Industry Window Dressing*

Huaizhi Chen
London School of Economics

Lauren Cohen
Harvard Business School and NBER

Dong Lou
London School of Economics

First draft: August 31, 2012
This draft: October 28, 2012

* We would like to thank Malcolm Baker, Nicholas Barberis, James Choi, Joshua Coval, Robin Greenwood, Kewei Hou, Christopher Malloy, Daniel Paravisini, Christopher Polk, Erik Stafford, Rene Stulz, Tuomo Vuolteenaho, and seminar participants at London School of Economics, Ohio State University, Harvard Business School, Princeton University, and Yale University 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.

ABSTRACT

We explore a new mechanism through which investors take correlated shortcuts. Specifically, we exploit a regulatory provision governing firm classification into industries, that a firm's industry classification will be determined by the segment that has the majority of sales. We find strong evidence that investors overly rely on this primary industry classification. Firms that are just above the industry classification cutoff have significantly higher betas with respect to, as well as more sector mutual fund holdings and analyst coverage from, that industry, compared to nearly identical firms just below the cutoff. We then show that managers undertake specific actions to take advantage of the shortcuts. Firms around the discontinuity cut-off of 50% sales in both top segments are significantly more likely to have just over 50% of sales from the "favorable" industry. These firms barely over the cut-off have significantly lower profit margins and inventory growth rates compared to other firms, consistent with these firms slashing prices to achieve sales targets. Identical firms (same industries) but not with compositions near the cut-offs exhibit none of these behaviors. Further, these same firms do not exhibit any 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. Lastly, firms garner tangible benefits from switching into favorable industries, such as engaging in significantly more SEOs and M&A transactions.

JEL Classification: G02, G10, G32.

Key words: Investor shortcuts, window dressing, discontinuity.

1. Introduction

Investors are continuously faced with a large number of potential signals that are available to collect and process. Faced with these, investors need to solve the complex time allocation problem with respect to the selection of, and the amount of time spent in processing each of the potential signals. If investors specialized in collecting disjoint signals, the processing constraints of each disparate investor would not matter for aggregate prices, as prices would reflect the sum of the capacity of all investors. However, if investors take correlated shortcuts in their investing, 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 impacts both prices and resultant managerial behavior. Specifically, we examine the primary industry into which each firms is classified. The Securities and Exchange Commission (SEC), in classifying firm operations, designates that each firm have a primary industry, which is determined by the segment 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 firm with nearly identical operations that gets 49% of its sales from Technology and 51% of sales from Lumber is classified as a Lumber firm.

If investors overly rely on this primary industry classification in their investment decisions without taking into account the underlying economic operations of firms, they may perceive or treat nearly identical firms around the discontinuity point in substantially different ways. We examine this idea of naïve categorization by examining both stock return patterns and (more directly) investor behavior. First, we explore how investors price these firms. We find that despite being nearly identical, firms right over the 50% point (in term of percentage sales from a particular industry) have significantly

[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)).

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

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

Lastly, we see the same behavior from sell-side analysts. For each firm, we measure the percentage of sell-side analysts covering the firm from each sector. We find a significant jump in sell-side analyst coverage at the industry classification discontinuity. In particular, firms right above the discontinuity have significantly more coverage from the classification industry than the nearly identical firms right below the 50% discontinuity cut-off; they have a 50% (t=2.27) higher percentage of analysts from the classification industry covering them. Again, we see no similar jumps in coverage percentage anywhere else in the distribution.

We next move on to explore how managers may be able to take advantage of these investor shortcuts' implications. In particular, we examine what actions managers can take to fool investors into thinking they are part of an industry. In order to do this, we need to identify situations where it would be advantageous to be considered part of a given industry (relative to other industries). For this purpose, we use periods in which certain industries have higher valuation (i.e., lower cost of capital) than others. We measure industry valuation in a number of ways: a proxy for investor preferences and beliefs based on capital flows into mutual funds investing in given industries, and an industry B/M measure; both produce identical results. Firms in these higher-valuation industries tend to a) enjoy higher announcement day returns around being classified into those highly-valued industries, b) engage in significantly more equity issuance at the higher valuation, and c) engage in more stock financed M&A activities.

To capture managerial behavior precisely to gain this favorable industry classification, we again exploit the discontinuity of industry classification. In particular, we focus on firms that are right around this discontinuity point precisely at those times when valuation of one of its industry segments is particularly high relative to the other segment. Specifically, we examine how managers industry window dress their firms at times when one industry is favorable and the other is 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 segment profit margins and inventory growth rates relative to other firms in the same industry, consistent with these firms slashing prices to achieve sales targets in the favorable industry. Again, we do not observe any changes in segment profit margins and inventory growth rates anywhere else on the distribution of favorable vs. non-favorable segment firms. Further, these exact same 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.

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

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,[2] 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 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.[3] 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,

[2] 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.

[3] 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.

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. 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. Investor Shortcuts

The main thesis of the paper is that investors take correlated shortcuts which result in simple pieces of information being systematically unreflected in firm prices. We then test whether managers are aware of these shortcuts, and then take specific actions to take advantage of the shortcuts' implications. In particular, in this section we focus on one shortcut that financial agents take, namely that of primary industry classification versus actual fundamental operations of the firm, and document how it impacts both financial agent behavior and prices.

4.1. Shortcuts and Betas

In this section, we examine whether investors' overreliance on industry classification aggregates to have an impact on 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 will 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.[4] 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 II, 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 0.286, while that in the 45%-50% bin is 0.178. The difference of 0.107, representing a 61% increase, is highly statistically significant (t = 4.91). The difference in industry beta between any of the other two bins is statistically zero. The structural break can be more easily seen in a diagram. As shown in the top left Panel of Figure 1, while there is a mildly increasing trend in industry beta in both the below-50% and above-50% regions, there is a clear jump in industry beta at the 50% point.

4.1. Sector Mutual Funds

To provide evidence on this behavior on the part of a set of (arguably) sophisticated investors, we examine mutual fund manager's holdings. In order to do this, we first need to identify those mutual funds that are concentrating on a specific sector.

[4] 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.

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%), either by choice or through institutional constraints, we classify the mutual fund as concentrating on that given sector.[5] 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 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 III 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 9.8% (t = 2.55), represents over a 40% jump in the percentage of sector mutual funds holding the stock (23.1 to 32.8). This pattern can be also seen from the bottom left panel of Figure 1, 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] Given that nearly all mutual funds have concentration limits on individual positions of 5% or less, 50% does require the mutual fund to take, for instance, 10 maximally concentrated positions in the same industry, which is suggestive that the fund is concentrating investment efforts there.

