Industry Window Dressing*

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First draft: August 31, 2012
This draft: September 18, 2012

* We would like to thank Malcolm Baker, Christopher Malloy, Daniel Paravisini, Christopher Polk, and seminar participants at London School of Economics for helpful comments and suggestions. We are grateful for funding from the National Science Foundation.

ABSTRACT

We explore a new mechanism by which firms take real actions to manage sales in order to be classified into "favorable" industries (i.e., industries receiving large capital inflows). We exploit an SEC regulatory provision that a firm's primary industry classification will be determined by the segment that has the majority of sales. We find strong evidence that firms around the discontinuity cutoff of industry classification are significantly more likely to have just over 50% of sales from a favorable industry (termed "discontinuity firms"). Discontinuity firms have significantly lower profit margins and inventory growth rates compared to other firms in the same industries, consistent with these firms slashing prices to achieve sales directly over the discontinuity. Further, these same discontinuity firms do not exhibit different behavior in any other aspect of their business (e.g., CapEx or R&D), suggesting that it is not a firm-wide shifting of focus. Firms also garner tangible benefits from being in favorable industries, such as engaging in significantly more SEOs and M&A transactions. Lastly, discontinuity firms have significantly higher betas to, significantly more analysts from, and significantly more sector mutual fund holdings from favorable industries, relative to nearly identical firms that are directly below the cut-off, consistent with the classification impacting the behavior of market participants.

JEL Classification: G02, G10, G32.

Key words: Window dressing, sales management, discontinuity, favorable industries.

1. Introduction

Managers are impacted by the beliefs and preferences of both existing and prospective stakeholders. While in many cases these beliefs and preferences may be congruent with maximizing long-run firm value, in many instances they are not. If investors switch their views or preferences in a way that can be exploited by the firm, it may make sense for managers to undertake actions to exploit these changes to maximize a short-term measure of firm value. However, firm behavior to exploit investor preferences is often difficult to pin down, both because investors may be responding to the same perceived investment opportunities as managers (with no causal link between), and because it is difficult to cleanly isolate these actions from other firm actions and tie them back definitively to investors' preferences or misperceptions.

We solve this problem by exploiting a regulatory discontinuity governing firm classification in financial markets. Specifically, our analysis exploits a rule of the Securities and Exchange Commission (SEC) that governs how firm operations are classified: namely, the primary industry of each conglomerate firm is determined by the segment that has the largest percentage sales.[1] Using this rule, we exploit situations where firms tightly surround the discontinuity point of industry classification. For example, a firm that gets 51% of its sales from Technology and 49% of sales from Lumber is classified as a Technology firm, whereas a nearly identical firm that gets 49% of its sales from Technology and 51% of sales from Lumber is classified as a Lumber firm. We take advantage of this fact by focusing on firms that are right around this discontinuity point precisely at those times when investor sentiment for one of its industry segments is particularly high relative to other segments.

By examining the distribution of firms right around this discontinuity, we can focus cleanly on how the incentive to join "favorable" industries[2] relates to how firms

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

[2] We show that firms have an incentive to be classified in favorable industries as they, for instance, receive higher valuations, and consequently do significantly more SEOs, and significantly more stock-financed mergers.

are actually classified. Specifically, we examine how managers *industry window dress* their firms at times when one industry is favorable (vs. not); more importantly, the discontinuity identification allows us to pin down opportunistic firm behavior by examining how two firms operating in the exact same industries behave if they are near vs. far away from the industry classification discontinuity at the same point in time. Additionally, the identification allows us to examine the behavior of two firms at the same point in time both facing a discontinuity, but one with a choice of favorable vs. non-favorable industry, and the other with two favorable (or two non-favorable) industries.

We find strong evidence across the universe of conglomerate firms whose two largest segments are one favorable and one non-favorable. In particular, firms close to the industry assignment discontinuity are considerably more likely to be just over the cut-off point to be classified into the favorable industry. We find no such jumps anywhere else in the distribution of these favorable vs. non-favorable segment firms; solely at the industry classification cut-off point of 50% of sales, suggesting that it is specific behavior to exploit this classification.

As further evidence of these firms taking real actions to achieve sales that allow them to be classified into favorable industries, we find that these "discontinuity firms" (those that are bunched right above the 50% sales cut-off to barely be classified in the favorable industry), have significantly lower profit margins and inventory growth rates relative to other firms in the same industries, consistent with these firms slashing prices to achieve sales targets. Again, we do not observe any changes in profit margins and inventory growth rates anywhere else on the distribution of favorable vs. non-favorable segment firms.

Further, these exact <u>same</u> discontinuity firms do not exhibit any 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. In addition, the significant results on profit margins and inventories suggest that it is not simply accounting fraud in sales reporting by these firms, as the

firms would then only need to mis-report sales (given that profits and inventories have zero impact on industry classification), but instead real actions taken by firms.

We go on to show that there are significant benefits that accrue to firms in favorable industries. Specifically, firms in favorable industries engage in significantly more seasoned equity offerings (SEOs) and mergers and acquisitions (M&As), but solely stock-financed M&As, relative to their peers in non-favorable industries. This is consistent with these firms taking advantage of their abnormally low discount rates (i.e., overpriced equity), and getting tangible benefits from it.

Lastly, we show that discontinuity firms that barely classify into favorable industries do trigger investors to treat them as a part of these favorable industries (relative to nearly identical firms that are directly below the cut-off). In particular, the betas of discontinuity firms are significantly higher to the favorable industry than those right below the cut-off, even though they are essentially identical firms. In addition, analyst coverage of these discontinuity firms is significantly different. Significantly more analysts from the favorable industry cover these firms, relative to nearly identical firms directly below the cut-off. Lastly, we show that mutual fund managers exhibit the same patterns in their portfolio choices: sector mutual funds focusing on the favorable industry load up more on discontinuity firms, while shunning identical firms directly below the 50% cut-off, again, despite these firms' actual industry make-ups being essentially identical.

The paper proceeds as follows. Section 2 lays out the background for the setting we examine in the paper. Section 3 presents our data collection procedures, and summary statistics. Section 4 provides our main results on industry window dressing and our discontinuity identification. Section 5 examines the importance of industry classification to market participants, while Section 6 shows the benefits to industry window dressing. Section 7 concludes.

2. Background

The findings of this paper are closely tied to recent studies on managerial behavior to manipulate market perceptions and short-term stock prices. Stein (1996)

argues that in an inefficient financial market, managers with a short horizon exploit investors' imperfect rationality by catering to time-varying investor sentiment. In a related vein, Hirshleifer and Teoh (2003) and Hirshleifer, Lim, and Teoh (2004) model managers strategic disclosure behavior in a setting with attention-constrained investors. A large volume of empirical studies subsequently confirm these predictions: Many important firm decisions, such as dividend policy, issuance, stock splits, firm name, and disclosure policy, are at least partially motivated by short-term share price considerations. 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 (2008); Polk and Sapienza (2008); Greenwood (2009); Lou (2011). Baker, Ruback, and Wurgler (2007) provide an excellent review of this topic. This paper contributes to this fast-growing literature by providing additional evidence that managers also make investment decisions, in part, to influence short-term firm value.

There is also an extensive literature on investors' limited attention to information. On the theoretical front, a number of studies (e.g., Merton, 1987; Hong and Stein, 1999; and Hirshleifer and Teoh, 2003) argue that, in economies populated by investors with limited attention, delayed information revelation can generate expected returns that cannot be fully explained by traditional asset pricing models. Subsequent empirical studies find evidence that is largely consistent with these models' predictions. For example, Huberman and Regev (2001), Barber and Odean (2008), DellaVigna and Pollet (2006), Hou (2007), Menzly and Ozbas (2006), Hong, Torous, and Valkanov (2007), Cohen and Frazzini (2008), and Cohen and Lou (2012) find that investors respond quickly to information that attracts their attention (e.g., news printed in the *New York Times*, stocks that have had extreme returns or trading volume in the recent past, and stocks that more people follow), but tend to ignore information that is less salient yet material to firm values. In addition, investors' limited attention can result in significant asset return predictability in financial markets.

Prior research has also examined investors' biased interpretations of information. Kahneman and Tversky (1974) and Daniel, Hirshleifer, and Subrahmanyam (1998), among many others, argue that investors tend to attach too high a precision to their

prior beliefs (or some initial values) and private signals, and too low a precision to public signals, which can result in predictable asset returns in subsequent periods. A large number of recent empirical studies confirm these predictions. For instance, Foster, Olsen, and Shevlin (1984), Bernard and Thomas (1989), Hong, Lim, and Stein (2000), Chan, Lakonishok, and Sougiannis (2001), Ikenberry and Ramnath (2002), Kadiyala and Rau (2004), and Cohen, Diether, and Malloy (2012) find that investors usually underreact to firm-specific (public) information (e.g., earnings reports, R&D expenditures, forecast revisions, etc.) and to various (publicly announced) corporate events (e.g., stock splits, share issuances and repurchases, etc.); furthermore, investors' under- (over-) reaction leads to significant return predictability based only on publicly available information.

