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Industry Window Dressing

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Industry Window Dressing*

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ABSTRACT

We explore a new mechanism through which investors take correlated shortcuts. Specifically, we exploit a regulatory provision governing firm classification into industries: A firm's industry classification is determined by the segment that has the majority of sales. We find strong evidence that investors overly rely on this primary industry classification. Firms just above the industry classification cutoff have significantly higher betas with respect to, as well as more sector mutual fund holdings and analyst coverage from, that industry, compared to nearly identical firms just below the cutoff. We then show that managers undertake specific actions to exploit investor shortcuts. Firms around the discontinuity point of 50% sales are significantly more likely to have just over 50% of sales from a "favorable" industry. Further, these firms just over the cutoff have significantly lower profit margins and inventory growth compared to other firms in the same industries, consistent with these firms slashing prices to increase sales. These same firms, however, do not exhibit different behaviors in any other aspect of their business (e.g., CapEx or R&D), suggesting that it is not a firm-wide shift of focus. Last, firms garner tangible benefits from switching into favorable industries, such as engaging in significantly more SEOs and stock-financed M&As.

JEL Classification: G02, G10, G32.

Key words: Investor shortcuts, industry classification, opportunistic managerial behavior, discontinuity.

1. Introduction

Investors are continuously faced with a large number of potential signals that are available to collect and process. Faced with these, investors need to solve the complex time allocation problem with respect to selecting and processing each potential signal. If investors specialized in collecting disjoint signals, the processing constraints of each disparate investor would not matter for aggregate prices, as prices would reflect the sum of their investment capacity. If, however, investors take correlated shortcuts in their investment decisions, then simple pieces of information can remain systematically unreflected in firm prices. Moreover, if firm managers are aware of these shortcuts and their implications, managers may take specific actions to exploit these investment shortcuts.

In this paper, we identify one such shortcut that financial agents take and document how it affects both prices and managerial behavior. Specifically, we examine the primary industry into which each firm is classified. The Securities and Exchange Commission (SEC), in classifying firm operations, designates that each firm have a primary industry, which is determined by the segment with the highest percentage of sales.[1] Using this rule, we exploit situations in which firms tightly surround the discontinuity point of industry classification. For example, a two-segment firm that gets 51% of its sales from technology and 49% of sales from lumber is classified as a technology firm, whereas a firm with nearly identical operations but that gets 49% of its sales from technology and 51% of sales from lumber is classified as a lumber firm.

If investors overly rely on this primary industry classification in their investment decisions without fully factoring in firms' underlying economic operations, they may perceive or treat nearly identical firms around the discontinuity point in different ways. We examine this idea of naive categorization by examining both stock return patterns and (more directly) investor behavior. First, we explore how investors price these two-segment firms at the cutoff. We find that despite being nearly identical, firms just over the 50% point (in terms of percentage sales from a particular industry) have

[1] Many large and diversified firms fall into multiple SIC categories; hence, the category that accounts for the largest share of sales is known as the company's "primary" industry (Guenther and Rosman, 1994; and Kahle and Walkling, 1996).

significantly higher betas with respect to that industry than firms just below the 50% point. So, in the example above, the 51% technology firm's price moves much more closely with the technology industry than does the 49% technology firm's price. The difference in industry beta is large both economically and statistically: firms just over the 50% cutoff, on average, have a 60% larger beta (t = 4.19) with respect to the industry in question than those just under the threshold. Importantly, there are no other jumps in industry beta anywhere else in the distribution of firm operations.

Second, corroborating the evidence on industry beta, we find that mutual fund managers exhibit differential investing behavior around the industry classification cutoff. In particular, we focus on mutual funds with a significant sector tilt. For firms that are nearly identical in their exposures to a particular industry, with the only difference being just above versus below the discontinuity, mutual funds that specialize in that industry are significantly more likely to hold firms just above the cutoff than firms just below it. Specifically, the fraction of sector mutual funds investing in a firm is 40% larger (t = 2.55) if the firm is just above the 50% point (in terms of sales from that industry), relative to firms just below the cutoff. Like the beta test, this is the only jump in sector mutual fund holdings throughout the distribution of firm operations.

We see the same behavior from sell-side analysts. For each firm, we measure the percentage of sell-side analysts covering the firm from each sector. We find a significant jump in sell-side analyst coverage at the industry classification cutoff. In particular, firms just above the cutoff have significantly more coverage from the classification industry than nearly identical firms just below the cutoff; the former have a nearly 50% (t = 2.27) higher fraction of analysts from the classification industry covering them compared to the latter. Again, we see no similar jumps in coverage percentage anywhere else in the distribution. It is important to note that while our results on industry beta, and analyst and mutual fund manager behavior, are consistent with financial agents taking correlated shortcuts, they could also be driven by institutional constraints imposed on analysts and investors.

We next explore how managers may take advantage of these investor shortcuts. To do this, we identify situations in which it would be advantageous to be considered

part of a given industry (relative to other industries). For this purpose, we use periods in which certain industries have higher valuation (that is, lower cost of capital) than others – which we term "favorable" industries. We measure industry valuation in several ways: a proxy for investor preferences and beliefs based on capital flows into mutual funds investing in given industries, and an industry M/B measure; both measures produce identical results. Importantly, this higher industry valuation need not be misvaluation; for instance, it could also represent increased investment opportunities.[2] We show that firms in these higher-valuation industries indeed enjoy tangible benefits: (a) they have large announcement day returns when being classified into these highly valued industries; (b) engage in significantly more equity issuance at the higher valuation; and (c) engage in more stock-financed M&A activities.

To capture managerial behavior to "window dress" their industry classification, we again exploit the discontinuity point—i.e., the 50% cutoff—in industry classification. In particular, we focus on all conglomerate firms whose top two segments are in one favorable and one non-favorable industry and examine the relative sales weight between the top two segments (thus, the 50% point is the relevant discontinuity cutoff for industry classification). This discontinuity identification allows us to pin down opportunistic firm behavior by examining how two firms operating in the exact *same* industries behave differentially if they are near versus far from the industry classification cutoff. Additionally, our identification strategy allows us to examine the behavior of two firms both near the discontinuity point, but one with a choice of favorable versus non-favorable industry classification, and the other without (i.e., whose top two segments are in both favorable (or in both non-favorable) industries).

We find strong evidence consistent with industry window dressing behavior among conglomerate firms. In particular, firms near the industry assignment discontinuity are considerably more likely to be just over the cutoff point to be classified into the favorable industry; there is a 29% (t = 2.59) discrete jump right at the 50%

[2] In fact, the only friction needed throughout the paper is that investors use the shortcut of categorizing firms based on the primary industry instead of underlying economic operations. In the presence of this, regardless of the reason of the higher valuation, managers will have an incentive to be classified into these higher-valued industries.

cutoff in the distribution of firm operations based on percentage sales from the favorable industry. We find no similar jumps anywhere else in the distribution, consistent with managers taking specific actions to be classified into favorable industries.[3] Note that an alternative story in which firms generally shift focus toward the favorable segment would generate a very different pattern. In this case, we should see a parallel shift in sales to the favorable segment amongst all firms, so no discontinuous jump anywhere in the distribution.

As further evidence of these firms taking actions to increase segment sales that allow them to be classified into favorable industries, we find that firms just above the 50% sales cutoff in the favorable industry have significantly lower segment profit margins and inventory growth rates relative to other firms in the same industries. This is consistent with these firms slashing prices to achieve sales targets in the favorable industry. Again, we do not observe any changes in segment profit margins and inventory growth rates anywhere else in the distribution. Further, these exact same firms do not exhibit different behavior in any other aspect of their business (for instance, capital expenditures and R&D expenditures), suggesting that it is not a firm-wide shift of focus toward the favorable industry.

Another way that firms work to gain classification into the favorable sector is by manipulating accounting statements (without any real changes in sales). If firms indeed manipulate reported sales figures, this manipulation will eventually need to be corrected in a future restatement that more accurately reflects firm operations. We find evidence consistent with this prediction in future restatements.

The paper proceeds as follows. Section 2 lays out the background for the setting we examine in the paper. Section 3 presents our data collection procedures and summary statistics. Section 4 provides our results on the impact of investor shortcuts on investor behavior and asset prices. Section 5 presents results on industry window dressing by firm managers, and the benefits of doing so. Section 6 concludes.

[3] We discuss in Section 5.6 the potential impact of managerial opportunistic behavior around the discontinuity point on the regression discontinuity approach that we take in the industry beta, as well as analyst and mutual fund behavior, tests.

2. Background

Our findings are closely tied to recent studies on managerial opportunistic behavior to influence market perceptions and short-term stock prices. Stein (1996) argues that in an inefficient financial market, managers with a short horizon may exploit investors' imperfect rationality by catering to time-varying investor preferences and beliefs; relatedly, managers may also exploit various constraints and frictions faced by investors. Subsequently, many empirical studies confirm these predictions: important firm decisions including dividend policy, issuance, stock splits, firm name, and disclosure policy are motivated at least in part by short-term share price considerations.[4] There is a related strand of literature in management that shows that firm classification impacts how market participants view these firms (Zuckerman (2000, 2004)). This paper contributes to this fast-growing literature by providing evidence that managers also take actions to influence firms' industry classification, and in turn firm valuation.

This paper also contributes to the literature on style investment, categorization, and co-movement. Barberis and Shleifer (2003) argue that investors tend to group assets into a small number of categories in order to simplify their investment decisions. This causes the capital flows into assets within the same category to be correlated and induces excess correlation in asset price movements (relative to actual underlying cash flow correlations). Vijh (1994) and Barberis, Shleifer, and Wurgler (2005) provide one such example using S&P 500 Index additions and deletions. In particular, they show that stocks that are added to (deleted from) the index experience an increase (decrease) in correlation with other constituent firms subsequently. Other examples in the empirical literature include Froot and Dabora (1999), Cooper, Gulen, and Rau (2005), and Kruger, Landier, and Thesmar (2012), who find that mutual fund styles, industries, and countries all appear to be categories that have a substantial impact on investor behavior (and asset price movements). Mullainathan (2002) provides a more general framework for categorization in decision making.

[4] See, for example, Aboody and Kasznik (2000); Cooper, Dimitrov, and Rau (2001); Baker, Stein, and Wurgler (2003); Baker and Wurgler (2004a,b); Gilchrist, Himmelberg, and Huberman (2005); Baker, Greenwood, and Wurgler (2009; Polk and Sapienza (2008); Greenwood (2009); and Lou (2011). Baker, Ruback, and Wurgler (2007) provide an excellent review of this topic.

Our study is also related to the extensive literature on investors' limited attention to information. For example, Huberman and Regev (2001), DellaVigna and Pollet (2006), Menzly and Ozbas (2006), Hong, Torous, and Valkanov (2007), Hou (2007), Barber and Odean (2008), Cohen and Frazzini (2008), Cohen, Diether, and Malloy (2012), and Cohen and Lou (2012) find that investors respond quickly to information that attracts their attention (for example, news printed in the *New York Times*, stocks that have had extreme returns or trading volume in the recent past, and stocks that more people follow) but tend to ignore information that is less salient yet material to firm values. Furthermore, investors' limited attention can result in significant asset return predictability in financial markets.

3. Data

Our main dataset is the financial data for each industry segment within a firm. Starting in 1976, all firms are required by Statement of Financial Accounting Standard (SFAS) No. 14 (Financial reporting for segments of a business enterprise, 1976) and No. 131 (Reporting desegregated information about a business enterprise, 1998) to report relevant financial information of any industry segment that comprises more than 10% of total annual sales. Among other things, we extract from the Compustat segment files conglomerate firms' assets, sales, earnings, and operating profits in each segment.

Industries are defined using two-digit Standard Industrial Classification (SIC) codes. Our results are also robust to using alternative definitions of industries (e.g. based on the North American Industry Classification System (NAICS)). Conglomerate firms in our sample are defined as those operating in more than one industries. We require that the top two segments of a conglomerate firm account for more than 75% and less than 110% of the firm's total sales. The relative sales of the two top segments are then used to sort these conglomerate firms into different bins in our analyses. The lower cutoff of 75% ensures that the top two segments comprise the majority of the

operations of the firm,[5] whereas the upper cutoff of 110% weeds out apparent data errors. At the end of the paper, we also report results based on two-segment conglomerate firms alone.

