On a Spending Spree: The Real Effects of Heuristics in Managerial Budgets*

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Abstract

Using micro data on managerial expenditures, we uncover heuristics in capital budgets, such as nominal rigidity, anchoring, and sharp reset deadlines. Such heuristics engender managerial opportunism and erode investment efficiency. Managers with a budget surplus increase investment sharply before budget deadlines, and such investments yield lower sales, weaker margins, and more negative NPV projects. Managers who reach a budget constraint early in the fiscal cycle halt further spending until their budget is reset, irrespective of investment options. These effects are stronger at firms with more hierarchical layers and a greater subordinates-to-executives ratio. Overall, simplifying budgeting rules engender strategic behavior and wasteful spending.

JEL Codes: D22, G30, G31, G34, G41

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* Researchers' own analyses derived based in part on (i) retail measurement/consumer data from Nielsen Consumer LLC ("NielsenIQ"); (ii) media data from The Nielsen Company (US), LLC ("Nielsen"); and (iii) marketing databases provided through the respective NielsenIQ and the Nielsen Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ and Nielsen data are those of the researcher(s) and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein. Jovene Cheah, Bo Li, and Zachary Stack provided excellent research assistance. Contact information: Paul Décaire: paul.decaire@asu.edu and Denis Sosyura: dsosyura@asu.edu.

According to academic theory, the main job of top management is to allocate a firm's capital to the best investment opportunities. In practice, a typical firm faces thousands of resource allocation options every day, and the majority of day-to-day operating decisions are delegated to agents outside the executive suite. Since it is impractical to review each of these decisions, the dominant practice in the modern firm is to endow midlevel managers with pre-determined spending budgets under some simplifying rules and heuristics. Much like academic research budgets, managerial spending budgets are anchored on round amounts, remain persistent in nominal terms over time, and often carry special provisions such as a mandatory review of any overage expenses or a recapture of the remaining funds at the fiscal year-end.

The benefit of such annual budgets is that they endow agents with control rights, impose a clear budget constraint, and reduce monitoring costs associated with the approval of day-to-day expenses. However, the limitation of such a simplifying framework is that it hardly incorporates the complex dynamics of a firm's investment opportunities, which should be the ultimate focus of capital allocation decisions. For example, investment opportunities vary greatly over time, do not come in round amounts, and arise independently of the remaining budget balances and fiscal year deadlines.

Our main finding is that the divergence between the heuristic rules in capital budgeting with rigid deadlines and real-world investment opportunities reduces investment efficiency and generates investment frictions. Such frictions manifest in wasteful spending around fiscal year-end deadlines and lead managers to forego some attractive investments that unexpectedly arrive late in the budget cycle when the manager is close to the private budget constraint. Managerial budgeting frictions are more pronounced in complex firms where spending is more difficult to monitor, such as firms with a greater number of hierarchical layers, more product divisions, and a higher subordinates-to-executives ratio.

To offer a granular analyses of managerial spending behavior under budget constraints, we study one of the largest types of corporate budgets—namely, advertising expenditures. Our analyses exploit daily transaction-level data on the allocation of nearly $400 billion across 3.4 million itemized expenditures by 347 publicly traded firms in 2010–2019. To assess the outcome of advertising projects, we match each project to transaction-level scanner data on product sales, which detail the selling price, quantity, and location of the sale. Reported weekly, the sales data cover 100 billion transactions for 4.5 million products and account for the majority of physical sales in grocery stores and drug stores (53% and 55%, respectively).

While our empirical setting provides a rare glance at high-frequency managerial decisions throughout the budgetary cycle, it also illuminates an economically important resource allocation for the firm. The annual advertising expenditures for a mean firm in our sample are comparable to the annual expenditures on capital investment (84% of CapEx) and exceed the spending on research and development (155% of R&D), consistent with theory models that highlight advertising expenditures as a key driver of a firm's competitive advantage, along with CapEx and R&D (Telser 1964; Comanor 1967; Spence 1980).