Finally, this paper is also related to the literature on style investment, categorization, and comovement. Barberis and Shleifer (2003) argue that a number of investors group assets into categories in order to simplify investment decisions. This causes the flows into the assets within a category to be correlated, and induces excess correlation in asset price movements (relative to actual underlying cash flow correlations). Vijh (1994) and Barberis, Shleifer, and Wurgler (2005) show one example of this using S&P 500 Index inclusion, and correlation to other constituent firms in the index before and after inclusion (or deletion). Other examples shown in the empirical literature are Froot and Dabora (1999), Cooper, Gulen, and Rau (2005), and Kruger, Landier, and Thesmar (2012), who find evidence that mutual fund, industry structure, and country all appear to be categories that have a substantial impact on investor behavior (and asset price movements), while Mullainathan (2002) provides a more general framework for categorization in decision making.

3. Data

The main dataset used in this study 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 the 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. Conglomerate firms in our sample are defined as those operating in more than one two-digit SIC code industry. 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% is to ensure that the top two segments comprise the majority of the operations of the firm,[3] while the upper cutoff of 110% is to weed out apparent data errors. At the end of paper, we also report results based on two-segment conglomerate firms alone.

The segment data is 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 $5 a share and whose market capitalizations are below the 10th percentile of NYSE stocks in our calculation of industry average variables, such as industry returns, and industry average fund flows.

Our main measure of industry favorability among investors is motivated by recent studies on mutual fund flows. Coval and Stafford (2007) and Lou (2012) find that mutual fund flows to individual stocks are positively associated with contemporaneous stock returns, and negatively forecast future returns. We follow Lou (2012) to compute a *FLOW* measure for each individual stock, assuming that fund managers proportionally scale up or down their existing holdings in response to capital flows. We then aggregate

[3] 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 this is true) through 85%, and the results are unchanged in magnitude and significance.

such *FLOW* to the industry level by taking the equal-weighted average across all stocks in a two-digit SIC code industry, excluding all micro-cap stocks. We define an industry as favorable if it belongs to one of the top twenty industries (i.e., the top 30%) as ranked by mutual fund flows in the previous year, and as non-favorable otherwise.[4] We use equal-weighted industry *FLOW* in our main analyses because capital flows to smaller stocks in an industry may better reflect investor views and preferences. In robustness checks, we also use value-weighted industry *FLOW*, and all our results go through, which is not surprising given the correlation between the equal- and value-weighted measures is over 0.9.

Mutual fund flow data is obtained from the CRSP survivorship-bias-free mutual fund database. In calculating capital flows, we assume 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 quarter end. The two datasets are then merged using MFLINKS provided by Wharton Research Data Services (WRDS). Given that reporting of segment financial information is first enforced in 1976 and the mutual fund holdings data starts in 1980, our sample of conglomerate firms covers the period of 1980 to 2010.

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

[4] Again, we have experimented with defining favorable as the top 20%, 25%, 30%, 35%, and 40%, and the results are very similar in magnitude and significance with all of these.

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.

With all the data selection and screening procedures described above, we end up with a sample of 45,904 firm-year observations. We then categorize these firm-year observations into smaller bins based on the relative sales of the top two segments. Summary statistics for our sample are shown in Table I. Specifically, the first bin includes all conglomerate firms whose smaller segment out of the top two contributes less than 10% of the combined sales of these two segments, and the second bin includes all conglomerate firms whose smaller segment out of the top two contributes somewhere between 10% and 20% of the combined sales, and similarly for other bins. We have, on average, between 396 and 566 firms per annum in each of these sales-based bins. There is also a clear U-shaped pattern in the distribution: there are significantly more firms whose top two segments are of vastly different sizes. In addition, there are on average 138 firms that change their SIC industry classifications – i.e., to cross the 50% line – in each year. The summary statistics of other variables are in line with prior literature. For example, the average industry *FLOW* over a year is a positive 8.1%, consistent with the fact that the mutual fund industry is growing rapidly in our sample period.

4. Industry Window Dressing

4.1. Identification of Industry Window Dressing

The main thesis of the paper is that investors have preferences for certain firm characteristics (industry classification, for example). They drive the value of firms having these desired characteristics above fundamental value, and firms respond to this by altering aspects of their business to take advantage of the mispricing. Our identification relies on being able to first capture investor preference shifts that lead to mispricing. Second, we need to be able to cleanly identify firm behavior changes to take advantage of these shifts.

We thus begin by choosing a measure to capture shifts in investor preferences that lead to mispricing at the industry-level. Specifically, we look at the behavior of investors allocating capital to mutual funds, and the resultant impact of these flows on firm (and industry) valuation. Lou (2012) shows that capital flows into mutual funds have a predictable impact on the prices of stocks held by these mutual funds. We use a similar identification, but now aggregating these individual stock flows to the industry level. If investment flows to an industry can temporarily impact industry valuation, we should see a concurrent rise in prices as investors push industry prices away from fundamental value, and then a subsequent reversal in prices as the mispricing is corrected. Table II shows that the flow measure of investors' sentiment for industries does precisely this: in the year that investors pile into an industry through their mutual fund purchase decisions, industry values rise significantly, by over 100 basis points per month ($t = 4.45$). In the following two years, this 12% return completely reverses.[5] We label these overpriced industries (top 20 as ranked by industry $FLOW$) "favorable" industries as investors are pushing up their prices.

The biggest innovation of the paper relative to the existing literature is the clean identification of firm behavior in direct response to this mispricing. In particular, we exploit a rule of the Securities and Exchange Commission (SEC) that governs how firms classify their operations. Using this rule, we exploit situations where firms tightly surround the discontinuity point of industry classification (e.g., for two segment firms, this would be 50%).

By examining the distribution of conglomerate firms right around this discontinuity, we can focus cleanly on how the incentive for managers to join favorable industries relates to how they classify their firms relative to non-favorable industries (i.e., the complement set to the favorable industries). We show in Section 6 that firms do receive significant tangible benefits from being classified into a favorable industry. However, in order for firms to be able to take advantage of this, we need two conditions from investors: i.) investors sometimes get excited about certain industries, which then

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

leads to higher industry valuation and better access to the equity market, and ii.) investors have limited resources and capacity to process information, and hence rely on a firm's primary industry classification rather than the economics of its actual operations. We have shown evidence for (i) in Table II, and we show in Section 5 evidence of (ii).

Thus, given these conditions, we can then test whether firms take actions to take advantage of this industry mispricing. Many conglomerate firms operate in each industry (including favorable industries). Each conglomerate firm in the favorable industry by definition has a sales weight in the industry between 10-90% (as they need not report segments below 10%). If firms truly are manipulating operations in an opportunistic manner, we expect to see firms bunched right above the cutoff point of sales from favorable industries (e.g., 50% for two segment firms), so that they take advantage of being classified as a member of these favorable industries.

To test this, we first examine the distribution of conglomerate firms' segment makeup. We examine the two largest segments of each conglomerate firm in terms of sales (as those will determine the primary industry classification), requiring that one of the top two segments is in a favorable industry and the other in a non-favorable industry. Figure 1 shows the distribution of conglomerate firms whose top two segments operate in a favorable and a non-favorable industries and are around the 50% cut-off in relative sales. The top two segments' sales in the firm are scaled against each other, as the larger of the two will determine the industry classification of the firm. Thus, the 50% sales cut-off is the relevant cut-off for industry status.

Included in Figure 1 are all conglomerate firms whose top, favorable segment accounts for between 40-60% of the combined sales of the top two segments (gray area), as well as for 45-55% of the combined sales (block area). Any firm with sales over 50% from a favorable industry (x-axis) is classified into the favorable industry (whereas below that cut-off 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% discontinuity cutoff is precisely the point at which firms are classified into favorable vs.

non-favorable industries (e.g., the 51% Tech-49% Lumber firm will be presented to investors as a Tech firm, while the nearly identical 49% Tech-51% Lumber will be classified as a Lumber firm), we expect firms exhibiting opportunistic behavior to exploit industry mispricing by bunching up right over the 50% classification cut-off.

Figure 1 shows strong evidence that firms in fact do bunch up right above the 50% cut-off of sales from favorable industries, resulting in significantly more firms classifying themselves into favorable industries (relative to right below). 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 larger if we look at the tighter band around the 50% cut-off of only firms that are between 45-55% in a favorable industry (vs. the complement in a non-favorable). Note that an alternative story that all firms containing a favorable segment experience increasing sales in the segment would generate a very different pattern. In this case, we should see all firms containing a favorable industry segment increasing their weights in the favorable industry, which would result in a parallel shift for all firms such that the buckets around the 50% would have no difference (discontinuous jump) between the two.

