25	0.28	16
All	0.00	0.01	0.04	0.10	0.20	0.31	0.99	134
C: $E_{\bar{y}}^s$ (continuous explanatory variables)								
Profitability	0.01	0.03	0.06	0.18	0.47	1.40	7.85	40
Value	0.00	0.02	0.05	0.09	0.19	0.53	1.43	43
Leverage	0.00	0.02	0.03	0.07	0.16	0.46	60.42	44
Investment	0.00	0.03	0.05	0.10	0.20	0.33	0.62	42
Payouts	0.00	0.01	0.04	0.09	0.27	0.47	2.26	20
Cash	0.02	0.03	0.04	0.18	0.43	3.16	5.46	12
All	0.00	0.02	0.04	0.10	0.23	0.54	60.42	201
D: $E_{\bar{y}}^1$ (dummy explanatory variables)								
Profitability	0.01	0.02	0.07	0.15	0.38	1.38	10.79	37
Value	0.00	0.02	0.06	0.14	0.33	1.55	12.00	36
Leverage	0.00	0.01	0.05	0.11	0.19	0.28	2.79	47
Investment	0.00	0.02	0.07	0.18	0.38	1.11	1.91	49
Payouts	0.02	0.02	0.08	0.15	0.27	0.61	0.88	19
Cash	0.02	0.03	0.07	0.14	0.27	0.48	9.00	22
All	0.00	0.02	0.06	0.13	0.27	0.96	12.00	210

The table reports statistics on the economic significance of key findings from corporate finance regressions (of the categories shown) in the *Journal of Finance, Journal of Financial Economics,* and *Review of Financial Studies* between 2000 and 2018. The sample size in each row is the number of regressions for which the paper provides the necessary summary statistics to calculate the measure of economic significance. For definitions of the measures of economic significance, see Section 1.2.1. Papers that study only financial firms are excluded from the statistics.

Table 5
Economic significance of commonly used control variables

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Industry FE		Firm FE	
Category	Most common proxy	Most common control variables	Usage rate in literature (%)	E_s^s	$E_{\bar{y}}^s$	E_s^s	$E_{\bar{y}}^s$
Profitability	Return on assets	Firm size	81	0.27	3.69	0.44	6.07
		Leverage	38	0.21	2.86	0.19	2.60
		Value	33	0.51	6.95	0.38	5.12
Value	Tobin's q	Firm size	84	0.09	0.20	0.40	0.84
		Investment	55	0.03	0.06	0.03	0.06
		Leverage	53	0.15	0.33	0.16	0.33
		Profitability	50	0.60	1.27	0.44	0.94
Leverage	Total debt/total assets	Firm size	87	0.06	0.08	0.07	0.10
		Profitability	73	0.33	0.44	0.28	0.37
		Value	65	0.23	0.31	0.21	0.28
		Asset tangibility	52	0.20	0.27	0.19	0.25
		Investment	25	0.07	0.09	0.05	0.07
Investment	CAPX/total assets	Firm size	64	0.03	0.04	0.10	0.13
		Value	58	0.05	0.06	0.05	0.06
		Profitability	58	0.01	0.01	0.04	0.04
		Leverage	34	0.00	0.00	0.03	0.03
Payouts	Dividends/total assets	Firm size	80	0.16	0.35	0.03	0.07
		Profitability	66	0.16	0.35	0.05	0.12
		Value	53	0.20	0.44	0.07	0.15
		Leverage	44	0.10	0.22	0.06	0.13
Cash	Cash/total assets	Firm size	81	0.20	0.26	0.28	0.37
		Profitability	65	0.08	0.11	0.02	0.03
		Value	51	0.16	0.22	0.14	0.18
		Leverage	47	0.31	0.42	0.18	0.24
		Investment	40	0.10	0.13	0.08	0.11
		Payouts	33	0.00	0.00	0.04	0.06

The table reports measures of economic significance for commonly used control variables in regressions of the categories shown. Control variables used more than 25% of the time in the literature are reported, based on a survey of 954 regressions reported from 2000 to 2018. For each category, one regression is performed with all listed control variables as explanatory variables. All regressions include year fixed effects and either industry fixed effects (two-digit SIC) or firm fixed effects, as noted. Data come from the Compustat database for the years 1963 to 2018. For definitions of the measures of economic significance, see Section 1.2.1.

Table A1
Variable definitions

Variable	Definition
Return on assets	Annual earnings before interest, taxes, depreciation, and amortization (EBITDA) divided by total assets (AT)
Return on equity	Annual net income (NI) divided by total common equity (CEQ)
Tobin's q	Total assets (AT) less total common equity (CEQ) plus market equity, all divided by total assets
Market-to-book	Market equity divided by total common equity (CEQ)
Book leverage	Long-term debt (DLTT) plus debt in current liabilities (DLC), all divided by total assets (AT)
Market leverage	Long-term debt (DLTT) plus debt in current liabilities (DLC), all divided by the sum of long-term debt, debt in current liabilities, and market equity
Investment/assets	Total annual capital expenditures (CAPX) divided by total assets (AT)
Investment/capital	Total annual capital expenditures (CAPX) divided by net property, plant, and equipment (PPENT)
Dividends/assets	Annual common/ordinary dividends (DVC) divided by total assets (AT)
Dividend yield	Annual common/ordinary dividends (DVC) divided by market equity
Cash/assets	Cash and short-term investments (CHE) divided by total assets (AT)
Cash/net assets	Cash and short-term investments (CHE) divided by net assets (AT−CHE)
Total assets	Total assets (AT) in $ millions
Sales	Total annual sales (SALE) in $ millions
Market equity	Stock price (PRCC_C) times shares outstanding (CSHO), in $ millions
Asset tangibility	Net property, plant, and equipment (PPENT) divided by total assets (AT)
Firm age	One plus the current year minus the first year for which Compustat has data for the firm

The table defines the Compustat variables used in the empirical analysis. Compustat mnemonics are indicated in parentheses. Nonpositive values of AT, SALE, PRCC_C, and CSHO are deleted; negative values of CAPX, CHE, PPENT, DVC, DLTT, and DLC are deleted. Balance sheet items are year-end values in all cases.