Survey evidence indicates that an analysis of advertising expenditures is a suitable laboratory for testing the role of managerial heuristics in capital budgeting. According to a recent survey of CFOs, advertising budgets are largely fixed within the year, follow fiscal year deadlines, and remain sticky in nominal terms, with the majority of executives (62%) reporting minimal year-over-year budget adjustments (Agrawal et al. 2020). In contrast, only 10% of executives report revising their budgets during the year to respond to changing market conditions.

Our evidence confirms the reliance on heuristics in advertising budgets. We uncover several empirical patterns in advertising expenditures symptomatic of managerial heuristics. First, expenditures show strong nominal rigidity over time, with year-over-year autocorrelation of 0.97 and an R-squared of 89%. Second, budgets follow rigid fiscal year deadlines, and budget cycles shift when a firm changes its fiscal year-end. Next, we study the impact of such budgetary rigidities on investment spending and the efficiency of capital allocation.

Our first results show that managers raise their spending sharply during the final four weeks before the budget reset deadline. As a result, the average expenditures in the final budgetary month spike by 44%, but only if the manager is running a budget surplus relative to the previous year's realized expenditures. In contrast, when a manager appears to reach his budget constraint early in the fiscal year, his expenditures drop sharply throughout the rest of the budgetary cycle (an average decline of 46% in the pre-deadline month), but recover immediately after the onset of the new fiscal year.

The spike in the spending of excess funds before the budgetary deadlines is associated with a decline in investment efficiency, as measured by the impact on sales, market penetration, and customer reach. For example, ad projects funded from budgets with excess funds (relative to prior year) during the last month of the budgetary cycle generate 62% less revenue, are 39% less efficient at penetrating markets, and cost 52% more to reach the same amount of potential customers (measured by Nielsen) than other projects of the same manager in the same year but after the budget reset deadline. Such close-to-deadline projects are more likely to be value-destroying—that is, to generate less than a dollar of cumulated sales per dollar of initial investment.

The underperformance of close-to-deadline projects is robust to controlling for unobservable factors affecting a given firm and product category in each year via various combinations of high-dimensional fixed effects. For example, the results persist in specifications with firm*year*product category fixed effects that account for a firm's capital availability and investment opportunities, as well as temporal shifts in product demand. The results are also robust to controlling for intra-year seasonality in product sales and advertisement efficacy, using product category*month*market fixed effects. For example, these specifications compare the performance of ad projects for shampoo in June 2018 between firms whose fiscal year ends in June against the performance of projects for the same product in June 2018 but for firms whose fiscal year ends in September. In another robustness test, we show that the results are not driven by a December effect or end-of-calendar year effect and persist after removing firms with budgetary cycles expiring in December.

We identify two drivers of the variation in project performance: (i) the project's temporal proximity to the budget reset deadline and (ii) the manager's budget surplus remaining before the reset deadline. When a firm changes its budget deadlines (fiscal year-end), say from June to December, the underperformance of projects funded in June disappears and reemerges in December. Likewise, the underperformance of close-to-deadline projects disappears for projects funded from budgets running at an overage (relative to the prior year) and reemerges for budgets running at a surplus.

Next, we provide evidence on the mechanisms underlying the underperformance of close-to-deadline projects. We find that managers select the same project categories (a similar mix of advertising channels) but implement lower-quality projects. Our evidence suggests that the higher intensity of spending before the budget deadlines is associated with the stepping down in project quality and, hence, weaker performance. Consistent with this explanation, the most attractive investment opportunities for advertising expenditures (such as salient space in print media and primetime TV slots) are pre-booked 6-12 months in advance. Thus, managers with a budget surplus before the reset deadline face three options. They can spend the remaining funds on less attractive projects (effectively, leftover ads), return the unused funds to the firm, or signal a lack of investment opportunities at the risk of receiving a smaller budget next year (Moorman 2021). We find that managers elect to retain control over the remaining funds and expend them despite weak investment opportunities, investing in at least some projects with negative estimated NPV.

