Industry Window Dressing*

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This draft: February, 2016

* We thank Malcolm Baker, Nicholas Barberis, John Beshears, Patrick Bolton, Alex Chinco, James Choi, Josh Coval, Robin Greenwood, Kewei Hou, Dirk Jenter, Andrew Karolyi, Owen Lamont, Stefan Lewellen, Laura Liu, Chris Malloy, Daniel Paravisini, Christopher Polk, Michael Roberts, Erik Stafford, Rene Stulz, Geoff Tate, Belen Villalonga, Tuomo Vuolteenaho, Toni Whited and seminar participants at Columbia University, Harvard Business School, London School of Economics, University of Mannheim, Ohio State University, Princeton University, University of Rochester, Yale University, the 2012 NBER Behavioral Economics Fall Meeting, the 2012 Financial Research Association Annual Meeting, the 2013 UNC-Duke Corporate Finance Conference, the 2013 Western Finance Association Annual Meeting, the 2013 HKUST Finance Symposium, and the 2014 SFS cavalcade for helpful comments and suggestions. We are grateful for funding from the National Science Foundation and the Paul Woolley Center at the London School of Economics.

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ABSTRACT

We explore a new mechanism by which investors take correlated shortcuts, and present evidence that managers undertake actions—in the form of sales management —to take advantage of these shortcuts. Specifically, we exploit a regulatory provision wherein a firm's primary industry is determined by the highest sales segment. Exploiting this regulation, we provide evidence that investors classify operationally nearly identical firms vastly differently depending on their placement around this sales cut-off. Moreover, managers appear to exploit this by manipulating sales to be just over the cut-off in favorable industries. Further evidence suggests that managers then engage in activities to realize large, tangible benefits from this opportunistic action.

JEL Classification: G02, G10, G32.

Key words: Industry window dressing, opportunistic management, discontinuity, favorable industries.

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 resource allocation problem with respect to selecting and processing each potential signal. Indeed, if 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 may affect prices, and further how firm managers may react. 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 conglomerate firm have a primary industry, determined by the segment with the highest percentage of sales. 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 53% of its sales from technology and 47% of sales from lumber is classified as a technology firm, whereas a firm with nearly identical[1] operations but that gets 47% of its sales from technology and 53% 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 the idea of "naive categorization" by examining both stock return patterns and more directly investor behavior. First, we explore how investors price these conglomerate 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] We use *"nearly identical" but on either side of the threshold* throughout the paper to refer to two firms that operate in two identical segments, but sit on opposite sides of the 50% threshold within a 5% band of that threshold. While we control for observable characteristics, there are many potentially unobservable firm attributes amongst the two firms that may be related to the choice of primary industry classification.

significantly higher betas with respect to that industry than firms just below the 50% point. So, in the example above, the 53% technology firm's price moves much more closely with the technology industry than does the 47% 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 ($t = 4.91$) 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 (based on past holdings). For firms that are nearly identical in their exposures to a particular industry, with the only difference being just above versus below the discontinuity,[2] 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 entire 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, and 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 60% ($t = 2.27$) 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

[2] Throughout the paper, when using "just above" or "just below" the 50% industry classification threshold, we are referring to firms in the five percent bands to either side of the 50% threshold (i.e., 45.00%-49.99% for just below and 50.00%-54.99% for just above).

distribution. It is important to note that while our results on industry beta, as well as 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.

The main focus of the paper is to examine how firm managers may take advantage of these investor shortcuts.[3] Our empirical design builds on the existing literature on earnings manipulation by firms and return manipulation by hedge funds. For example, prior studies on earnings manipulation around the zero earnings surprise threshold (e.g., Burgstahler and Dichev (1997) and Degeorge, Patel, and Zeckhauser (1999)) first establish that there is a discontinuous jump in investor response directly around the zero threshold: The return differential between just meeting versus missing the consensus by a single penny is much larger than any other penny movement in reported earnings. They then show that disproportionately more firms cluster just to the right of the zero earnings surprise cut-off than to the left, suggesting that managers manipulate earnings in order to land on the right side of the threshold. In other words, by exploiting a discontinuity in investor response, and correspondingly firm distribution, these studies provide evidence that managers manipulate firm operations (e.g., earnings) for short-term valuation purposes.[4]

The analog in our setting is the discontinuity around the industry classification threshold. To this end, we identify situations in which it would be advantageous to be

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[3] An example of this is Rock of Ages Corporation (ROAC). Rock of Ages was a business engaged in mining materials and manufacturing headstones and tombstones, which they sold directly to cemeteries. Their main line of business and sales revenue (and therefore primary SIC code) was in Retail. In 2008, the mining sector became favorable, partly due to soaring commodity prices. Consequent with this, mining funds were getting large fund inflows. Rock of Ages, at the same time, shifted some of its sales to the mining sector – enough to barely be over the 50% classification threshold as a mining firm. In 2008 – in fact - the firm received 50.7% of its sales from the mining industry, officially shifting to being classified as a Mining sector firm.

[4] Relatedly, in the asset management setting, Bollen and Poole (2009, 2012) exploit a discontinuity at 0% for reported returns by hedge funds (i.e., investors view 0% as a natural benchmark for evaluating hedge fund performance). They first document a discontinuous jump in capital flows to hedge funds around this zero return cut-off. They then provide evidence that disproportionately more hedge funds cluster just to the right of this return threshold than to the left.

considered part of a given industry (relative to other industries). Specifically, we use periods in which certain industries have higher valuation 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 market-to-book measure; both measures produce identical results. Importantly, this higher industry valuation need not be misvaluation; for instance, it could also represent lower industry risk or increased investment opportunities.[5]

To capture managerial behavior to "window dress" their industry classification, we 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 explore 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 both non-favorable industries).

We find 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% cutoff in the distribution of firm operations based on percentage sales from the favorable industry. We find no

[5] 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.

similar jumps anywhere else in the distribution, consistent with managers taking specific actions to be classified into favorable industries. 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 among *all* firms, so no discontinuous jump anywhere in the distribution.

As further evidence consistent with these firms taking real 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 or 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 may 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.

After providing evidence consistent with firm manipulation, we explore in depth the multitude of benefits afforded to firms, and importantly to managers themselves, from this manipulated classification. We begin with the market's reaction to a firm's entry into the favorable industry. We find that at the first announcement of their switch to the favorable industry, firms experience significant abnormal returns of 140 basis points ($t = 2.38$). These occur around annual earnings announcements where segment sales are also revealed; so in total, their cumulative abnormal returns (CARs) around earnings announcements are almost four times the average earnings announcement return in our sample. For firms switching to just above the discontinuity cutoff, where there is likely more uncertainty in the classification prior to announcements, this abnormal return is even larger at 280 basis points ($t = 3.78$).

These switching firms also appear to take advantage of the higher valuation in many ways. First, they undertake significantly more Seasoned Equity Offerings (SEOs), as well as more stock-financed mergers and acquisitions (M&As), consistent with these firms exploiting the temporary overvaluation in their equity. In terms of the economic magnitude, we see a 41% increase ($t = 2.53$) in SEOs and a 20% increase ($t = 4.46$) in stock-financed M&A activity. Second, managers of firms that switch into favorable industries engage in significantly more insider trading, nearly 31% ($t = 2.34$) higher than non-switching firms. These switching managers also exercise significantly more their stock options, by about 42% ($t = 2.45$), following their switch into the higher-valued industry. All of these suggest tangible and sizable benefits to managers and firms from industry window dressing.

We believe the sum of these results point most consistently to firm manipulation around industry classification, and that there are a number of features of this setting that allow us to more cleanly identify manipulation relative to the prior literature. That said, the results must be interpreted with an appropriate caveat. Namely, given that firms can manipulate sales to select into their industry classification, this potentially violates the random assignment assumption of regression discontinuity design (RDD) to establish a causal impact of primary industry assignment on investor behavior and asset prices (which we discuss further in Section 3.3).

Our results make several contributions to the literature. First, our results are novel from the industrial organization perspective. There is an extensive literature examining the determinants of industry entries and exits. Jovanovic (1982) proposes a survival of the fittest type equilibrium model of industry dynamics. Bresnahan and Reiss (1991) develop a framework for measuring the impact of competitive response to firm entry into industries based on the concentration of the industries, while Dunne, Roberts and

Samuelson (1988) document long-horizon rates of firm entry and exit across different U.S manufacturing industries.[6] Berry (1992) and Khandiyali (1996) examine determinants of entry (and deterrence) in oligopolistic markets, specifically focusing on the airline and photographic film industries, respectively. Samaniego (2010) then examines a broad set of industry entry (and exit) decisions, relating these to the industry-wide rates of investment-specific technical change. Lastly, Doraszelski and Markovitch (2007) propose a dynamic model of advertising competition in which advertising impacts consumer awareness and loyalty, and firm entry and exit decisions are made jointly with advertising. Rather than focusing on competitive- and product-market based incentives for firms' switching industries, we document industry choices based on valuation motives.

Second, our evidence complements the findings in the real earnings management literature (e.g., Roychowdhury (2006) and Cohen et. al (2008)), which examines firm operations such as R&D spending, SG&A expenditures, disposal of long-lived assets, and price discounts, along with their impacts on earnings.[7] Our industry window dressing setting is unique in that it works directly through industry classification, in contrast to the real earnings management literature which relies on actions taken—e.g., advanced sales recognition—working first through reported earnings, and then solely through the impact of earnings on prices.