In order to test more formally this jump around the 50% cut-off, we look at the entire distribution of conglomerate firms. The estimation strategy of discrete jumps in firm distribution at the discontinuity point then follows the two-step procedure as 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. In the second step, we 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 distribution at the discontinuity point is shown to be consistent and follows a normal distribution asymptotically by McCrary (2008).

Table III Panel A shows the entire distribution of conglomerate firms that operate in favorable vs. non-favorable industries across 5% bins based on percentage sales from the favorable industry. From Table I, there is a clear U-shaped pattern in conglomerate firm distributions (conglomerate firms are mainly dominated by one segment or the other, with relatively fewer that are near the 50-50 cut-off). We see the same overall pattern for these favorable vs. non-favorable conglomerates, with one distinct difference: there is a large jump in the fraction of firms directly over the 50% cut-off to qualify as a member of the favorable industry. The density difference at the 50% cut-off (following the McCrary procedure) is 0.25 (t = 2.59) compared to the preceding bin. For comparison, if these firms are uniformly distributed in sales weights, the distribution density in each bin is exactly 1. For the rest of the distribution, there is no change in density nearly as large, and none are significant. Thus, the entire distribution of conglomerate firms across bins of percentage sales, and the spike right at the discontinuity of classification into the favorable industry, is consistent with firms opportunistically adjusting sales in order to be classified into favorable industries.

4.2. Falsification Tests

Although the distinct discontinuous pattern in firm distribution is difficult to reconcile with stories other than reclassification that occurs directly at the discontinuity point, one might think that firms are simply ramping up all operations, such that sorting on any firm balance sheet or income statement variable will yield identical behavior. To be clear, the Securities and Exchange Commission rule specifically states that it is sales alone that determine industry classifications. Thus, if managers' opportunistic behavior to classify the firm is the driving force, the only variable the managers care to affect should be sales. Thus, we would not expect to see sorting on any other firm variables showing a discontinuity in distribution at 50% (as 50% is no more meaningful than any other percentage). In contrast, if what we document is some odd empirical pattern in firm operations unrelated to firms actively assuring they are just above the discontinuity to be classified in the favorable industry, we should expect to see similar patterns based on other accounting variables.

To test this, we conduct the exact same sorts as in Table III Panel A with the same set of conglomerate firms, but instead of sorting on sales, we sort on other accounting variables, such as assets and profits. In other words, we rank these conglomerate firms by the percentage of assets (profits) they have in the favorable segment, and show the entire distribution in Panel B (Panel C). From Panels B and C, we see no significant jumps between any two adjacent bins when sorting by these other firm variables, and a stable frequency in each of these bins, consistent with sales (the variable that drives industry classification) being the sole focus of firms.

Lastly, as a further falsification test, we rank industries based on the average industry book-to-market ratio, rather than industry *FLOW*. We then perform the exact same sorts as in Table III Panel A based on percentage sales from favorable industries. As can be seen from the bottom right panel of Figure 2, there are no observable jumps at the 50% cut-off (i.e., the discontinuity point in industry classification). This evidence suggests that our documented pattern is not driven by mutual fund flows reflecting differences in industry growth opportunities.

4.3. Mechanism

In this section we explore the mechanism through which firms may be opportunistically adjusting sales such that they are classified into favorable industries. Specifically, there are two potential explanations for the results we find. The first is that firms are simply fraudulently reporting sales (on the margin) in order to be classified into favorable industries, and accrue the benefits we show in Section 6. The second is that firms are taking real actions in order to sell more in the favorable industry segment such that it could be reclassified there. We show evidence for the latter, using a number of different measures.

First, if a firm is trying to increase sales revenue, one way to do this is to lower the price of goods. This will lead to more booked sales, but a lower profit margin, and a depletion of inventories as the abnormal sales volume is realized. We test both of these implications. In order to do this, we use the exact same sorting on favorable industry segment sales as is used in Table III. If firms truly are exhibiting this behavior, then

the firms that are stretching to be classified in the favorable industry, (e.g., those firms directly above the 50% sales classification cut-off) should be the exact firms with lower profit margins and depleted inventories. Panel A of Table IV reports test results for profit margins, and we see precisely this pattern. We see significantly lower profit margins for those firms that are in the 50-55% sales bin in the favorable industry, right above the cut-off. The drop in profit margins is economically meaningful at nearly 20% lower ($t = 2.93$) compared to the two adjacent bins. Importantly, this pattern in profit margin arises solely for the favorable segment (as shown in the bottom half of Panel A), exactly where the sales are being opportunistically adjusted.

Second, we conduct the same test for inventories in Panel C to see if inventories are also depleted for these firms that are barely above the sales discontinuity. Unfortunately, inventories are only reported at the firm level (and not the segment level), and are more sparsely populated, so we aggregate firm-year observations to 10% bins. Again, we see evidence consistent with firms making more actual sales in order to be classified into favorable industries. Inventory growth is over 30% lower ($t = 2.28$) for those firms right above the cut-off, and statistically identical (and nearly identical in magnitude) for all other bins.

Panel B then runs, for profit margins, the falsification test examining firms that have both top segments as favorable industry segments (so there is no need to change real behavior to affect classification). Exactly consistent with this idea, we see no differences in profit margins for these two favorable segment firms anywhere in the distribution.

Table V then does one last test of mechanism. In particular, one might think that instead of capturing firms changing their sales behavior in an opportunistic way, we are simply capturing a firm-wide shift in policy toward the more favorable industry. This would not explain why we see a discontinuous jump in firm-wide policy "shifts" at the 50% cut-off, but it would be less of a manipulation of solely sales for industry classification, and signal more firm-wide behavior. We test this alternative story by exploring whether firm investments are in line with the sales increases we see in favorable industries. In particular, in Table V we examine whether capital expenditures

and R&D expenditures in the favorable industry line up with the strong sales behavior we see around the discontinuity. Both Panels A and B tell the same story: for both capital expenditures and R&D[6] we observe no difference at all in the investment behavior of these firms around the discontinuity. This is in sharp contrast to profit margins and inventory growth, and is more evidence suggesting that firms are solely changing their sales for the purpose of being classified into favorable industries.

As firms are not required to report, at the segment level, accruals or any other accounting variables that are linked to earnings manipulation by prior literature, we do not have any direct test for the accounting fraud explanation of our results. However, in untabulated analyses, we find that firms that are barely classified into favorable industries do not have a higher likelihood of restating their earnings in the following year relative to other firms in the same industries. For example, the percentage of firms restating their earnings in the 50-60% bin is 0.9% (t = -1.11) *lower* than that in the two adjacent bins.

In sum, both the results on profit margins and inventories are consistent with firms changing real behavior in order to stretch to produce the sales necessary to be classified into favorable industries. Further, the results on capital expenditures and R&D suggest that in contrast to this being a firm-wide policy shift toward the favorable industry, it is solely a change in firm sales in order to secure classification into favorable industry status. In the remainder of the paper, we explore all of the benefits that accrue to firms from this behavior.

5. The Importance of Industry Classification to Investors

5.1. Industry Beta

We have so far provided evidence that firms manipulate their segment sales in order to be classified in one of the favorable industries. A key assumption in our hypothesis is that investors are affected by firms' primary industry classifications. In this section, we take this assumption directly to the data. In particular, we start by

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

examining the return correlation between each conglomerate firm and the industries it operates in, and how this correlation changes as we vary the fraction of sales from these segments.

More specifically, at the end of each quarter, we sort all two-segment firms into twenty 5% bins based on percentage sales from either segment; that is, each firm in our sample will appear in two of these 5% bins on both sides of the 50% point. For example, a firm that receives 49% of its sales from industry A and 51% of its sales from industry B appear in both the 45%-50% bin (when ranked based on industry A) and the 50%-55% bin (when ranked based on industry B). We focus on two-segment firms in this analysis because the presence of a third segment adds noise to our estimation of industry betas.[7] We then compute the industry beta with regard to either segment for each conglomerate firm in our sample by regressing weekly stock returns on the weekly returns of the two-digit SIC-code industry that the conglomerate firm operates in, using data from months 6 to 18 after the fiscal year ends. 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 do not have processing constraints in assessing the details of firm operations in different segments, we expect to see a gradual increase in industry beta as we move from bins of lower fractional sales to bins of higher fractional sales. The results, as shown in Table VI, indicate otherwise. While the industry beta is generally increasing as we move from the bottom bin to the top bin, there is a clear structural break at the 50% point. The average industry beta for firms in the 50%-55% bin, after controlling for known risk factors, is 0.282, while that in the 45%-50% bin is 0.177. The difference of 0.105, representing a 60% increase, is highly statistically significant ($t = 4.76$). The difference in industry beta between any of the other two bins is statistically zero. The

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

structural break can be more easily seen in a diagram. As shown in the top left Panel of Figure 3, while there is a mild increasing trend in industry beta in both the below-50% and above-50% regions, there is a clear jump in industry beta at the 50% point.