Table A2
Summary statistics

Category	Variable	Mean	Minimum	Median	Maximum	SD	N
Profitability	Return on assets	-0.05	-4.85	0.09	0.43	0.64	394,538
	Return on equity	-0.12	-6.11	0.09	1.02	0.86	364,235
Value	Tobin's q	2.58	0.47	1.25	46.32	5.48	348,857
	Market-to-book	3.00	0.18	1.57	38.45	5.07	324,481
Leverage	Book leverage	0.30	0.00	0.22	3.01	0.40	399,463
	Market leverage	0.28	0.00	0.22	0.95	0.27	348,954
Investment	Investment/assets	0.06	0.00	0.04	0.45	0.08	377,106
	Investment/capital	0.26	0.00	0.20	1.09	0.23	356,673
Payout	Dividends/assets	0.01	0.00	0.00	0.15	0.02	400,257
	Dividend yield	0.02	0.00	0.00	0.15	0.03	352,373
Cash	Cash/total assets	0.16	0.00	0.07	0.95	0.21	400,665
	Cash/net assets	0.51	0.00	0.07	14.07	1.75	399,586
Firm size	log(Total assets)	4.77	-1.92	4.71	11.21	2.69	403,768
	log(Sales)	4.44	-2.88	4.47	10.36	2.63	383,987
	log(Market equity)	4.51	-0.92	4.41	10.51	2.40	390,174
Other	Asset tangibility	0.30	0.00	0.22	0.94	0.27	396,762
	Firm age	13.17	2.00	9.00	55.00	11.39	456,444

The table reports summary statistics of variables used in the empirical analysis. See Table A1 in the appendix for variable definitions. All data come from the Compustat database for the years 1963 to 2018. The resported statistics are calculated after winsorization of the data at the 1st and 99th percentiles.

Table A3
Economic significance of proposed determinants of profitability

Proposed determinant	Economic significance	Sign	Statistically insignificant	Citation
A: Continuous explanatory variables				
Passive ownership (%)	0.360	+		Appel et al. 2016 (*JFE* 121:111–41)
Volatility of profitability	0.336	–		Pástor et al. 2009 (*RFS* 22:3005–46)
Campaign contributions	0.303	–		Claessens et al. 2008 (*JFE* 88:554–80)
Proximity to bank branch	0.279	+		Dass and Massa 2011 (*RFS* 24:1204–60)
Creditor rights	0.214	–		Houston et al. 2010 (*JFE* 96:485–512)
Pay redistribution index	0.165	–		Duchin et al. 2017 (*RFS* 30:1696–743)
Independent directors (%)	0.154	+		Knyazeva et al. 2013 (*RFS* 26:1561–605)
Directors from related industries	0.140	+		Dass et al. 2014 (*RFS* 27:1533–92)
Governance rating	0.137	+		Daines et al. 2010 (*JFE* 98:439–61)
Risk management index	0.121	+		Ellul and Yerramilli 2013 (*JF* 68:1757–803)
Ultimate ownership	0.111	+		Almeida et al. 2011 (*JFE* 99:447–75)
Relative effective spread	0.105	–	X	Fang et al. 2009 (*JFE* 94:150–69)
Anti-self-dealing index during crisis	0.099	+		Levine et al. 2016 (*JFE* 120:81–101)
Managerial integrity	0.093	+	X	Guiso et al. 2015 (*JFE* 117:60–76)
CSR during the financial crisis	0.088	+		Lins et al. 2017 (*JF* 72:1785–824)
Spread of analyst bull and bear estimates	0.082	+		Joos et al. 2016 (*JFE* 121:645–63)
Ownership by institutional investors (%)	0.080	+		Cornett et al. 2008 (*JFE* 87:357–73)
Within-quarter sales	0.072	+		Froot et al. 2017 (*JFE* 125:143–62)
Politicians receive contribution/divest stock (%)	0.070	–		Tahoun 2014 (*JFE* 111:86–110)
Industry relative valuation	0.064	–		Hoberg and Phillips 2010 (*JF* 65:45–86)
Negative words in news	0.064	–		Tetlock et al. 2008 (*JF* 63:1437–67)
Market-oriented media article tone	0.061	+		You et al. 2018 (*RFS* 31:43–96)
Ownership concentration	0.059	+		Joh 2003 (*JFE* 68:287–322)
Peer pay effect	0.047	+		Albuquerque et al. 2013 (*JFE* 108:160–81)
Policy sensitivity	0.044	+		Liu et al. 2017 (*JFE* 125:286–310)
Political homophily index	0.038	–		Lee et al. 2014 (*JFE* 112:232–50)
Customer concentration	0.036	+	X	Campello and Gao 2017 (*JFE* 123:108–36)
CEO overconfidence after SOX	0.032	+		Banerjee et al. 2015 (*RFS* 28:2812–58)
Fraction of female directors	0.031	–		Adams and Ferreira 2009 (*JFE* 94:291–309)
G-index	0.028	–		Core et al. 2006 (*JF* 61:655–87)
Maximum unemployment benefit	0.025	–	X	Agrawal and Matsa 2013 (*JFE* 108:449–70)
Years to director election	0.021	–		Fos et al. 2018 (*RFS* 31:1499–531)
Foreign institutional ownership	0.012	+		Ferreira and Matos 2008 (*JFE* 88:499–533)
Religiosity in county	0.006	+		Hilary and Hui 2009 (*JFE* 93:455–73)
Number of sons of founder	0.001	–		Bertrand et al. 2008 (*JFE* 88:466–98)