Our work also adds 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. Subsequent empirical studies provide some evidence for these predictions: Using the

[6] A number of other papers examine firm entry and exit, both proposing theoretical dynamics and establishing empirical regularities (e.g., Hopenhayn (1992), Ericson and Pakes (1995), and Agarwal and Gort (1996)).

[7] We also complement the literature on the laddering down of earnings forecasts (e.g., Richardson, Teoh, and Wysocki (2004), Ke and Yu (2006)).

market-to-book ratio as a measure of equity misvaluation (or investor sentiment), prior studies show that many firm decisions, such as dividend payments, equity issuance, stock splits, and disclosure policy are motivated in part by short-term share price considerations.[8]

Finally, our study contributes to the literatures on style investment. Barberis and Shleifer (2003) argue that investors tend to group assets into a small number of categories, causing correlated capital flows and correlated asset price movements. Vijh (1994) and Barberis, Shleifer, and Wurgler (2005) provide one such example using S&P 500 Index membership changes.[9] Our work complements these studies by showing that investors also categorize firms along the industry dimension.[10]

1. 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

[8] 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 (2014). Baker, Ruback, and Wurgler (2007) provide an excellent review of this topic. There is a related strand of literature in management that shows that firm classification impacts how market participants view these firms (Zuckerman (2000, 2004)).

[9] Other examples in the empirical literature include Froot and Dabora (1999), Cooper, Gulen, and Rau (2005), Boyer (2011), 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).

[10] There is also a growing literature on investors' limited attention to information and asset prices. 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), Cohen and Lou (2012), and Dechow, Lawrence, and Ryans (2015) find that investors respond quickly to information that attracts their attention (in our case, the primary industry classification) but tend to ignore information that is less salient yet material to firm values (in our case, the actual operations of different segments).

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 various alternative definitions of industries (e.g. the North American Industry Classification System (NAICS)), as these different industry definitions are fairly similar at the two-digit level. (We also obtain similar results using one-digit SIC codes.) Conglomerate firms in our sample are defined as those operating in more than one industry.[11] 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,[12] whereas the upper cutoff of 110% weeds out apparent data errors. In the robustness check session, 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.

[11] We also check that the primary SIC code of the firm matches the SIC code of the firm's largest segment, which holds 95% of the time. In addition, we also run our discontinuity tests kicking out this small percentage of non-matches, and the results become stronger in magnitude and significance.

[12] 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.

Our main measure of industry favorability among investors is motivated by recent studies on mutual fund flows. (In robustness checks, we also use the industry M/B ratio to measure industry favorability, and obtain similar results.) Coval and Stafford (2007), Frazzini and Lamont (2008), and Lou (2012) find that mutual fund flows to individual stocks reflect investor sentiment: flows are positively associated with contemporaneous firm valuation and negatively forecast expected returns. We follow Lou (2012) to compute a $FLOW$ measure for each individual stock,[13] drawing on the empirical finding that fund managers proportionally scale up or down their existing holdings in response to capital flows.[14] 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 (and similarly for other industry definitions). 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.[15] 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.

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

[13] $FLOW$ is a measure of flow-induced trading defined as dollar flows multiplied by portfolio weight summed across all mutual funds for that firm-quarter.

[14] Lou (2012) shows that 62 cents of each dollar of inflows goes into scaling up current positions; for outflows, mutual funds scale down their current positions dollar for dollar.

[15] We have experimented with defining favorable industries as the top 20%, 25%, 30%, 35%, and 40%, and the results are very similar in both magnitude and significance.

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 that gained favorable industry classifications engage in more M&A transactions. We also analyze firms' equity issuance decisions in response to industry favorability. We construct equity issuance from the SDC database. Next, we obtain information on top executives' compensation from Compustat's ExecuComp database, and information on insider trading from Thomson Reuters. 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.

Table I shows summary statistics of our sample. 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. The first bin includes all conglomerate firms whose smaller segment out of the top two contributes between 10% and 20% of the combined sales of these two segments, the second bin includes all conglomerate firms whose smaller segment out of the top two contributes between 20% and 30% 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, out of about 1800 (so roughly 7% switchers per 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.

2. Investor Shortcuts

2.1 Shortcuts and Industry 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. 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.[16] For example, a firm that receives 47% of its sales from industry A and 53% 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 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 lower to higher fractional sales. The results, shown in Panel A of Table II, indicate

[16] We focus on two-segment firms in this analysis because the presence of a third segment adds noise to our estimation of industry betas. 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.

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 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 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.

2.2 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 particular industry sector. As very few mutual funds 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%) in the prior year, either by choice or due to institutional constraints, we classify the mutual fund as concentrating on that given sector.[17] For every two-segment conglomerate firm, We then compute the proportion of sector funds holding the stock from each industry, in which the conglomerate firm operates, in months 6 to 18 after the fiscal year end. 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.[18]

[17] 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. We exclude the firm in question from this exercise to avoid any mechanical relation.

[18] We focus on the number of sector funds holding the stock rather than the total value invested, because the latter also reflects fund managers' views on the stock's future returns.

Panel B of Table II shows the proportion of sector mutual funds that hold the stock as we vary the fractional sales from that sector. As with industry beta, 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. These results suggest that in their investments, mutual fund managers rely on conglomerate firms' primary industry classification rather than actual firm operations. In Appendix Table A1, we provide further evidence that the jump in industry beta and that in sector fund holdings across the 50% cutoff are closely linked: larger jumps in industry beta are indeed accompanied by larger increases in sector fund holdings.

2.3 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 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 Panel A of Table II.

As in our tests on sector mutual funds, at the end of each quarter, we 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.[19] We then compute the proportion of analyst

[19] We use coverage data provided by IBES in the previous five years for each analyst (our results are robust if we use coverage information in the previous one to four years). For instance, using a 3-year definition of analyst covering, the jump at the 50% cut-off is large and significant 0.175 (t=2.07). We exclude the stock

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.

Table II Panel C shows the fraction of analysts covering a firm as we vary the fractional sales from that sector. 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 in the 50–55% bin, 52.0% of the analyst coverage is from that industry.[20] 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 small in magnitude and statistically insignificant from zero. This pattern can be also seen from the bottom right panel of Figure 1.

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, 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 heuristics. 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.

3. Industry Window Dressing

The main thesis of the paper is to identify opportunistic actions managers take to

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in question in the procedure of analyst industry assignments to ensure that our results are not mechanically driven.

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

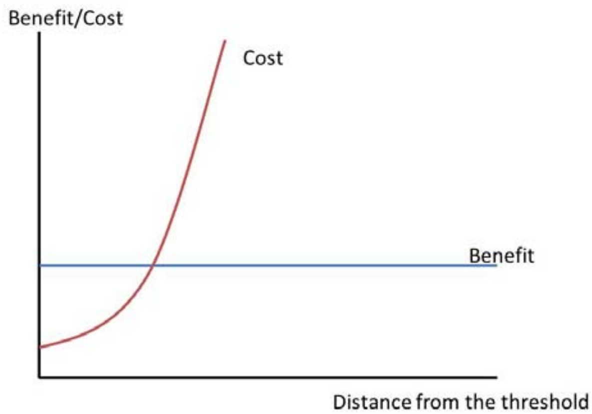
exploit investor shortcuts, and to document managers' private benefits, along with firm benefits, from these opportunistic actions. In order to do this, we again exploit the SEC regulation of primary industry classification to establish specific actions managers take to "fool" investors into thinking that they are part of a given industry. We term such actions Industry Window Dressing.

3.1 Identification of Industry Window Dressing

We first identify situations where certain industries in certain periods are more "favorable"—i.e., have a higher valuation or a lower cost of capital—than others. Thus, it would be advantageous to be considered part of these "favorable" industries in precisely these periods. 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 driven by shifts in investor sentiment. We are agnostic to 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. Appendix Table A2 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. Specifically, the industry decile with the largest capital inflows outperforms the decile with the largest capital outflows by more than 1% per month (t = 4.45) in a calendar-time portfolio analysis. In the following two years, this 12% return differential *gradually* reverses. We label these high valuation industries—i.e., top 20 as ranked by industry $FLOW$—"favorable" industries, and the complement set as "non-favorable" industries. (We show nearly identical results in magnitude and significance using the industry M/B ratio as a measure of industry valuation. These are shown in Panel C of Table XII and Figure 3, and are discussed in Section 5.2.)

Even with industry valuation being time-varying, it still leaves the question of when it is optimal for firms to opportunistically switch into a favorable industry. The cost-benefit tradeoff of industry windows dressing can be illustrated in a simple figure:[21]



Benefit/cost of switching into the favorable industry as a function of distance from the threshold

The reason we focus on firms just around the 50% discontinuity cut-off is that while they have a similar benefit for being reclassified into the favorable industry (as shown above), their cost of manipulating sales sufficiently to reach the threshold is sharply lower.[22] This means that the benefit-cost trade-off of window dressing is the highest for firms just below the threshold (close to zero in the figure above), and therefore we expect this to be the most likely place in the distribution to identify industry window dressing behavior.