The segment data are then merged with Compustat annual files to obtain firm-level financial and accounting information, such as book equity, total firm sales, inventory growth, etc. We then augment the data with stock return and price information from Center for Research in Security Prices (CRSP) monthly stock files. We require that firms have non-missing market and book equity data at the end of the previous fiscal year end. Moreover, to mitigate the impact of micro-cap stocks on our test results, we exclude firms that are priced below five dollars a share and whose market capitalizations are below the tenth percentile of NYSE stocks in our calculation of industry average variables, such as industry returns, and industry average fund flows.

Our main measure of industry favorability among investors is motivated by recent studies on mutual fund flows. Coval and Stafford (2007) and Lou (2012) find that mutual fund flows to individual stocks are positively associated with contemporaneous stock returns and negatively forecast future returns. We follow Lou (2012) to compute a $FLOW$ measure for each individual stock, assuming that fund managers proportionally scale up or down their existing holdings in response to capital flows. We then aggregate such $FLOW$ to the industry level by taking the equal-weighted average across all stocks in a two-digit SIC code industry, excluding all micro-cap stocks. We define an industry as favorable if it is one of the top twenty industries (i.e., the top 30% out of around 70 industries) as ranked by mutual fund flows in the previous year, and as non-favorable otherwise.[6] We use equal-weighted industry $FLOW$ in our main analyses because capital flows to smaller stocks in an industry may better reflect investors' beliefs and preferences. In robustness checks, we also use value-weighted industry $FLOW$, which has a correlation over 0.9 with the equal-weighted version, and all our results go through.

[5] This also ensures that the larger of the two segments will determine the primary industry of the firm. For robustness, we have experimented with this percentage from 2/3 (the lower bound to ensure that this is true) through 85%, and the results are unchanged in magnitude and significance.

[6] Again, we experimented with defining favorable industries as the top 20%, 25%, 30%, 35%, and 40%, and the results are very similar in magnitude and significance.

Mutual fund flow data are obtained from the CRSP survivorship-bias-free mutual fund database. In calculating capital flows, we assume that all flows occur at the end of each quarter. Quarterly fund holdings are extracted from CDA/Spectrum 13F files, which are compiled from both mandatory SEC filings and voluntary disclosures. Following prior literature, we assume that mutual funds do not trade between the report date and the quarter end. The two datasets are then merged using MFLINKS provided by Wharton Research Data Services (WRDS). Because the reporting of segment financial information is first enforced in 1976 and the mutual fund holdings data start in 1980, our sample of conglomerate firms covers the period 1980 to 2010.

In further analyses, we obtain information on merger and acquisition (M&A) transactions from Thomson Reuter's Security Data Corporation (SDC) database in order to examine whether firms in more favorable industries engage in more M&A transactions. We also analyze firms' equity issuance decisions in response to industry favorability. To construct a comprehensive issuance measure (which captures both public and private issuance), we follow Greenwood and Hanson (2012) to define net issuance as the change in book equity over two consecutive years divided by lagged assets. We then label a firm as an issuer if its net issuance in the year is greater than 10%, and as a repurchaser if its net issuance in the year is below -0.5%. Finally, we extract, from Institutional Brokers' Estimate System (IBES), information on analyst coverage for each conglomerate firm. In particular, we classify analysts into different industries based on the stocks they cover in the past five years, and then calculate analyst coverage for a conglomerate firm from each industry segment in which the firm operates.

The data selection and screening procedures described above yield a sample of 45,904 firm-year observations. We then categorize these firm-year observations into smaller bins based on the relative sales of the top two segments. Summary statistics for our sample are shown in Table I. Specifically, the first bin includes all conglomerate firms whose smaller segment out of the top two contributes less than 10% of the combined sales of these two segments, and the second bin includes all conglomerate firms whose smaller segment out of the top two contributes between 10% and 20% of the combined sales, and similarly for other bins. There are, on average, between 396 and

566 firms per annum in each of these sales-based bins. The distribution also has a clear U-shaped pattern: there are significantly more firms whose top two segments are of vastly different sizes. In addition, 138 firms on average change their SIC industry classifications—that is, cross the 50% cutoff point—in each year. The summary statistics of other variables are in line with prior literature. For example, the average industry $FLOW$ over a year is a positive 8.1%, consistent with the rapid growth of the mutual fund industry in our sample period.

4. Investor Shortcuts

The main thesis of the paper is that investors take correlated shortcuts that cause simple pieces of information to be systematically unreflected in firm prices. We then test whether managers are aware of, and then act to take advantage of, these shortcuts. In this section we focus on one particular shortcut that market participants take—a firm's primary industry classification versus its actual underlying operations—and document how it affects both market participants' behavior and asset prices.

4.1. Shortcuts and Betas

We start by examining whether investors' overreliance on industry classification aggregates to affect the return correlation between a conglomerate firm and the industries it operates in, and how this correlation changes as we vary the fraction of sales from these industry segments. More specifically, at the end of each quarter, we sort all two-segment firms into twenty 5% bins based on the percentage sales from either segment; that is, each firm in our sample appears in two of these 5% bins, one on either side of the 50% point. For example, a firm that receives 49% of its sales from industry A and 51% of its sales from industry B appears in both the 45%–50% bin (when ranked based on industry A) and the 50%–55% bin (when ranked based on industry B). We focus on two-segment firms in this analysis because the presence of a third segment adds

noise to our estimation of industry betas.[7] We then compute the industry beta with regard to either segment for each conglomerate firm in our sample by regressing weekly stock returns on the weekly returns of the two-digit SIC-code industry in which the conglomerate firm operates, using data from months 6 to 18 after the fiscal year end. We skip 6 months in our analysis because some firms delay reporting their accounting statements by as much as 6 months. We also exclude the stock in question from calculating the corresponding industry returns to avoid any mechanical correlation. Finally, we control for known common risk factors, such as market, size, value, and momentum factors, in our regression specification.

If investors face no constraints in assessing the details of firm operations in different segments, we expect to see a gradual, smooth increase in industry beta as we move from bins of lower fractional sales to bins of higher fractional sales. The results, as shown in Table II, indicate otherwise. While the industry beta generally increases as we move from the bottom bin to the top bin, there is a clear, discrete jump at the 50% point. The average industry beta for firms in the 50%–55% bin, after controlling for known risk factors, is 0.286, whereas that in the 45%–50% bin is 0.178. The difference of 0.107, representing a 61% increase, is highly statistically significant (t = 4.91). The difference in industry beta between any other two adjacent bins is much smaller in magnitude and statistically insignificant from zero. The discrete jump can be seen more easily in a diagram. As shown in the top left panel of Figure 1, while there is a mildly increasing trend in industry beta in both the below-50% and above-50% regions, there is a clear jump in industry beta right at the 50% point.

4.1. Sector Mutual Funds

To provide more direct evidence of industry categorization by some sophisticated investors, we examine mutual fund managers' holdings. We first identify a subset of mutual funds that concentrate on a specific industry sector. As very few mutual funds

[7] For instance, consider a firm that receives 34%, 34% and 32% from industries A, B, and C, respectively, and another firm that receives 45%, 45%, and 10% from the same three industries. While both firms receive equal fractions of the total sales from the top two segments, the industry loadings of the two firms' returns on industries A and B can be very different.

list their sector concentration in their fund names, we infer such concentration from actual fund holdings. If a fund invests the majority of its portfolio in a single industry (i.e., >50%), either by choice or due to institutional constraints, we classify the mutual fund as concentrating on that given sector.[8] We exclude the firm in question from this exercise to avoid any mechanical relation. For every two-segment conglomerate firm, we then count the number of sector mutual funds that hold the firm in months 6 to 18 after the fiscal year end. We further require that the two segments be in two distinct one-digit SIC code industries, since sector mutual funds may also hold stocks from related sectors. We then compute the proportion of sector funds holding the stock from each industry in which the conglomerate firm operates. For instance, if a conglomerate firm operates in industries A and B, we calculate the percentage of industry A sector mutual funds and the percentage of industry B sector mutual funds that hold the firm.

Table III reports the distribution of sector mutual fund holdings. Panel A shows the proportion of sector mutual funds that hold the stock as we vary the fractional sales from that sector. As expected, the proportion of sector mutual funds holding the conglomerate firm increases in the percentage sales from that sector. As with industry beta, though, instead of observing a steady increase in sector fund ownership as percentage sales increase, we see a discontinuous, significant jump at the 50% classification cutoff. The increase in the proportion from the 45%–50% bin to the 50%–55% bin of 9.8% ($t = 2.55$) represents a more than 40% jump in the percentage of sector mutual funds that hold the stock (23.1% to 32.8%). This pattern can also be seen in the bottom left panel of Figure 1, where we plot the proportion of sector funds owning the conglomerate firm against the percentage sales from that sector: there is a discrete jump in sector fund ownership at the 50% cutoff point. Consistent with the results on industry beta, these results suggest that in their investments, mutual fund managers also rely on conglomerate firms' primary industry classification rather than actual firm operations.

[8] Given that nearly all mutual funds have concentration limits on individual positions of 5% or less, 50% does require the mutual fund to take, for instance, 10 maximally concentrated positions in the same industry, which is suggestive that the fund is concentrating investment efforts there.

4.2. Analyst Coverage

We also examine another set of financial agents that plays an important role in gathering, processing, and conveying information in financial markets: sell-side analysts. Prior research shows that investors closely follow analysts' guidance when making investment decisions. Given that individual analysts usually specialize in and follow stocks in one or two industries (e.g., Boni and Womack, 2006), it is conceivable that analyst coverage is strongly influenced by a firm's primary industry classification, which then affects how investors view the firm, and partially drives the industry beta result we document in Table II.

As in our tests on sector mutual funds, at the end of each quarter, we sort all two-segment firms with at least some analyst coverage into twenty 5% bins based on percentage sales from either segment. We then assign each sell-side analyst (covering five or more firms) to an industry if that industry accounts for more than half of the analyst's covered firms. We use coverage data provided by IBES in the previous three years for each analyst (our results are robust if we use coverage information in the previous one to five years). We exclude the stock in question in the procedure of analyst industry assignments to ensure that our results are not mechanically driven. We then compute the proportion of analyst coverage from each industry that the conglomerate firm operates in using coverage data in months 6 to 18 after the fiscal year end. So, for example, for a firm that operates in industries A and B and is covered by five analysts from industry A, four from industry B, and one from another industry, we label the firm as having 50% of its coverage from its operations in industry A and 40% of its coverage from its operations in industry B.

If firms' primary industry classifications indeed determine analyst coverage, we expect a jump in the fraction of analysts covering the firm when the segment in question crosses the 50% cutoff point. The results, shown in Table III, Panel B, confirm this prediction. While the fraction of analysts covering a firm from a particular industry generally increases as the industry accounts for a larger fraction of the firm's sales, there is a clear jump at the 50% cutoff point: for firms that derive 45%–50% of their total sales from the industry in question, 32.7% of the analysts covering these firms are from

that industry; in contrast, for firms that derive 50–55% of their sales from the industry in question, 52.0% of the analyst coverage is from that industry.[9] The difference in analyst coverage of 19.3%, representing an almost 60% increase from the lower bin, is economically and statistically significant (t = 2.27). On the other hand, the difference between any other two adjacent bins is much smaller in magnitude and statistically insignificant from zero. This pattern can be also seen from the bottom right panel of Figure 1, where we plot the proportion of analysts covering the firm from a particular industry against the segment percentage sales. There is a discrete jump in analyst coverage right at the 50% cutoff point.

In sum, the results presented in this section provide evidence that investors and other market participants take correlated shortcuts, relying on firms' primary industry classification, in some cases more so than actual firm operations. This may arise from investors' limited attention or processing capacity to sift through all segment-related information, thus forcing them to rely on simple statistics. Alternatively, this may arise from investors' reliance on analysts' guidance (who in turn use industry classifications to determine the stocks they follow), or from institutional constraints on portfolio holdings.

5. Industry Window Dressing

5.1. "Favorable" Industries

We next explore how managers may take advantage of the implications of investor behavior that we document in Section 4. In particular, we examine what actions managers can take to "fool" investors into thinking that they are part of a given industry. For this purpose, we identify situations where certain industries in certain periods are more "favorable" – have higher valuation (that is, lower cost of capital) – than others. Thus, it would be advantageous to be considered part of these "favorable" industries in precisely these periods.

[9] The sum of the two fractions is less than one because firms are also covered by analysts from outside the two segments.

We begin by choosing a measure to capture these times of higher valuation. These could be times when an industry, for instance, experiences positive shocks to its growth opportunities; alternatively, these could also be periods of higher valuation (lower expected returns) driven by shifts in investor preferences. We are agnostic regarding the source of the higher valuation, as irrespective of the source, firms benefit from being classified into these high valuation industries (of which we provide evidence below).