4.2. Analyst Coverage

We next examine another set of financial agents who are particularly important in the gathering, processing, and conveying of information in financial markets: sell-side analysts. 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 may impact how investors view these firms, helping drive the beta results we document in Table II.

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 III, 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.[6] 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 1, 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.

In sum, the results presented in this section provide evidence that investors take shortcuts, relying 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.

5. Industry Window Dressing

5.1. Favorable Industries

We next move on to explore how managers may be able to take advantage of implications from the investor behavior we document in Section 4. In particular, we examine what actions managers can take to fool investors into thinking they are part of a given industry. In order to do this, we need to identify situations where it would be advantageous to be considered part of a given industry (relative to other industries). For this purpose, we use periods in which certain industries have higher valuation (i.e., lower cost of capital) than others.

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

We thus begin by choosing a measure to capture shifts in investor preferences that lead to high-valuation 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 IV, Panel A 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.[7] We label these overpriced industries (top 20 as ranked by industry $FLOW$) "favorable" industries as investors are pushing up their prices.[8]

Using this favorable industry measure, we show that firms in these industries are afforded a number of benefits. In Table IV, Panel B we show that these firms engage in significantly more equity issuance at the higher industry valuation levels. The coefficient in Column 2 of 1.451 (t=4-09) implies that a one standard deviation increase in investment flows into an industry increases the SEO likelihood by roughly 20% (from a baseline of 9.7%). In addition, they engage in significantly more M&A activity. Consistent with the firms exploiting the higher favorable industry valuations, the entire increase in M&A activity is coming solely through stock-financed M&As. The coefficient in Column 4 of 3.133 (t=3.25) implies that a one standard deviation increase in investment flows into an industry increases the stock-financed M&A likelihood by roughly 26% (from a baseline of 1.1%).

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

[8] We show nearly identical results in magnitude and significance using industry M/B ratio as an alternative to the investor flows measure. These are shown in Table X and Figure 3, and are discussed in Section 5.6.

5.2. *Identification of Industry Window Dressing*

An 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 designates 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).

Many conglomerate firms have operations in both favorable and non-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 2 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 shaded area), as well as for 45-55% 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 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 2 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 V, 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 0.254 (t = 2.59) compared to the preceding bin. For comparison, if these firms are uniformly distributed in sales weights, the distribution density change between two consecutive bins should be exactly 0. For the rest of the distribution, there is no change in density nearly as large, and none are significant. This same result can be seen in Figure 3. The top left panel shows the discontinuity at the 50% cut-off of segment sales.

5.3. 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%. In contrast, if what we document is some odd empirical pattern in firm operations unrelated to firms actively assuring they are just above the sales discontinuity, we should expect to see similar patterns based on other accounting variables.

To test this, we conduct the exact same sorts as in Table V 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 profits (assets) they have in the favorable segment, and show the entire distribution in Table III, 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. This lack of discontinuity when sorting by segment profits or assets can also be seen in the top right panel and bottom left panel of Figure 3, respectively.

These results, particularly those based on profits, also help rule out an alternative explanation of tournament behavior by divisional managers to be promoted CEO. First, a nuanced version of the tournament explanation would be needed to differentially predict the desire (or ability) of managers in favorable industry segments engaging in this behavior relative to all other segment managers. Even if this were true, however, evidence shows that segment sales have no impact on the promotion of division managers (Cichello et al. (2009)). In fact, profits are the only statistically and economically relevant predictor. For our firms, we see no evidence of discontinuity when sorting on segment profits (or assets), but solely sorting on firm sales, inconsistent with this tournament explanation, but consistent with the window dressing explanation.

5.4. 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 taking real actions in order to sell more in the favorable industry segment in order to be classified into favorable industries, and accrue the benefits we show in

Section 5.1. The second explanation is that firms are simply fraudulently reporting sales (on the margin) in order to be classified into the favorable industries.

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 V. 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 VI reports test results for profit margins, and we see precisely this pattern. Panel A in fact measures the profitability of solely the favorable segment (on which we also see the jump in sales). We see significantly lower profit margins for those firms' segments 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, where the sales are being opportunistically adjusted. Panel B shows that the non-favorable segments of the exact same firms show no such pattern in profitability. We also run 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). Consistent with this idea, we see no differences in profit margins for these two favorable segment firms anywhere in the distribution.

Next, we conduct the same test for inventories in Panel C of Table VI to examine if inventories are also depleted for these firms that are barely above the sales discontinuity. As inventories are only reported at the firm level (and not the segment level), and are more sparsely populated, 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.

Table VII 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 VII 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[9] 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.

An alternative explanation to firms managing sales to be classified into the favorable sector is that they simply manipulate accounting statements to the same end (without any real changes in sales). While this would not explain the inventory and profitability results at the favorable segment level, given that these do not impact industry classification, it could still be a complimentary behavior that achieves the same goal. If firms are purely manipulating sales, this manipulation would eventually need to be undone in a future restatement that correctly states firm operations. We thus test this implication using accounting restatements. We use those firms that actively switch into the favorable industry from an unfavorable industry as the sample of firms on which to examine future restatements. We show in Section 5.5 that these switcher firms do gain the same significant benefits we document of favorable industry firms (in terms of stock issuance and stock-finance M&As).

The accounting restatement results are shown in Table VIII. Columns 1 and 2 run the accounting restatement test on all firms that switch industries: i.) from non-favorable to favorable, ii.) from non-favorable to non-favorable, iii.) from favorable to

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

favorable, and iv.) from favorable to non-favorable. From Column 2, the overall restatement likelihood of switchers is larger than that of other firms, but only marginally significantly so. Columns 3 and 4 then run the analysis examining only switchers from non-favorable to favorable industries. These firms, in sharp contrast, are significantly more likely to restate earnings. The coefficient in Column 4 of 0.382 (t=3.35) implies that switchers are 39% more likely to restate in the future. Importantly, these are significant even controlling for the change in percentage sales from the favorable segment (Δ%SALES$_{t-1}$), which is itself negatively related to restatements, as intuitively a firm that has moved from 40%-80% sales in the favorable industry is less likely to have used accruals to do so than one that moved from 49%-51%. Column 5 and 6 then runs the analysis for all other types of switchers (excluding non-favorable to favorable industry switchers). These firms have are no more likely to restate earnings, with a small negative and insignificant difference between their likelihood and all other firms. The combination of results suggest that the positive coefficients of switching on restatement probabilities in Columns 1 and 2 are being driven entirely by those firms that are switching from non-favorable to favorable industries.