Taken together, these results confirm our intuition that investors pay excessive attention to conglomerate firms' primary industry classifications in their investment, without going through the details of these firms' segment operations available in public documents. This result is consistent with investors' tendency to categorize stocks into different groups based, for example, on industry classifications, to simplify their investment decisions. Thus, the observed substantial jump in industry beta at the 50% point, the cut-off line for primary industry definition, provides support for our hypothesis that firm managers can influence investors through reclassifying their firms into more favorable industries.

5.2. Sector Mutual Funds

To provide direct evidence for this same categorization on the part of a set of arguably more sophisticated investors, we examine mutual fund holdings. In order to do this, we first need to identify those mutual funds that are concentrating on a specific sector. As very few mutual funds actually list their sector in their fund name, we do this by simply examining the actual fund holdings. If a fund invests the majority of its portfolio in a single industry (i.e., >50%), we classify the mutual fund as concentrating on that given sector.[8] For every two-segment conglomerate firm, we then count the number of sector mutual funds that are holding the firm in months 6-18 after the fiscal year end. We further require that the two segments to be in two distinct one-digit SIC code industries, as sector mutual funds may also hold stocks from related sectors. We then compute the proportion of sector funds from each industry in which the conglomerate firms are operating. For instance, if a conglomerate firm is operating in

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

industries A and B, we calculate the percentage of industry A sector mutual funds and industry B sector mutual funds that are holding the firm.

Table VII Panel A reports the distribution of sector mutual fund holdings. Panel A reports the proportion of the sector mutual funds covering the sector as that sector moves from being a 30% segment in the firm to being a 70% segment in the firm. As expected, the proportion of sector funds that are holding the conglomerate firm is increasing as the percentage of the conglomerate sales from that sector increases. As with beta, though, instead of observing a steady increase in sector fund ownership as sales increase, we see a large and significant discontinuity at the 50% classification cut-off. The increase in proportion from the 45%-50% bin to the 50%-55% bin of 10.2% (t = 2.75), represents over a 40% jump in the percentage of sector mutual funds holding the stock (23.2 to 33.4). This pattern can be also seen from the bottom left panel of Figure 3, where we plot the proportion of sector funds owning the conglomerate firm against the percent of sales from that industry. It is clear from the diagram that there exists a discrete jump in sector fund ownership at the 50% cutoff point. Consistent with the results on beta, these results suggests that mutual fund managers also rely on conglomerate firms' primary industry classifications in their investment, rather than actual firm operations.

5.3. Analyst Coverage

Along the same line of reasoning, we next turn our focus to financial analysts, who provide a crucial service of information dissemination in financial markets. It has been shown by prior research that investors closely follow analyst guidance when making investment decisions. Given that individual analysts usually follow stocks in one or two industries in which they specialize (e.g., Boni and Womack (2006)), it is conceivable that analyst coverage is, to a large extent, determined by firms' primary industry classifications, which would then affect how investors view these firms.

Similar to our tests on sector mutual funds, at the end of each quarter, we sort all two-segment firms with at least some analyst coverage into twenty 5% bins based on percentage of sales from either segment. We then assign each sell-side analyst (covering

five or more firms) to an industry if that industry accounts for more than half of the analyst's covered firms. We use coverage data provided by IBES in the previous three years for each analyst (our results are robust if we use coverage information in the previous one to five years). We exclude the stock in question in the procedure of analyst industry assignments to ensure that our results are not mechanically driven. We then compute the proportion of analyst coverage from each industry that the conglomerate firm operates in using coverage data in months 6 to 18 after the fiscal year ends. So, for example, for a firm that operates in industries A and B, and is covered by 5 analysts from industry A, 4 from industry B, and 1 from another industry, we label the firm as having 50% of its coverage from its operations in industry A and 40% of its coverage from its operations in industry B.

If analyst coverage is indeed determined by firms' primary industry classifications, we expect a jump in the fraction of analysts covering the firm when the segment in question crosses the 50% point in terms of percentage sales. The results, shown in Table VII, Panel B confirm this prediction. While the fraction of analysts covering a firm from a particular industry is generally increasing as the industry accounts for a larger fraction of the firm's sales, there is a clear jump at the 50% cutoff point: for firms that derive 45%-50% of their total sales from the industry in question, 32.7% of the analysts covering these firms are from that industry; in contrast, for firms that derive 50-55% of their sales from the industry in question, 52.0% of these analysts are from that industry.[9] The difference in analyst coverage of 19.3%, representing a close to 60% increase from the lower bin, is economically and statistically significant ($t = 2.27$). On the other hand, the difference between any other two bins is much smaller in magnitude and statistically insignificant from zero. This pattern can be also seen from the bottom right panel of Figure 3, where we plot the proportion of analysts covering the firm from a particular industry against the segment percentage sales. It is clear from the diagram that there exists a discrete jump in analyst coverage at the 50% cutoff point.

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

In sum, the results presented in this section provide evidence that investors rely on firms' primary industry classification, in some cases more so than actual firm operations. This can arise either from investors' limited attention/processing capacity to read through all segment-related information, thus overly relying on some simple statistics, from investors' reliance on analysts' guidance (who in turn use industry classifications to determine the stocks they follow), or from institutional constraints on holdings. These results thus provide support for firms' ability to influence investors and other financial agents through manipulating their industry classification into more favorable industries.

6. Benefits to Favorable Industry Status

6.1. Market Reactions to Earnings Announcements

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

To test this prediction, we examine the cumulative stock return in the three-day window surrounding conglomerate firms' annual earnings announcements. Our results are also robust to other window lengths. We then regress the cumulative return on a $SWITCH$ dummy that takes the value of one if the firm's main industry classification switches from a non-favorable to a favorable industry in the current fiscal year, and zero otherwise. We also control for standardized unexpected earnings (SUE), defined as the difference between the consensus forecast and reported earnings scaled by lagged stock

price, in the regression. Other control variables include firm size, the book-to-market ratio, lagged stock returns, share turnover, idiosyncratic volatility, institutional ownership, and number of analysts covering the firm. We also put in year-fixed effects to subsume common shocks to all firms.

The regression coefficients are reported in Table VIII. As shown in the first three columns, the coefficient on *SWITCH* is significantly positive in all regression specifications. In a univariate regression (Column 1), a firm that switches from a non-favorable industry to a favorable industry has an announcement day return that is 60bp (t = 1.86) higher than all other firms. Controlling for the contemporaneous earnings surprise increases the coefficient on *SWITCH* to 70bp (t = 1.93). Finally, in the full specification (Column 3), where we control for other firm characteristics that are linked to average firm returns, firms that switch from non-favorable to favorable industries outperform their peers by 100bp (t = 2.56).

In the next three columns of the same table, we exclude from our sample firms that stay put in a favorable or non-favorable industry in two consecutive years. Put differently, we are now comparing the announcement day returns between firms that switch from non-favorable to favorable and firms that switch from favorable to non-favorable industries. Not surprisingly, the return differential between these two groups is even larger. In a univariate regression (Column 4), the coefficient on *SWITCH* is a statistically significant 100bp (t = 2.33). After controlling for all other firm characteristics (Column 6), the coefficient rises to 110bp (t = 2.38). In other words, firms that switch from non-favorable to favorable industries outperform their peers that switch in the opposite direction by as much as 110bp in the three days around earnings announcements.

6.2. SEOs and M&As

As argued by Stein (1996), other than maximizing long-run fundamental value, firm managers also have an incentive to maximize current stock prices for a number of obvious reasons. For example, a higher stock price can reduce a firm's chance of becoming a takeover target, and also increase its bargaining power to acquire other

firms. A higher stock price also means larger proceeds from selling a fixed stake in the firm. In this section, we take these predictions to the data, with the particular goal of examining whether firms in favorable industries are more likely to issue additional equity and to engage in merger and acquisition activities than other firms.

Following Greenwood and Hanson (2012), we introduce a dummy of $Net\ Issuance$ that takes the value of one if the ratio of the change in book equity between two consecutive years over lagged firm assets is greater than 10%, zero if this ratio is between -0.5% and 10%, and minus one if that ratio is below -0.5%. Effectively, a positive $Net\ Issuance$ signifies net equity issuance in a year, and a negative $Net\ Issuance$ indicates net equity repurchase in the year. We use changes in book equity from the Compustat database instead of public issuance information from the Security Data Corporation (SDC) database, because the former also includes private placements, as well as issuance due to mergers and acquisitions. However, our main results would go through if we focus on public issuance alone.

We then conduct an ordered logit regression of $Net\ Issuance$ on our main measure of industry favorability ($INDFLOW$) from the previous year. We control for lagged stock-level $FLOW$, as it has been shown in Gao and Lou (2012) that firms experiencing mutual fund flow-induced purchases tend to issue more equity in the following year relative to firms experiencing flow-induced sales. Other control variables include firm size, the book-to-market ratio, lagged stock returns, share turnover, idiosyncratic volatility, and institutional ownership.