Specifically, we construct our industry-valuation measure drawing on the behavior of retail investors' allocating capital to mutual funds and the relation of these flows with firm (and industry) valuation. Lou (2012) shows that capital flows into mutual funds predict the price movements of stocks held by these mutual funds. We use a similar measure, but now aggregating these individual stock flows to the industry level. Table IV, Panel A shows that industry flows are significantly related to industry valuation: in the year that retail investors move capital into an industry through their mutual fund purchase/sales decisions, industry values rise significantly, by more than 100 basis points per month ($t = 4.45$) in a calendar-time portfolio analysis. In the following two years, this 12% return differential completely reverses.[10] We label these high valuation industries (top 20 as ranked by industry $FLOW$) "favorable" industries.[11]

Using this favorable industry measure, we first show that firms in these industries are afforded a number of benefits. In Table IV, Panel B, we show that these firms engage in significantly more equity issuance at the higher industry valuation levels. The coefficient in Column 2 of 1.451 ($z = 4.09$) implies that after controlling for known predictors of subsequent SEO activities, a one-standard-deviation increase in investment flows into an industry increases the SEO likelihood by roughly 20% (of a baseline of 9.7%). In addition, they engage in significantly more M&A activities. Consistent with these firms exploiting the higher industry valuations, the increase in M&A activities

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[10] Frazzini and Lamont (2008) use a similar measure and also find significant negative abnormal returns following investor flows into mutual funds.

[11] We show nearly identical results in magnitude and significance using the industry M/B ratio as an alternative to the investor flows measure. These are shown in Table X and Figure 3, and are discussed in Section 5.7.

comes solely through stock-financed M&As. The coefficient in Column 4 of 3.133 ($z =$ 3.25) implies that a one-standard-deviation increase in investment flows into an industry increases the stock-financed M&A likelihood by roughly 26% (of a baseline of 1.1%). Columns 5 and 6 show that industry flows have little impact on the likelihood of cash-financed M&As.

5.2. Identification of Industry Window Dressing

There is an extensive literature that examines managers' opportunistically changing firm policy to take advantage of temporary price movements. An innovation of this paper relative to the existing literature is the clean identification of firm behavior in direct response to temporary industry valuation. In particular, we exploit a rule of the Securities and Exchange Commission (SEC) that designates how firm operations are classified: each firm is assigned a primary industry, which is determined by the segment with the highest percentage of sales. Using this rule, we then exploit situations in which firms tightly surround the discontinuity point of industry classification. By examining the distribution of conglomerate firms right around the discontinuity point, we can examine cleanly how the incentives for managers to join favorable industries relate to the relative sales from favorable versus non-favorable industries (i.e., the complement set to the favorable industries).

Thus, we focus on a subset of conglomerate firms whose two largest segments are in one favorable and one non-favorable industries and examine the relative sales weight between the two segments. Each firm in this subsample has a sales weight in the favorable industry between 10% and 90% (scaled by the combined sales of the top two segments), and similarly for the sale weight in the non-favorable industry. If firms truly are manipulating operations opportunistically, we expect to see firms clustering just above the discontinuity cutoff of sales from favorable industries (i.e., 50%), so that they can take advantage of being classified as a member of these favorable industries.

To test this, we first examine the distribution of conglomerate firms' segment composition. We examine the two largest segments of each conglomerate firm in terms of sales, requiring that one of the top two segments is in a favorable industry and the

other in a non-favorable industry. Figure 2 shows the distribution of conglomerate firms that satisfy this requirement and are around the 50% cut-off in terms of sales from the favorable segment. The top two segments' sales in the firm are scaled against each other; the larger of the two determines the industry classification of the firm. The 50% sales cutoff is thus the relevant discontinuity point for industry status.

Specifically, Figure 2 includes all conglomerate firms whose top, favorable segment accounts for between 40% and 60% of the combined sales of the top two segments (gray shaded area), as well as between 45% and 55% of the combined sales (patterned area). Any firm with sales over 50% from a favorable industry (x-axis) is classified into the favorable industry (whereas below that cutoff is classified into the non-favorable industry). If there is no opportunistic behavior by managers, we should see no significant difference in the proportion of conglomerate firms around the 50% point. In contrast, as this 50% cutoff is precisely the point at which firms are classified into favorable versus non-favorable industries (e.g., the 51% tech–49% lumber firm will be presented to investors as a tech firm, whereas the 49% tech–51% lumber will be classified as a lumber firm), we expect firms exhibiting opportunistic behavior to exploit industry valuation by clustering just over the 50% classification cutoff.

Figure 2 shows strong evidence that firms indeed cluster just above the 50% cutoff of sales from favorable industries (relative to just below), resulting in significantly more firms being classified into favorable industries. For instance, looking at all conglomerate firms that have between 40% and 60% of sales from a favorable industry (and so the complement 60%–40% in a non-favorable industry), we see a much larger percentage of firms in the 50%–60% favorable industry sales bin than the converse. This difference becomes even greater if we look at a tighter band around the 50% cutoff of firms that are between 45% and 55% in a favorable industry (versus the complement 55%-45% in a non-favorable industry). Note that an alternative story in which all firms with a favorable segment experience increasing sales in that segment would generate a very different pattern. In this case, we should see *all* firms containing a favorable industry segment increasing their weights in the favorable industry, which would result in a parallel shift for all firms such that the bins around 50% would experience the same increase, and so have no discontinuous jump between the two.

To test the distribution discontinuity around the 50% cutoff more formally, we look at the entire distribution of conglomerate firms. The estimation strategy of discrete jumps in firm distributions at the discontinuity point follows the two-step procedure outlined in McCrary (2008). In particular, we first group all observations into bins to the left and right of the discontinuity point of interest such that no single bin includes observations on both sides of the discontinuity point. The size of the bin is determined by the standard deviation of the ranking variable (e.g., segment percentage sales) and the total number of observations in our sample. We then smooth the distribution histogram by estimating a local linear regression using a triangle kernel function with a pre-fixed bandwidth over the bins. The estimated log difference in firm distributions at the discontinuity point is shown to be consistent and to follow a normal distribution asymptotically by McCrary (2008).

Table V, Panel A shows the entire distribution of conglomerate firms, whose top two segments operate in one favorable and one non-favorable industries, across 5% bins based on percentage sales from the favorable industry. From Table I, we see a clear U-shaped pattern in conglomerate firm distributions (conglomerate firms are usually dominated by one segment, with relatively fewer that are near the 50-50 cutoff). We see a similar overall pattern for these favorable versus non-favorable conglomerate firms, with one distinct difference: there is a large jump in the fraction of firms just above the 50% cutoff relative to just below. The log density difference at the 50% cutoff (following the McCrary procedure) is 0.254 ($t = 2.59$), or a 29% jump.[12] For comparison, if these firms are smoothly distributed in sales weights, the distribution density change at each point should be insignificant from zero. Further, for the rest of the distribution, there is no change in density nearly as large, and none are statistically significant.

This same result can be seen in Figure 3. The top left panel shows the discontinuity in firm distributions at the 50% cutoff of segment sales.[13] Each blue circle

[12] We have used a number of methods of adjusting these standard errors from the McCrary procedure; for instance, clustering by year or bootstrapping. The corresponding standard errors are a bit lower, resulting in larger t-stats of 3.52 and 3.40, respectively.

[13] In addition to getting into favorable industries, firms may also want to avoid being classified into the least favorable industries (e.g., the bottom 20 industries ranked by industry flows). We test this idea by looking at the difference in distribution jumps between the two scenarios (a negative jump vs. a positive

represents the distribution density of a 5% bin ranked by percentage sales from the favorable segment, and the red curves are the estimated smoothed density functions, as well as the 2.5% to 97.5% confidence intervals of the estimated density. There is a clear jump in density at the 50% cutoff: the 2.5% confidence band to the right of the 50% cutoff is above the 97.5% confidence band to the left of the cutoff.

5.3. Falsification Tests

Although the discrete jump pattern in firm distributions is difficult to reconcile with explanations other than industry reclassification that occurs precisely at the 50% discontinuity point, one might think that firms are simply ramping up all operations, such that sorting on any firm balance sheet or income statement variable would yield identical patterns. To be clear, the SEC rule states that sales *alone* determine industry classification. Thus, if managers' opportunistic behavior to gain favorable industry classification is the driving force of our result, the only variable that managers care to affect should be sales. In other words, we should not see a discontinuity in the distribution at 50% if firms are sorted by any other financial/accounting variables. In contrast, if what we document is some odd empirical pattern in firm operations unrelated to industry classification motives, we should expect to see similar jumps at the 50% point based on other accounting variables.

To test this, we conduct the exact same sort as in Table V, Panel A, using the *same* set of conglomerate firms. But instead of sorting on sales, we sort on other accounting variables, such as profits and assets. More specifically, we show the entire distribution of conglomerate firms that are ranked by the percentage of profits (assets) in the favorable segment. From Panels B and C, we see no significant jumps anywhere in the distribution when sorting firms by these other accounting variables. This is consistent with sales (the variable that drives industry classification) being the sole focus of firms. This smooth distribution function when firms are sorted by segment

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jump in distributions). We see both of these in the data, and the difference between the two is strongly statistically significant.

profits or assets can also be seen in the top right and bottom left panels of Figure 3, respectively.

These results, particularly those based on segment profits, also help rule out an alternative explanation of tournament behavior by divisional managers to be promoted. First, a nuanced version of the tournament explanation would be needed to predict a stronger desire (or ability) of managers in favorable industry segments to engage in this behavior relative to all other segment managers. Even if this were true, however, prior evidence shows that segment sales have no clear impact on the promotion of divisional managers (Cichello et al., 2009); instead, segment profits are the only statistically and economically relevant predictor. However, as shown in Table V, we see no evidence of discontinuous jumps when sorting firm on segment profits, but solely when sorting on segment sales. This is inconsistent with the tournament explanation, but consistent with the industry window dressing motive.

5.4. Mechanisms

We next explore the mechanisms through which firms may opportunistically adjust segment sales such that they are classified into favorable industries. There are, broadly speaking, two such channels. The first is that firms, on the margin, take real actions to sell more in the favorable industry segment in order to be classified into favorable industries, and accrue the benefits we show in Section 5.1. The second explanation is that firms simply fraudulently report segment sales in order to be classified into the favorable industries.

5.4.1. Window dressing through sales management

If a firm wants to increase its sales revenue in any segment, one way to do this is to lower the price of goods in that segment.[14] This can lead to more booked sales, but at the time a lower profit margin, and a depletion of inventories as the abnormal sales volume is realized. We test both implications concerning profit margins and inventory

[14] The implicit assumption here is that the price elasticity of demand is below -1 for an average industry.

growth. We use the same setting as in Table V—i.e., firms are ranked into 5% bins based on their percentage sales from the favorable segment. If firms indeed lower the price of goods to increase sales, then these firms that are barely classified into the favorable industry (i.e., firms just above the 50% classification cutoff) should have lower profit margins and depleted inventories compared to other firms. Panel A of Table VI reports test results for profit margins *solely* in the favorable segment, and we see precisely this pattern: the average profit margin in the 50-55% bin is almost 18% lower ($t = 2.93$) compared to both adjacent bins.

In theory, to increase the *relative* sales in the favorable sector to just above the 50% cutoff, firms can either cut prices in the favorable industry segment to increase sales, or raise prices in the non-favorable segment to reduce sales. If firms chose the latter, this would imply higher profitability in the non-favorable segment for firms that are barely classified into favorable industries. In Panel B, we examine this implication by looking at the profitability in the non-favorable segment for firms that surround the 50% cutoff. Panel B shows that firms just to the right of the 50% cutoff (which exhibit significant drops in favorable segment profitability) show no difference in non-favorable segment profitability compared to firms in adjacent bins. The same results on profitability can be also seen in the top two panels of Figure 4.

Next, we conduct the same test for inventories to examine if inventories are also depleted for firms that are just above the sales discontinuity. Because inventories are reported only at the firm level (not the segment level) and the data are much more sparsely populated, we aggregate firm-year observations to 10% bins (instead of 5% bins) to improve statistical power. Again, we see evidence consistent with firms increasing sales to be classified into favorable industries. As shown in Table VI, Panel C, inventory growth is 30% lower ($t = 2.28$) for firms in the 50-55% bin compared to both adjacent bins; further, there is no statistically significant difference between any other two bins.

We also run the falsification test focusing on firms whose top segments are both in favorable (or non-favorable) industries, so there is little incentive to opportunistically change segment sales, which then determine industry classification. Consistent with this

idea, we see no differences in profit margins or inventory growth for these two-favorable-segment (or two-non-favorable-segment) firms anywhere in the distribution.