[21] We are grateful to the referee for suggesting this framing.

[22] The sharply increasing cost of manipulating sales as a firm moves away from the threshold is driven by a number of factors. For instance, we discuss two potential mechanisms through which firms can industry window dress: i.) through price discounts and, ii.) through inflated sales reporting which requires future restatements. Both of these mechanisms are locally feasible for small manipulations of sales (e.g., 49% sales to 50%), but are much more costly for larger magnitudes of sales manipulation (e.g., 30% sales to 50%) – due to, for example, the probability of being caught for larger manipulations.

To implement this idea, 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 these 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 sales weight in the non-favorable industry. Since the larger of the two segments determines the industry classification of the firm, the 50% sales cutoff is the relevant discontinuity point for industry status. If firms truly are manipulating operations opportunistically, we expect to see disproportionately more firms clustering just above the discontinuity cutoff of sales from the favorable industry (i.e., 50%), so that they can benefit from being classified as a member of these favorable industries.

Figure 2 shows the distribution of conglomerate firms in our sample around the 50% cut-off. Specifically, it 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 53% tech–47% lumber firm will be presented to investors as a tech firm, whereas the 47% tech–53% 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 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 explanation 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. Thus, firms in both bins around the 50% discontinuity would experience the same increase in sales activities, and would display no discontinuous jump between the two.

To test the 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 III, 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 increase 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.[23] 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.[24] Each blue circle 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.

We conduct two further tests to ensure robustness. First, we split our sample into two sub-periods of large versus small differences in mutual fund flows between the favorable and non-favorable industries. The idea is that when there is a larger difference in mutual fund flows, there are also larger differences in relative industry valuation, and thus managers are more incentivized to manipulate industry classification. As can be seen in in Appendix Figure A2, the discontinuous jump in firm distribution is much higher in periods with larger fund flow differentials than in periods with smaller differentials: 35% ($t = 2.78$) versus 19% ($t = 1.41$).

Second, we focus on conglomerate firms where the top two segments of the firm are sufficiently different in their favorability/popularity ranking. In particular, rather than

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

[24] 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 versus a positive jump in distributions). We see both of these in the data, and the difference between the two is strongly statistically significant.

requiring the two segments to be one favorable and one non-favorable (based on some fixed cutoff), we require the ranking difference between the top two segments to be at least 25 (out of around 70 industries). (The results are similar if we require the difference to be at least 20, 30, or 35.) As shown in Appendix Figure A3, we see a similar discontinuous jump in distribution at the 50% cutoff point for this subsample of conglomerates: 27% ($t = 2.43$).

3.2 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% 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 segment 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 III, Panel A, using the *same* set of conglomerate firms. But instead of sorting on segment sales, we sort on other accounting variables, such as segment 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 Table III, 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 profits or assets can also be seen in the top right and bottom left panels of Figure 3, respectively.[25]

3.3 Regression Discontinuity (RD) versus Discontinuity

It is important to distinguish the different methodologies we use in Section 2 versus Section 3. Section 2 - on investor and financial agent behavior - uses a regression discontinuity approach, where the key assumption is that firms are randomly assigned to the left and right sides of the 50% cutoff. In contrast, Section 3 - the main focus of the paper - uses a discontinuity approach whereby firms strategically select which side of the cutoff to be on. Clearly, the potential issue is that the behavior of firms we document in Section 3 violates the key assumption of regression discontinuity in Section 2. This is similar to the earnings manipulation literature in which firms manipulate earnings to meet or barely beat earnings expectations – i.e., to actively select which side of the zero earnings surprise point to be on; this however violates the assumption needed to establish that meeting or barely beating earnings expectations actually affects investor behavior and stock returns.

To help address this concern, recall that a key condition in Section 3 is that the top two segments of these conglomerate firms are one favorable and one non-favorable, so that managers are incentivized to manipulate the primary industry classification. Here, we focus on a different subsample of conglomerate firms whose top two segments operate both in non-favorable industries (or *both* in favorable industries). This sample of firms has no apparent incentives to select and thus is closer to the assumption of random

[25] 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 III, we see no evidence of discontinuous jumps when sorting firms 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.

assignment around the 50% cutoff. We run our investor behavior tests on this subsample and see identical results to those reported in Table II. For instance, as shown in Table XII, Panel A, the average industry beta for firms in this subsample in the 50%–55% bin is 0.235 after controlling for known risk factors, whereas that in the 45%–50% bin is 0.156. The difference of 0.079, representing a 51% increase, is statistically significant ($t = 2.38$). Moreover, the difference in industry beta between any other two adjacent bins is statistically zero.

3.4 Mechanisms

We next explore the mechanisms through which firms may opportunistically adjust segment sales to ensure 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. The second is that firms strategically report segment sales in order to be classified into the favorable industries.

3.4.1 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.[26] This can lead to more booked sales, but at the same 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 growth. We use the same setting as in Table III—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

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

industry (i.e., firms just above the 50% classification cutoff[27]) should have lower profit margins and depleted inventories compared to other firms. Panel A of Table IV 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 possibility by looking at the profitability in the non-favorable segment for firms that surround the 50% cutoff. 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 IV, Panel C, inventory growth is 30% lower (t = 2.28) for firms in the 50-60% bin compared to both adjacent bins; further, there is no statistically significant difference between any other two bins.

We also run falsification tests focusing on firms whose top segments are both in favorable (or non-favorable) industries, so there is little incentive to opportunistically

[27] Throughout the empirical analysis, when using “just above” or “just below” the 50% industry classification threshold, we are referring to firms in the five percent bands to either side of the 50% threshold (i.e., 45.00%-49.99% for just below and 50.00%-54.99% for just above).

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 discontinuous jumps in firm distributions, segment profitability, and inventory growth at the 50% sales cutoff. Nonetheless, we test this alternative story by exploring whether firm segment investment (capital expenditures and R&D spending) also exhibits a similar discontinuous pattern at the industry classification cutoff. As shown in Appendix Table A3, Panels A and B, for both capital expenditures and R&D spending, there is no difference in firm investment around the discontinuity point.[28] 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.

3.4.2 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

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

a non-favorable industry for statistical power reasons (more discussion on this test design is in Section 4).

The accounting restatement results are shown in Table V.[29] Columns 1 and 2 run the accounting restatement analysis with a variable to capture opportunistic switchers from non-favorable to favorable industries (*SWITCH*). These firms are significantly more likely to restate earnings compared to non-switchers. The coefficient in Column 2 of 0.382 ($t = 3.35$) 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. Importantly, after controlling for ($\Delta\%SALES_{t-1}$), the switch dummy now mainly captures the effect of crossing the 50% cutoff.

Columns 3 and 4 then run the analysis including a variable to capture all other types of switchers: (i) from a non-favorable to another non-favorable industry; (ii) from a favorable to another favorable industry; or (iii) from a favorable to a non-favorable industry. We term these firms *PLACEBO SWITCHERS*. 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.'

4. Market Reaction, Private Benefits to Managers, and Benefits to Firms

In this section, we provide evidence that both managers and firm investors accrue significant benefits from industry window dressing. Throughout the paper, we use a 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

[29] Restatement data begins in 1994, cutting our sample (which begins in 1980) roughly by half.

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; yet, we gain a group of firms that act decisively to move into favorable industries.[30] Along with this, we gain the exact timing of *when* firms take the actions to move into the favorable industry. Given how important this timing is for our measurement of the marginal benefits to firms and managers, we use this switching sample for these tests.

4.1 Market Reaction

The first potential benefit we examine is that of a firm value increase at the time of announcing a switch into the favorable industry. Investors find out about firm's reclassification at the annual reporting of sales figures, which usually takes place at the fourth quarter earnings announcement. We focus on stock returns around this event. Specifically, we predict that firms that switch from non-favorable to favorable industries (e.g., from machinery to tech during the NASDAQ boom) should have higher announcement day returns than their peers.[31]

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 a dummy for firms that switch from non-favorable to favorable industries at the given announcement (*SWITCH*). 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 mainly reflects the effect of crossing the 50% cutoff. We

[30] 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 increases by 0.046 ($t = 2.53$), representing a more than 20% increase in beta.

[31] 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 (over the prior three quarters), so may be partially anticipated before the official financial statements are released.

also control for standardized unexpected earnings (*SUE*),[32] defined as the difference between the consensus forecast and reported earnings scaled by lagged stock price. The results are reported in Table VI. As can be seen from Column 2, switching firms have cumulative announcement returns that are 140 basis points ($t = 2.38$) larger, relative to the average announcement return of 46 basis points. Thus, the total announcement return for switchers of 186 basis points (140+46) is close to four times the size of the average announcement return. This holds after controlling for firm characteristics that are linked to average stock returns, as firms that switch from non-favorable to favorable industries continue to outperform their peers by 120 basis points ($t = 2.08$) around the announcements.