(continued)

Table A3
Continued

Proposed determinant	Economic significance	Sign	Statistically insignificant	Citation
B: Dummy explanatory variables				
Business combination law	0.700	+		Gormley and Matsa 2016 (*JFE* 122:431–55)
Founder CEO	0.300	+		Adams et al. 2005 (*RFS* 18:1403–32)
Broad-based employee option plan	0.274	+		Hochberg and Lindsey 2010 (*RFS* 23:4148–86)
Firm run by founder	0.258	+		Mehrotra et al. 2013 (*JFE* 108:840–54)
Split-share structure reform	0.252	+		Chen et al. 2012 (*RFS* 25:3610–44)
Directors from related industries	0.239	+		Dass et al. 2014 (*RFS* 27:1533–92)
IPO in hot market	0.197	–		Alti 2006 (*JF* 61:1681–710)
High tangibility after SARFAESI Act	0.174	+		Vig 2013 (*JF* 68:881–928)
Investor protection laws	0.169	+		Agrawal 2013 (*JFE* 107:417–35)
After LBO	0.152	+		Boucly et al. 2011 (*JFE* 102:432–53)
Net receiver of intragroup loans	0.149	+		Buchuk et al. 2014 (*JFE* 112:190–212)
CEO ownership positive but <10%	0.145	+		Lilienfeld-Toal and Ruenzi 2014 (*JF* 69:1013–50)
Family firm	0.115	+		Anderson and Reeb 2003 (*JF* 58:1301–28)
Weather shock	0.088	–		Pérez-González and Yun 2013 (*JF* 68:2143–76)
Young firms after Riegle-Neal Act	0.082	+		Zarutskie 2006 (*JFE* 81:503–37)
Board reform	0.030	+		Fauver et al. 2017 (*JFE* 125:120–42)
Busy outside directors	0.018	–		Fich and Shivdasani 2006 (*JF* 61:689–724)
Recession	0.015	–	X	Schoar and Zuo 2017 (*RFS* 30:1425–56)
Cross ownership	0.014	+		He and Huang 2017 (*RFS* 30:2674–718)
Hurricane strike in headquarters county	0.012	–	X	Dessaint and Matray 2017 (*JFE* 126:97–121)
Good faith exception	0.011	+	X	Serfling 2016 (*JF* 71:2239–86)
Capital controls	0.009	+	X	Desai et al. 2006 (*RFS* 19:1433–64)
CEO difficult work experience	0.005	–		Dittmar and Duchin 2016 (*RFS* 29:565–602)

The table reports the economic significance of proposed determinants of profitability from papers published in three top finance journals between 2000 and 2018. Economic significance is based on the regression coefficients and summary statistics reported in the cited paper. Panel A reports the economic significance of continuous explanatory variables and the measure of significance is the standardized beta coefficient. Panel B reports the economic significance of dummy explanatory variables and the measure of significance is the change in profitability, as a percentage of its standard deviation, associated with a zero-to-one change in the explanatory variable. The sign of the coefficient for the proposed determinant is also reported. Proposed determinants marked with an "X" are not statistically significant in the cited paper. Papers studying only financial firms are excluded from the table. Economic significance of interaction terms are reported as incremental effects.

Table A4
Economic significance of proposed determinants of firm value

Proposed determinant	Economic significance	Sign	Statistically insignificant	Citation
A: Continuous explanatory variables				
Premarket P/E	0.950	+		Chang et al. 2017 (*RFS* 30:835–65)
Relative effective spread	0.446	–		Fang et al. 2009 (*JFE* 94:150–69)
Directors with foreign experience (%)	0.385	+		Giannetti et al. 2015 (*JF* 70:1629–82)
Campaign contributions	0.296	–		Claessens et al. 2008 (*JFE* 88:554–80)
Proximity to bank branch	0.288	+		Dass and Massa 2011 (*RFS* 24:1204–60)
Value of hedging	0.275	+		MacKay and Moeller 2007 (*JF* 62:1379–419)
Divisional diversity between parent and spin-off	0.237	+		Burch and Nanda 2003 (*JFE* 70:69–98)
Lead IPO underwriter centrality	0.221	+		Bajo et al. 2016 (*JFE* 122:376–408)
Founder ownership	0.210	+		Anderson et al. 2009 (*JFE* 92:205–22)
Managerial integrity	0.190	+		Guiso et al. 2015 (*JFE* 117:60–76)
Independent directors (%)	0.121	+		Knyazeva et al. 2013 (*RFS* 26:1561–605)
Directors from related industries	0.120	+		Dass et al. 2014 (*RFS* 27:1533–92)
Ownership structure complexity	0.116	–		Laeven and Levine 2008 (*RFS* 21:579–604)
Fraction of shares held by CEO	0.112	+		Kim and Lu 2011 (*JFE* 102:272–92)
Debt ratio	0.105	–		Kemsley and Nissim 2002 (*JF* 57:2045–73)
Diversity of investment opportunities	0.098	–		Rajan et al. 2000 (*JF* 55:35–80)
Ownership share of the CEO	0.088	+		Coles et al. 2012 (*JFE* 103:149–68)
Dispersion of division valuation during crisis	0.079	+		Matvos and Seru 2014 (*RFS* 27:1143–89)
Injuries/hour	0.078	–		Cohn and Wardlaw 2016 (*JF* 71:2017–58)
Ownership of nonofficer blockholders	0.074	+		Bharath et al. 2013 (*JF* 68:2515–47)
Readability of disclosure documents	0.067	+		Hwang and Kim 2017 (*JFE* 124:373–94)
Centrality in group structure	0.063	–		Almeida et al. 2011 (*JFE* 99:447–75)
Geographic diversification	0.062	–		Goetz et al. 2013 (*RFS* 26:1787–823)
Governance rating	0.061	–		Daines et al. 2010 (*JFE* 98:439–61)
Foreign institutional ownership	0.059	+		Bena et al. 2017 (*JFE* 126:122–46)
Diversity of industry investment	0.056	–		Lamont and Polk 2002 (*JFE* 63:51–77)
Top management pay/performance sensitivity	0.055	+		Aggarwal and Samwick 2003 (*JF* 58:71–118)
Local trading ratio	0.052	–		Shive 2012 (*JFE* 104:145–61)
G-index	0.041	–		Cremers and Ferrell 2014 (*JF* 69:1167–96)
Foreign institutional ownership	0.034	+		Ferreira and Matos 2008 (*JFE* 88:499–533)
Local ownership by mutual funds	0.027	–		Gaspar and Massa 2007 (*JFE* 83:751–92)
Political homophily index	0.027	–		Lee et al. 2014 (*JFE* 112:232–50)
CEO pay slice	0.024	–		Bebchuk et al. 2011 (*JFE* 102:199–221)
CEO overconfidence after SOX	0.018	+	X	Banerjee et al. 2015 (*RFS* 28:2812–58)
Ownership by dedicated institutional investors (%)	0.016	+		Borochin and Yang 2017 (*JFE* 126:171–99)
Takeover index	0.012	+		Cain et al. 2017 (*JFE* 124:464–85)