One might argue that instead of capturing firms opportunistically changing their segment sales, our results may reflect a firm-wide shift in policy toward the more favorable industry (hence the higher sales). First of all, this would not explain why we should observe a discontinuous jump in firm distributions, segment profitability, and inventory growth at the 50% sales cutoff. Nonetheless, we test this alternative story by exploring whether firm investment also exhibits a similar discontinuous pattern at the industry classification cutoff. In particular, we examine whether capital expenditures and R&D spending in the favorable industry line up with the profitability pattern around the discontinuity. As shown in Table VII, Panels A and B, for both capital expenditures and R&D spending, there is no difference in firm investment around the discontinuity point.[15] The results on firm investment are also shown in the bottom two panels of Figure 4. This is in sharp contrast to profit margins and inventory growth, and provides additional evidence that firms are manipulating their sales for the sole purpose of being classified into favorable industries.

Another alternative explanation is that firms signal to the market that they are expanding into high-growth sectors by increasing their sales in the favorable segment. We provide evidence that cuts against this signaling story. First, this simple signaling story makes no distinction at the 50% cutoff; that is, firms everywhere in the distribution (e.g., 27%, 42%, 61%, etc.) signal their expansion by increasing sales in the favorable segment. However, as shown in Table V, firms are not uniformly increasing their exposures to the favorable segment; instead, we see a jump in the distribution only at the industry classification cutoff of 50%. To accommodate this pattern, the signaling story would need to be combined with some investor cognitive constraint such that investors pay attention only to situations where firms cross the 50% threshold. Inconsistent with this more complicated signaling story, we find no evidence that firms just above the 50% cutoff actually move into these favorable industries. For instance, in the two to three years following the industry classification, we see no increase in

[15] Like inventories, R&D expenditures are sparsely populated, so we aggregate to the 10% bin level.

investment, R&D, or sales in the favorable segment. This then reduces to a pseudo-signaling story, which is essentially equivalent to the industry window dressing explanation.

5.4.2. Window dressing through accounting manipulation

An alternative explanation to firms managing sales to be classified into favorable industries is that they simply manipulate accounting statements to the same end (without any real changes in sales). Although this would not explain the inventory and profitability results at the segment level, it could still be a complementary channel that achieves the same goal. If firms indeed manipulate sales figures in accounting statements, this manipulation would eventually need to be corrected in a future restatement that accurately reflects firm operations. We thus test this implication using accounting restatement data. We focus on firms that actively switch into a favorable industry from a non-favorable industry for statistical power reasons (more discussion on this test design in the next section). We further show in Section 5.5 that these switcher firms indeed gain the same significant benefits accrued to all firms in favorable industries (in terms of stock issuance and stock-financed M&As).

The accounting restatement results are shown in Table VIII. Columns 1 and 2 run the accounting restatement test on all firms that switch industries: (a) from non-favorable to favorable; (b) from non-favorable to non-favorable; (c) from favorable to favorable; and (d) from favorable to non-favorable. It can be seen from Column 2 that the overall restatement likelihood of switchers is larger than that of other firms, but only marginally significantly so. Columns 3 and 4 then run the same analysis only on switchers from non-favorable to favorable industries. These firms, in contrast, are significantly more likely to restate earnings compared to non-switchers. The coefficient in Column 4 of 0.382 (z = 3.35) implies that after controlling for various firm characteristics, switchers are 39% (of a baseline of 4.5%) more likely to restate in the future. This is significant even controlling for the actual change in percentage sales from the favorable segment ($\Delta\%SALES_{t-1}$), which itself is negatively related to future

restatements.[16] Importantly, after controlling for (Δ%SALES$_{t-1}$), the switch dummy now captures solely the effect of crossing the 50% cutoff. Columns 5 and 6 then run the analysis for all other types of switchers (i.e., excluding switchers from non-favorable to favorable industries). These firms are no more likely to restate their accounting figures, with a small negative and insignificant difference between their likelihood and the non-switchers. Thus, the positive overall effect of switching on restatement probabilities in Columns 1 and 2 are driven entirely by firms that switch from non-favorable to favorable industries.

In sum, Tables VI–VIII suggest both channels through which firms can manipulate their segment sales in order to be classified into favorable industries: a) by slashing the price of goods in the favorable segment, thus reducing profitability and inventories; and b) by manipulating their accounting statements to achieve favorable industry status, are present amongst conglomerate firms.

5.5. Benefits to Switching

Throughout this paper, we use the discontinuity approach to examine the behavior of conglomerate firms to be classified into favorable industries. Another sample of interest is firms that actively switch from non-favorable to favorable industries. While these will include many of the same firms just above the discontinuity, they will also include firms that make larger changes in firm operations or shifts in firm focus (i.e., through acquiring other firms or dispositions of segments). We thus lose the identification of comparing nearly identical firms right around the classification cutoff, since the decision to switch is not random. But we gain a group of firms that act decisively to move into favorable industries.[17]

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[16] This negative association between Δ%SALES and future restatement is intuitive, as a firm that moves from 40% to 80% sales in the favorable industry is less likely to have used accruals to do so than a firm that moves from 49% to 51%.

[17] We find that investors behave similarly with regard to these switching firms as they do around the discontinuity point (shown in Table II and Figure 1). For instance, in the analog to the test in Table II, we find that the industry beta of switchers to the favorable industry increases by 0.046 (t = 2.53), representing a more than 20% increase in beta.

We show that these switchers accrue significant benefits of being classified into favorable industries. We run identical tests to those in Table IV, except now only on the subsample of firms that switch from a non-favorable to a favorable industry. The results are reported in Columns 1–4 of Table IX. Despite the much smaller sample size, Columns 1-4 show that these switchers engage in significantly more stock issuance and stock-financed M&As. The magnitudes are similar to those in Table IV (the point estimates are even larger), and all are highly statistically significant. Again, we control for the actual change in percentage sales from the favorable segment ($\Delta\%SALES_{t-1}$) in our regression specifications, so the coefficient on the switch dummy solely reflects the effect of crossing the 50% cutoff. Another benefit that the literature shows of having overvalued equity is that managers are paid more. We find the same to be true in our setting. In the analog to Column 4 of Table IX (using total compensation as a percentage of market equity as the dependent variable), we find that the switchers in our sample increase the total compensation to their top managers by 15% (t=2.49) more in the subsequent year compared to non-switchers.

Further, if investors use shortcuts based on primary industry classifications in their investment decisions, a switch of a firm's primary industry could have a sizable impact on its valuation. We focus on stock returns around an important information event during which information regarding a firm's primary industry is announced: its annual release of financial statements. Specifically, we predict that firms that switch from non-favorable to favorable industries (e.g., from machinery to the tech during the NASDAQ boom) should have higher announcement day returns than their peers. It is also important to note that this test provides a lower bound for the return effect of industry switching, as annual sales information is gradually disseminated to the market and can be largely anticipated before the official financial statements are released.

To test this prediction, we examine the cumulative stock return in the three-day window surrounding conglomerate firms' annual earnings announcements. Our results are also robust to other window lengths. We then regress the cumulative announcement return on the same switch dummy as in Columns 1-4 of Table IX. We also control for standardized unexpected earnings (SUE), defined as the difference between the

consensus forecast and reported earnings scaled by lagged stock price. The results are reported in the last two columns of Table IX. As can be seen from Column 6, after controlling for firm characteristics that are linked to average stock returns, firms that switch from non-favorable to favorable industries outperform their peers by 120 basis points ($t = 2.08$) around the announcements.

An alternative way of testing this announcement day return effect is to focus on situations in which there is some uncertainty over industry classification (i.e., firms that tightly surround the 50% discontinuity). When we run the identical announcement return test on a subsample of firms having between 45% and 55% of sales from the favorable segment, the announcement day return effect doubles in magnitude and is even more statistically significant, despite the much smaller sample size. For example, firms reporting sales of 50-55% from the favorable segment has an announcement day return that is 260 basis points ($t = 3.27$) higher than those reporting sales of 45-50% from the favorable segment.

5.6. Regression Discontinuity (RD) vs. Discontinuity

It is important to distinguish the different methodologies we use in the first and second parts of this paper. The section on investor and financial agent behavior (Section 4) uses a regression discontinuity approach. The key assumption is that firms are randomly allocated to the left and right sides of the 50% cutoff.

In contrast, the second part of the paper on firm opportunistic behavior (Section 5) uses a discontinuity approach relying on the 50% industry classification criterion. Here, we show that firms strategically select which side of the cutoff to be on. This is similar to the earnings management literature of firms manipulating earnings to meet or barely beat earnings expectations (by zero or one penny). Clearly, the potential issue is that the behavior of firms we document in Section 5 (firms selecting to be classified into favorable industries) violates the key assumption of regression discontinuity in Section 4.

To address this concern, we focus *solely* on a subsample of conglomerate firms whose top two segments operate both in non-favorable industries. These firms have no apparent incentives to select, and by construction, there can be no jump in the

distribution at any point, because the distribution is entirely symmetric – every (49%, 51%) firm is also a (51%, 49%) firm operating in two non-favorable industries. This sample thus adheres to the regression discontinuity assumption of random assignment around the 50% cutoff. We run our investor behavior tests on this subsample and see identical results to those reported in Section 4. For instance, Table X, Panel A shows the jump in industry beta at the 50% cutoff for this subsample (analog to Table II). The average industry beta for firms in the 50%–55% bin, after controlling for known risk factors, is 0.219, whereas that in the 45%–50% bin is 0.143. The difference of 0.076, representing a 53% increase, is statistically significant (t = 2.58). Moreover, the difference in industry beta between any other two adjacent bins is statistically zero.

5.7. Robustness Checks

We run a number of robustness checks of our main results. First, we run tests using different measures of industry classification. Throughout the paper we use the two-digit SIC code. When we run the same tests using the coarser one-digit SIC code or the North American Industry Classification System (NAICS), we see the same discrete jump in firm distributions at the 50% cutoff ranked by percentage sales from the favorable segment. Second, we run this analysis using both the pre- and post-1998 sub-periods (due to the accounting standard change from SFAS 14 to SFAS 131), and the results are nearly identical in both magnitude and significance. Third, we look solely at the subsample of two segment conglomerate firms (i.e., further excluding conglomerate firms with more than two segments). This test is shown in Table X, Panel B. Although the sample is smaller, the magnitude is nearly identical, and the jump in firm distributions is statistically significant.

We also use an alternative measure of industry valuation, industry M/B, in addition to the investor flow measure. Because there is large base variation in M/B at the industry level due to, for instance, fundamental differences in operations (Cohen and Polk, 1996), we adjust for this using the method of Rhodes-Kropf, Robinson, and Viswanathan (2005). Using their measure of the deviation between current industry M/B and long run average industry M/B, we define favorable industries as the top 20

ranked by this deviation, and run the same analysis of firm behavior. We find nearly identical results with this alternative measure. As shown in the bottom right panel of Figure 3, there is a clear jump in firm distributions around the 50% sales cutoff when favorable industries are defined by industry M/B. The same results are also reported in Table X, Panel C. The log density difference of 0.242 (t = 2.54), or a more than 27% jump, at the discontinuity point is nearly identical to that in Table V.

6. Conclusion

We document a shortcut that financial agents take and show how it impacts both prices and managerial behavior. Specifically, we exploit a regulatory provision governing firms' classification into industries: A firm's primary industry classification is determined by the segment with the majority of sales. As this empirically always falls between the two largest segments, the 50% cutoff between these two segments determines the industry classification. We find evidence that investors overly rely on this industry classification in their investment decisions without sufficiently factoring in firms' underlying economic operations.

For instance, we find that even when firms have nearly identical sales profiles, firms just over the 50% point (in term of percentage sales from a particular industry) have significantly higher industry betas with respect to that industry than firms just below the 50% point. Sector mutual fund managers also invest significantly more in the firms just above the discontinuity point than just below it. Sell-side analysts exhibit similar patterns in their coverage decisions around the discontinuity. Importantly, the significant jumps in industry beta and mutual fund and analyst behavior occur solely at the 50% classification cutoff, and nowhere else in the distribution of firm operations.

We also show evidence that managers take specific actions to be classified into "favorable" industries (i.e., those with high valuations). In particular, firms near the industry assignment cutoff are considerably more likely to be just over the 50% point in terms of percentage sales from the favorable segment; we find no such jumps anywhere else in the distribution of these favorable versus non-favorable segment firms, consistent with managerial behavior specifically to exploit industry classification.