A more economically powerful way of testing this announcement day return effect is to focus on situations with more 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 switching firms having between 45% and 55% of sales from the favorable segment (i.e., to focus on switchers that are barely classified into favorable industries and those that barely miss), the announcement day return effect doubles in magnitude and is even more statistically significant, despite the much smaller sample size. These are reported in Table VI, Columns 4-6. As can be seen from Column 5, firms reporting sales of 50-55% from the favorable segment have an announcement day return that is 280 basis points ($t = 3.78$) higher than those reporting sales of 45-50% from the favorable segment. This again remains economically large and statistically significant after including firm-level controls.

As further evidence that managers are opportunistically timing their entrance into the favorable industries, we find that these high valuations are gradually reversed in the subsequent years. We show this in Appendix Figure A1. The solid blue curve corresponds

[32] When we merge in IBES data (which is needed to calculate SUEs), this reduces the cross-section, as not all firms are covered by analysts.

to the set of switchers from a non-favorable to a favorable industry; the dashed green curve corresponds to all "placebo switchers" (i.e., those switching from non-favorable to non-favorable, from favorable to favorable, and from favorable to non-favorable industries). The dotted red curve shows the difference in event-time returns between the two subsamples. First, we see that only switchers into the favorable industry see the valuation jump at the time of switching. Subsequently, this difference in cumulative returns following switching (from months 0 to 18) shows a significant reversal of -9.09% with a t-statistic of -2.04.

4.2 Private Benefits – Insider Trading and Compensation

We then explore the private benefits that managers receive from switching into the favorable industry. We start by examining managers' insider trading in their firms following the switch into favorable industries, with the idea that managers may want to exploit the higher firm-valuation upon joining the favorable industry by selling more shares (and similarly for their exercise of stock options).[33] We measure this using net insider selling (i.e., insider sales net of insider purchases). The main independent variable of interest is again (*SWITCH*), a dummy variable for firms that have switched from non-favorable to favorable industries during the past year. The control variables are the same as those used in Table VI, including the actual change in percentage sales from the favorable segment (Δ%SALES).

Columns 1 and 2 of Table VII show that insiders indeed engage in significantly more insider selling following the switch into favorable industries. The coefficient in Column 2 of 0.267 ($t = 2.34$) implies that net insider selling by top executives increases by 31% following switching into the favorable industry. Columns 3 and 4 then examine the value of options exercised by top executives, while Columns 5 and 6 examine the

[33] Merging in the insider trading data from Thomson Reuters cuts our sample period start date to the beginning of that dataset (1986).

number of options exercised following the switch into the favorable industry.[34] The coefficients in Column 4 and Column 6 imply that the value and number of options exercised by top executives increase by over 60% ($t = 2.88$) and 42% ($t = 2.45$) following the switch into the favorable industry, respectively.

We then move on to analyze the impact of primary industry switching on managers' total compensation. To test this, we obtain data on the total compensation of the top executives in our firms from ExecuComp. We also segregate out the cash bonus component of the compensation along with stock-based component, and test the impacts on both separately. The results are reported in Table VIII. Columns 1 and 2 show the impact of switching into favorable industries on top managers' compensation is large and significant. The coefficient in Column 2 of 0.149 ($t = 3.00$) implies that total compensation increases by over 10% (again controlling for Δ%SALES such that the coefficient on the switch dummy mainly reflects the effect of crossing the 50% cutoff). Columns 3 and 4 then examine the impact on solely the cash bonus piece of compensation, while Columns 5 and 6 look at the impact on solely the stock-linked components—i.e., restricted stock grants and option grants. Columns 4 and 6 show, respectively, that the cash bonus increases by roughly 15% ($t = 2.13$), while the stock-linked compensation increases by 23% ($t = 3.39$) following the switch into the favorable industry. If we instead use stock compensation as a fraction of total compensation, this rises by 14.1% ($t = 3.14$).

4.3 Firm-wide Benefits – SEOs and M&A

We next explore how firms may take advantage of their higher stock valuations in the favorable industry, and find a range of benefits accruing to firms. In particular, we examine firms' SEO activity along with stock-financed M&As, with the idea that firms can now issue shares at a higher, potentially inflated price. We use the identical empirical

[34] We use a dummy for net insider trading following prior literature (Jeng, Metrick, and Zeckhauser (2003) and Cohen, Malloy, and Pomorski (2012)).

set up of Tables VII and VIII, with the dependent variables now being SEO and stock-financed M&A activity. The independent variable of interest remains *SWITCH*, a dummy variable for firms that have just switched from non-favorable to favorable industries. We continue controlling for the actual change in percentage sales from the favorable segment (Δ%SALES) in our regression specifications.

The results are reported in Table IX. The coefficient on *SWITCH* in Column 2 of 0.328 ($t = 2.53$) implies a 41% increase in equity issuance in the year following the switch. Relatedly, the coefficient in Column 4 of 1.224 ($t = 4.46$) implies a 20% increase in stock-financed M&A activity in the year following the switch into the favorable industry.[35] [36]

Appendix Table A4 then studies what firms do with the proceeds that they raise from equity issuance. We already provide evidence from Table VIII that firms use a portion of the proceeds to pay larger cash bonuses to top executives. Other potential uses of the proceeds could be to increase investment, to pay down debt, or to pad cash reserves. In particular, we examine the cash balances, investment activity, and leverage ratios of firms following the switch into the favorable industry. Columns 4 and 6 indicate that with all the controls (including Δ%SALES), there is no significant change in investment or paying down of debt. Column 2, however, shows that switching firms do significantly increase cash reserves. The coefficient on *SWITCH* from Column 2 of 0.042 ($t = 2.02$) implies that cash reserves increase by over 4% following the switch into the favorable industry.

[35] When we run this same regression on cash-financed M&A activity (as opposed to stock-financed), we find no significant impact, suggesting it is something unique to using the higher-valued currency of favorable industry equity in these transactions.

[36] We repeat the analysis on insider trading and firm benefits for the tighter switching sample of solely those firms tightly surrounding the discontinuity (45%-55% sales in the favorable industry). We find that the economic significance in this cleaner sample is larger (reported in Appendix Tables A5 and A6).

4.4 *Truthful Switchers*

So far in this section we have focused on all firms that switch from non-favorable to favorable industries. However, some of these firms may be moving into the favorable industry "truthfully" (i.e., costly moves in firm operations and focus). Given their different entry motives, we may expect these truthful switchers to behave differently than opportunistic switchers once entering the new industry. In order to test this, we need a way to empirically delineate, and so separate out, "truthful" switchers from the opportunistic switchers in the sample. We do this using the costly real activities of the firms.

We show in Section 3 that the industry window dressers, while having percentage sales in the favorable industry right above the 50% threshold, do not exhibit the same ramping up of investment in physical or intellectual capital in the favorable industry. Here, we focus on switchers that also shift their actual operations (e.g., capital expenditures) into the favorable sector. We label these firms "truthful switchers."

We then run each of our benefit tests on these segregated-out truthful switching firms. First, we show that these truthful switchers experience roughly the same magnitude of positive return on announcement date as all other switching firms, of 93 basis points.[37] However, we do not find a large difference in other benefits to the firms and managers of truthful switchers, shown in Table X. In particular, when we replicate exactly Tables VII-IX, but solely on the subset of truthful switchers, we find that these firms are no more likely to do SEOs or stock-financed M&A following the switch. Further, the managers engage in no more insider selling or option exercising, nor do they receive more compensation. This is in contrast to opportunistic switchers, who do more SEOs, stock-

[37] While the return is large, and of roughly similar magnitude as all switchers, it is not significant due to the sample size.

financed M&A, along with engaging in significantly more insider selling and option exercise following their switch.[38]

5. Window Dressing during Conference Calls and Robustness Checks

5.1 Window Dressing by Managers during Quarterly Earnings Conference Calls

In Table XI, we test whether managers of the opportunistic switching firms also take other actions in public forums to signal to investors that they are now part of the favorable industry. In particular, we examine all quarterly conference calls of publicly traded firms and their managers' references to the favorable industry (vis-à-vis their other segments) right after the switch.

We begin with the universe of all earnings conference call transcripts from 2003-2013. We then create a list of industry-specific keywords (Appendix Table A8) in order to classify the text of each managerial presentation section within the conference call (this is the portion of the conference call that managers have complete discretion over, and create before the call begins to deliver at the beginning of the call to frame discussion). Once we classify the text of the presentation section for every conference call, we then use this data to test for managers' differing usage of these words in the earnings conference calls as they opportunistically switch industries. We find that opportunistic switchers use significantly more keywords from the favorable industry precisely around the times of the switch, as shown in Table XI. For instance, the coefficient of 0.379 (t=2.21) from Column 4 implies that the opportunistic switchers increase their use of favorable industry references by close to 40%.[39]

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[38] We further repeat our analyses of manager and firm benefits focusing on placebo switchers. As shown in Appendix Table A7, there is no significant difference between these placebo switchers and other firms.

[39] We also run these tests for placebo switchers as a falsification test, finding that – as expected - they exhibit no commensurate increase in industry word usage following their switch (Table XI, Columns 5 and 6).

5.2 Additional Robustness Tests

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. For instance, using the one-digit SIC code to define segments, the jump in the distribution density at the 50% sales cut-off is 23% ($t = 2.37$). 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). As shown in Table XII, 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 XII, 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 III.