In sum, Tables VI-VIII suggest that while firms do seem to be engaging in real activities to manipulate their sales in order to be classified into favorable industries: slashing prices which reduce profitability and inventories; we also find some evidence that firms switching from non-favorable to favorable industries are engaging in accounting manipulation to achieve that industry status.

5.5. Benefits to Switching

Although we use the discontinuity approach throughout the paper to examine the behavior of firms to be classified into favorable industries, another sample of interest is solely those firms that actively switch from non-favorable to favorable industries. While these will include many of the same firms right above the discontinuity, they will also include firms that make larger changes in firm operations or focus shifts (i.e., mergers or dispositions of segments). Thus, we will lose the identification of comparing two nearly identical firms right around the classification, but will gain a group that are taking decisive actions to be in the favorable segment.

We first show that these switchers accrue the same benefits of being in the favorable industry as other favorable industry firms. We thus run identical tests to Table IV (all favorable industry firms), except now on solely the subsample of firms that switch from non-favorable to the favorable industry. These results are reported in Columns 1-4 of Table IX. Despite the much smaller sample size of the switchers, Table IX Columns 1-4 show that these switchers engage in significantly more stock issuance and stock-financed M&A. The magnitudes are similar to those in Table IX (the point estimates are even larger), and all are highly significant, again even controlling for the change in percentage sales from the favorable segment ($\Delta\%SALES_{t-1}$).

If investors use shortcuts based on primary industry classifications, in their investment decisions, a switch of a firm's primary industry could have a sizable impact on its valuation. We focus on stock returns around an important information event during which information regarding a firm's primary industry is announced – its annual release of financial statements. Specifically, we predict that firms that switch from non-favorable to favorable industries (e.g., from machinery to the tech during the NASDAQ boom) should have higher announcement day returns than their peers, 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 the last two columns of Table IX. In Column 5, a firm that switches from a non-favorable industry to a favorable industry has an announcement day return that is 140bp (t = 2.38) higher than all other firms. In the full specification (Column 2), 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 120bp (t = 2.08).

An alternative method for running this announcement return effect is to focus solely on those firms where there is investor uncertainty as to which industry they will be classified into (i.e., those firms in the closest bins to the 50% discontinuity, between 45-55%). When we run the identical announcement return test on this subsample, while the sample is much smaller, the returns double in magnitude and are more significant. For example, the analog of Column 6 for this sample has announcement returns of 260 basis points (t=3.27).

5.6. Robustness checks

We run three main robustness checks to discontinuity results regarding the sales of firms directly around the classification discontinuity. First, we have also run tests using different measures of industry classification. Throughout the paper we have used 2-digit SIC code. However, we have also tried NAICS, and the coarser 1-digit SIC code classifications, and we see the same discontinuity in sales behavior. Second, we look solely at the subsample of two segment conglomerate firms. This test is shown in Panel A of Table X. While the sample is smaller, the magnitude is nearly identical, and the jump is statistically significant.

Finally, we also use an alternative measure of industry valuation, in addition to the investor flow behavior measure. Namely, we use industry M/B as a measure. Because there is large base-variation in M/B at the industry level (Cohen and Polk (1996)), we adjust for this using the method of Rhodes–Kropf, Robinson, and

Viswanathan (2005). Using this measure of industry M/B, we then define favorable industries, and run the exact same analysis of firm behavior to be classified in these favorable industries. We find nearly identical results with this alternative measure, which are shown in Figure 3 and Panel B of Table X. In particular, the bottom right panel of Figure 3 shows a nearly identical jump around the 50% sales cut off as when classifying industries using the investor flow measure (top left panel), while Panel B also shows the density jump of 0.242 (t=2.54) at the discontinuity point is nearly identical to that from Table V.

6. Conclusion

We document a shortcut that financial agents take, and show how it impacts both prices and resultant managerial behavior. Specifically, we examine the primary industry into which each firms is classified. We exploit a regulatory provision governing firm classification into industries, and the resultant discontinuity it implies. The provision states that a firm's industry classification will be determined by the segment that has the majority of sales. As this empirically always between the two largest segments, the 50% cut-off between these segments determines the industry of the firm. We find evidence that investors overly rely on this primary industry classification in their investment decisions without taking into account the underlying economic operations of firms.

For instance, we find that despite being nearly identical, firms right over the 50% point (in term of percentage sales from a particular industry) have significantly higher betas with respect to that industry than firms right below the 50% point. Sector mutual fund managers also invest significantly more in the firms right over the discontinuity point than directly below it. Sell-side analysts exhibit similar patterns in their coverage of these firms around the discontinuity. Importantly, these significant jumps in beta and behaviors we document occur solely at the 50% classification cut-off, and nowhere else in the distribution of firm operations.

We then show evidence that managers take actions to fool investors into thinking they are part of favorable industries (i.e., those with high valuations). 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 firms barely classified into favorable industries have significantly lower segment profit margins and inventory growth rates relative to other firms in the same industry, consistent with these firms slashing prices to achieve sales targets in the favorable industry. Again, we do not observe any changes in segment profit margins and inventory growth rates anywhere else on the distribution of favorable vs. non-favorable segment firms. Further, these exact same 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.

Lastly, we show that firms that switch into favorable industries have significantly higher announcement returns around their switching into the favorable industries. In addition, they engage in significantly more SEOs and M&A transactions after switching, but solely stock-financed M&As.

In sum, we provide evidence that investors take correlated shortcuts which result in simple pieces of information being systematically unreflected in firm prices. We then show that managers take specific actions to take advantage of the investor shortcuts, providing tangible benefits to their existing shareholders.

References

Aboody, D., Kasznik, R., 2000. CEO stock option awards and the timing of voluntary corporate disclosures, Journal of Accounting and Economics 29, 73-100.

Baker, M., Greenwood, R., Wurgler, J., 2009. Catering through nominal share prices, Journal of Finance 64, 2559-2590.

Baker, M., Stein, J., Wurgler, J., 2003. When does the market matter? Stock prices and the investment of equity-dependent firms, Quarterly Journal of Economics 118, 969-1005.

Baker, M., Ruback, R., Wurgler, J., 2007. Behavioral corporate finance: A survey, Handbook of Empirical Corporate Finance.

Baker, M., Wurgler, J., 2004a. A catering theory of dividends, Journal of Finance 59, 1125-1165.

Baker, M., Wurgler, J., 2004b. Appearing and disappearing dividends: The link to catering incentives, Journal of Financial Economics 73, 271-288.

Barber, B., Odean, T., 2008. All that glitters: the effect of attention and news on the buying behavior of individual and institutional investors. Review of Financial Studies 21, 785–818.