We present micro evidence in support of the hypothesis that the underperformance of close-to-deadline projects is linked to excessive spending relative to available investment options, consistent with theory models of investment under limited options (Baldwin 1982; Bernanke 1983; Weeds 2003; Kogan and Papanikolaou 2013). To test this prediction, we exploit a unique institutional feature of the TV advertising market that generates intra-year variation in investment opportunities for select markets. In the US, primetime TV ads for the year are made available for booking during a fixed period between mid-May and the end of June (Shapiro et al. 2021). Thus, managers left with budget surpluses scheduled to expire during this booking period get access to attractive investment options before their budgets expire. For this subsample of managers with access to attractive investments, the performance of close-to-deadline projects is no worse, and sometimes better, than that of the same managers' projects earlier in the budget cycle, and year-end expenditures surge are absent.

Finally, we study whether the spike in the pre-deadline spending aligns with shareholders' incentives or represents an agency friction and find evidence consistent with the agency view. To assess internal controls, we collect data on each firm's organizational structure, hierarchy, and managerial subordination from Lexis Nexis Corporate Affiliations. The value-eroding effect of the spike in managerial spending before budgetary deadlines is more pronounced at complex firms with more reporting units and a greater number of hierarchical layers between marketing managers and the CEO. Similarly, such effect is stronger at firms with laxer internal monitoring—those whose CEO approaches retirement, serves on multiple external boards, and own few shares of the firm. In contrast, the pre-deadline spending spree is tempered when the CEO is a large shareholder, suggesting that such a spending pattern diverges from shareholders' interests. Consistent with agency theory, the performance of end-of-year projects improves when their funding is likely to be scrutinized—namely, during economic downturns or periods of budget deficit, as predicted by the free cash flow hypothesis (Jensen and Meckling 1976; Jensen 1986) and the disciplining effect of downturns (Schmalz and Zhuk 2019).

The central contribution of this paper is to provide granular project-level evidence on the real effects of heuristics in managerial budgets. In contrast to traditional models of capital budgeting as a continuous allocation of resources to stochastically arriving investment opportunities, corporate budgets exhibit nominal rigidity in capital spending, anchoring on round numbers, fiscal year horizons, and sharp expiration deadlines. While such institutional rules facilitate delegation in capital spending, they give rise to managerial opportunism, eroding investment efficiency. Our findings add to three research strands: (i) managerial heuristics, (ii) intra-year corporate spending cycles, and (iii) the practice of capital budgeting.

Our paper adds to the literature on managerial heuristics in financial decisions. Prior work shows that managers rely on various shortcuts and fallacies in their decisions, often to the detriment of firm value. For example, managers apply the same discount rate to projects with different risk (Kruger et al. 2015), anchor the cost of capital on prior deals (Dougal et al. 2015), incorporate sunk costs in project evaluation (Guenzel 2021), rely excessively on the CAPM in estimating the discount rate (Dessaint et al. 2021), and improperly account for idiosyncratic risk (Decaire 2021). We add to this research by revealing managerial heuristics in capital budgets and offering micro evidence on their economic consequences.

We also expand the literature on intra-year patterns in corporate investment. So far, this literature has mostly focused on the role of tax incentives and earnings management. Kinney et al. (1993) and Xu and Zwick (2022) show that firms are more likely to place equipment in service in the fourth quarter of the fiscal year to maximize tax benefits from depreciation. Research in accounting finds that firms manipulate year-end earnings by strategically timing income recognition from asset sales (Bartov 1993), delaying R&D and maintenance investments (Dechow and Skinner 2000), and overproducing to reduce the reported cost of goods sold (Roychowdhury 2006). In complement to this work, we provide evidence on the less explored channel of managerial budgets. Our study is among the few in this literature to offer high-frequency project-level evidence and evaluate real outcomes on product prices, sale quantities, and contribution margins. In its focus on projects, our paper is closest to Liebman and Mahoney (2017), who find that the U.S. government accelerates spending on procurement contracts in the final week of the year.

Finally, we add to the literature on the practice of capital budgeting. While capital budgeting is one of the most fundamental corporate decisions, field evidence on firms' budgeting practices has been scarce because project investments and their outcomes are typically unobservable, and even aggregate financial data are available at only quarterly levels, obfuscating the analysis of managerial behaviors. Yet, survey evidence suggests that managers employ various shortcuts and rules of thumb in capital budgeting decisions (Graham and Harvey 2005), and the overwhelming majority (78%) of executives are willing to sacrifice value to accommodate targeted financial thresholds (Graham, Harvey, and Rajgopal 2005). Graham Harvey, and Puri (2015) show that across all of the financial policies in their survey, top executives are most likely to delegate capital spending to their subordinates and, in doing so, 42% admit to relying on a "gut feel" as an important factor in the allocation decisions. Our paper studies the foundation of such delegation decisions via annual spending budgets and traces the effects of budgeting rules on project outcomes.