Finally, we examine the cross-sectional variation in the extent to which firms are able to benefit from industry window dressing. First, we examine the impact of price-elasticity of demand on firms' industry window dressing. We use a common proxy from the literature, industry competitiveness (Domowitz, Hubbard, and Petersen (1986)), measured using the Herfindahl index of firm sales within the industry. We find that the higher the price elasticity of demand, the higher the tendency to engage in industry window dressing (as firms can now more easily manipulate total sales through price discounts). This is shown in Appendix Figure A4.

Next, we use a number of proxies for limited attention and difficulty in information processing: the number of segments, share turnover, idiosyncratic volatility, and firm size. We find evidence, reported in Table XII, Panel D that both the industry beta change and announcement day return results are stronger in the subsample of firms that are more complex and attract less attention (e.g., firms with smaller size, lower turnover, higher idiosyncratic volatilities, and a larger number of segments). Further, we find similar corroborating results for the discontinuity in the sales distribution. This latter evidence suggests that managers understand (at least partially) the extent to which their investor base might be more or less susceptible to industry window dressing.

6. Conclusion

We document a shortcut that financial agents take and show evidence that it impacts both prices and managerial and firm 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. We find evidence that investors overly rely on this industry classification in their investment decisions without sufficiently factoring in firms' underlying economic operations.

We then show evidence suggestive of managers taking specific actions in order to take advantage of this - to gain classification into "favorable" industries (i.e., those with high valuations). In particular, firms that operate in favorable and non-favorable sectors and are near the industry assignment cutoff are significantly more likely to be just over the 50% classification cut-off point in terms of percentage sales from the favorable segment; we find no such jumps anywhere else in the sales distribution of these firms, consistent with managerial/firm behavior specifically to exploit the industry classification cut-off. These industry window dressers also dedicate a disproportionate amount of their earnings conference calls to the favorable industry; however, they show no move in actual operations (capital expenditure or R&D) toward the favorable industry.

Lastly, our evidence suggests that both current investors and top executives gain large tangible benefits from opportunistically industry switching. First, 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. Managers also engage in significantly more insider trading following the switch into the favorable industry through both elevated levels of insider selling and elevated exercising of stock options.

In sum, we exploit a novel setting in which investors take correlated shortcuts that can cause simple pieces of information to be systematically unreflected in firm prices. More importantly, we show evidence consistent with firm managers taking opportunistic actions to exploit these investor shortcuts, providing tangible benefits to both themselves and 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 flow-induced trading in each industry—over the prior year, where industries are defined 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 calculate $INDFLOW$. Panels B and C report segment and firm specific characteristics. Profit margin is defined as the segment's operating profit divided by 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: Industry Categorization

This table shows results on industry categorization. In Panel A, 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 (controlling for known risk factors), using data from months 6 to 18 after the fiscal year end. In Panel B, 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 in Panel C, we assign each sell-side analyst covering at least five 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 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 exclude the stock in question from the corresponding industry portfolio in all panels. We focus on conglomerate firms that operate in exactly two 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 of each panel reports the average in each bin, the second and third rows report the difference 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 10%, 5%, and 1% 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 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
Panel B: 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 C: 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
	(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 III: 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 compute $INDFLOW$. 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 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 10%, 5%, and 1% 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 IV: 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 compute $INDFLOW$. 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, 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. T-statistics, shown in parentheses, are based on standard errors clustered at the year level. *, **, *** denote significance at the 10%, 5%, and 1% 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								
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								
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				
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 V: 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 from a non-favorable to a favourable industry in the fiscal year, and zero otherwise. $PLACEBO\ SWITCH$ is a dummy that takes the value of one for all other industry switchers: (i) from a non-favorable to another non-favorable industry; (ii) from a favorable to another favorable industry; or (iii) from a favorable to a non-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 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 10%, 5%, and 1% level, respectively.

	Restate Dummy	Restate Dummy	Restate Dummy	Restate Dummy
	[1]	[2]	[3]	[4]
$SWITCH_{t-1}$	0.285***	0.382***	0.283***	0.365***
	(2.93)	(3.35)	(2.89)	(2.88)
$PLACEBO\ SWITCH_{t-1}$			-0.096	-0.002
			(-0.69)	(-0.01)
$\Delta\%SALES_{t-1}$		-0.803***		-0.769**
		(-2.27)		(-2.29)
$MKTCAP_{t-1}$		0.033		0.040
		(0.66)		(0.83)
BM_{t-1}		0.070		0.050
		(1.01)		(0.76)
$RET12_{t-1}$		-0.131		-0.149
		(-1.12)		(-1.31)
$TURNOVER_{t-1}$		0.073*		0.079*
		(1.74)		(1.88)
$IDIOVOL_{t-1}$		0.278***		0.274***
		(5.45)		(5.61)
$INSTOWN_{t-1}$		3.211***		3.218***
		(2.67)		(2.77)
Pseudo R^2	0.00	0.09	0.00	0.09
No. Obs.	22,338	22,338	23,769	23,769

Table VI: Return Effect around Annual Announcements

This table reports regressions of earnings announcement day returns on primary industry classification changes. The dependent variable is the cumulative 3-day return around an annual earnings announcement. The main independent variable in the first three columns is a $SWITCH$ dummy that takes 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. The main independent variable in columns 4-6, $SWITCH$, now takes the value of one if the firm gets 50-55% of its sales from a favorable industry, and zero if it receives 45-50% of its sales from a favorable industry. 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 all columns. T-statistics, shown in parentheses, are based on standard errors that are clustered at the year level. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

DepVar	Announcement Day Returns					
	[1]	[2]	[3]	[4]	[5]	[6]
$SWITCH_{t-1}$	0.015**	0.014**	0.012**	0.026***	0.028***	0.018**
	(2.42)	(2.38)	(2.08)	(3.53)	(3.78)	(2.35)
SUE_t		0.199***	0.240***		0.621***	0.757***
		(5.47)	(5.02)		(3.84)	(4.46)
$\Delta\%SALES_{t-1}$			0.006			0.002
			(0.42)			(0.14)
$MKTCAP_{t-1}$			-0.001			0.006
			(-1.25)			(1.61)
BM_{t-1}			0.001			-0.014
			(0.39)			(-1.13)
$RET12_{t-1}$			-0.005			-0.013
			(-1.63)			(-1.44)
$TURNOVER_{t-1}$			0.001			0.001
			(0.23)			(0.26)
$IDIOVOL_{t-1}$			-0.065			-0.148
			(-0.34)			(-1.33)
$INSTOWN_{t-1}$			0.011**			0.064**
			(2.21)			(2.09)
Adj. R^2	0.01	0.03	0.04	0.02	0.04	0.08
No. Obs.	10,648	10,648	10,648	543	543	543

Table VII: Insider Selling and Option Exercise

This table reports regressions of insider selling and managerial option exercises on primary industry classification changes. The dependent variable in columns 1 and 2 is a net insider selling (i.e., sales – purchases) dummy that takes the value of one if the amount of net insider sales is above the median in the fiscal year, and zero otherwise. The dependent variable in columns 3 and 4 is the logarithm of the dollar value of options exercised scaled by the firm's lagged market capitalization, and that in columns 5 and 6 is the logarithm of the number of options exercised scaled by the firm's lagged shares outstanding. The main independent variable is a $SWITCH$ dummy that takes 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 firm size, book-to-market ratio, lagged one-year stock return, monthly share turnover, stock idiosyncratic volatility, and proportion of institutional ownership. Columns 1 and 2 conduct panel logit regressions, and columns 3-6 conduct panel OLS regressions with year-fixed effects. Z-statistics and T-statistics, shown in parentheses, are based on standard errors that are clustered at the year level. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

	Net Insider Sales	Net Insider Sales	Value of Options Exercised	Value of Options Exercised	Number Options Exercised	Number Options Exercised
	[1]	[2]	[3]	[4]	[5]	[6]
$SWITCH_{t-1}$	0.428***	0.267**	1.023***	0.675***	0.542***	0.421**
	(4.19)	(2.34)	(3.48)	(2.88)	(3.03)	(2.45)
$\Delta\%SALES_{t-1}$		-0.163		0.273		0.004
		(-0.47)		(0.58)		(0.01)
$MKTCAP_{t-1}$		0.0686***		-0.463***		-0.441***
		(4.28)		(-7.13)		(-10.44)
BM_{t-1}		-0.193**		-0.200**		-0.174***
		(-1.94)		(-2.16)		(-2.93)
$RET12_{t-1}$		0.138		0.550**		0.473***
		(0.82)		(2.21)		(3.30)
$TURNOVER_{t-1}$		0.479***		0.431***		0.314***
		(7.05)		(4.16)		(5.24)
$IDIOVOL_{t-1}$		-0.049		0.083		-0.187***
		(-0.01)		(0.76)		(-2.66)
$INSTOWN_{t-1}$		1.919***		3.771***		2.285***
		(7.13)		(15.70)		(16.91)
Pseudo/Adj. R^2	0.03	0.10	0.00	0.13	0.00	0.14
No. Obs.	15,744	15,744	13,933	13,933	13,933	13,933