Barberis, N., Shleifer, A., 2003. Style investing. Journal of Financial Economics 68, 161–199.

Barberis, N., Shleifer, A., Wurgler, J., 2005. Comovement. Journal of Financial Economics 75, 283–317.

Bernard, V., Thomas, J., 1989. Post-earnings-announcement drift: Delayed price response or risk premium? Journal of Accounting Research 27, 1–27.

Boni, L. and Womack, K. L., 2006, Analysts, industries, and price momentum. Journal of Financial and Quantitative, 41, 85-109.

Chan, L., Lakonishok, J., Sougiannis, T., 2001. The stock market valuation of research and development expenditures. Journal of Finance 56, 2431–2456.

Cichello, M., Fee, C., Hadlock, C., Sonti, R., 2009, Promotions, turnover, and performance evaluation: Evidence from the careers of division managers. Accounting Review 84, 1119-1143.

Cohen, L., Diether, K., Malloy, C., 2012. Misvaluing innovation. Unpublished working paper. Harvard University and Dartmouth University.

Cohen, L., Frazzini, A., 2008. Economic links and predictable returns. Journal of Finance 63, 1977–2011.

Cohen, L., Lou, D., 2012. Complicated firms. Journal of Financial Economics 104, 383–400.

Cooper, M., Gulen, H., Rau, R., 2005. Changing names with style: Mutual Fund name changes and their effects on fund flows. Journal of Finance 60, 2825-2858.

Cooper, M., Dimitrov, O., and Rau, R., 2001. A rose.com by any other name, Journal of Finance 56, 2371-2388.

Coval, J., Stafford, E., 2007. Asset fire sales (and purchases) in equity markets. Journal of Financial Economics 86, 479–512.

Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998. Investor psychology and security market under- and overreactions. Journal of Finance 53, 1839–1886.

DellaVigna, S., Pollet, J., 2006. Investor inattention, firm reaction, and friday earnings announcements. Journal of Finance 64, 709–749.

Fama, E., MacBeth, J., 1973. Risk, return and equilibrium: empirical tests. Journal of Political Economy 81, 607–636.

Foster, G., Olsen, C., Shevlin, T., 1984. Earnings releases, anomalies, and the behavior of security returns. Accounting Review 59, 574–603.

Frazzini, A., Lamont, O., 2008. Dumb money: Mutual fund flows and the cross-section of stock returns. Journal of Financial Economics 88, 299-322.

Froot, K., Dabora, E., 1999. How are stock prices affected by the location of trade? Journal of Financial Economics 53, 189–216.

Gao, P., Lou, D., 2012. Cross-Market Timing in Security Issuance. Unpublished working paper. London School of Economics.

Gilchrist, S., Himmelberg, C., Huberman, G., 2005, Do stock price bubbles influence corporate investment?, Journal of Monetary Economics 52, 805–827.

Greenwood, R., 2009. Trading restrictions and stock prices, Review of Financial Studies 22, 509-539.

Greenwood, D., Hanson, S., 2012. Share issuance and factor timing. Journal of Finance 67, 761-798.

Guenther, D., Rosman, A., 1994. Differences between COMPUSTAT and CRSP SIC codes and related effects on research. Journal of Accounting & Economics 18, 115-128.

Hirshleifer, D. Lim, S., Teoh, S., 2004. Disclosure to an audience with limited attention. Unpublished working paper. UC Irvine and DePaul University.

Hirshleifer, D., Teoh, S., 2003. Limited attention, information disclosure, and financial reporting. Journal of Accounting and Economics 36, 337–386.

Hong, H., Lim, T., Stein, J., 2000. Bad news travels slowly: size, analyst coverage, and the profitability of momentum strategies. Journal of Finance 55, 265–295.

Hong, H., Stein, J., 1999. A unified theory of underreaction, momentum trading, and overreaction in asset markets. Journal of Finance 54, 2143–2184.

Hong, H., Tourus ,W., Valkanov, R., 2007. Do industries lead the stock market? Journal of Financial Economics 83, 367–396.

Hou, K., 2007. Industry information diffusion and the lead-lag effect in stock returns. Review of Financial Studies 20, 1113.

Huberman, G., Regev, T., 2001. Contagious speculation and a cure for cancer: a nonevent that made stock prices soar. Journal of Finance 56, 387–396.

Ikenberry, D.L., Ramnath, S., 2002. Underreaction to self-selected news events: The case of stock splits. Review of Financial Studies 15, 489–526.

Kadiyala, P., Rau, P.R., 2004. Investor reaction to corporate event announcements: underreaction or overreaction? Journal of Business 77, 357–386.

Kahle, K., Walkling, R., 1996, The impact of industry classifications on financial research. Journal of Financial and Quantitative Analysis 31, 309-335.

Kahneman, D., Tversky, A., 1974. Judgment under uncertainty: heuristics and biases. Science 185, 1124–1131.

Kruger, P., Landier, A., and Thesmar, D., 2012, Categorization Bias in the Stock Market. Unpublished working paper. University of Geneva, Toulouse School of Economics, and HEC.

Lou, D., 2011, Attracting Investor Attention through Advertising. Unpublished working paper. London School of Economics.

Lou, D., 2012, A Flow-Based Explanation for Return Predictability, Review of Financial Studies, forthcoming.

McCrary, J., 2008. Manipulation of the running variable in the regression discontinuity design: A density test. Journal of Econometrics 142, 698-714.

Menzly, L., Ozbas, O., 2006. Cross-industry momentum. Unpublished working paper. University of Southern California.

Merton, R., 1987. A simple model of capital market equilibrium with incomplete information. Journal of Finance 42, 483–510.

Mullainathan, S., 2002. Thinking through categories. Unpublished working paper, Harvard University.

Newey, W.K., West, K.D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.

Polk, C., Sapienza, P., 2008. The stock market and corporate investment: A test of catering theory. Review of Financial Studies 22, 187-217.

Rhodes–Kropf, M., Robinson D. T., and Viswanathan S., 2005, Valuation waves and merger activity: The empirical evidence, Journal of Financial Economics 77, 561-603.

Stein, J., 1996. Rational capital budgeting in an irrational world. Journal of Business 69, 429-455.

Vijh, A., 1994. S&P 500 trading strategies and stock betas. Review of Financial Studies 7, 215–251.