Institutional Details

1.1. The Advertising Industry

Firms in the United States spent 294.8 billion dollars per year in advertising in 2010-2019, on average. To give a sense of the relative important of this industry, US firms allocated 1,455.8 billion dollars per year to capital expenditure (CapEx) over the same period. This suggests that resources allocated to the advertising industry represent 20.5% of that amount (Figure 1.1.), a share that rivals any single industry reported in the US Census Bureau CapEx survey[1]. For comparison, the single largest industry in terms of capital expenditure, manufacturing (NAICS 31-33), simply accounts for 15.7% of the annual total. Simultaneously, firms spend $0.84 on advertising per dollar of CapEx, and $1.55 on advertising per dollar of research and

[1] Source: Capital Spending Report "Tables 2a. Total Capital Expenditures for Companies with Employees by Industry Sector" (link: https://www.census.gov/data/tables/time-series/econ/aces).

development (Figure 1.2. and 1.3.). The prominence of advertising expenditure squares with the broad set of economic theories discussing its complementary role with capital expenditure and research and development in helping firms build and maintain their competitive position (e.g., Telser (1960), Comanor (1967), Spence (1980)).

The advertising business is also characterized by rigid cycles regarding how and when TV networks sell advertising space to prospective clients. In particular, the TV ad market can be broken into two broad "seasons." The upfronts run between mid-May and the end of June, (Geving, (2018)), and it is estimated that 70% of the annual TV advertising dollars are allocated at that time (Shapiro et al. 2021). This period is meant to woo potential advertisers and provide access to the upcoming year's most valuable slots—primetime[2]. In contrast, the slots purchased during the rest of the year are called "non-preemptible" or "remnant." These are usually meant to air in the month or week during which they are booked and generally relate to slots of lower quality compared to "primetime."

At last, survey evidence offers unparallel visibility on how marketing managers allocate resources. Budgets are usually fixed within the year, and these tend to be sticky over time (Agrawal, (2020)). Few managers (10%) systematically adjust their budgets during the year to dynamically meet company objectives, while most (62%) admit to performing minimum to little budgeting evaluation in setting next year's budget. They either use the previous year's total expenditure as a guideline for the upcoming yearly budget (41%), or they set it as a proportion of the expected revenues, which are themselves based on the previous year's revenues (21%) (Moorman (2021)). This lack of adaptive evaluation induces nominal rigidity in budgets allocation while forcing managers to individually vet extra spending when budgets are depleted for the year. We confirm the persistency of advertising expenditure in our data. The year-over-year total annual expenditure autocorrelation coefficient is equal to 0.97 with an R-square value of 0.89 (Figure 2 and Internet Appendix Table IA.1).

1.2. Fiscal Year-End and Seasonality

In principle, firms' fiscal year-end can fall on any date. In practice, 54% of firms opt for a fixed year-end date on December 31st, while 31% of firms have year-end dates that are not perfectly fixed over time for

[2] https://digiday.com/marketing/upfrontses-wtf-upfronts/

our sample of firms[3] (Compustat). For example, fiscal year-end of Apple Inc. falls on the last Saturday of September (e.g., September 24th in 2011, and September 29th in 2012). For the 46% of firms not ending their fiscal year on December 31st, we do not systematically find that firms tend to bunch around other specific dates (Figure 3.1).

Specific industry seasonality patterns may shape firms' decision in selecting their year-end month. However, our evidence suggests that not all firms in the same industry select the same year-end month. We find that most product categories are associated with more than one year-end month (65%), where the average (median) category is associated with 2.28 (2) year-end months (Figure 4.1.). Moreover, for the average (median) year-end month in our sample, we observe 126.5 (118) distinct product categories, which creates substantial cross-sectional variation (Figure 4.1.).