Table VIII: Top Executives' Compensation

This table reports regressions of executive compensation on primary industry classification changes. The dependent variable in columns 1 and 2 is the logarithm of total compensation of the top five executives (i.e., the sum of base salary, bonus, other annual, restricted stock grants, option grants, and all other payments); the dependent variable in columns 3 and 4 is the logarithm of the cash bonus component; finally, the dependent variable in columns 5 and 6 is the logarithm of the stock component (i.e., the sum of restricted stock grants and option grants). The main independent variable is a $SWITCH$ dummy that takes 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 firm size, book-to-market ratio, lagged one-year stock return, monthly share turnover, stock idiosyncratic volatility, and proportion of institutional ownership. Firm- and year-fixed effects are included in all columns. T-statistics, shown in parentheses, are based on standard errors that are clustered at the year level. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

	Total Comp	Total Comp	Cash Bonus	Cash Bonus	Total Stock Comp	Total Stock Comp
	[1]	[2]	[3]	[4]	[5]	[6]
$SWITCH_t$	0.181***	0.149***	0.118	0.152**	0.387***	0.231***
	(2.72)	(3.00)	(1.52)	(2.13)	(4.16)	(3.39)
$MKTCAP_t$	0.419***	0.446***	0.394***	0.404***	0.549***	0.589***
	(64.86)	(60.30)	(31.69)	(34.57)	(38.30)	(37.94)
$\Delta\%SALES_t$		0.344***		0.262		0.428***
		(3.23)		(1.48)		(2.64)
BM_t		0.182***		0.275***		0.098***
		(8.89)		(6.93)		(4.17)
$RET12_t$		0.168***		0.391***		0.217***
		(4.56)		(4.55)		(3.97)
$TURNOVER_t$		0.044***		-0.106**		0.73***
		(3.65)		(-2.21)		(3.81)
$IDIOVOL_t$		0.010***		-0.033		0.021***
		(5.66)		(-0.73)		(5.41)
$INSTOWN_t$		0.976***		0.873***		0.965***
		(4.86)		(3.16)		(5.08)
Adj. R^2	0.49	0.56	0.26	0.32	0.38	0.43
No. Obs.	8,642	8,642	6,812	6,812	5,860	5,860

Table IX: Firm Benefits from Industry Switching

This table reports regressions of firm equity issuance and stock-financed M&A 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 issues equity in year t as reported in the SDC database, 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 year t as reported in the SDC database. The main independent variable is a $SWITCH$ dummy that takes 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 firm size, book-to-market ratio, lagged one-year stock return, monthly share turnover, stock idiosyncratic volatility, proportion of institutional ownership, firm age and firm assets. Reported below are panel logit regressions. Z-statistics, shown in parentheses, are based on standard errors that are clustered at the year level. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

	Equity Issue	Equity Issue	Stock M&A	Stock M&A
	[1]	[2]	[3]	[4]
$SWITCH_{t-1}$	0.373***	0.328**	1.183***	1.224***
	(3.39)	(2.53)	(3.95)	(4.46)
$\Delta\%SALES_{t-1}$		-0.0658		-1.270
		(0.16)		(-1.16)
$MKTCAP_{t-1}$		0.123***		0.235***
		(3.20)		(2.88)
BM_{t-1}		0.258***		-0.043
		(3.91)		(-0.13)
$RET12_{t-1}$		0.144		0.082
		(1.39)		(0.64)
$TURNOVER_{t-1}$		0.027		0.034**
		(1.35)		(2.19)
$IDIOVOL_{t-1}$		0.026		0.190***
		(0.46)		(3.82)
$INSTOWN_{t-1}$		-0.520*		0.402
		(-1.92)		(0.61)
Pseudo R^2	0.00	0.01	0.00	0.03
No. Obs.	16,167	16,167	18,644	18,644

Table X: Truthful Switchers

This table reports regressions of managerial and firm actions on primary industry classification changes. Panel A examines managerial selling decisions. The dependent variable in columns 1 and 2 is a net insider selling (i.e., sales – purchases) dummy that takes the value of one if the amount of net insider sales is above the median in the fiscal year, and zero otherwise. The dependent variable in columns 3 and 4 is the logarithm of the dollar value of options exercised scaled by the firm's lagged market capitalization, and that in columns 5 and 6 is the logarithm of the number of options exercised scaled by the firm's lagged shares outstanding. Panel B examines top executives' compensation. The dependent variable in columns 1 and 2 is the logarithm of total compensation of the top five executives (i.e., the sum of base salary, bonus, other annual, restricted stock grants, option grants, and all other payments); the dependent variable in columns 3 and 4 is the logarithm of the cash bonus component; finally, the dependent variable in columns 5 and 6 is the logarithm of the stock component (i.e., the sum of restricted stock grants and option grants). Panel C examines firm decisions. The dependent variable in columns 1 and 2 is an equity issuance dummy that takes the value of one if the firm issues equity in year t as reported by SDC, 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 as reported by SDC. The main independent variable is the $TRUE\_SWITCH$ dummy that takes the value of one if the conglomerate firm's main industry classification switches from a non-favorable to a favorable industry, and that its segment Assets and Capex in the favorable industry is also above the 50% cut-off, 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 firm size, book-to-market ratio, lagged one-year stock return, monthly share turnover, stock idiosyncratic volatility, and proportion of institutional ownership. Columns 1 and 2 of Panel A as well as the entire Panel B conduct panel logit regressions, and columns 3-6 of Panel A conduct OLS regressions with year-fixed effects. The control variables of firm size, B/M, past year returns, turnover, idiosyncratic volatility, and institutional ownership are also included in each specification (identical to Table VIII). Z-statistics and T-statistics, shown in parentheses, are based on standard errors that are clustered at the year level. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Insider Selling and Option Exercise						
	Net Insider Sales	Net Insider Sales	Value of Options Exercised	Value of Options Exercised	Number Options Exercised	Number Options Exercised
	[1]	[2]	[3]	[4]	[5]	[6]
$TRUE\_SWITCH_{t-1}$	-0.483**	-0.436*	0.502*	0.333	0.214	0.204
	(-2.31)	(-1.88)	(1.82)	(1.50)	(1.35)	(1.59)
$\Delta\%SALES_{t-1}$		0.003		0.397		0.081
		(0.01)		(0.84)		(0.25)
Other Controls		Yes		Yes		Yes
Pseudo/Adj. R^2	0.03	0.10	0.00	0.13	0.00	0.14
No. Obs.	15,744	15,744	13,933	13,933	13,933	13,933

Panel B: Top Executives' Compensation						
	Total Comp	Total Comp	Cash Bonus	Cash Bonus	Total Stock Comp	Total Stock Comp
	[1]	[2]	[3]	[4]	[5]	[6]
$TRUE\_SWITCH_t$	0.116	0.092	-0.060	0.020	0.166	0.046
	(1.58)	(1.18)	(-0.61)	(0.27)	(1.47)	(0.40)
$\Delta\%SALES_t$		0.367***		0.170		0.366***
		(3.15)		(1.17)		(3.23)
Other Controls		Yes		Yes		Yes
Adj. R^2	0.49	0.55	0.28	0.32	0.38	0.42
No. Obs.	8,642	8,642	6,812	6,812	5,860	5,860

Panel C: Firm Benefits				
	Equity Issue	Equity Issue	Stock M&A	Stock M&A
	[1]	[2]	[3]	[4]
$TRUE\_SWITCH_{t-1}$	-0.001	-0.331	0.239	0.445
	(-0.02)	(-1.42)	(0.45)	(0.86)
$\Delta\%SALES_{t-1}$		0.286**		-0.750
		(1.96)		(-0.69)
Other Controls		Yes		Yes
Pseudo R^2	0.00	0.04	0.00	0.03
No. Obs.	16,167	16,167	18,644	18,644

Table XI: Textual Analysis

This table examines the tendency/frequency of firm managers referencing keywords associated with the favorable industry in their quarterly earnings conference calls right after they switch into that industry. The dependent variable in columns 1, 2 and 5 is the change in the number of keywords related to the primary industry mentioned in the quarterly earnings conference call compared to four quarter ago, and that in columns 3, 4 and 6 is the change in the logarithm of one plus the number of industry keywords. The main independent variable in columns 1-4 is a $SWITCH$ dummy that takes 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. The main independent variable In columns 5 and 6 is the $PLACEBO\_SWITCH$ dummy that takes the value of one if the conglomerate firm's main industry classification switches in a direction other than from a non-favorable to a favorable industry, 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 firm size, book-to-market ratio, lagged one-year stock return, monthly share turnover, stock idiosyncratic volatility, proportion of institutional ownership, firm age and firm assets. T-statistics, shown in parentheses, are based on standard errors that are clustered at the year level. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