(continued)

Table A4
Continued

Proposed determinant	Economic significance	Sign	Statistically insignificant	Citation
B: Dummy explanatory variables				
Weather derivatives	0.403	+		Pérez-González and Yun 2013 (*JF* 68:2143–76)
Low private benefits/high AI/two-tiered board	0.339	–		Belot et al. 2014 (*JFE* 112:364–85)
Founder CEO	0.309	+		Adams et al. 2005 (*RFS* 18:1403–32)
Firm run by founder	0.267	+		Mehrotra et al. 2013 (*JFE* 108:840–54)
Directors from related industries	0.250	+		Dass et al. 2014 (*RFS* 27:1533–92)
High impact of home leverage in leverage model	0.222	–		Cronqvist et al. 2012 (*JFE* 103:20–40)
Sin stock	0.183	–		Hong and Kacperczyk 2009 (*JFE* 93:15–36)
Diversified	0.169	–		Santalo and Becerra 2008 (*JF* 63:851–83)
Family ownership	0.163	+		Villalonga and Amit 2006 (*JFE* 80:385–417)
Founder on board	0.160	+		Li and Srinivasan 2011 (*JFE* 102:454–69)
Classified board	0.147	–		Faleye 2007 (*JFE* 83:501–29)
Board reform	0.133	+		Fauver et al. 2017 (*JFE* 125:120–42)
Investor protection laws	0.068	+		Agrawal 2013 (*JFE* 107:417–35)
CEO difficult work experience	0.065	–		Dittmar and Duchin 2016 (*RFS* 29:565–602)
Year of vote to remove antitakeover provision	0.057	–	X	Cuñat et al. 2012 (*JF* 67:1943–77)
Say on pay law	0.054	+		Correa and Lel 2016 (*JFE* 122:500–20)
Brokerage house merger/closure	0.042	–	X	Billett et al. 2017 (*JFE* 123:357–76)
Staggered board	0.038	–		Cremers et al. 2017 (*JFE* 126:422–44)
Diversified	0.014	–	X	Custódio 2014 (*JF* 69:219–40)

The table reports the economic significance of proposed determinants of firm value from papers published in three top finance journals between 2000 and 2018. Economic significance is based on the regression coefficients and summary statistics reported in the cited paper. Panel A reports the economic significance of continuous explanatory variables and the measure of significance is the standardized beta coefficient. Panel B reports the economic significance of dummy explanatory variables and the measure of significance is the change in firm value, as a percentage of its standard deviation, associated with a zero-to-one change in the explanatory variable. The sign of the coefficient for the proposed determinant is also reported. Proposed determinants marked with an "X" are not statistically significant in the cited paper. Papers studying only financial firms are excluded from the table. Economic significance of interaction terms are reported as incremental effects.