The results, as shown in the first two columns of Table IX, strongly support the view that firms in more favorable industries take advantage of the temporary industry overpricing to issue more equity. As can be seen from Column 1, in a univariate logit regression, the coefficient on $INDFLOW$ is 0.306 ($t = 3.77$). This coefficient drops a little in the full specification (Columns 2) after controlling for the aforementioned variables, but remains statistically significant at 0.216% ($t = 3.46$).

We next turn our attention to equity-financed mergers and acquisitions. We repeat the same analysis as for equity issuance, except that now we replace the dependent variable with a $Stock\ Financed\ M\&A$ dummy that takes the value of one if

the firm has at least one 100% stock-financed acquisition in the fiscal year as reported in the SDC database, and zero otherwise. The results, as shown in the next two columns of Table IX, again support our prediction that firms exploit temporary industry misevaluation. The coefficient on lagged *INDFLOW* in a univariate regression is 0.551 (t = 5.77) and that in the full specification with all the additional controls is 0.497 (t = 8.02).

Finally, as a placebo test, we examine the effect of industry favorability on firms' cash-financed acquisition activities. For this purpose, we define a *Cash Financed M&A* dummy that takes the value of one if the firm has at least one 100% cash-financed acquisition in the fiscal year, and zero otherwise. Not surprisingly, the coefficient on *INDFLOW* is statistically insignificant from zero for both the univariate and multivariate regressions: We report a coefficient of -0.034 (t = -0.35) for the univariate logit regression (Column 5), and a coefficient of 0.034 (t = 0.48) for the multivariate case (Column 6). In sum, the results shown in this section provide support for the notion that firms benefit from temporary stock/industry overvaluation, and thus have an incentive to adjust firm operations to maximize current stock valuation.

7. Conclusion

We explore a new mechanism by which firms take *real* actions to manage sales in order to be classified into "favorable" industries. We exploit a regulatory provision of the SEC governing firm classification into industries, and the resultant discontinuity it implies. Specifically, the provision states that a firm's industry classification will be determined by the segment that has the majority of sales. As this is empirically always a choice between the two largest segments, we can rescale so that the 50% cut-off between these segments determines the industry of the firm. We find strong evidence that firms around the discontinuity cutoff of 50% sales in both segments are significantly more likely to have just over 50% of sales from the favorable industry (termed "discontinuity firms"). These discontinuity firms have significantly lower profit margins and inventory growth rates compared to other firms, consistent with these firms slashing prices to achieve sales targets. Firms in the same industries but not near the

cut-off point exhibit none of these behaviors. Further, these exact same discontinuity firms do not exhibit any different behavior in any other aspect of their business (e.g., CapEx or R&D expenditures), suggesting that it is not a firm-wide shifting of focus.

We further show that there are significant benefits that accrue to firms from being in favorable industries. Specifically, firms in favorable industries engage in significantly more SEOs and M&A transactions, but solely stock-financed M&As. This is consistent with these firms taking advantage of their abnormally low discount rates (i.e., overpriced equity), and getting tangible benefits from it, thus providing incentives for the sales management behavior we document.

Lastly, we show that discontinuity firms that barely classify into favorable industries do fool investors into thinking that they are a part of these industries (relative to the nearly identical firms that are directly below the cut-off). In particular, the betas of discontinuity firms are significantly higher to the favorable industry than those right below the cut-off; in addition, sector mutual funds and analysts from the favorable industry hold and cover these firms significantly more relative to firms directly below the cut-off, despite their actual industry make-ups being essentially identical. In sum, we provide evidence that firms change real behavior opportunistically to manipulate their industry classifications in a clean setting that allows us to directly observe firms' exploiting investor preferences.

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Table I: Summary Statistics

This table reports summary statistics of our sample that spans the period of 1980-2010. Panel A reports the statistics of our main variable, mutual fund flows to each industry over a year, based on two-digit SIC codes. Specifically, at the end of each quarter, we compute a *FLOW* measure as the aggregate flow-induced trading across all mutual funds in the previous year for each stock. We then take the average *FLOW* across all stocks in each two-digit SIC code industry to derive *INDFLOW*. Panels B and C report segment and firm specific characteristics. Profit margin is defined as the segment's operating profit divided by segment sales. Both capital expenditures and R&D spending are scaled by total firm assets. Industry beta is from the regression of weekly stock returns on corresponding industry returns (excluding the stock in question) over a one-year horizon, after controlling for the Carhart four-factor model. The announcement return is the 3-day cumulative return around an annual earnings announcement. Net equity issuance is defined as the change in book equity in two consecutive years scaled by lagged firm assets. 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
Inventory growth	0.091	0.242	-0.065	0.062	0.201
Announcement returns	0.007	0.083	-0.031	0.004	0.044
Net equity issuance	0.036	0.358	-0.052	0.036	0.155
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: Return Predictability of Industry Flows

This table shows the results of return predictive tests. It reports calendar-time monthly returns to industry portfolios ranked by *INDFLOW*. Specifically, at the end of each quarter, we compute a *FLOW* measure for each stock as the aggregate flow-induced trading across all mutual funds in the previous year. We then take the average *FLOW* across all stocks in each two-digit SIC code industry to derive *INDFLOW*. We then sort all industries into decile portfolios based on *INDFLOW* in each quarter and hold these decile portfolios for the next two years. To deal with overlapping portfolios in each holding month, we follow Jegadeesh and Titman (1993) to take the equal-weighted average return across portfolios formed in different quarters. Monthly portfolio returns with various risk adjustments are reported: the return in excess of the risk-free rate, CAPM alpha, and Fama-French three-factor alpha. T-statistics, shown in parentheses, are computed based on standard errors corrected for serial-dependence with 12 lags (Newey and West 1987). Estimates significant at the 5% level are indicated in bold.

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

Table III: Conglomerate Firm Distributions

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

	30% to 35%	35% to 40%	40% to 45%	45% to 50%	50% to 55%	55% to 60%	60% to 65%	65% to 70%
Panel A: Segments ranked by sales, favorable vs. non-favorable segments								
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: Segments ranked by profits, favorable vs. non-favorable segments								
Frequency	0.061	0.059	0.053	0.052	0.056	0.052	0.054	0.055
Density difference	0.142	-0.042	-0.142	-0.076	0.071	-0.185*	-0.074	-0.042
at the lower bound	(1.39)	(-0.41)	(-1.33)	(-0.72)	(0.66)	(-1.76)	(-0.74)	(-0.40)
No. Obs.	336	327	294	285	314	288	298	305
Panel C: Segments ranked by assets, favorable vs. non-favorable segments								
Frequency	0.055	0.050	0.057	0.056	0.053	0.053	0.050	0.058
Density difference	0.002	-0.106	0.150	-0.021	0.012	0.018	-0.105	0.124
at the lower bound	(0.02)	(-0.98)	(1.42)	(-0.23)	(0.11)	(0.17)	(-0.92)	(1.15)
No. Obs.	396	358	409	400	381	379	357	414

Table IV: Profit Margins and Inventory Growth

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

	30% to 35%	35% to 40%	40% to 45%	45% to 50%	50% to 55%	55% to 60%	60% to 65%	65% to 70%
Panel A: Profit margins, favorable vs. non-favorable segments								
Profit margin	0.104	0.101	0.100	0.104	0.081	0.099	0.094	0.101
Current bin vs.	0.001	-0.002	-0.002	0.014	-0.021***	0.013	-0.006	0.002
neighboring bins	(0.18)	(-0.21)	(-0.24)	(1.57)	(-2.93)	(1.71)	(-0.74)	(0.23)
Other segment	0.099	0.091	0.085	0.089	0.087	0.094	0.088	0.091
Current bin vs.	0.009	0.000	-0.007	0.005	-0.004	0.007	-0.004	0.005
neighboring bins	(1.17)	(-0.04)	(-0.83)	(0.65)	(-0.44)	(0.64)	(-0.56)	(0.64)
No. Obs.	385	350	303	298	342	290	285	339
Panel B: Profit margins, favorable vs. favorable segments								
Profit margin	0.099	0.092	0.094	0.085	0.088	0.102	0.086	0.095
Current bin vs.	0.008	-0.005	0.005	-0.007	-0.006	0.015	-0.013	0.009
neighboring bins	(0.60)	(-0.35)	(0.41)	(-0.44)	(-0.46)	(1.01)	(-0.84)	(0.73)
No. Obs.	163	126	145	116	116	145	126	163

	30% to 40%	40% to 50%	50% to 60%	60% to 70%
Panel C: Inventory growth, favorable vs. non-favorable segments				
Inventory growth	0.083	0.086	0.060	0.084
Current bin vs.	0.000	0.014	-0.025**	0.004
neighboring bins	(-0.01)	(1.19)	(-2.28)	(0.24)
No. Obs.	522	428	458	453