	Change in Industry Keywords	Change in Industry Keywords	Change in Log Indus Keywords	Change in Log Indus Keywords	Change in Industry Keywords	Change in Log Indus Keywords
	[1]	[2]	[3]	[4]	[5]	[6]
$SWITCH_{t-1}$	4.341***	4.808***	0.323*	0.379**		
	(3.17)	(4.03)	(1.89)	(2.21)		
$PLACEBO\_SWITCH_{t-1}$					0.188	0.097
					(0.09)	(1.18)
$\Delta\%SALES_{t-1}$		-5.010		-0.568**	-4.070	-0.639**
		(-1.47)		(-2.52)	(-0.62)	(-2.06)
$MKTCAP_{t-1}$		-0.057		-0.003	-0.056	-0.005
		(-0.33)		(-0.15)	(-0.34)	(-0.30)
BM_{t-1}		-0.089		0.006	-0.085	0.010
		(-0.53)		(0.16)	(-0.52)	(0.29)
$RET12_{t-1}$		0.618*		0.088**	0.614**	0.074***
		(1.95)		(2.45)	(2.05)	(3.07)
$TURNOVER_{t-1}$		-0.113		-0.009	-0.116	-0.013
		(-0.68)		(-0.37)	(-0.72)	(-0.60)
$IDIOVOL_{t-1}$		0.247		0.025	0.238	0.018
		(1.04)		(0.88)	(0.91)	(0.74)
$INSTOWN_{t-1}$		-0.152		-0.063	-0.191	-0.039
		(-0.17)		(-0.79)	(-0.22)	(-0.55)
Adj. R^2	0.00	0.01	0.00	0.01	0.01	0.01
No. Obs.	1,450	1,450	1,450	1,450	1,450	1,450

Table XII: Robustness Checks

This table reports 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 compute $INDFLOW$. 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 either two non-favorable or two 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 and one non-favorable industries. 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 10%, 5%, and 1% 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 or favorable vs. favorable)								
Industry beta	0.137	0.134	0.117	0.156	0.235	0.187	0.198	0.271
$beta_b$ - $beta_{b-1}$	0.008	-0.003	-0.017	0.039	0.079**	0.048	0.011	0.073
	(0.30)	(-0.09)	(-0.30)	(0.71)	(2.38)	(-1.03)	(0.26)	(1.56)
No. Obs.	706	586	562	605	605	562	586	706

	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

Table XII: Robustness Checks (Continued)

This panel reports subsample analyses (of Tables II, III, and VI). Columns 1-2 report the difference in industry beta between the 45-50% and 50-55% sales bins. At the end of each quarter, we compute an industry beta for each two-segment conglomerate firm 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. Columns 3-4 report the jump in distribution density at the 50% cut-off based on the relative weight of the favorable segment. 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. Columns 5-6 report the difference in announcement day returns between switchers from non-favorable to favorable sectors and all other firms. Announcement day returns are measured as the cumulative 3-day return around an annual earnings announcement. A switcher is defined as one whose industry classification switches from a non-favorable to a favorable industry in the fiscal year. We sort the entire sample into two sub-samples based on four firm characteristics: market capitalization, turnover, idiosyncratic volatility, and operation complexity (measured by the number of segments in the firm). T-statistics, shown in parentheses, are based on standard errors clustered at the year level. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively. Further, differences in coefficients between the high and low subsamples that are statistically significant at the 10% level are indicated in bold.

Panel D: Double Sort on Firm Characteristics

	Beta Change		Distribution Discontinuity		Announcement Day Return	
	Low	High	Low	High	Low	High
	[1]	[2]	[3]	[4]	[5]	[6]
$MKTCAP$	0.129**	0.078	0.296**	0.168	0.025*	0.012
	(2.23)	(1.39)	(2.32)	(1.23)	(1.89)	(1.15)
$TURNOVER$	**0.185*** **	**0.040**	**0.382*** **	**0.073**	0.022**	0.012
	(3.12)	**(0.86)**	**(2.91)**	**(0.55)**	(2.06)	(0.92)
$IDIOVOL$	**0.012**	**0.195*** **	**0.187**	**0.293** **	0.016	0.022**
	(0.28)	**(3.28)**	**(1.30)**	**(2.28)**	(1.26)	(2.21)
$COMPLEXITY$	**0.064**	**0.198*** **	0.258**	0.201*	0.014	0.020**
	(1.01)	**(2.71)**	(2.21)	(1.68)	(1.33)	(2.45)

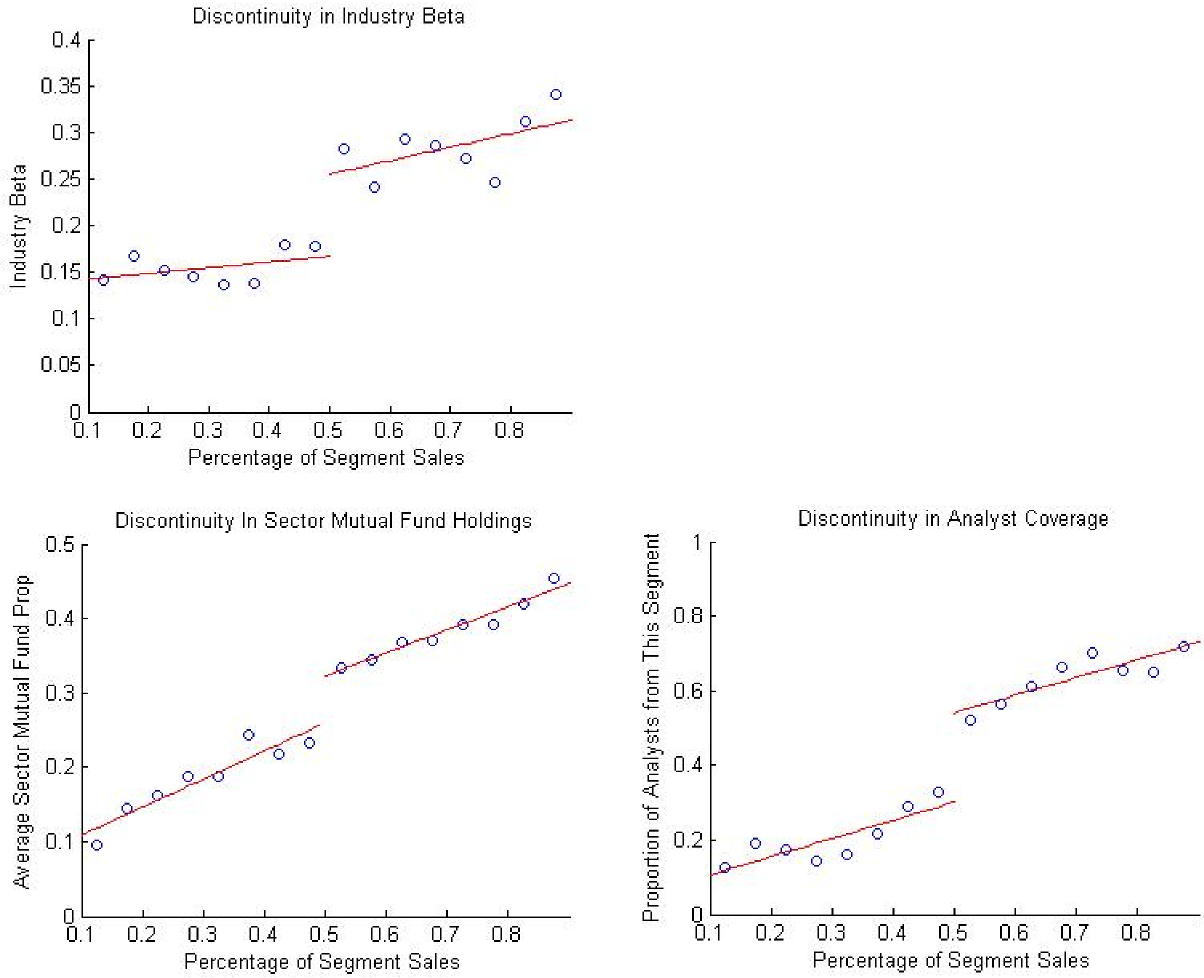

Figure 1: This figure shows the average industry beta, proportion of sector mutual funds that hold, and proportion of analysts that cover the firm from each segment a conglomerate firm operates in. We focus only on conglomerate firms that operate in two two-digit SIC code industries. All firms are then 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 five 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.

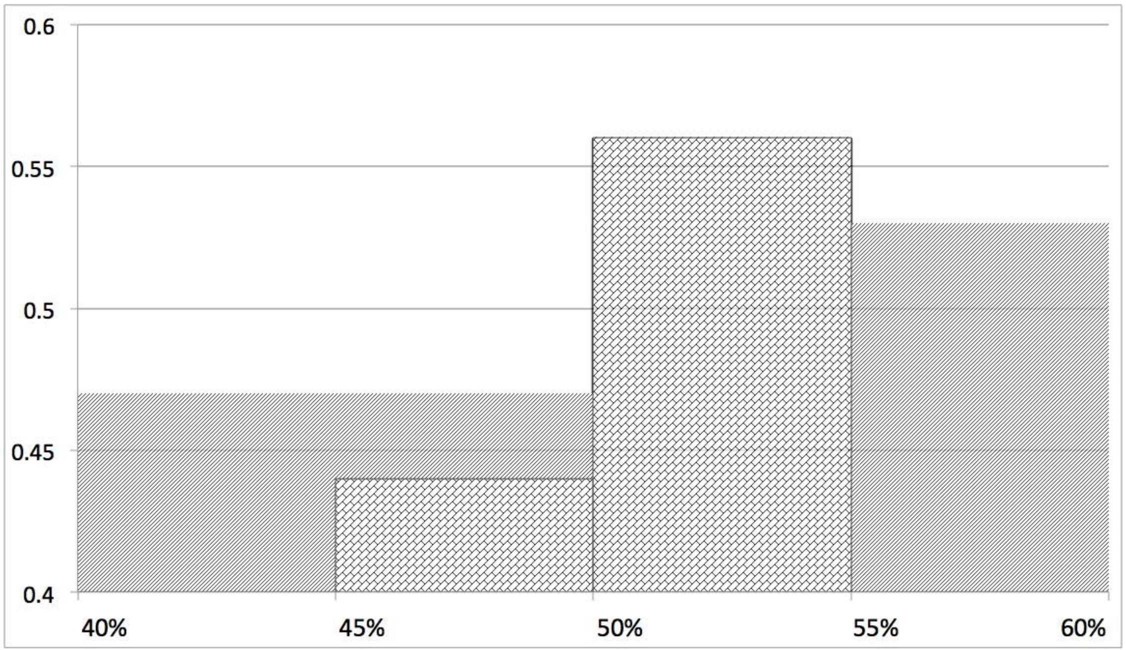

Figure 2: This figure shows the distribution of conglomerate firms based on relative sales weights of the top two segments. For each conglomerate firm in our sample, we require one of the top two segments to operate in a favorable industry and the other in a non-favorable industry, where an industry 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.