Table A5
Economic significance of proposed determinants of leverage

Proposed determinant	Economic significance	Sign	Statistically insignificant	Citation
A: Continuous explanatory variables				
Lagged debt ratio	0.620	+		Flannery and Rangan 2006 (*JFE* 79:469–506)
Relative effective spread	0.531	–		Fang et al. 2009 (*JFE* 94:150–69)
External finance weighted average M/B	0.304	+		Baker and Wurgler 2002 (*JF* 57:1–32)
Production process flexibility	0.266	–	X	MacKay 2003 (*RFS* 16:1131–65)
Campaign contributions	0.233	+		Claessens et al. 2008 (*JFE* 88:554–80)
Industry q with low legal protection	0.217	+		Foley and Greenwood 2010 (*RFS* 23:1231–60)
Import penetration	0.214	–		Xu 2012 (*JFE* 106:427–46)
Indirect sovereign risk	0.181	+		Acharya et al. 2018 (*RFS* 31:2855–96)
Profitability in refinancing firms	0.176	+		Danis et al. 2014 (*JFE* 114:424–43)
Real estate value	0.172	+		Cvijanovic 2014 (*RFS* 27:2690–735)
Control/ownership wedge	0.132	+		Lin et al. 2013 (*JFE* 109:517–34)
Frequency of price adjustment	0.129	+		D'Acunto et al. 2018 (*JFE* 129:46–68)
Union coverage	0.123	+		Matsa 2010 (*JF* 65:1197–232)
Brand perception	0.122	+		Larkin 2013 (*JFE* 110:232–53)
Maximum unemployment benefit	0.112	+		Agrawal and Matsa 2013 (*JFE* 108:449–70)
Leverage in CEO home purchase	0.112	+		Cronqvist et al. 2012 (*JFE* 103:20–40)
Long-term debt dependence during MEP	0.110	+		Foley-Fisher et al. 2016 (*JFE* 122:409–29)
Country tax rate	0.110	+		Desai et al. 2004 (*JF* 59:2451–87)
Redeployability of assets	0.101	+		Kim and Kung 2017 (*RFS* 30:245–80)
Run-up time of plants	0.091	–		Reinartz and Schmid 2016 (*RFS* 29:1501–48)
Housing price index	0.080	–	X	Chakraborty et al. 2018 (*RFS* 31:2806–53)
Political risk exposure	0.058	–		Desai et al. 2008 (*JFE* 88:534–53)
Marginal tax rate	0.058	+		Molina 2005 (*JF* 60:1427–59)
Supplier industries R&D	0.055	–		Kale and Shahrur 2007 (*JFE* 83:321–65)
Firm-level bank exposure	0.048	–		Cingano et al. 2016 (*RFS* 29:2737–73)
Credit from banks that ended relationship (%)	0.044	–		Patti and Gobbi 2007 (*JF* 62:669–95)
Marginal tax rate	0.043	+		Chemmanur et al. 2013 (*JFE* 110:478–502)
Firm effective tax rate	0.042	+		Faulkender and Smith 2016 (*JFE* 122:1–20)
Bond rate	0.038	–		Cookson 2017 (*JFE* 123:292–312)
Proximity to industry capital/labor ratio	0.036	–		MacKay and Phillips 2005 (*RFS* 18:1433–66)
Vega of CEO wealth	0.034	+		Coles et al. 2006 (*JFE* 79:431–68)
Sales to customers with CDS (%)	0.030	–		Li and Tang 2016 (*JFE* 120:491–513)
Corruption convictions near headquarters	0.027	+		Smith 2016 (*JFE* 121:350–67)
Tobin's q during expansions	0.027	+		McLean and Zhao 2014 (*JF* 69:1377–409)
Mandatory pension contributions	0.023	+	X	Rauh 2006 (*JF* 61:33–71)
Antitakeover index	0.021	+	X	Wald and Long 2007 (*JFE* 83:297–319)
Tax incentive to shift debt	0.019	+		Huizinga et al. 2008 (*JFE* 88:80–118)
Local debt issuance in other industries	0.016	+		Dougal et al. 2015 (*JF* 70:163–210)
Threat of entry	0.014	+	X	Parise 2018 (*JFE* 127:226–47)
Earnings repatriated from foreign affiliates	0.013	–	X	Dharmapala et al. 2011 (*JF* 66:753–87)
Heterogeneity of input goods	0.013	+		Chu 2012 (*JFE* 106:411–26)
Cash flow	0.012	–	X	Gatchev et al. 2010 (*JF* 65:725–63)
Ownership by dedicated institutional investors (%)	0.001	–	X	Borochin and Yang 2017 (*JFE* 126:171–99)

(continued)

Table A5
Continued

Proposed determinant	Economic significance	Sign	Statistically insignificant	Citation
B: Dummy explanatory variables				
Parity employee representation	0.700	+		Lin et al. 2018 (*JFE* 127:303–24)
High weather exposure	0.512	–		Pérez-González and Yun 2013 (*JF* 68:2143–76)
Net receiver of intragroup loans	0.451	+		Buchuk et al. 2014 (*JFE* 112:190–212)
Antirecharacterization law	0.346	+		Li et al. 2016 (*RFS* 29:1453–500)
High CEO inside debt holdings	0.338	–		Cassell et al. 2012 (*JFE* 103:588–610)
Reduced tax advantage of debt	0.239	+		Schepens 2016 (*JFE* 120:585–600)
CDS trading	0.234	+		Subrahmanyam et al. 2017 (*JFE* 124:395–414)
High tangibility after SARFAESI Act	0.225	–		Vig 2013 (*JF* 68:881–928)
Sin stock	0.208	+		Hong and Kacperczyk 2009 (*JFE* 93:15–36)
CEO longtime option holder	0.200	+		Malmendier et al. 2011 (*JF* 66:1687–733)
Access to shelf registration for small firms	0.188	–		Gustafson and Iliev 2017 (*JFE* 124:580–98)
CEO medium early-life fatality experience	0.183	+		Bernile et al. 2017 (*JF* 72:167–206)
CDS trading	0.143	+		Saretto and Tookes 2013 (*RFS* 26:1190–247)
Option traded on firm's stock	0.122	+		Gao 2010 (*JFE* 97:218–38)
Blockholder	0.114	+	X	Cronqvist and Fahlenbrach 2009 (*RFS* 22:3941–76)
New financial covenant violation	0.104	–		Nini et al. 2012 (*RFS* 25:1713–61)
Covenant violation	0.097	+		Roberts and Sufi 2009 (*JF* 64:1657–95)
Employment protection legislation	0.089	–		Simintzi et al. 2015 (*RFS* 28:561–91)
CEO difficult work experience	0.084	–		Dittmar and Duchin 2016 (*RFS* 29:565–602)
Good faith exception	0.079	–		Serfling 2016 (*JF* 71:2239–86)
Young firms after Riegle-Neal Act	0.062	–		Zarutskie 2006 (*JFE* 81:503–37)
Debt recovery tribunal	0.058	+		Gopalan et al. 2016 (*RFS* 29:2774–813)
High tangibility after collateral reform	0.052	+		Campello and Larrain 2016 (*RFS* 29:349–83)
Recession	0.052	–		Schoar and Zuo 2017 (*RFS* 30:1425–56)
Financial expert CEO	0.049	+		Custódio and Metzger 2014 (*JFE* 114:125–54)
Inevitable disclosure doctrine	0.037	+		Klasa et al. 2018 (*JFE* 128:266–86)
Loan rating	0.029	+	X	Sufi 2009 (*RFS* 22:1659–91)
Family control in crisis period	0.024	+	X	Lins et al. 2013 (*RFS* 26:2583–619)
Delaware firms after 1991	0.023	+		Becker and Strömberg 2012 (*RFS* 25:1931–69)
IPO in hot market	0.021	–	X	Alti 2006 (*JF* 61:1681–710)
Brokerage house merger/closure	0.011	+	X	Billett et al. 2017 (*JFE* 123:357–76)
Split-share structure reform	0.005	+	X	Chen et al. 2012 (*RFS* 25:3610–44)