As further evidence of these firms taking real actions to achieve sales levels that would allow them to be classified into favorable industries, we find that firms just over the classification cutoff have significantly lower segment profit margins and inventory growth rates relative to other firms in the same industries, consistent with these firms slashing prices to increase sales in the favorable industry. Again, we observe no changes in segment profit margins and inventory growth rates anywhere else in the distribution of favorable versus non-favorable segment firms. Further, these *same* firms do not exhibit different behavior in any other aspect of their business (for instance, capital expenditures and R&D expenditures), suggesting that they are not making a firm-wide shift of focus toward the favorable industry.

Last, we show that firms that switch into favorable industries have significantly higher announcement returns around the time of switching. In addition, they engage in significantly more SEOs and (stock-financed) M&As after switching.

In sum, we provide evidence that investors take correlated shortcuts that cause simple pieces of information to be systematically unreflected in firm prices. Managers take specific actions to exploit these investor shortcuts, providing tangible benefits to their existing shareholders.

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Table I: Summary Statistics

This table reports summary statistics of our sample that spans the period 1980-2010. Panel A reports the statistics of our main variable, mutual fund flows to each industry over a year, based on two-digit SIC codes. Specifically, at the end of each quarter, we compute a $FLOW$ measure as the aggregate flow-induced trading across all mutual funds in the previous year for each stock. We then take the average $FLOW$ across all stocks in each two-digit SIC code industry to derive $INDFLOW$. Panels B and C report segment and firm specific characteristics. Profit margin is defined as the segment's operating profit divided by segment sales. Both capital expenditures and R&D spending are scaled by total firm assets. Industry beta is from the regression of weekly stock returns on corresponding industry returns (excluding the stock in question) over a one-year horizon, after controlling for the Carhart four-factor model. The announcement return is the 3-day cumulative return around an annual earnings announcement. Panel D reports the distribution of conglomerate firms year by year. We classify conglomerate firms into four groups, based on the relative sales of the *top two* segments. For example, a 10-20% conglomerate firm has one of the top two segments contributing between 10-20% of the combined sales and the other segment contributing 80-90% of the combined sales of the top two segments. We also report the number of conglomerate firms that switch their major industry classifications in each year.

	Mean	Std. Dev.	Q1	Median	Q3
Panel A: Industry Characteristics					
$INDFLOW$	0.081	0.122	0.003	0.070	0.142
Panel B: Segment Characteristics					
Profit margin	0.076	0.145	0.023	0.081	0.150
Segment sales (millions)	1103	5789	13	70	421
Capital expenditures	0.024	0.027	0.005	0.013	0.032
R&D Spending	0.004	0.010	0.000	0.000	0.000
Panel C: Firm Characteristics					
Industry beta	0.228	0.685	-0.151	0.184	0.593
Announcement returns	0.007	0.083	-0.031	0.004	0.044
Panel D: Distribution of Conglomerate Firms Year by Year					
# 10%-20% conglomerates	566	102	493	558	633
# 20%-30% conglomerates	485	117	397	487	574
# 30%-40% conglomerates	424	102	332	440	509
# 40%-50% conglomerates	396	97	325	420	466
# industry classification changes	138	87	75	136	223

Table II: Naive Industry Categorization: Industry Beta

This table reports the average industry beta of conglomerate firms. At the end of each quarter, we compute an industry beta for each two-segment conglomerate firm with regard to each segment by regressing weekly stock returns on the weekly returns of the two-digit SIC code industry that the conglomerate firm operates in, using data from months 6 to 18 after the fiscal year end. We exclude the stock in question from calculating the corresponding industry returns. We also control for common risk factors, such as the market, size, value, and momentum in the regression specification. We focus on conglomerate firms that operate in exactly two industries (i.e., excluding firms with greater than or equal to three segments). All firms are then sorted into twenty 5% bins based on the sales from one of the two segments as a fraction of the combined sales. The first row reports the average industry beta with regard to the segment in question for all firms in each bin, the second and third rows report the difference in industry beta between the current bin and the preceding bin after controlling for year fixed effects, and the fourth and fifth rows report the same difference after controlling for year and industry fixed effects. T-statistics, shown in parentheses, are based on standard errors clustered at the year level. *, **, *** denote significance at the 90%, 95%, and 99% level, respectively.

	30% to 35%	35% to 40%	40% to 45%	45% to 50%	50% to 55%	55% to 60%	60%to 65%	65% to 70%
Industry Beta with Regard to the Segment in Question								
Industry beta	0.136	0.120	0.179	0.178	0.286	0.245	0.286	0.284
$beta_b$ - $beta_{b-1}$	-0.010	-0.020	0.055	0.003	0.107***	-0.033	0.043	-0.005
(year)	(-0.35)	(-0.81)	(1.23)	(0.10)	(4.91)	(-0.85)	(0.95)	(-0.13)
$beta_b$ - $beta_{b-1}$	-0.013	-0.005	0.043	0.012	0.085***	-0.039	0.046	0.008
(year + SIC)	(-0.45)	(-0.19)	(0.93)	(0.35)	(3.86)	(-0.92)	(1.03)	(0.20)
No. Obs.	730	616	590	638	638	590	616	730

Table III: Sector Mutual Fund Holdings and Analyst Coverage

This table reports the proportion of sector mutual funds that hold (Panel A) and analysts that cover (Panel B) a conglomerate firm from each segment the firm operates in. At the end of each quarter, we assign a mutual fund holding more than ten stocks to a two-digit SIC code industry, if that industry accounts for more than half of the fund's portfolio value; similarly, we assign each sell-side analyst covering more than three firms to a two-digit SIC code industry, if that industry accounts for more than half of all the firms that the analyst covers. We exclude the conglomerate firm in question in the procedure of mutual fund/analyst industry assignments. We then compute the proportion of sector mutual funds holding and analysts covering the conglomerate firm from each industry that the conglomerate firm operates in using fund holdings and analyst coverage data in months 6 to 18 after the fiscal year end. We focus on conglomerate firms that operate in exactly two segments based on two-digit SIC codes; in addition, we require the two segments to operate in two distinct one-digit SIC code industries. All firms are then sorted into twenty 5% bins based on the sales from one of the two segments as a fraction of the combined sales. The first row of each panel reports the average proportion of sector mutual funds and analysts from the segment in question for all firms in each bin, the second and third rows report the difference in proportions between the current bin and the preceding bin after controlling for year fixed effects, and the fourth and fifth rows report the same difference after controlling for year and industry fixed effects. T-statistics, shown in parentheses, are based on standard errors clustered at the year level. *, **, *** denote significance at the 90%, 95%, and 99% level, respectively.

	30% to 35%	35% to 40%	40% to 45%	45% to 50%	50% to 55%	55% to 60%	60%to 65%	65% to 70%
Panel A: Proportion of Sector Mutual Fund Holdings from the Segment in Question								
Sector mutual funds	0.176	0.235	0.219	0.231	0.328	0.334	0.354	0.362
$prop_b$ - $prop_{b-1}$	-0.005	0.050	-0.018	0.015	0.098**	0.010	0.034	-0.004
(year)	(-0.19)	(1.54)	(-0.48)	(0.60)	(2.55)	(0.30)	(1.10)	(-0.15)
$prop_b$ - $prop_{b-1}$	-0.004	0.045	-0.020	0.005	0.081**	0.029	-0.005	-0.015
(year + SIC)	(-0.19)	(1.60)	(-1.12)	(0.27)	(2.35)	(0.92)	(-0.20)	(-0.66)
No. Obs.	402	381	309	295	295	309	381	402
Panel B: Proportion of Analyst Coverage from the Segment in Question								
Analyst coverage	0.161	0.219	0.288	0.327	0.520	0.564	0.613	0.663
$prop_b$ - $prop_{b-1}$	0.018	0.057	0.070*	0.039	0.193**	0.044	0.049	0.050
(year)	(0.52)	(1.32)	(1.89)	(0.70)	(2.27)	(0.80)	(1.34)	(1.00)
No. Obs.	91	92	88	62	62	88	92	91

Table IV: Mutual Fund Flows and Industry Valuation

This table shows the effect of mutual fund flows on industry valuation. Panel A reports the calendar-time monthly returns to industry portfolios ranked by $INDFLOW$. Specifically, at the end of each quarter, we compute a $FLOW$ measure for each stock as the aggregate flow-induced trading across all mutual funds in the previous year. We then take the average $FLOW$ across all stocks in each two-digit SIC code industry to derive $INDFLOW$. We then sort all industries into decile portfolios based on $INDFLOW$ in each quarter and hold these decile portfolios for the next two years. To deal with overlapping portfolios in each holding month, we follow Jegadeesh and Titman (1993) to take the equal-weighted average return across portfolios formed in different quarters. Monthly portfolio returns with various risk adjustments are reported: the return in excess of the risk-free rate, CAPM alpha, and Fama-French three-factor alpha. T-statistics, shown in parentheses, are computed based on standard errors corrected for serial-dependence with 12 lags (Newey and West 1987). *, **, *** denote significance at the 90%, 95%, and 99% level, respectively.

Panel A: Calendar-Time Portfolio Analysis									
Decile	Excess Return	1-Factor Alpha	3-Factor Alpha	Excess Return	1-Factor Alpha	3-Factor Alpha	Excess Return	1-Factor Alpha	3-Factor Alpha
	Formation Year			Year 1 after Formation			Year 2 after Formation		
1	1.01%	0.47%	0.25%	0.68%	0.14%	0.10%	1.02%	0.40%	0.19%
(Low)	(3.49)	(3.45)	(2.07)	(2.40)	(1.08)	(0.92)	(3.53)	(2.73)	(1.87)
2	1.06%	0.51%	0.36%	0.88%	0.32%	0.15%	0.98%	0.33%	0.18%
	(3.70)	(4.09)	(3.16)	(3.04)	(2.45)	(1.37)	(3.32)	(2.37)	(1.95)
3	1.20%	0.66%	0.53%	0.67%	0.10%	-0.08%	0.91%	0.26%	0.07%
	(4.18)	(5.04)	(4.50)	(2.26)	(0.78)	(-0.73)	(3.07)	(1.83)	(0.74)
4	1.28%	0.70%	0.58%	0.62%	0.07%	-0.12%	0.98%	0.32%	0.14%
	(4.23)	(5.27)	(5.01)	(2.16)	(0.56)	(-1.24)	(3.28)	(2.33)	(1.53)
5	1.37%	0.81%	0.67%	0.55%	0.01%	-0.18%	0.93%	0.29%	0.08%
	(4.72)	(6.74)	(6.37)	(1.96)	(0.09)	(-2.02)	(3.20)	(2.15)	(0.89)
6	1.53%	0.99%	0.84%	0.69%	0.16%	0.06%	0.65%	0.01%	-0.16%
	(5.35)	(7.40)	(8.62)	(2.50)	(1.33)	(0.64)	(2.28)	(0.09)	(-1.56)
7	1.54%	1.02%	0.91%	0.48%	-0.04%	-0.17%	0.69%	0.10%	-0.11%
	(5.51)	(7.22)	(8.88)	(1.75)	(-0.30)	(-1.55)	(2.54)	(0.74)	(-1.05)
8	1.68%	1.14%	1.10%	0.50%	-0.03%	0.00%	0.42%	-0.21%	-0.29%
	(5.58)	(7.13)	(9.34)	(1.68)	(-0.19)	(-0.02)	(1.47)	(-1.56)	(-2.23)
9	1.76%	1.25%	1.25%	0.33%	-0.20%	-0.14%	0.41%	-0.21%	-0.26%
	(5.79)	(6.90)	(8.52)	(1.10)	(-1.16)	(-1.09)	(1.36)	(-1.27)	(-1.50)
10	2.03%	1.46%	1.40%	0.21%	-0.37%	-0.30%	0.41%	-0.26%	-0.31%
(High)	(6.26)	(7.90)	(9.30)	(0.65)	(-1.94)	(-1.89)	(1.27)	(-1.55)	(-1.79)
L/S	1.02%***	0.99%***	1.15%***	-0.47%**	-0.51%**	-0.41%*	-0.62%***	-0.66%***	-0.50%***
	(4.45)	(4.45)	(4.92)	(-2.09)	(-2.12)	(-1.95)	(-3.21)	(-3.34)	(-2.57)

Table IV: Mutual Fund Flows and Industry Valuation (Continued)

This panel reports logit regressions of equity issuance and merger and acquisition activities of conglomerate firms. The dependent variable in columns 1 and 2 is an *Equity Issuance* dummy that takes the value of one if the firm increases shares outstanding (after adjusting for splits) by more than 10% in fiscal year t, and zero otherwise. The dependent variable in columns 3 and 4 is a *Stock Financed M&A* dummy that takes the value of one if the firm has at least one 100% stock-financed acquisition in fiscal year t as reported in the SDC database, and zero otherwise; finally, the dependent variable in columns 5 and 6 is a *Cash Financed M&A* dummy that takes the value of one if the firm has at least one 100% cash-financed acquisition in fiscal year t, and zero otherwise. The main independent variable is the industry flow ($INDFLOW$) measured in the previous year (t-1). Other control variables include the firm-level aggregate flow-induced trading in the previous year ($FLOW$), firm size, book-to-market ratio, lagged one-year stock return, monthly share turnover, stock idiosyncratic volatility, and proportion of institutional ownership. Z-statistics, shown in parentheses, are based on standard errors that are clustered at the year level *, **, *** denote significance at the 90%, 95%, and 99% level, respectively.