Table V: Capital Expenditures and R&D Spending

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

	30% to 35%	35% to 40%	40% to 45%	45% to 50%	50% to 55%	55% to 60%	60% to 65%	65% to 70%
Panel A: Capital expenditures, favorable vs. non-favorable segments								
Capex	0.019	0.022	0.023	0.022	0.022	0.026	0.029	0.031
Current bin vs.	0.000	0.001	0.001	0.000	-0.002	0.001	0.000	0.000
neighboring bins	(0.25)	(0.83)	(0.43)	(-0.32)	(-1.56)	(0.66)	(0.13)	(0.25)
No. Obs.	109	131	104	105	131	110	148	132

	30% to 40%	40% to 50%	50% to 60%	60% to 70%
Panel B: R&D, favorable vs. non-favorable segments				
R&D	0.003	0.002	0.003	0.003
Current bin vs.	0.001	-0.001	0.000	0.000
neighboring bins	(1.32)	(-1.13)	(0.30)	(-0.08)
No. Obs.	140	115	97	114

Table VI: Industry Beta

This table reports the average industry beta of conglomerate firms. At the end of each quarter, we compute industry betas 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. We also control for known common risk factors, such as the market, size, value, and momentum in the regression specification. To reduce the noise in our industry beta measure (as we do not observe segment returns), 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 first row of each panel reports the average industry beta with regard to the segment in question for all firms in each bin, while the second row reports the difference in industry beta between the current bin and the preceding bin. We include year-fixed effects in testing the difference across bins. T-statistics, shown in parenthesis, are based on standard errors clustered at the year level. *, **, *** denote significance at the 90%, 95%, and 99% level, respectively.

	30% to 35%	35% to 40%	40% to 45%	45% to 50%	50% to 55%	55% to 60%	60%to 65%	65% to 70%
Industry beta of conglomerate firms								
Industry Beta	0.137	0.137	0.180	0.177	0.282	0.241	0.293	0.285
Current bin vs.	-0.009	0.001	0.044	-0.001	0.105***	-0.039	0.052	-0.012
the lower bin	(-0.32)	(0.05)	(1.00)	(-0.03)	(4.76)	(-1.05)	(1.16)	(-0.32)
No. Obs.	730	616	590	638	638	590	616	730

Table VII: Sector Mutual Fund Holdings and Analyst Coverage

This table reports the proportion of sector mutual funds that hold (Panel A) and analysts that cover (Panel B) a conglomerate firm from each segment the firm operates in. At the end of each quarter, we assign a mutual fund holding more than ten stocks to a two-digit SIC code industry, if that industry accounts for more than half of the fund's portfolio value; similarly, we assign each sell-side analyst covering more than 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 provided by IBES in the previous three years. We exclude the conglomerate firm in question in the procedure of mutual fund/analyst industry assignments to ensure that our results are not mechanically driven. 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. To reduce the noise in our analysis, we focus only on conglomerate firms that operate in two segments based on two-digit SIC codes; in addition, we require the two segments to operate in two distinct one-digit SIC code industries. All firms are then sorted into twenty 5% bins based on the sales from one of the two segments as a fraction of the combined sales. The first row of each panel reports the average proportion of sector mutual funds and analysts from the segment in question for all firms in each bin, while the second row reports the difference in proportions between the current bin and the preceding bins. We include year-fixed effects in testing the difference across bins. T-statistics, shown in parenthesis, are based on standard errors clustered at the year level. *, **, *** denote significance at the 90%, 95%, and 99% level, respectively.

	30% to 35%	35% to 40%	40% to 45%	45% to 50%	50% to 55%	55% to 60%	60%to 65%	65% to 70%
Panel A: Proportion of sector mutual funds from the segment in question								
Sector mutual funds	0.188	0.244	0.219	0.232	0.334	0.345	0.369	0.371
Current bin vs.	0.001	0.057*	-0.026	0.014	0.102***	0.011	0.024	0.002
the lower bin	(0.03)	(1.77)	(-0.77)	(0.56)	(2.75)	(0.32)	(0.69)	(0.06)
No. Obs.	402	381	311	296	296	311	381	402
Panel B: Proportion of analysts from the segment in question								
Analyst coverage	0.161	0.219	0.288	0.327	0.520	0.564	0.613	0.663
Current bin vs.	0.018	0.057	0.070*	0.039	0.193**	0.044	0.049	0.050
the lower bin	(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 VIII: Market Reactions to Annual Announcements

This table reports regressions of annual earnings announcement day returns on primary industry classification changes. The dependent variable in all regression specifications is the cumulative 3-day return around an annual earnings announcement. The main independent variable is a $SWITCH$ dummy that take the value of one if the firm's main industry classification switches from a non-favorable to a favorable industry in the fiscal year, and zero otherwise. 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, proportion of institutional ownership, and number of analysts covering the firm. The first three columns report regression results of all firms in our sample. The next three columns report regression results of a subsample of firms that either switch from a non-favorable to a favorable industry or from a favorable to non-favorable industry. Year-fixed effects are included in all specifications. T-statistics, shown in parenthesis, are based on standard errors that are clustered at the year level. *, **, *** denote significance at the 90%, 95%, and 99% level, respectively.

	DepVar = Earnings announcement return in month t					
	[1]	[2]	[3]	[4]	[5]	[6]
$SWITCH_t$	0.006*	0.007*	0.010***	0.010**	0.010**	0.011**
	(1.86)	(1.93)	(2.56)	(2.33)	(2.30)	(2.38)
SUE_t		0.022***	0.023***		0.023***	0.018***
		(11.32)	(11.11)		(4.82)	(6.21)
$MKTCAP_{t-1}$			-0.001			-0.002
			(-1.09)			(-1.34)
BM_{t-1}			-0.001			(-0.00)
			(-0.43)			(-0.85)
$RET12_{t-1}$			-0.002			-0.001
			(-0.92)			(-0.19)
$TURNOVER_{t-1}$			0.000			-0.003
			(-0.12)			(-1.04)
$IDIOVOL_{t-1}$			-0.079			0.069
			(-0.47)			(0.26)
$INSTOWN_{t-1}$			0.014***			0.009
			(2.39)			(0.83)
$NUMEST_{t-1}$			0.000			0.000
			(0.52)			(0.90)
Yearly Fixed Effect	YES	YES	YES	YES	YES	YES
Adj. R^2	0.02	0.03	0.04	0.02	0.03	0.04
No. Obs.	7,200	7,200	7,200	1,904	1,904	1,904

Table IX: Equity Issues and M&As

This table reports (ordered) logit regressions of equity issuance and merger and acquisition activities of conglomerate firms. The dependent variable in columns 1 and 2 is a *Net Issuance* dummy that takes the value of one if the ratio of (the change in book equity between years t and t-1) over (total firm assets in year t-1) is greater than 10%, the value of zero if the ratio is between -0.5% and 10%, and minus one if that ratio is below -0.5%. In other words, the *Net Issuance* dummy captures both seasoned equity issuance and share repurchase decisions. The dependent variable in columns 3 and 4 is a *Stock Financed M&A* dummy that takes the value of one if the firm has at least one 100% stock-financed acquisition in fiscal year t as reported in the SDC database; and that in columns 5 and 6 is a *Cash Financed M&A* dummy that takes the value of one if the firm has at least one 100% cash-financed acquisition in fiscal year t. The main independent variable is the industry flow (*INDFLOW*) measured in the previous year (t-1). Other control variables include the firm-level aggregate flow-induced trading in the previous year (*FLOW*), firm size, book-to-market ratio, lagged one-year stock return, monthly share turnover, stock idiosyncratic volatility, and proportion of institutional ownership. T-statistics, shown in parentheses, are computed based on standard errors corrected for serial-dependence with 12 lags (Newey and West 1987). *, **, *** denote significance at the 90%, 95%, and 99% level, respectively.