The table reports the economic significance of proposed determinants of leverage from papers published in three top finance journals between 2000 and 2018. Economic significance is based on the regression coefficients and summary statistics reported in the cited paper. Panel A reports the economic significance of continuous explanatory variables and the measure of significance is the standardized beta coefficient. Panel B reports the economic significance of dummy explanatory variables and the measure of significance is the change in leverage, as a percentage of its standard deviation, associated with a zero-to-one change in the explanatory variable. The sign of the coefficient for the proposed determinant is also reported. Proposed determinants marked with an "X" are not statistically significant in the cited paper. Papers studying only financial firms are excluded from the table. Economic significance of interaction terms are reported as incremental effects.

Table A6
Economic significance of proposed determinants of investment

Proposed determinant	Economic significance	Sign	Statistically insignificant	Citation
A: Continuous explanatory variables				
Total *q*	0.493	+		Peters and Taylor 2017 (*JFE* 123:251–72)
Local ownership by mutual funds	0.334	–		Gaspar and Massa 2007 (*JFE* 83:751–92)
Indirect sovereign risk	0.291	+		Acharya et al. 2018 (*RFS* 31:2855–96)
Cash flow	0.289	+		Brown et al. 2009 (*JF* 64:151–85)
Cash flow with commercial banker on board	0.268	–		Güner et al. 2008 (*JFE* 88:323–54)
Cash flow	0.174	+		Gatchev et al. 2010 (*JF* 65:725–63)
Tobin's q with enforcement of insider trading laws	0.164	+		Edmans et al. 2017 (*JFE* 126:74–96)
Tobin's q	0.163	+		Campello and Graham 2013 (*JFE* 107:89–110)
M/B of peers	0.139	+		Foucault and Fresard 2014 (*JFE* 111:554–77)
Housing price index	0.137	–		Chakraborty et al. 2018 (*RFS* 31:2806–53)
Transitory cash flow	0.128	+		Chang et al. 2014 (*RFS* 27:3628–57)
State ownership	0.126	–		Boubakri et al. 2013 (*JFE* 108:641–58)
Tobin's q during expansions	0.117	+		McLean and Zhao 2014 (*JF* 69:1377–409)
Interest rate and currency hedging	0.116	+		Campello et al. 2011 (*JF* 66:1615–47)
Vega of CEO wealth	0.116	+		Coles et al. 2006 (*JFE* 79:431–68)
Industry *q* with low legal protection	0.103	–		Foley and Greenwood 2010 (*RFS* 23:1231–60)
Campaign contributions	0.101	+	X	Claessens et al. 2008 (*JFE* 88:554–80)
Pay gap between CEO and VPs	0.100	+		Kini and Williams 2012 (*JFE* 103:350–76)
CEO tenure	0.097	+		Pan et al. 2016 (*RFS* 29:2955–99)
Inflows from option exercise	0.091	+		Babenko et al. 2011 (*JF* 66:981–1009)
Social connectedness	0.087	+		Duchin and Sosyura 2013 (*JF* 68:387–429)
WACC	0.079	+		Frank and Shen 2016 (*JFE* 119:300–15)
Intraindustry value spread	0.068	+		Bustamante 2015 (*RFS* 28:297–341)
Discretionary accruals	0.067	+		Polk and Sapienza 2009 (*RFS* 22:187–217)
Fraction of shares held by CEO	0.066	+		Kim and Lu 2011 (*JFE* 102:272–92)
Local investment in other industries	0.063	+		Dougal et al. 2015 (*JF* 70:163–210)
Relative bond price	0.062	+		Lin et al. 2018 (*JFE* 130:620–40)
Mandatory pension contributions	0.047	–		Rauh 2006 (*JF* 61:33–71)
Firm-level bank exposure	0.041	–		Cingano et al. 2016 (*RFS* 29:2737–73)
Cash holdings after credit crisis	0.038	+		Duchin et al. 2010 (*JFE* 97:418–35)
Directors appointed after CEO took office (%)	0.031	+		Coles et al. 2014 (*RFS* 27:1751–96)
Tobin's q during crisis	0.023	+		Matvos and Seru 2014 (*RFS* 27:1143–89)
Sensitivity of vesting equity to stock price	0.021	–		Edmans et al. 2017 (*RFS* 30:2229–71)
Foreign institutional ownership	0.017	+		Bena et al. 2017 (*JFE* 126:122–46)
Religiosity in county	0.016	–		Hilary and Hui 2009 (*JFE* 93:455–73)
Foreign institutional ownership	0.016	–		Ferreira and Matos 2008 (*JFE* 88:499–533)
Buyer payable days	0.012	–		Murfin and Njoroge 2015 (*RFS* 28:112–45)
Default probability	0.010	–		Favara et al. 2017 (*JFE* 123:22–41)
Earnings repatriated from foreign affiliates	0.002	+	X	Dharmapala et al. 2011 (*JF* 66:753–87)

(continued)