Panel B: Equity Issues and M&As						
	Equity Issuance	Equity Issuance	Stock-Financed M&A	Stock-Financed M&A	Cash-Financed M&A	Cash-Financed M&A
	[1]	[2]	[3]	[4]	[5]	[6]
$INDFLOW_{t-1}$	1.419***	1.451***	2.383**	3.133***	-0.034	0.034
	(3.07)	(4.09)	(2.29)	(3.25)	(-0.35)	(0.48)
$FLOW_{t-1}$		0.346***		0.234***		0.096
		(3.37)		(3.44)		(1.04)
$MKTCAP_{t-1}$		-0.093***		0.317***		0.170***
		(-4.42)		(4.54)		(4.49)
BM_{t-1}		-0.246***		-0.245**		-0.045
		(-3.37)		(-2.06)		(-0.88)
$RET12_{t-1}$		0.053*		0.176**		-0.164***
		(1.87)		(2.26)		(-2.77)
$TURNOVER_{t-1}$		0.074***		0.085***		0.064***
		(5.01)		(5.69)		(4.45)
$IDIOVOL_{t-1}$		0.156***		0.169***		0.105
		(4.42)		(4.76)		(0.32)
$INSTOWN_{t-1}$		0.015		-0.575**		0.946***
		(0.15)		(-2.32)		(4.42)
Pseudo R^2	0.00	0.03	0.01	0.05	0.00	0.04
No. of Obs.	78,727	78,727	83,564	83,564	83,564	83,564

Table V: Discontinuity in Conglomerate Firm Distributions

This table reports the distribution of conglomerate firms based on the relative weights of the top two segments. At the end of each quarter, we compute a $FLOW$ measure for each stock as the aggregate flow-induced trading across all mutual funds in the previous year. We then take the average $FLOW$ across all stocks in each two-digit SIC code industry to derive $INDFLOW$. An industry is labeled as favorable in a year if it is one of the top 20 industries as ranked by $INDFLOW$ in that year. For each conglomerate firm in our sample, we require one of the top two segments to operate in a favorable industry and the other in a non-favorable industry. All firms are then sorted into twenty 5% bins based on the weight of the favorable segment as a fraction of the top two segments. In the first row of each panel, we report the frequency of observations in each 5% bin, calculated as the proportion of the conglomerate firms in the bin as a fraction of the total number of conglomerate firms between 10% and 90% of the ranking variable. The second row of each panel reports the difference in distribution *density* at the lower bound of the bin. The density differences, along with the T-statistics shown in brackets, are calculated using the methodology outlined in McCrary (2008). In panel A, firms are sorted into 5% bins based on sales from the favorable segment as a fraction of combined sales from the top two segments. For example, bin 50-55% contains all the conglomerate firms whose favorable segment accounts for 50-55% of the combined sales of the top two segments. In panels B and C, such grouping is done on the basis of segment profits and segment assets, respectively. *, **, *** denote significance at the 90%, 95%, and 99% level, respectively.

	30% to 35%	35% to 40%	40% to 45%	45% to 50%	50% to 55%	55% to 60%	60% to 65%	65% to 70%
Panel A: Firms Sorted by %sales in the Favorable Segment								
Frequency	0.061	0.058	0.048	0.048	0.059	0.051	0.051	0.056
Density difference	-0.056	0.003	-0.056	0.080	0.254***	-0.156	0.056	0.117
at the lower bound	(-0.60)	(0.04)	(-0.52)	(0.76)	(2.59)	(-1.62)	(0.51)	(1.18)
No. Obs.	477	451	386	386	455	391	400	446
Panel B: Firms Sorted by %profit in the Favorable Segment								
Frequency	0.059	0.057	0.056	0.052	0.058	0.055	0.055	0.056
Density difference	0.019	-0.061	-0.082	-0.088	0.059	-0.120	-0.097	-0.018
at the lower bound	(-0.22)	(-0.66)	(-0.94)	(-1.28)	(0.65)	(-1.31)	(-1.14)	(-0.19)
No. Obs.	382	370	362	334	372	352	352	364
Panel C: Firms Sorted by %assets in the Favorable Segment								
Frequency	0.060	0.058	0.062	0.068	0.060	0.056	0.054	0.062
Density difference	-0.034	-0.047	0.087	0.103	-0.038	-0.083	-0.022	0.112
at the lower bound	(-0.29)	(-0.38)	(1.03)	(1.24)	(-0.33)	(-0.71)	(-0.18)	(1.45)
No. Obs.	266	254	273	299	266	248	240	276

Table VI: Discontinuity in Segment Profit Margins

This table reports segment profit margins of conglomerate firms. At the end of each quarter, we compute a $FLOW$ measure for each stock as the aggregate flow-induced trading across all mutual funds in the previous year. We then take the average $FLOW$ across all stocks in each two-digit SIC code industry to derive $INDFLOW$. An industry is labelled as favorable in a year if it is one of the top 20 industries as ranked by $INDFLOW$ in that year. For each conglomerate firm in our sample, we require one of the top two segments to operate in a favorable industry. All firms are then sorted into twenty 5% bins based on the sales from the favorable segment as a fraction of the combined sales from the top two segments. The first row of each panel reports the average characteristic of all firms in each bin, the second and third rows report the difference in that characteristic between the current bin and the two neighboring bins after controlling for year fixed effects, and the fourth and fifth rows report the same difference after controlling for year and industry fixed effects. Panels A and B report the average segment profit margin, defined as the segment's operating profit divided by segment sales, in each bin. Panel C reports the average firm-level inventory growth rate between years t and t-1 for all firms in each bin. We require that the conglomerate firm's other top segment operates in a non-favorable industry. T-statistics, shown in parentheses, are based on standard errors clustered at the year level. *, **, *** denote significance at the 90%, 95%, and 99% level, respectively.

	30% to 35%	35% to 40%	40% to 45%	45% to 50%	50% to 55%	55% to 60%	60% to 65%	65% to 70%
Panel A: Profit Margin in the Favorable Segment (Favorable vs. Non-favorable)								
Profit margin	0.104	0.101	0.100	0.104	0.081	0.099	0.094	0.101
vs. neighbors	0.001	-0.002	-0.002	0.014	-0.021***	0.013	-0.006	0.002
(year)	(0.18)	(-0.21)	(-0.24)	(1.57)	(-2.93)	(1.71)	(-0.74)	(0.23)
vs. neighbors	0.007	-0.007	0.000	0.014	-0.016***	0.013	-0.010	0.006
(year + SIC)	(0.84)	(-1.29)	(0.00)	(1.54)	(-2.79)	(1.61)	(-1.25)	(0.85)
No. Obs.	385	350	303	298	342	290	285	339
Panel B: Profit Margin in the Non-favorable Segment (Favorable vs. Non-favorable)								
Profit margin	0.099	0.091	0.085	0.089	0.087	0.094	0.088	0.091
vs. neighbors	0.007	0.000	-0.003	0.002	0.002	0.000	-0.006	0.008
(year)	(0.91)	(0.03)	(-0.48)	(0.31)	(0.23)	(-0.04)	(-0.80)	(1.11)
vs. neighbors	0.008	-0.002	-0.003	0.004	0.001	0.000	-0.007	0.007
(year + SIC)	(1.04)	(-0.38)	(-0.39)	(0.79)	(0.09)	(0.03)	(-0.86)	(0.88)
No. Obs.	385	350	303	298	342	290	285	339

	30% to 40%	40% to 50%	50% to 60%	60% to 70%
Panel C: Inventory Growth Rates (Favorable vs. Non-favorable)				
Inventory growth	0.083	0.086	0.060	0.084
vs. neighbors	0.000	0.014	-0.025**	0.004
(year)	(-0.01)	(1.19)	(-2.28)	(0.24)
No. Obs.	522	428	458	453

Table VII: Segment Capital Expenditures and R&D Spending

This table reports average segment capital expenditures and R&D spending of conglomerate firms. At the end of each quarter, we compute a $FLOW$ measure for each stock as the aggregate flow-induced trading across all mutual funds in the previous year. We then take the average $FLOW$ across all stocks in each two-digit SIC code industry to derive $INDFLOW$. An industry is labelled as favorable in a year if it is one of the top 20 industries as ranked by $INDFLOW$ in that year. For each conglomerate firm in our sample, we require one of the top two segments to operate in a favorable industry and the other in a non-favorable industry. All firms are then sorted into twenty 5% bins based on the sales from the favorable segment as a fraction of the combined sales from the top two segments. The first row of each panel reports the average characteristic of all firms in each bin, the second and third rows report the difference in that characteristic between the current bin and the two neighboring bins after controlling for year fixed effects, while the fourth and fifth rows report the same difference after controlling for year and industry fixed effects. Panel A reports the average segment capex, defined as the segment capital expenditures divided by lagged firm total assets, in each bin. Panel B reports the average segment R&D, defined as the segment R&D spending divided by lagged firm total assets. T-statistics, shown in parentheses, are based on standard errors clustered at the year level. *, **, *** denote significance at the 90%, 95%, and 99% level, respectively.

	30% to 35%	35% to 40%	40% to 45%	45% to 50%	50% to 55%	55% to 60%	60% to 65%	65% to 70%
Panel A: Capital Expenditures in the Favorable Segment (Favorable vs. Non-favorable)								
CapEx	0.019	0.022	0.023	0.022	0.022	0.026	0.029	0.031
vs. neighbors	0.000	0.001	0.001	-0.001	-0.001	0.002	0.000	0.000
(year)	(0.18)	(0.78)	(0.83)	(-0.84)	(-0.68)	(0.86)	(0.15)	(-0.11)
vs. neighbors	0.001	0.001	0.000	0.000	-0.002	0.002	-0.001	0.000
(year + SIC)	(0.48)	(0.67)	(-0.04)	(-0.28)	(-1.22)	(1.25)	(-0.25)	(0.06)
No. Obs.	358	326	282	275	315	266	258	310

	30% to 40%	40% to 50%	50% to 60%	60% to 70%
Panel B: R&D in the Favorable Segment (Favorable vs. Non-favorable)				
R&D	0.003	0.002	0.003	0.003
vs. neighbors	0.001	-0.001	0.000	0.000
(year)	(1.12)	(-1.20)	(0.35)	(-0.33)
vs. neighbors	0.000	-0.001	0.000	0.000
(year + SIC)	(0.43)	(-1.05)	(0.27)	(-0.22)
No. Obs.	140	115	97	114

Table VIII: Accounting Restatements

This table reports logit regressions of accounting restatements on primary industry classification changes. The dependent variable in all columns is a dummy variable that takes the value one if there is an accounting restatement in the following year, and zero otherwise. The main independent variable is a $SWITCH$ dummy that takes the value of one if the conglomerate firm's main industry classification switches in the fiscal year, and zero otherwise. In columns 1 and 2, we include all switchers in our sample; in columns 3 and 4, we only include switchers from a non-favorable to a favorable industry in the sample; finally, in columns 5 and 6, we include all the other switchers (i.e., those switching from non-favorable to non-favorable, from favorable to favorable, and from favorable to non-favorable industries) in the sample. We also control for the growth in the fraction of sales contributed by the favorable segment ($\Delta\%SALES$). Other control variables include firm size, book-to-market ratio, lagged one-year stock return, monthly share turnover, stock idiosyncratic volatility, and proportion of institutional ownership. Z-statistics, shown in parentheses, are based on standard errors that are clustered at the year level. *, **, *** denote significance at the 90%, 95%, and 99% level, respectively.