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. 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: Naïve Industry Categorization: Industry Beta

This table reports the average industry beta of conglomerate firms. At the end of each quarter, we compute an industry beta for each two-segment conglomerate firm with regard to each segment by regressing weekly stock returns on the weekly returns of the two-digit SIC code industry that the conglomerate firm operates in, using data from months 6 to 18 after the fiscal year end. We exclude the stock in question from calculating the corresponding industry returns. We also control for common risk factors, such as the market, size, value, and momentum in the regression specification. We focus on conglomerate firms that operate in exactly two industries (i.e., excluding firms with greater than or equal to three segments). All firms are then sorted into twenty 5% bins based on the sales from one of the two segments as a fraction of the combined sales. The first row of each panel reports the average industry beta with regard to the segment in question for all firms in each bin, the second and third rows report the difference in industry beta between the current bin and the preceding bin after controlling for year fixed effects, while the fourth and fifth rows report the same difference after controlling for year and industry fixed effects. 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 with Regard to the Segment in Question								
Industry beta	0.136	0.120	0.179	0.178	0.286	0.245	0.286	0.284
$beta_b$ - $beta_{b-1}$	-0.010	-0.020	0.055	0.003	0.107***	-0.033	0.043	-0.005
(year)	(-0.35)	(-0.81)	(1.23)	(0.10)	(4.91)	(-0.85)	(0.95)	(-0.13)
$beta_b$ - $beta_{b-1}$	-0.013	-0.005	0.043	0.012	0.085***	-0.039	0.046	0.008
(year + SIC)	(-0.45)	(-0.19)	(0.93)	(0.35)	(3.86)	(-0.92)	(1.03)	(0.20)
No. Obs.	730	616	590	638	638	590	616	730

Table III: Sector Mutual Fund Holdings and Analyst Coverage

This table reports the proportion of sector mutual funds that hold (Panel A) and analysts that cover (Panel B) a conglomerate firm from each segment the firm operates in. At the end of each quarter, we assign a mutual fund holding more than ten stocks to a two-digit SIC code industry, if that industry accounts for more than half of the fund's portfolio value; similarly, we assign each sell-side analyst covering more than three firms to a two-digit SIC code industry, if that industry accounts for more than half of all the firms that the analyst covers. We exclude the conglomerate firm in question in the procedure of mutual fund/analyst industry assignments. We then compute the proportion of sector mutual funds holding and analysts covering the conglomerate firm from each industry that the conglomerate firm operates in using fund holdings and analyst coverage data in months 6 to 18 after the fiscal year end. We focus on conglomerate firms that operate in exactly two segments based on two-digit SIC codes; in addition, we require the two segments to operate in two distinct one-digit SIC code industries. All firms are then sorted into twenty 5% bins based on the sales from one of the two segments as a fraction of the combined sales. The first row of each panel reports the average proportion of sector mutual funds and analysts from the segment in question for all firms in each bin, the second and third rows report the difference in proportions between the current bin and the preceding bin after controlling for year fixed effects, while the fourth and fifth rows report the same difference after controlling for year and industry fixed effects. 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 Fund Holdings from the Segment in Question								
Sector mutual funds	0.176	0.235	0.219	0.231	0.328	0.334	0.354	0.362
$prop_b$ - $prop_{b-1}$	-0.005	0.050	-0.018	0.015	0.098**	0.010	0.034	-0.004
(year)	(-0.19)	(1.54)	(-0.48)	(0.60)	(2.55)	(0.30)	(1.10)	(-0.15)
$prop_b$ - $prop_{b-1}$	-0.004	0.045	-0.020	0.005	0.081**	0.029	-0.005	-0.015
(year + SIC)	(-0.19)	(1.60)	(-1.12)	(0.27)	(2.35)	(0.92)	(-0.20)	(-0.66)
No. Obs.	402	381	309	295	295	309	381	402
Panel B: Proportion of Analyst Coverage from the Segment in Question								
Analyst coverage	0.161	0.219	0.288	0.327	0.520	0.564	0.613	0.663
$prop_b$ - $prop_{b-1}$	0.018	0.057	0.070*	0.039	0.193**	0.044	0.049	0.050
(year)	(0.52)	(1.32)	(1.89)	(0.70)	(2.27)	(0.80)	(1.34)	(1.00)
No. Obs.	91	92	88	62	62	88	92	91

Table IV: Mutual Fund Flows and Industry Valuation

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

Panel A: Calendar-Time Portfolio Analysis

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

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

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

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

Table V: Discontinuity in Conglomerate Firm Distributions

This table reports the distribution of conglomerate firms based on the relative weights of the top two segments. At the end of each quarter, we compute a $FLOW$ measure for each stock as the aggregate flow-induced trading across all mutual funds in the previous year. We then take the average $FLOW$ across all stocks in each two-digit SIC code industry to derive $INDFLOW$. An industry is 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: Firms Sorted by %sales in the Favorable Segment								
Frequency	0.061	0.058	0.048	0.048	0.059	0.051	0.051	0.056
Density difference	-0.056	0.003	-0.056	0.080	0.254***	-0.156	0.056	0.117
at the lower bound	(-0.60)	(0.04)	(-0.52)	(0.76)	(2.59)	(-1.62)	(0.51)	(1.18)
No. Obs.	477	451	386	386	455	391	400	446
Panel B: Firms Sorted by %profit in the Favorable Segment								
Frequency	0.059	0.057	0.056	0.052	0.058	0.055	0.055	0.056
Density difference	0.019	-0.061	-0.082	-0.088	0.059	-0.120	-0.097	-0.018
at the lower bound	(-0.22)	(-0.66)	(-0.94)	(-1.28)	(0.65)	(-1.31)	(-1.14)	(-0.19)
No. Obs.	382	370	362	334	372	352	352	364
Panel C: Firms Sorted by %assets in the Favorable Segment								
Frequency	0.060	0.058	0.062	0.068	0.060	0.056	0.054	0.062
Density difference	-0.034	-0.047	0.087	0.103	-0.038	-0.083	-0.022	0.112
at the lower bound	(-0.29)	(-0.38)	(1.03)	(1.24)	(-0.33)	(-0.71)	(-0.18)	(1.45)
No. Obs.	266	254	273	299	266	248	240	276