Table A6
Continued

Proposed determinant	Economic significance	Sign	Statistically insignificant	Citation
B: Dummy explanatory variables				
High threat of entry	0.448	–		Parise 2018 (*JFE* 127:226–47)
Net receiver of intragroup loans	0.354	+		Buchuk et al. 2014 (*JFE* 112:190–212)
Year of vote to remove antitakeover provision	0.266	–	X	Cuñat et al. 2012 (*JF* 67:1943–77)
Ratings upgrade	0.234	+		Tang 2009 (*JFE* 93:325–51)
Below lender cutoff rule	0.200	–		Berg 2018 (*RFS* 31:4912–57)
High CEO inside debt holdings	0.148	–		Cassell et al. 2012 (*JFE* 103:588–610)
Access to shelf registration for small firms	0.137	+		Gustafson and Iliev 2017 (*JFE* 124:580–98)
After Gulf War	0.115	–		Kim and Kung 2017 (*RFS* 30:245–80)
Split-share structure reform	0.113	+		Chen et al. 2012 (*RFS* 25:3610–44)
High maturing debt industry in downturn	0.109	–		Carvalho 2015 (*RFS* 28:2463–501)
Liberalization	0.100	+		Desai et al. 2006 (*RFS* 19:1433–64)
IPO in hot market	0.099	–		Alti 2006 (*JF* 61:1681–710)
Performing risk category in financial crisis	0.092	+		Rodano et al. 2018 (*RFS* 31:2943–82)
New financial covenant violation	0.087	–		Nini et al. 2012 (*RFS* 25:1713–61)
Loan rating	0.084	+	X	Sufi 2009 (*RFS* 22:1659–91)
CEO difficult work experience	0.077	–		Dittmar and Duchin 2016 (*RFS* 29:565–602)
Family control in crisis period	0.071	–		Lins et al. 2013 (*RFS* 26:2583–619)
Delaware firms after 1991	0.068	+		Becker and Strömberg 2012 (*RFS* 25:1931–69)
Syndicated loan refinanced	0.052	+		Mian and Santos 2018 (*JFE* 127:264–84)
CEO ownership positive but <10%	0.051	+		Lilienfeld-Toal and Ruenzi 2014 (JF 69:1013–50)
Recession	0.048	–		Schoar and Zuo 2017 (*RFS* 30:1425–56)
Election year	0.044	–		Julio and Yook 2012 (*JF* 67:45–83)
Third quarter in gubernatorial election year	0.029	–		Jens 2017 (*JFE* 124:563–79)
New airline route from headquarters to plant	0.014	+		Giroud and Mueller 2015 (*JF* 70:1767–804)
Tax increase	0.013	–		Mukherjee et al. 2017 (*JFE* 124:195–221)
Currency depreciation	0.012	+	X	Desai et al. 2008 (*RFS* 21:2857–88)
Blockholder	0.009	+	X	Cronqvist and Fahlenbrach 2009 (*RFS* 22:3941–76)
Hurricane strike in headquarters county	0.006	–	X	Dessaint and Matray 2017 (*JFE* 126:97–121)
High weather exposure	0.003	–	X	Pérez-González and Yun 2013 (*JF* 68:2143–76)

The table reports the economic significance of proposed determinants of investment from papers published in three top finance journals between 2000 and 2018. Economic significance is based on the regression coefficients and summary statistics reported in the cited paper. Panel A reports the economic significance of continuous explanatory variables and the measure of significance is the standardized beta coefficient. Panel B reports the economic significance of dummy explanatory variables and the measure of significance is the change in investment, as a percentage of its standard deviation, associated with a zero-to-one change in the explanatory variable. The sign of the coefficient for the proposed determinant is also reported. Proposed determinants marked with an "X" are not statistically significant in the cited paper. Papers studying only financial firms are excluded from the table. Economic significance of interaction terms are reported as incremental effects.

Table A7
Economic significance of proposed determinants of payouts

Proposed determinant	Economic significance	Sign	Statistically insignificant	Citation
A: Continuous explanatory variables				
Earnings repatriated from foreign affiliates	0.323	+		Dharmapala et al. 2011 (*JF* 66:753–87)
Management options/shares outstanding	0.272	–		Fenn and Liang 2001 (*JFE* 60:45–72)
Local product fluidity	0.147	–		Hoberg et al. 2014 (*JF* 69:293–324)
Ownership by dedicated institutional investors (%)	0.138	–		Borochin and Yang 2017 (*JFE* 126:171–99)
Cash flow	0.116	+		Gatchev et al. 2010 (*JF* 65:725–63)
Sales growth	0.088	–		Michaely and Roberts 2012 (*RFS* 25:711–46)
Shareholder distraction	0.050	+		Kempf et al. 2017 (*RFS* 30:1660–95)
Transitory cash flow	0.046	+		Chang et al. 2014 (*RFS* 27:3628–57)
Investor-management voting agreement	0.038	+		Huang and Thakor 2013 (*RFS* 26:2453–91)
Seniors in headquarters county (%)	0.037	+		Becker et al. 2011 (*JF* 66:655–83)
Mandatory pension contributions	0.036	–		Rauh 2006 (*JF* 61:33–71)
Stock return volatility	0.028	–		Chay and Suh 2009 (*JFE* 93:88–107)
Inflows from option exercise	0.020	–	X	Babenko et al. 2011 (*JF* 66:981–1009)
CEO overconfidence after SOX	0.014	+		Banerjee et al. 2015 (*RFS* 28:2812–58)
Dividend-averse institutional shareholders	0.008	–		Desai and Jin 2011 (*JFE* 100:68–84)
Anti-self-dealing index during crisis	0.003	–	X	Levine et al. 2016 (*JFE* 120:81–101)
Housing price index	0.001	–		Chakraborty et al. 2018 (*RFS* 31:2806–53)
Distance of firm to controlling family	0.000	–	X	Almeida et al. 2011 (*JFE* 99:447–75)
B: Dummy explanatory variables				
Civil law country	0.988	–		La Porta et al. 2000 (*JF* 55:1–33)
Business combination law	0.600	+		Gormley and Matsa 2016 (*JFE* 122:431–55)
High weather exposure	0.400	–		Pérez-González and Yun 2013 (*JF* 68:2143–76)
Investor protection laws	0.200	+		Agrawal 2013 (*JFE* 107:417–35)
Capital controls	0.195	+		Desai et al. 2006 (*RFS* 19:1433–64)
Net receiver of intragroup loans	0.190	+		Buchuk et al. 2014 (*JFE* 112:190–212)
IPO in hot market	0.183	+		Alti 2006 (*JF* 61:1681–710)
Dual holder of debt and equity	0.156	–		Chu 2018 (*RFS* 31:3098–121)
Split-share structure reform	0.083	+	X	Chen et al. 2012 (*RFS* 25:3610–44)
Negative EPS surprise	0.072	+		Almeida et al. 2016 (*JFE* 119:168–85)
Large tariff reduction	0.039	–		Xu 2012 (*JFE* 106:427–46)
Hurricane strike in headquarters county	0.026	–		Dessaint and Matray 2017 (*JFE* 126:97–121)
Financial expert CEO	0.014	+		Custódio and Metzger 2014 (*JFE* 114:125–54)
Delaware firms after 1991	0.010	–	X	Becker and Strömberg 2012 (*RFS* 25:1931–69)
Sin stock	0.004	–	X	Hong and Kacperczyk 2009 (*JFE* 93:15–36)