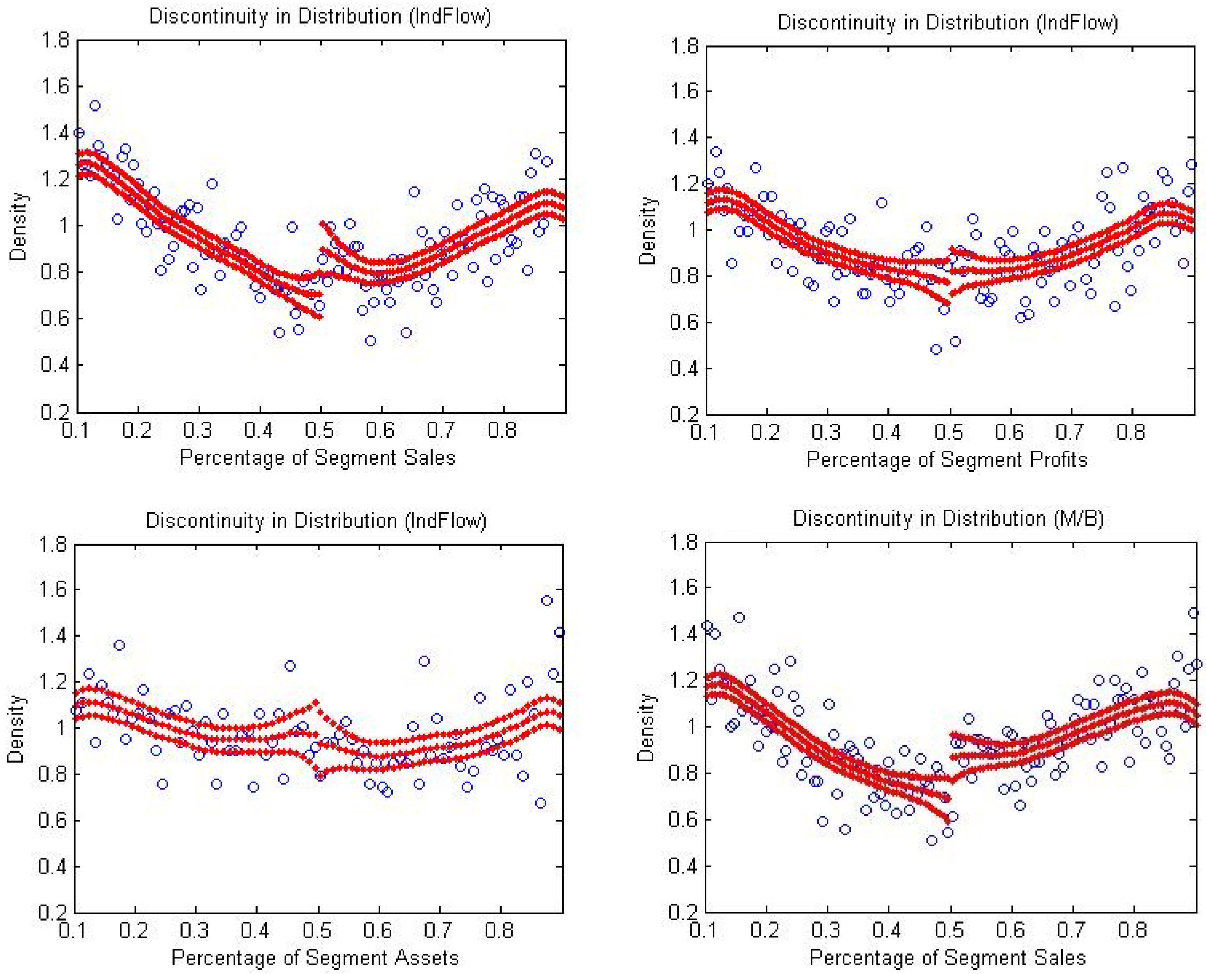

Figure 3: This figure shows the smoothed density functions based on the relative weights of the top two segments of conglomerate firms. The estimation methodology is outlined in McCrary (2008). The blue circles represent the distribution density of each bin grouped by the sorting variable. The red curves 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 market-to-book ratio in that year (following the M/B 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.

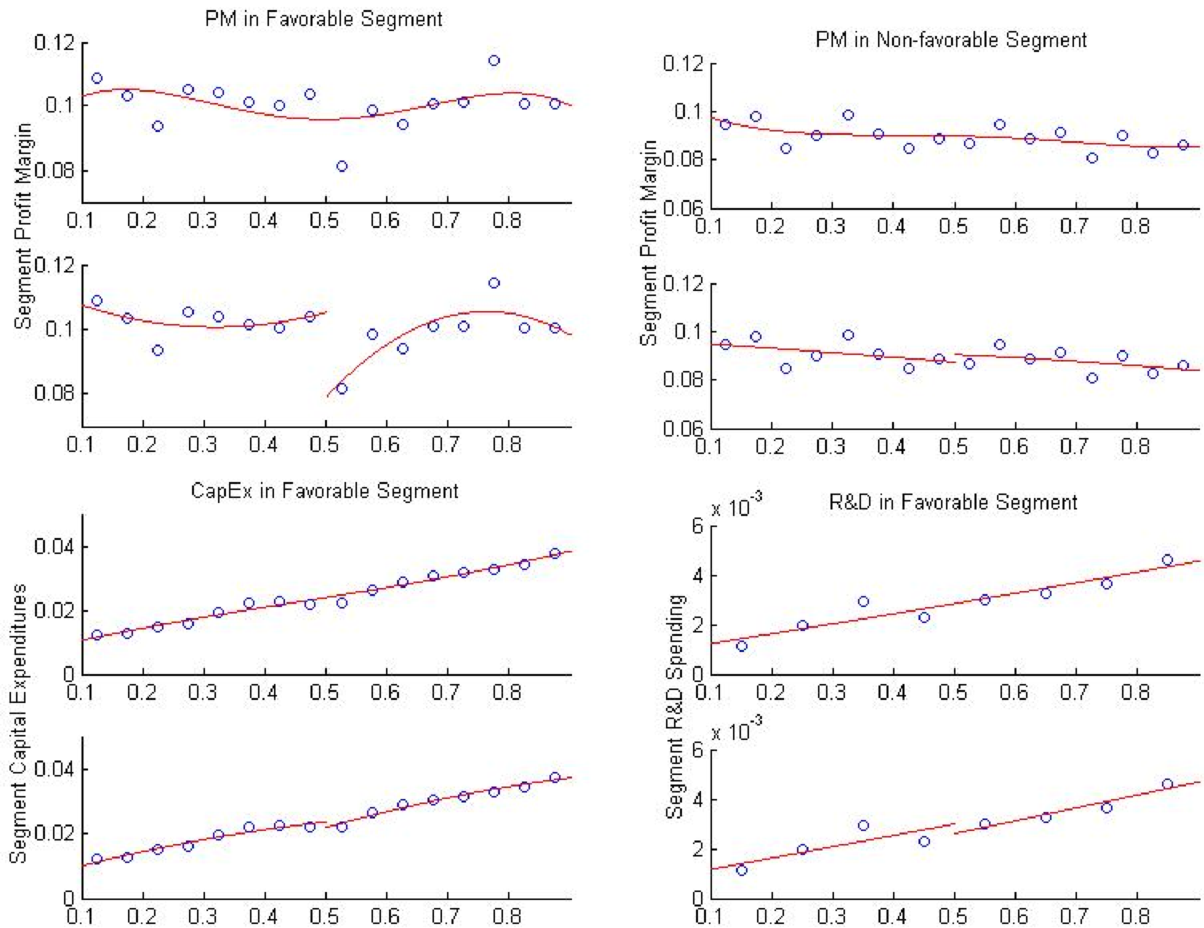

Figure 4: This figure shows various financial/accounting characteristics of conglomerate firms. For each conglomerate firm in our sample, we require one of the top two segments to operate in a favorable industry and the other to operate in a non-favorable industry. An industry is labelled as favorable 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 (PM) 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 (PM) 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.