Table VI: Discontinuity in Segment Profit Margins

This table reports segment profit margins of conglomerate firms. At the end of each quarter, we compute a $FLOW$ measure for each stock as the aggregate flow-induced trading across all mutual funds in the previous year. We then take the average $FLOW$ across all stocks in each two-digit SIC code industry to derive $INDFLOW$. An industry is labelled as favorable in a year if it is one of the top 20 industries as ranked by $INDFLOW$ in that year. For each conglomerate firm in our sample, we require one of the top two segments to operate in a favorable industry. All firms are then sorted into twenty 5% bins based on the sales from the favorable segment as a fraction of the combined sales from the top two segments. The first row of each panel reports the average characteristic of all firms in each bin, the second and third rows report the difference in that characteristic between the current bin and the two neighboring bins after controlling for year fixed effects, while the fourth and fifth rows report the same difference after controlling for year and industry fixed effects. Panels A and B report the average segment profit margin, defined as the segment's operating profit divided by segment sales, in each bin. Panel C reports the average firm-level inventory growth rate between years t and t-1 for all firms in each bin. We require that the conglomerate firm's other top segment operates in a non-favorable industry. T-statistics, shown in 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 Margin in the Favorable Segment (Favorable vs. Non-favorable)								
Profit margin	0.104	0.101	0.100	0.104	0.081	0.099	0.094	0.101
vs. neighbors	0.001	-0.002	-0.002	0.014	-0.021***	0.013	-0.006	0.002
(year)	(0.18)	(-0.21)	(-0.24)	(1.57)	(-2.93)	(1.71)	(-0.74)	(0.23)
vs. neighbors	0.007	-0.007	0.000	0.014	-0.016***	0.013	-0.010	0.006
(year + SIC)	(0.84)	(-1.29)	(0.00)	(1.54)	(-2.79)	(1.61)	(-1.25)	(0.85)
No. Obs.	385	350	303	298	342	290	285	339
Panel B: Profit Margin in the Non-favorable Segment (Favorable vs. Non-favorable)								
Profit margin	0.099	0.091	0.085	0.089	0.087	0.094	0.088	0.091
vs. neighbors	0.007	0.000	-0.003	0.002	0.002	0.000	-0.006	0.008
(year)	(0.91)	(0.03)	(-0.48)	(0.31)	(0.23)	(-0.04)	(-0.80)	(1.11)
vs. neighbors	0.008	-0.002	-0.003	0.004	0.001	0.000	-0.007	0.007
(year + SIC)	(1.04)	(-0.38)	(-0.39)	(0.79)	(0.09)	(0.03)	(-0.86)	(0.88)
No. Obs.	385	350	303	298	342	290	285	339

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

Table VII: Segment Capital Expenditures and R&D Spending

This table reports average segment capital expenditures and R&D spending of conglomerate firms. At the end of each quarter, we compute a $FLOW$ measure for each stock as the aggregate flow-induced trading across all mutual funds in the previous year. We then take the average $FLOW$ across all stocks in each two-digit SIC code industry to derive $INDFLOW$. An industry is labelled as favorable in a year if it is one of the top 20 industries as ranked by $INDFLOW$ in that year. For each conglomerate firm in our sample, we require one of the top two segments to operate in a favorable industry and the other in a non-favorable industry. All firms are then sorted into twenty 5% bins based on the sales from the favorable segment as a fraction of the combined sales from the top two segments. The first row of each panel reports the average characteristic of all firms in each bin, the second and third rows report the difference in that characteristic between the current bin and the two neighboring bins after controlling for year fixed effects, while the fourth and fifth rows report the same difference after controlling for year and industry fixed effects. Panel A reports the average segment capex, defined as the segment capital expenditures divided by lagged firm total assets, in each bin. Panel B reports the average segment R&D, defined as the segment R&D spending divided by lagged firm total assets. T-statistics, shown in 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 in the Favorable Segment (Favorable vs. Non-favorable)								
CapEx	0.019	0.022	0.023	0.022	0.022	0.026	0.029	0.031
vs. neighbors	0.000	0.001	0.001	-0.001	-0.001	0.002	0.000	0.000
(year)	(0.18)	(0.78)	(0.83)	(-0.84)	(-0.68)	(0.86)	(0.15)	(-0.11)
vs. neighbors	0.001	0.001	0.000	0.000	-0.002	0.002	-0.001	0.000
(year + SIC)	(0.48)	(0.67)	(-0.04)	(-0.28)	(-1.22)	(1.25)	(-0.25)	(0.06)
No. Obs.	358	326	282	275	315	266	258	310

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

Table VIII: Accounting Restatements

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

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

Table IX: Benefits to Industry "Window Dressing"

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

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

Table X: Robustness Checks

This table reports 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, we include only two-segment firms in the sample (that is, we exclude all firms with more than two segments). In Panel B, an industry is labelled as favorable if it is one of the top 20 industries as ranked by the industry market-to-book ratio in that year (following the M/B industry decomposition in Rhodes–Kropf, Robinson, and Viswanathan, 2005). *, **, *** denote significance at the 90%, 95%, and 99% level, respectively.

	30% to 35%	35% to 40%	40% to 45%	45% to 50%	50% to 55%	55% to 60%	60% to 65%	65% to 70%
Panel A: 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 B: Discontinuity in Distribution, Industries Ranked by M/B								
Frequency	0.056	0.053	0.050	0.049	0.060	0.059	0.059	0.062
Density difference	0.102	0.055	0.020	-0.073	0.242**	0.031	-0.058	0.110
at the lower bound	(1.07)	(0.58)	(0.21)	(-0.74)	(2.54)	(0.35)	(-0.53)	(1.23)
No. Obs.	386	365	347	338	411	404	403	426