	Net Issuance	Net Issuance	Stock-Financed M&A	Stock-Financed M&A	Cash-Financed M&A	Cash-Financed M&A
	[1]	[2]	[3]	[4]	[5]	[6]
$INDFLOW_{t-1}$	0.306***	0.216***	0.551***	0.497***	-0.034	0.034
	(3.77)	(3.46)	(5.77)	(8.02)	(-0.35)	(0.48)
$FLOW_{t-1}$		0.346***		0.234***		-0.042
		(3.37)		(3.44)		(-1.13)
$MKTCAP_{t-1}$		-0.237***		0.301***		0.168***
		(-16.51)		(14.63)		(11.11)
BM_{t-1}		-0.339***		-0.297***		-0.021
		(-9.14)		(-2.66)		(-0.54)
$RET12_{t-1}$		0.116***		0.151***		0.021
		(7.92)		(8.94)		(0.61)
$TURNOVER_{t-1}$		0.076		-0.609***		1.036***
		(0.47)		(-2.73)		(5.34)
$IDIOVOL_{t-1}$		0.057***		0.062***		0.068***
		(2.63)		(3.67)		(7.37)
$INSTOWN_{t-1}$		0.534***		0.174***		-0.201***
		(9.62)		(5.48)		(-3.01)
Pseudo R^2	0.00	0.05	0.01	0.05	0.00	0.04
No. of Obs.	66,044	66,044	83,564	83,564	83,564	83,564

Table X: Robustness Checks: Two-Segment Firms

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

	30% to 35%	35% to 40%	40% to 45%	45% to 50%	50% to 55%	55% to 60%	60% to 65%	65% to 70%
Panel A: Segments ranked by sales, favorable vs. non-favorable segments								
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

	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: Profit margins, favorable vs. non-favorable segments								
Profit margin	0.096	0.090	0.094	0.104	0.058	0.072	0.082	0.092
Current bin vs.	0.002	-0.005	-0.003	0.028***	-0.030***	0.002	0.000	0.007
neighboring bins	(0.17)	(-0.41)	(-0.21)	(2.57)	(-2.60)	(0.28)	(0.00)	(0.55)
No. Obs.	220	194	175	172	194	172	157	179

	30% to 40%	40% to 50%	50% to 60%	60% to 70%
Panel C: Inventory growth, favorable vs. non-favorable segments				
Inventory growth	0.101	0.103	0.052	0.115
Current bin vs.	0.012	0.026	-0.057***	0.036
neighboring bins	(0.60)	(1.23)	(-2.59)	(1.27)
No. Obs.	287	234	254	219

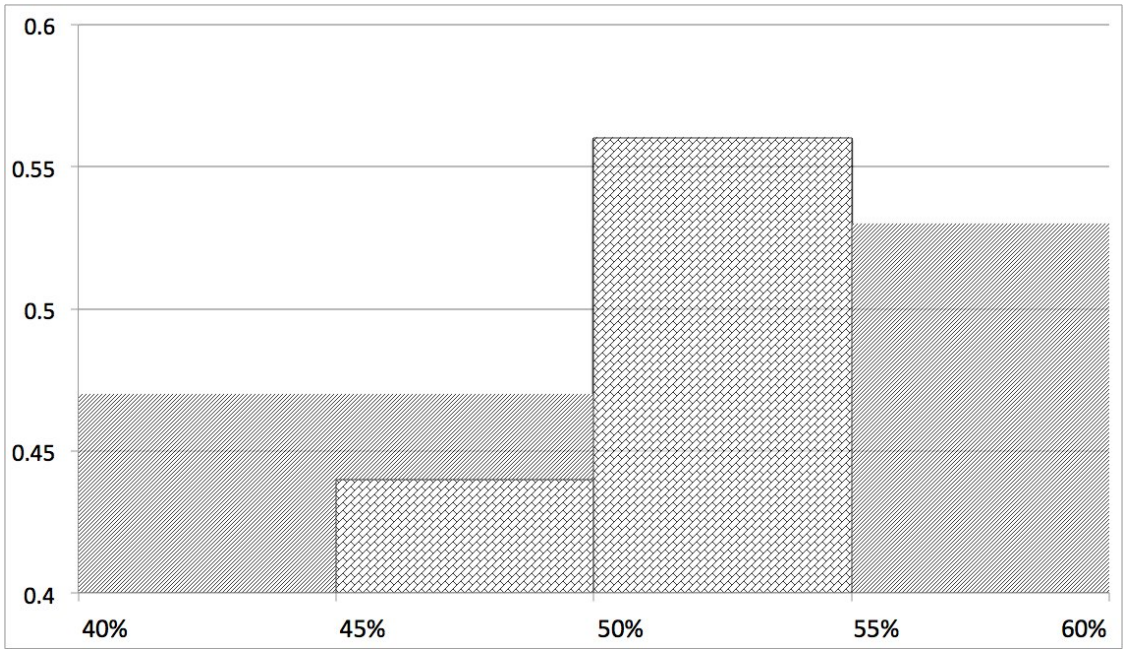

Figure 1: This figure shows the distribution of conglomerate firms based on relative sales weights of the top two segments. For each conglomerate firm in our sample, we require one of the top two segments to operate in a favorable industry and the other in a non-favorable industry, where an industry 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.

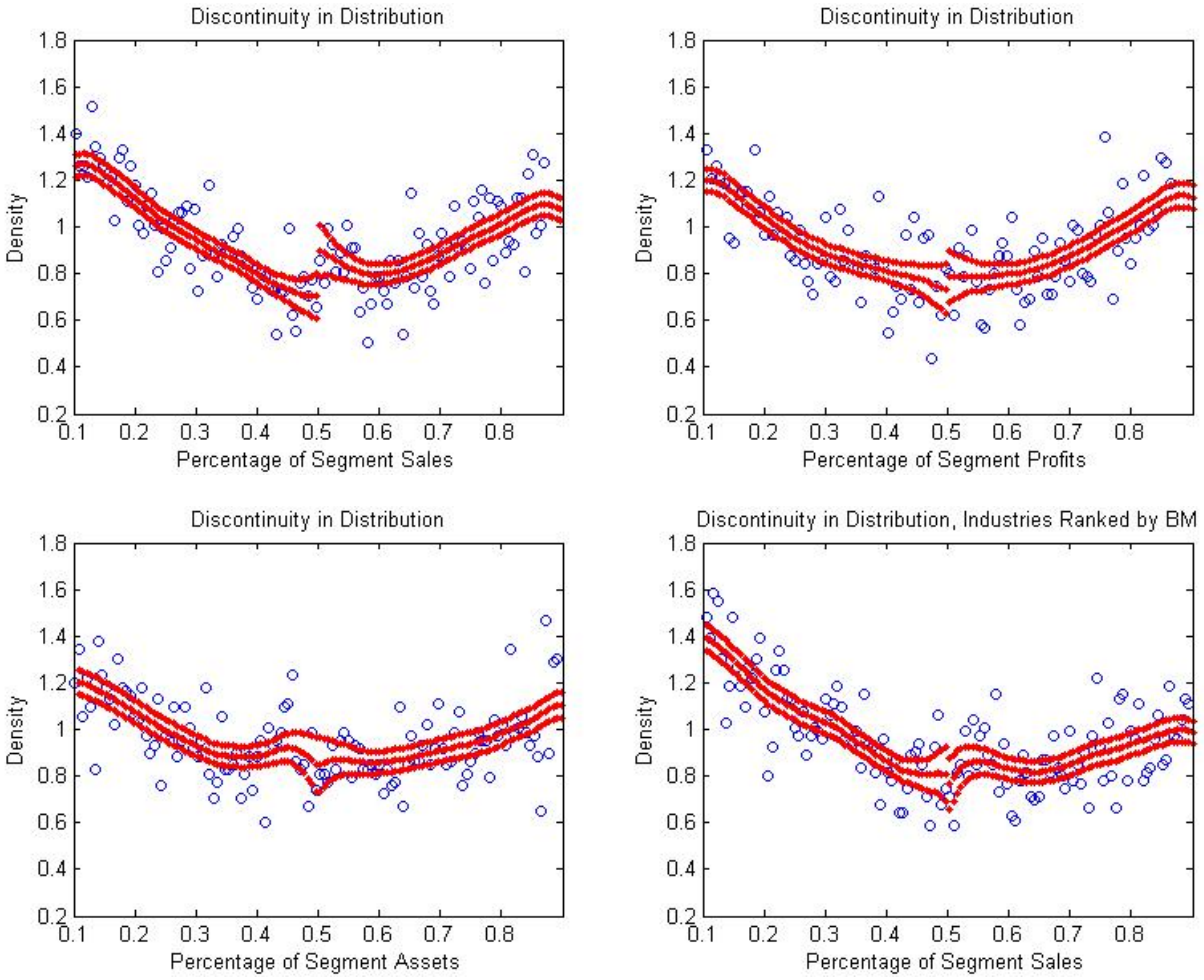

Figure 2: This figure shows the smoothed density functions based on the relative weights of the top two segments of conglomerate firms. The estimation methodology is outlined in McCrary (2008). The blue circles represent the distribution density of each bin grouped by the sorting variable. The red curves are the estimated smoothed density functions, and the 2.5% to 97.5% confidence intervals of the estimated density. Both the bandwidth and bins size 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 industry-average *BM* in that year. 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.