	Restate Dummy	Restate Dummy	Restate Dummy	Restate Dummy	Restate Dummy	Restate Dummy
	All Switchers		Non-Favorable to Favorable		Other Switchers	
	[1]	[2]	[3]	[4]	[5]	[6]
$SWITCH_{t-1}$	0.080	0.179*	0.285***	0.382***	-0.093	-0.025
	(0.86)	(1.85)	(2.93)	(3.35)	(-0.67)	(-0.16)
$\Delta\%SALES_{t-1}$		-0.739**		-0.803***		-0.583
		(-1.99)		(-2.27)		(-1.30)
$MKTCAP_{t-1}$		0.042		0.033		0.040
		(0.86)		(0.66)		(0.85)
BM_{t-1}		0.049		0.070		0.051
		(0.67)		(1.01)		(0.70)
$RET12_{t-1}$		-0.132		-0.131		-0.137
		(-1.17)		(-1.12)		(-1.18)
$TURNOVER_{t-1}$		0.076*		0.073*		0.076*
		(1.80)		(1.74)		(1.78)
$IDIOVOL_{t-1}$		0.278***		0.278***		0.293***
		(5.63)		(5.45)		(5.82)
$INSTOWN_{t-1}$		3.192***		3.211***		3.264***
		(2.77)		(2.67)		(2.99)
Pseudo R^2	0.00	0.09	0.00	0.09	0.00	0.09
No. Obs.	23,769	23,769	22,338	22,338	22,827	22,827

Table IX: Benefits to Industry "Window Dressing"

This table reports regressions of earnings announcement day returns, and SEO and M&A activities on primary industry classification changes. The dependent variable in columns 1 and 2 is an $Equity\ Issuance$ dummy that takes the value of one if the firm increases shares outstanding (after adjusting for splits) by more than 10% in the fiscal year, and zero otherwise; the dependent variable in columns 3 and 4 is a $Stock\ Financed\ M\&A$ dummy that takes the value of one if the firm has at least one 100% stock-financed acquisition in fiscal year t as reported in the SDC database; finally, the dependent variable in columns 5 and 6 is the cumulative 3-day return around an annual earnings announcement. The main independent variable is a $SWITCH$ dummy that take the value of one if the conglomerate firm's main industry classification switches from a non-favorable to a favorable industry in the fiscal year, and zero otherwise. We also control for the growth in the fraction of sales contributed by the favorable segment ($\Delta\%SALES$). Other control variables include the standardize unexpected earnings (SUE), defined as the difference between the actual earnings and consensus analyst forecast scaled by lagged stock price, firm size, book-to-market ratio, lagged one-year stock return, monthly share turnover, stock idiosyncratic volatility, and proportion of institutional ownership. Year-fixed effects are included in columns 5 and 6. T-statistics and Z-statistics, shown in parentheses, are based on standard errors that are clustered at the year level. *, **, *** denote significance at the 90%, 95%, and 99% level, respectively.

	Equity Issuance	Equity Issuance	Stock-Financed M&A	Stock-Financed M&A	Anncmnt Return	Anncmnt Return
	[1]	[2]	[3]	[4]	[5]	[6]
$SWITCH_{t-1}$	0.475***	0.414***	1.150***	1.260***	0.014**	0.012**
	(4.45)	(3.90)	(3.77)	(3.35)	(2.38)	(2.08)
SUE_t					0.199***	0.240***
					(5.47)	(5.02)
$\Delta\%SALES_{t-1}$		-0.142		-1.573		0.006
		(-0.47)		(-1.39)		(0.42)
$MKTCAP_{t-1}$		-0.075***		0.242***		-0.001
		(-4.24)		(2.71)		(-1.25)
BM_{t-1}		-0.222***		-0.063		0.001
		(-3.61)		(-0.17)		(0.39)
$RET12_{t-1}$		0.072		0.106		-0.005
		(1.23)		(0.86)		(-1.63)
$TURNOVER_{t-1}$		0.075*		0.030*		0.000
		(1.70)		(1.81)		(0.23)
$IDIOVOL_{t-1}$		0.158***		0.196***		-0.065
		(3.09)		(3.88)		(-0.34)
$INSTOWN_{t-1}$		-0.151		0.324		0.011**
		(-0.88)		(0.45)		(2.21)
Pseudo/Adj. R^2	0.01	0.03	0.01	0.04	0.03	0.03
No. Obs.	24,504	24,504	23,577	23,577	10,648	10,648

Table X: Robustness Checks

This table reports some robustness checks. At the end of each quarter, we compute a $FLOW$ measure for each stock as the aggregate flow-induced trading across all mutual funds in the previous year. We then take the average $FLOW$ across all stocks in each two-digit SIC code industry to derive $INDFLOW$. An industry is labelled as favorable in a year if it is one of the top 20 industries as ranked by $INDFLOW$ in that year. All firms are then sorted into twenty 5% bins based on the weight of the favorable segment as a fraction of the top two segments. Panel A reports the discontinuity in industry beta for a subsample of firms that operate in two non-favorable industries. The first row reports the average industry beta with regard to the segment in question, and the second row reports the difference in industry beta between the current bin and the preceding bin. Panels B and C report the distribution of conglomerate firms whose top two segments are in one favorable industry and one non-favorable industry. In the first row of either panel, we report the frequency of observations in each 5% bin. The second row reports the difference in distribution *density* at the lower bound of the bin. The density differences, along with the T-statistics shown in brackets, are calculated using the methodology outlined in McCrary (2008). In panel B, we include only two-segment firms in the sample (that is, we exclude all firms with more than two segments). In Panel C, an industry is labelled as favorable if it is one of the top 20 industries as ranked by the industry market-to-book ratio in that year (following the M/B industry decomposition in Rhodes–Kropf, Robinson, and Viswanathan, 2005). *, **, *** denote significance at the 90%, 95%, and 99% level, respectively.

	30% to 35%	35% to 40%	40% to 45%	45% to 50%	50% to 55%	55% to 60%	60%to 65%	65% to 70%
Panel A: Industry Beta (non-favorable vs. non-favorable)								
Industry beta	0.131	0.132	0.115	0.143	0.219	0.185	0.193	0.264
$beta_b$ - $beta_{b-1}$	0.016	-0.002	-0.020	0.022	0.076***	-0.027	0.007	0.066
	(0.47)	(-0.04)	(-0.31)	(0.38)	(2.58)	(-0.56)	(0.16)	(1.38)
No. Obs.	644	522	504	546	546	504	522	644

	30% to 35%	35% to 40%	40% to 45%	45% to 50%	50% to 55%	55% to 60%	60% to 65%	65% to 70%
Panel B: Discontinuity in Distribution, Two Segment Firms Only								
Frequency	0.059	0.054	0.046	0.044	0.053	0.047	0.050	0.052
Density difference	0.074	-0.061	0.027	0.142	0.267**	-0.198	-0.043	0.171
at the lower bound	(0.63)	(-0.48)	(0.20)	(0.99)	(2.01)	(-1.62)	(-0.28)	(1.28)
No. Obs.	277	250	223	212	256	223	241	250
Panel C: Discontinuity in Distribution, Industries Ranked by M/B								
Frequency	0.056	0.053	0.050	0.049	0.060	0.059	0.059	0.062
Density difference	0.102	0.055	0.020	-0.073	0.242**	0.031	-0.058	0.110
at the lower bound	(1.07)	(0.58)	(0.21)	(-0.74)	(2.54)	(0.35)	(-0.53)	(1.23)
No. Obs.	386	365	347	338	411	404	403	426

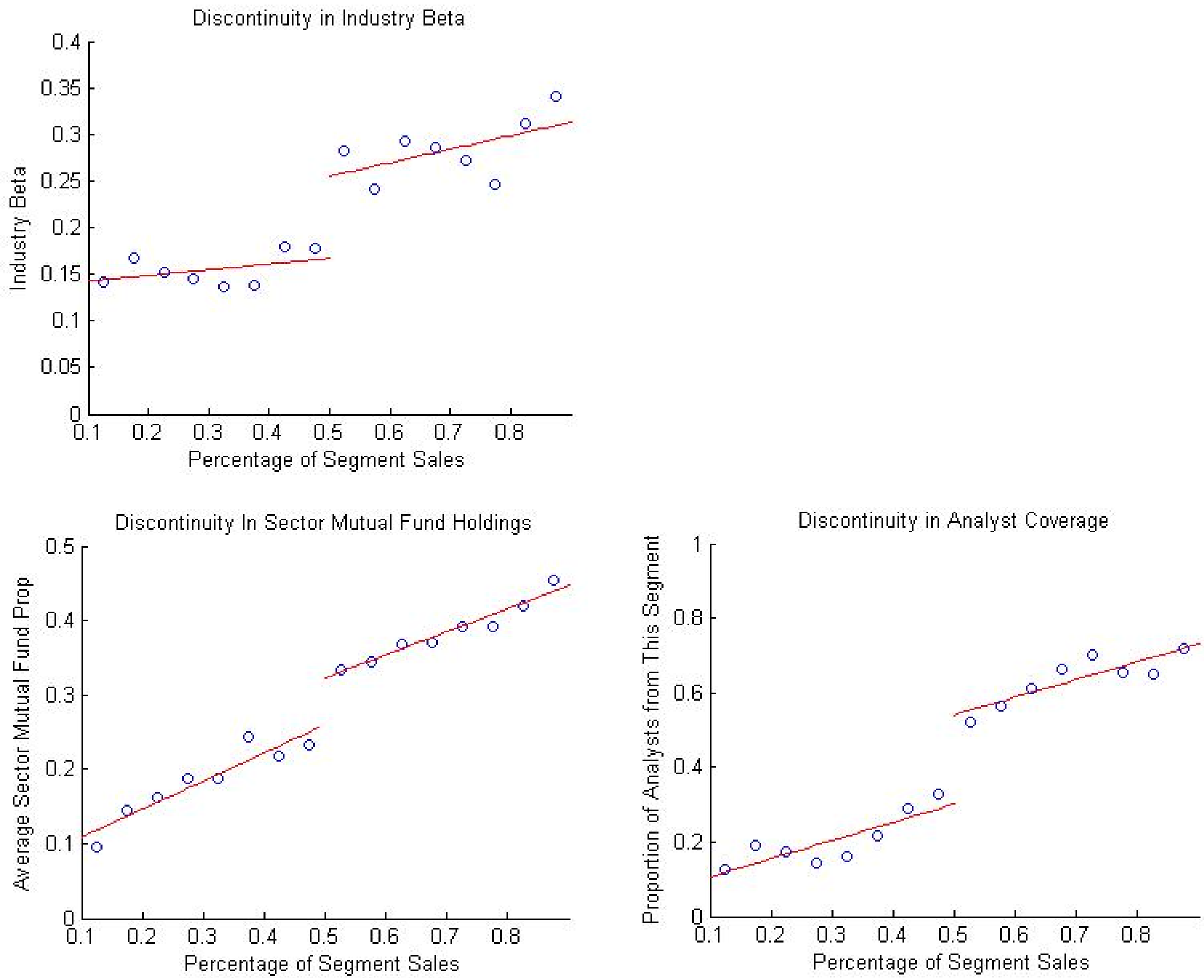

Figure 1: This figure shows the average industry beta and proportion of sector mutual funds that hold and analyst that cover the firm from each segment a conglomerate firm operates in. We focus only on conglomerate firms that operate in two two-digit SIC code industries. All firms are then sorted into twenty 5% bins based on the sales from one of the two segments as a fraction of the combined sales. The blue circles represent the average characteristics of all firms in each bin, while the red curves represent the smoothed estimated linear functions that fit over these observations. The top left panel shows the average industry beta. Specifically, at the end of each quarter, we compute an industry beta for each conglomerate firm in our sample by regressing weekly stock returns on the weekly returns of the two-digit SIC code industry that the conglomerate firm operates in, using data from months 6 to 18 after the fiscal year end. We exclude the stock in question from calculating the corresponding industry returns. The bottom two panels report the proportion of sector mutual funds that hold and analysts that cover the firm from each segment, respectively. Specifically, at the end of each quarter, we assign a mutual fund holding more than ten stocks to a two-digit SIC code industry, if that industry accounts for more than half of the fund's portfolio value; similarly, we assign each sell-side analyst covering more than four firms to a two-digit SIC code industry, if that industry accounts for more than half of all the firms that the analyst covers, using coverage data in the previous three years. We exclude the stock in question in industry assignments to ensure that our results are not mechanical. We then compute the proportion of sector mutual funds and analysts from each industry that the conglomerate firm operates in using fund holdings and analyst coverage data in months 6 to 18 after the fiscal year end.