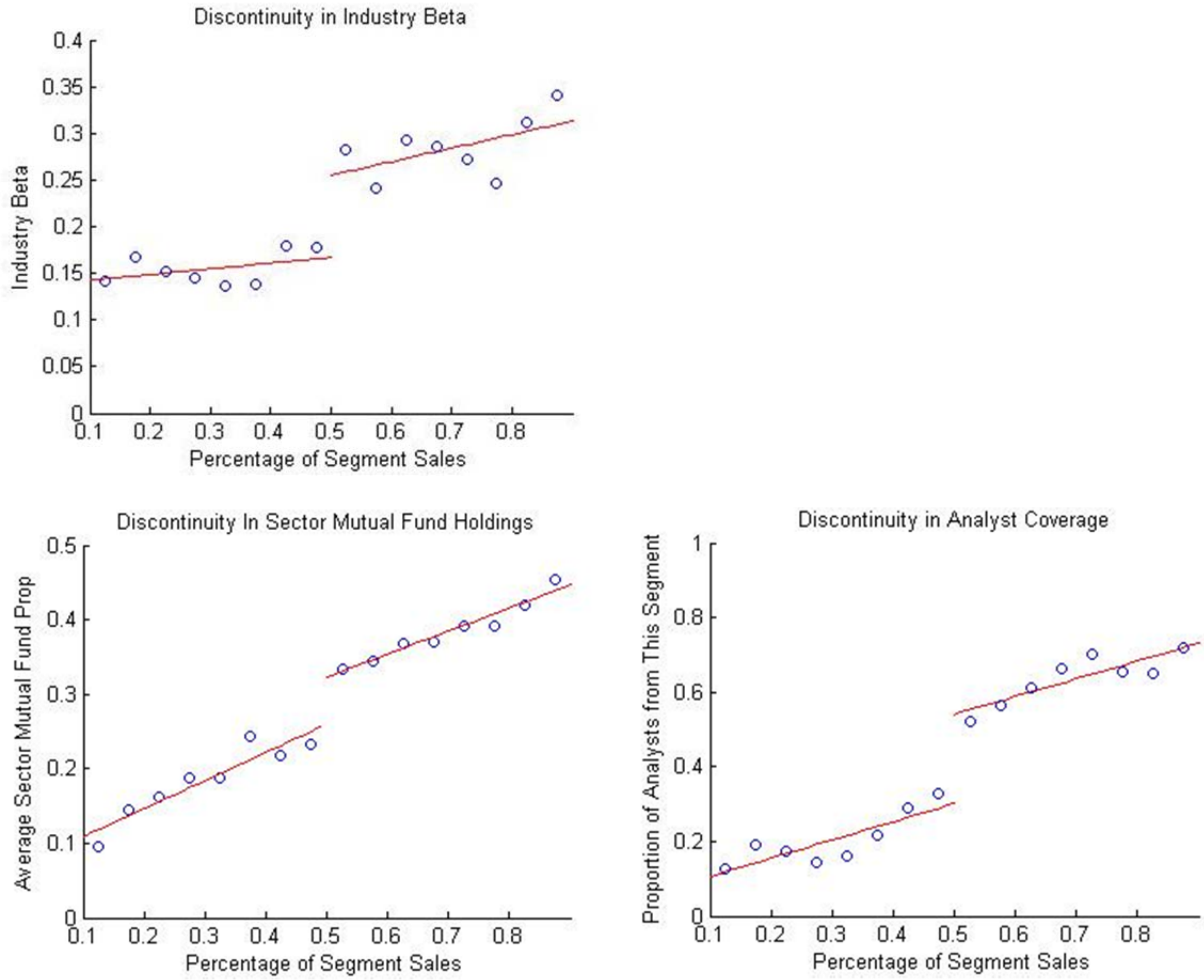

Figure 1: This figure shows the average industry beta and proportion of sector mutual funds that hold and analyst that cover the firm from each segment a conglomerate firm operates in. We focus only on conglomerate firms that operate in two two-digit SIC code industries. All firms are then sorted into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

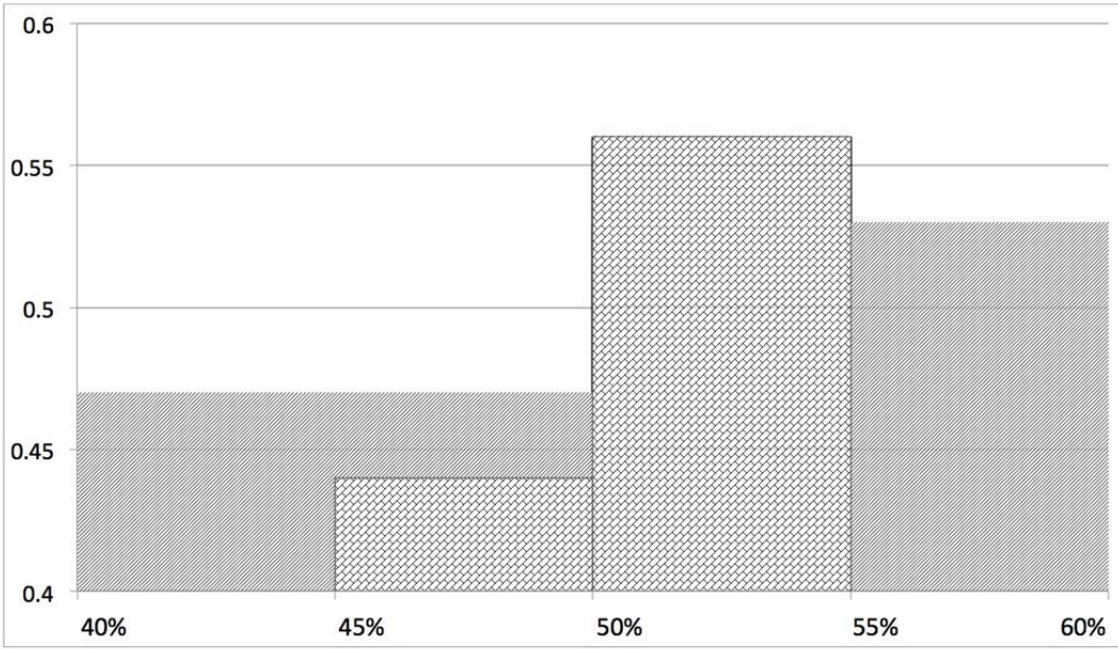

Figure 2: This figure shows the distribution of conglomerate firms based on relative sales weights of the top two segments. For each conglomerate firm in our sample, we require one of the top two segments to operate in a favorable industry and the other in a non-favorable industry, where an industry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