The table reports the economic significance of proposed determinants of payouts from papers published in three top finance journals between 2000 and 2018. Economic significance is based on the regression coefficients and summary statistics reported in the cited paper. Panel A reports the economic significance of continuous explanatory variables and the measure of significance is the standardized beta coefficient. Panel B reports the economic significance of dummy explanatory variables and the measure of significance is the change in payouts, as a percentage of its standard deviation, associated with a zero-to-one change in the explanatory variable. The sign of the coefficient for the proposed determinant is also reported. Proposed determinants marked with an "X" are not statistically significant in the cited paper. Papers studying only financial firms are excluded from the table. Economic significance of interaction terms are reported as incremental effects.

Table A8
Economic significance of proposed determinants of cash holdings

Proposed determinant	Economic significance	Sign	Statistically insignificant	Citation
A: Continuous explanatory variables				
Proceeds from share issuance	0.563	+		McLean 2011 (*JFE* 99:693–715)
Technology spillovers	0.456	+		Qiu and Wan 2015 (*JFE* 115:558–73)
Transitory cash flow	0.279	+		Chang et al. 2014 (*RFS* 27:3628–57)
Labor skill index	0.185	+		Ghaly et al. 2017 (*RFS* 30:3636–68)
Local product fluidity	0.127	+		Hoberg et al. 2014 (*JF* 69:293–324)
Brand perception	0.110	–		Larkin 2013 (*JFE* 110:232–53)
Cash flow	0.045	+		Gatchev et al. 2010 (*JF* 65:725–63)
Tax cost of repatriating earnings	0.031	+		Foley et al. 2007 (*JFE* 86:579–607)
Tobin's q correlation	0.029	+		Duchin 2010 (*JF* 65:955–92)
Corruption convictions near headquarters	0.026	–		Smith 2016 (*JFE* 121:350–67)
CEO vega	0.020	+		Liu and Mauer 2011 (*JFE* 102:183–98)
B: Dummy explanatory variables				
Ratings upgrade	0.277	–		Tang 2009 (*JFE* 93:325–51)
Financial expert CEO	0.248	–		Custódio and Metzger 2014 (*JFE* 114:125–54)
CDS trading	0.228	+		Subrahmanyam et al. 2017 (*JFE* 124:395–414)
Below lender cutoff rule	0.179	+		Berg 2018 (*RFS* 31:4912–57)
High movable assets after collateral reform	0.136	–		Campello and Larrain 2016 (*RFS* 29:349–83)
Split-share structure reform	0.115	–		Chen et al. 2012 (*RFS* 25:3610–44)
High tangibility after SARFAESI Act	0.113	+		Vig 2013 (*JF* 68:881–928)
IPO in hot market	0.105	+		Alti 2006 (*JF* 61:1681–710)
Addition of stock to MSCI ACWI	0.086	–		Bena et al. 2017 (*JFE* 126:122–46)
CEO medium early-life fatality experience	0.086	–		Bernile et al. 2017 (*JF* 72:167–206)
CEO difficult work experience	0.075	+		Dittmar and Duchin 2016 (*RFS* 29:565–602)
Sin stock	0.067	–	X	Hong and Kacperczyk 2009 (*JFE* 93:15–36)
Increased rollover risk	0.052	+	X	Choi et al. 2018 (*JFE* 130:484–502)
Hurricane strike in headquarters county	0.038	+		Dessaint and Matray 2017 (*JFE* 126:97–121)
Brokerage house merger/closure	0.019	–	X	Billett et al. 2017 (*JFE* 123:357–76)
Family control in crisis period	0.018	+	X	Lins et al. 2013 (*RFS* 26:2583–619)

The table reports the economic significance of proposed determinants of cash holdings from papers published in three top finance journals between 2000 and 2018. Economic significance is based on the regression coefficients and summary statistics reported in the cited paper. Panel A reports the economic significance of continuous explanatory variables and the measure of significance is the standardized beta coefficient. Panel B reports the economic significance of dummy explanatory variables and the measure of significance is the change in cash holdings, as a percentage of its standard deviation, associated with a zero-to-one change in the explanatory variable. The sign of the coefficient for the proposed determinant is also reported. Proposed determinants marked with an "X" are not statistically significant in the cited paper. Papers studying only financial firms are excluded from the table. Economic significance of interaction terms are reported as incremental effects.