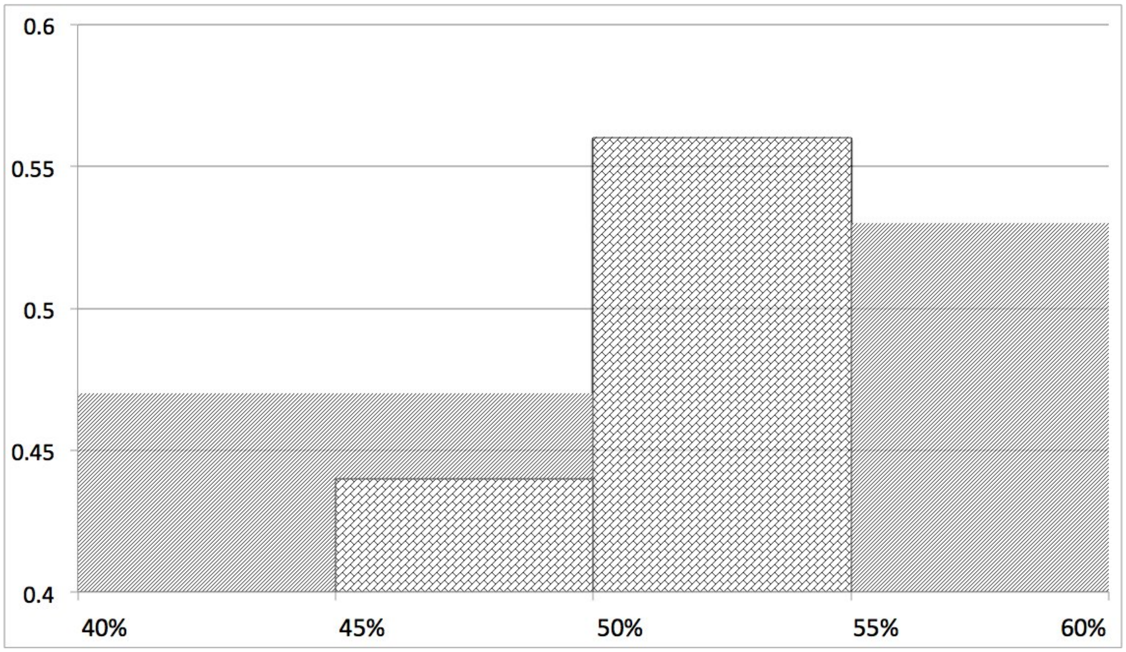

Figure 2: This figure shows the distribution of conglomerate firms based on relative sales weights of the top two segments. For each conglomerate firm in our sample, we require one of the top two segments to operate in a favorable industry and the other in a non-favorable industry, where an industry is labelled as favorable in a year if it is one of the top 20 industries as ranked by $INDFLOW$ in that year. Since the larger of the two segments determines the industry classification of the conglomerate firm, the 50% point in relative sales is the discontinuity point in our empirical analysis. The grey area shows the distribution of conglomerate firms whose sales from favorable industries account for 40%-60% of the total sales, while the block area shows the distribution of conglomerate firms whose sales from favorable industries account for 45%-55% of the total sales. Any firm over the 50% point in this figure is classified to a favorable industry, whereas any firm below 50% is classified to a non-favorable industry.

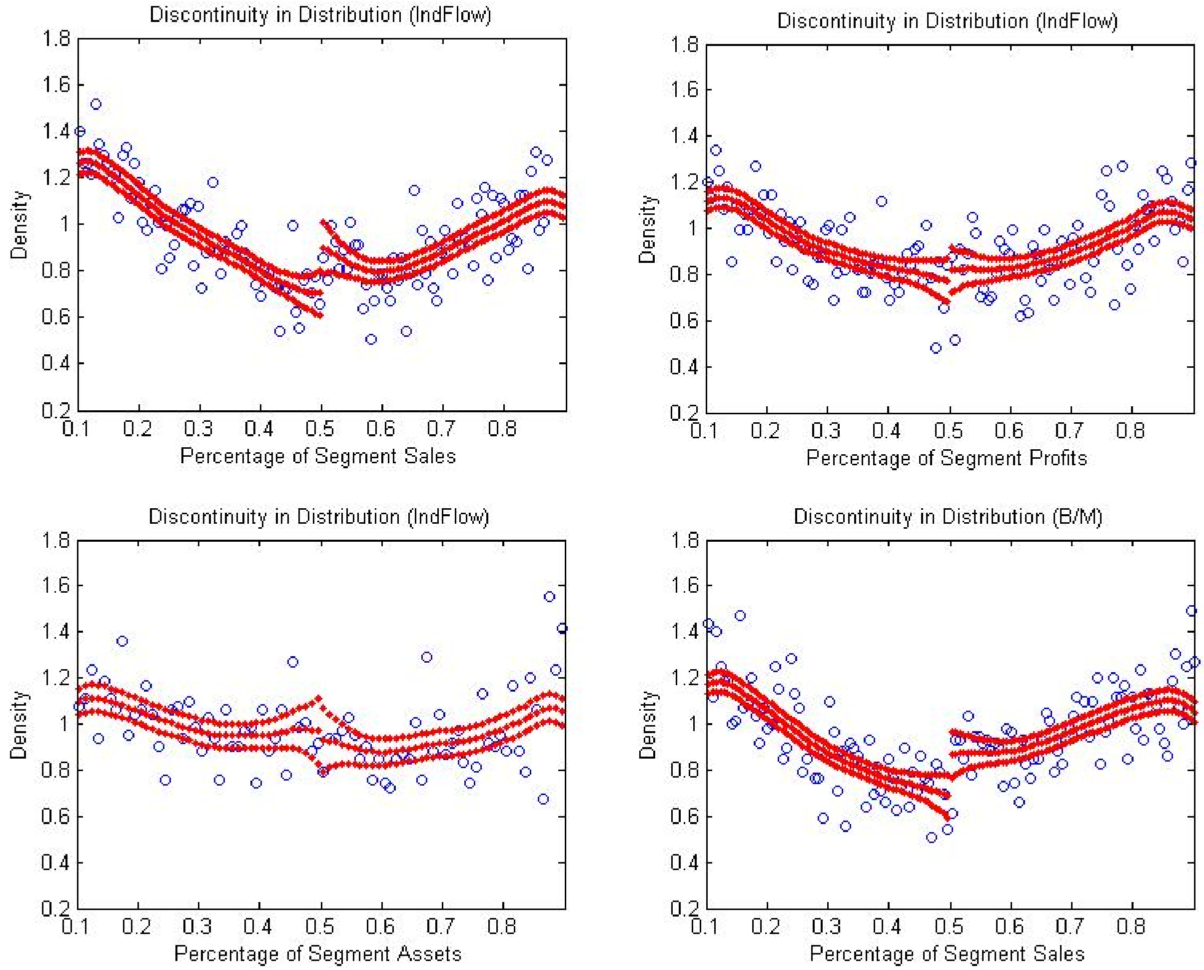

Figure 3: This figure shows the smoothed density functions based on the relative weights of the top two segments of conglomerate firms. The estimation methodology is outlined in McCrary (2008). The blue circles represent the distribution density of each bin grouped by the sorting variable. The red curves are the estimated smoothed density functions, and the 2.5% to 97.5% confidence intervals of the estimated density. Both the bins size and bandwidth are chosen optimally using the automatic selection criterion. The densities to the left and right of the discontinuity point (the 50% cut-off in our case) are then estimated using local linear regressions. For each conglomerate firm in our sample, we require one of the top two segments to operate in a favorable industry and the other in a non-favorable industry. In the first three panels, an industry is labelled as favorable in a year if it is one of the top 20 industries as ranked by $INDFLOW$ in that year. In the last panel, an industry is labelled as favorable if it is one of the top 20 industries as ranked by the industry book-to-market ratio in that year (following the B/M industry decomposition in Rhodes–Kropf, Robinson, and Viswanathan, 2005). In the top left and bottom right panels, firms are ranked based on sales from the favorable segment as a fraction of combined sales from the top two segments. In the top right and bottom left panels, such grouping is done on the basis of segment profits and segment assets, respectively.

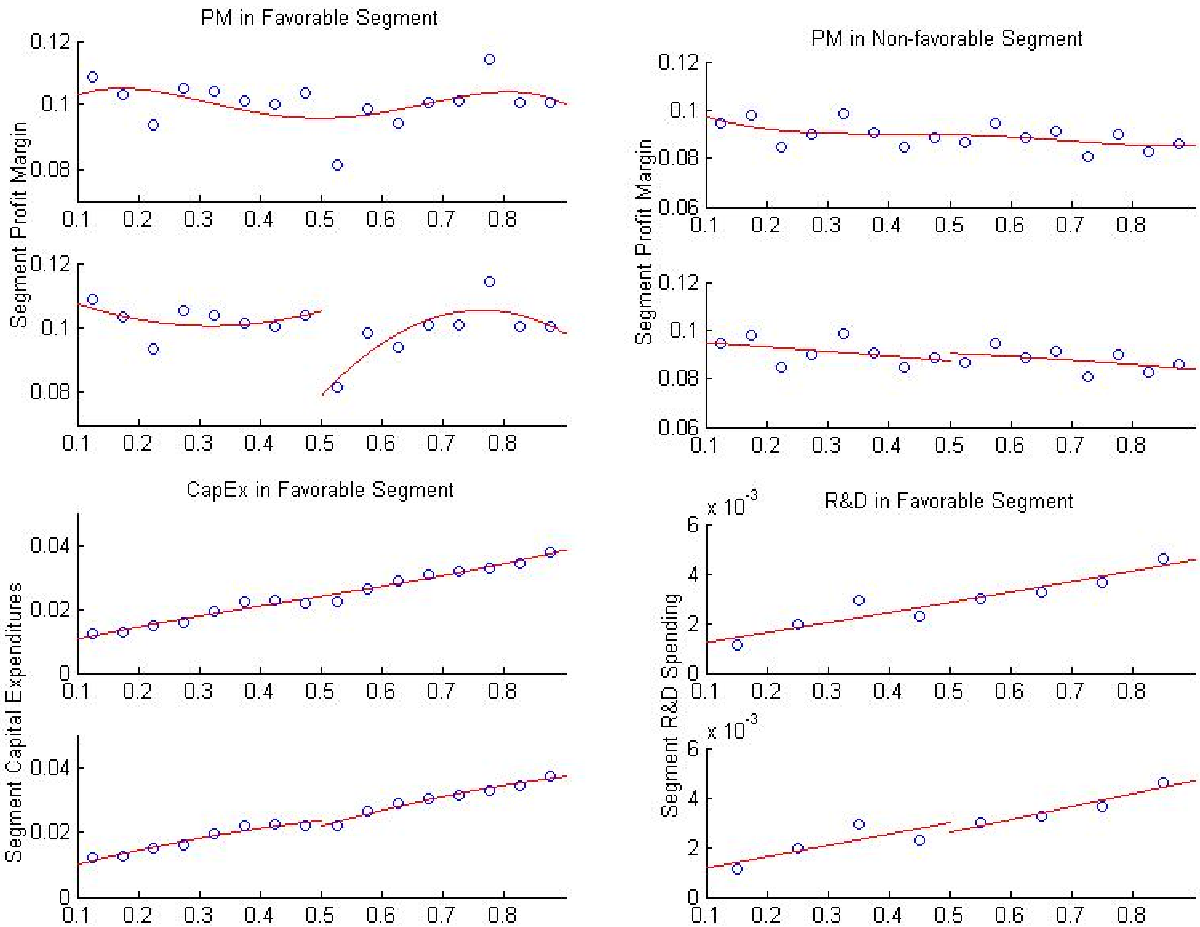

Figure 4: This figure shows various financial/accounting characteristics of conglomerate firms. For each conglomerate firm in our sample, we require one of the top two segments to operate in a favorable industry and the other to operate in a non-favorable industry. An industry is labelled as favorable in a year if it is one of the top 20 industries as ranked by $INDFLOW$ in that year. All firms are then sorted into twenty 5% bins based on the sales from the favorable segment as a fraction of the combined sales from the top two segments. The blue circles represent the average characteristics of all firms in each bin, while the red curves represent the smoothed estimated polynomial functions (up to three degrees) that fit over these observations. The top left panel shows the average profit margin in the favorable segment, defined as the segment's operating profit divided by segment sales, in each bin. The top right panel shows the average profit margin in the non-favorable segment. The bottom left panel shows the average capex in the favorable segment, defined as the segment capital expenditures divided by lagged firm assets, in each bin, and the bottom right panel shows the average R&D in the favorable segment, defined as the segment R&D spending divided by lagged firm assets.