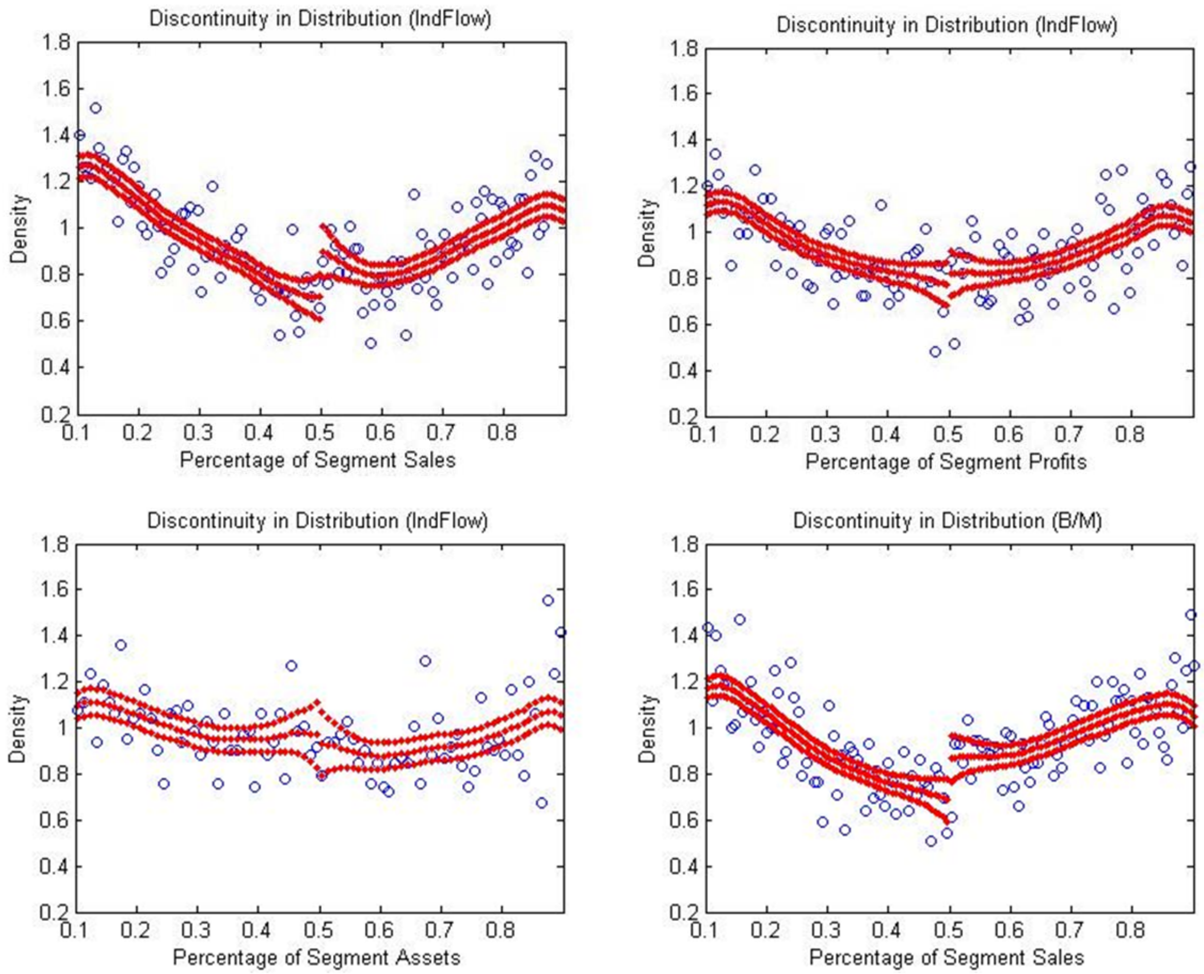

Figure 3: This figure shows the smoothed density functions based on the relative weights of the top two segments of conglomerate firms. The estimation methodology is outlined in McCrary (2008). The blue circles represent the distribution density of each bin grouped by the sorting variable. The red curves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

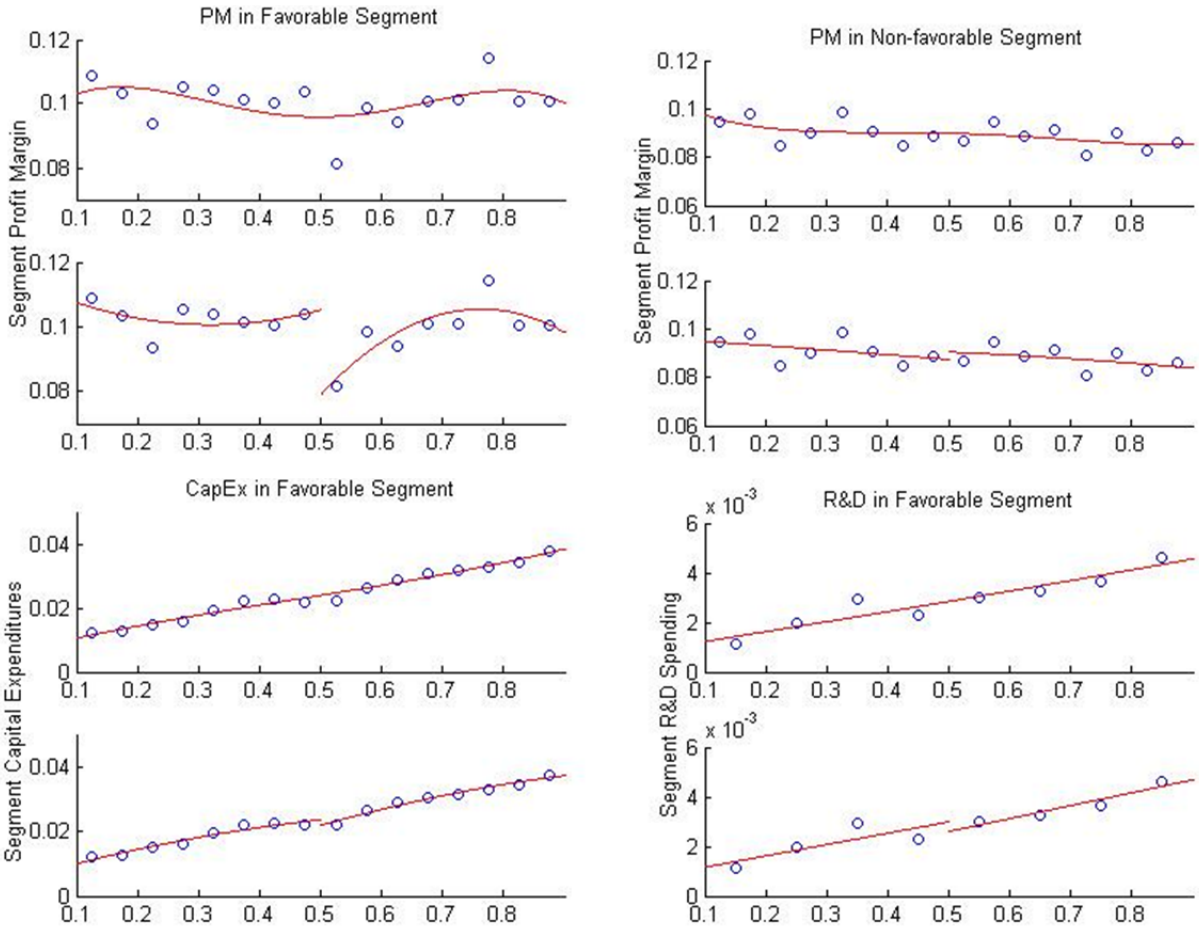

Figure 4: This figure shows various financial/accounting characteristics of conglomerate firms. For each conglomerate firm in our sample, we require one of the top two segments to operate in a favorable industry and the other to operate in a non-favorable industry. An industry is labelled as favorable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