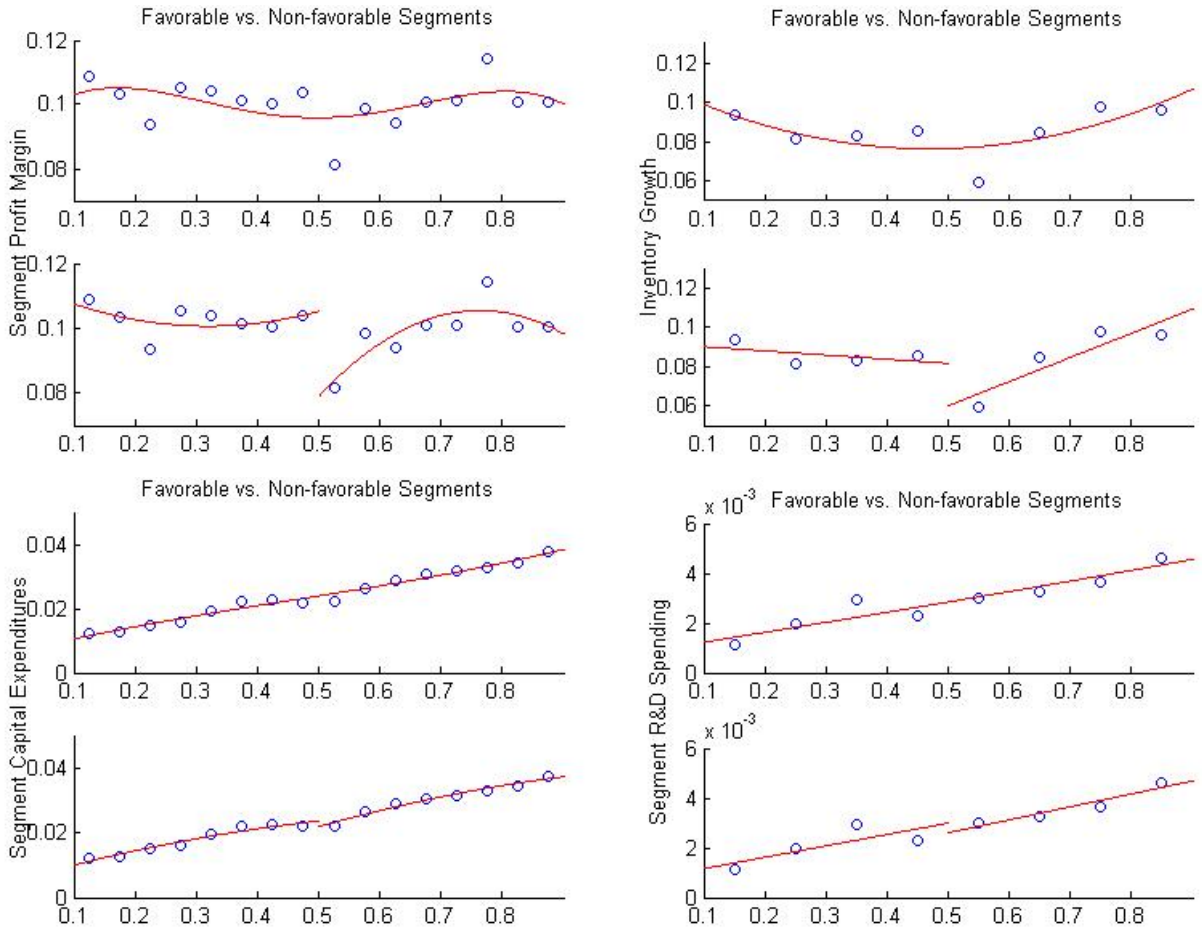

Figure 3: This figure shows various financial/accounting characteristics of conglomerate firms. For each conglomerate firm in our sample, we require one of the top two segments to operate in a favorable industry and the other to operate in a non-favorable industry. An industry is labelled as favorable 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 segment profit margin, defined as the segment's operating profit divided by segment sales, in each bin. The top right panel shows the average firm-level inventory growth rate between years t and t-1 for all firms in each bin. The bottom left panel shows the average segment capex, defined as the segment capital expenditures divided by lagged firm total assets, in each bin, and the bottom right panel shows the average segment R&D, defined as the segment R&D spending divided by lagged firm total assets.

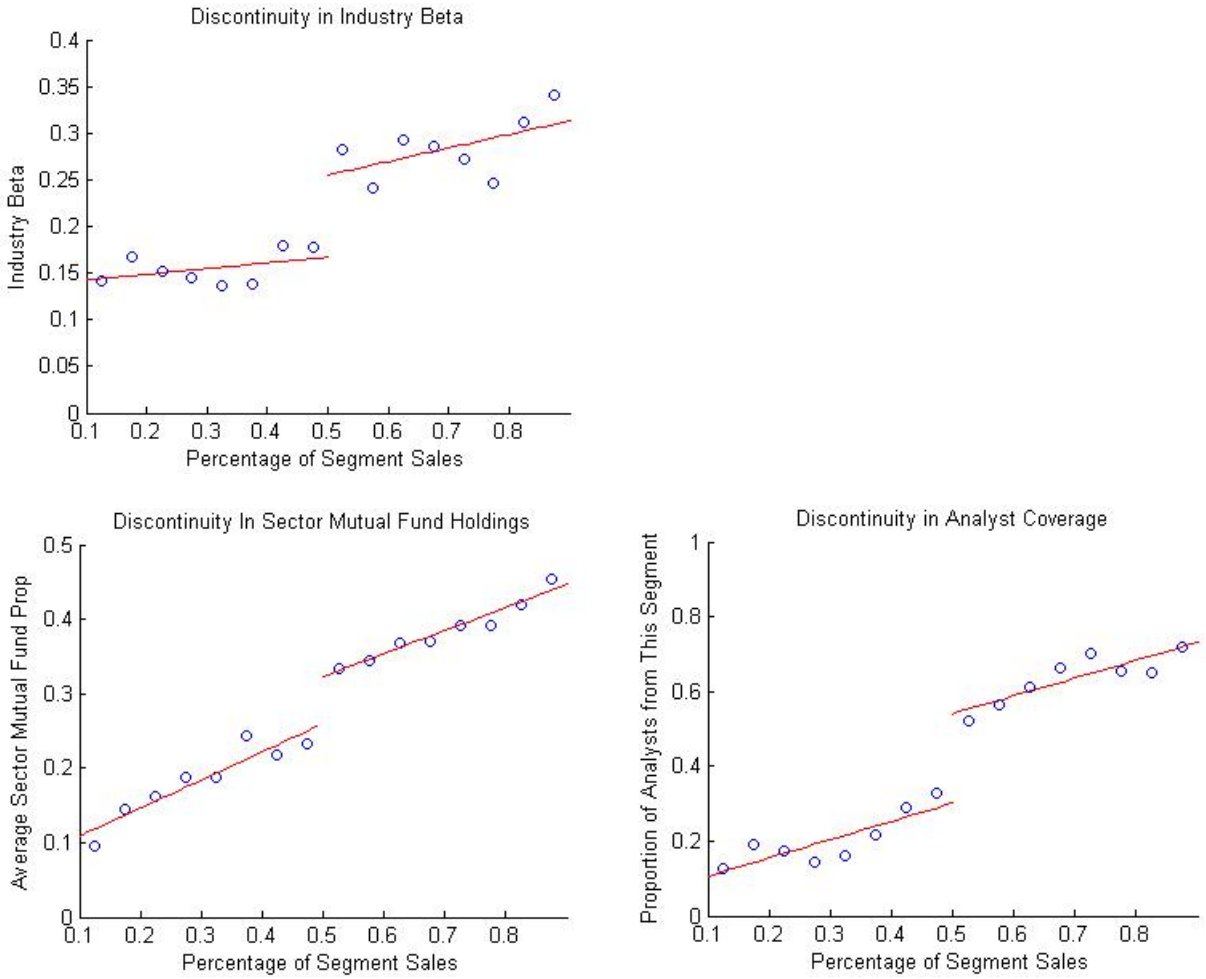

Figure 4: This figure shows the average industry beta and proportion of sector mutual funds that hold and analyst that cover the firm from each segment a conglomerate firm operates in. To reduce the noise in our measures, we focus only on conglomerate firms that operate in two two-digit SIC code industries. All firms are then sorted into twenty 5% bins based on the sales from one of the two segments as a fraction of the combined sales. The blue circles represent the average characteristics of all firms in each bin, while the red curves represent the smoothed estimated linear functions that fit over these observations. The top left panel shows the average industry beta. Specifically, at the end of each quarter, we compute an industry beta for each conglomerate firm in our sample by regressing weekly stock returns on the weekly returns of the two-digit SIC code industry that the conglomerate firm operates in, using data from months 6 to 18 after the fiscal year end. We exclude the stock in question from calculating the corresponding industry returns. The bottom two panels report the proportion of sector mutual funds that hold and analysts that cover the firm from each segment, respectively. Specifically, at the end of each quarter, we assign a mutual fund holding more than ten stocks to a two-digit SIC code industry, if that industry accounts for more than half of the fund's portfolio value; similarly, we assign each sell-side analyst covering more than four firms to a two-digit SIC code industry, if that industry accounts for more than half of all the firms that the analyst covers, using coverage data in the previous three years. We exclude the stock in question in industry assignments to ensure that our results are not mechanical. We then compute the proportion of sector mutual funds and analysts from each industry that the conglomerate firm operates in using fund holdings and analyst coverage data in months 6 to 18 after the fiscal year end.