Overall, this can be explained by the fact that the average (median) firm is active in 12.9 (8) distinct product categories, and only 10% of firms specialize in a single product category (e.g., candies, school supplies) (Figure 4.2. and 4.3.). This indicates that diversified firms might experience different seasonality patterns for each of the product category they sell. This helps explain why there are no clear clustering patterns of firms' fiscal year-end month within specific product categories.

2. Data and Methodology

Our main two datasets are from the Nielsen Retail Measurement Service scanner data and the Nielsen Ad Intel dataset. Jointly, they provide us with a measure of firms' sales and their associated advertising efforts. The Ad Intel data is measured at multiple frequencies (i.e., daily, weekly, and monthly) depending on the type of advertising medium recorded, such as television, radio, internet, and outdoor ads. To make sure that we aggregate at the lowest frequency of our data, but also to match the diffusion cycle in the "remnant" market, we aggregate the data at the monthly frequency.

2.1. Sales Data

The sales data come from the Nielsen Retail Measurement Services (RMS) scanner dataset provided by the Kilts-Nielsen Data Center at the University of Chicago Booth School of Business. The Nielsen RMS

[3] When looking at every firm included in Compustat, 29% of firms opt for a fixed year-end date on December 31st, while 37% of firms have year-end dates that are not perfectly fixed over time.

scanner dataset is collected from point of sales systems in retail stores. Weekly, each individual retail location reports the sales and quantities of every product sold in the store. The raw data consist of more than 100 billion unique observations, for 4.5 million distinct products directly identified at universal product code (UPC) level covering approximately $2 trillion in sales.

These sales account for a large fraction of all sales in retail locations in the United States. For example, it represents 53% of all sales in grocery stores, 55% in drug stores, and 32% in mass markets, according to Nielsen. Importantly, Nielsen covers 90 of the most important retailers in the US. While it provides decent coverage of the universe of products sold by firms in our sample, it does not capture all of these firms' US sales. Two arguments alleviate concerns regarding this limiting feature of the data in the context of our study. First, retail sales in physical stores accounted for 93% of all retail sales in the US (Figure 5), indicating the predominant role of brick-and-mortar stores in customer buying habits. This mitigates concerns regarding a shift in consumers' propensity to buy online toward the end of firms' fiscal year, especially after including our month*product category fixed effect. Furthermore, we find that firms neither change their ads mix (e.g., tv, radio, digital) over the fiscal year (Figure 6.1. and 6.2.), nor do they change the intensity at which they advertise across each of their regions of activity.

While the retail scanner data provide product level information, it does not readily identify the firm producing and selling it. Using products' UPC, we link the RMS data with data from GS1, a dataset that contains the identity of firms producing each item. This provides us with a link between the producing firm and each individual item sold.

2.2. Advertising Expenditure

The advertising data comes from the Nielsen Ad Intel dataset provided by the Kilts-Nielsen Data Center at the University of Chicago Booth School of Business. The Nielsen Ad Intel data cover each individual advertising occurrence for a variety of media types (e.g., television, radio, print, digital) across the US. The data allow us to directly observe the identity of the firm advertising and provide highly disaggregated information regarding the specific brand and product being promoted, the price paid for the ad, the amount of time it aired (for television advertising), the number of viewers reached, and the maximum population that the ad could have reached.

To evaluate the performance of advertising campaigns on their corresponding sales, we merge the advertising with the sales datasets. We perform two separate exercises to accomplish this goal at different levels of data aggregation. For our first strategy, use data aggregated at the firm and month-year level, and we manually link both datasets using firms' name and month for each observation. This strategy has the benefit of being more complete, as it includes all available observations for the 347 firms in our sample, but it reduces the richness of the setting, because information is aggregated at the firm level. The second strategy utilize data measure at the firm-product category and month-year level, enabling us to capitalize on the rich nature of Nielsen's data. It is important to note that product category in the Ad Intel dataset does not perfectly map into the categories listed in the retail scanner data. Moreover, category definitions vary by firms for products of similar nature, rendering the creation of a unique key to bridge both datasets impossible. To produce the most reliable bridge, we manually match each firm's product categories in the Ad Intel with its corresponding match in the retail scanner dataset. When a match is not possible or is too ambiguous for a given firm, we do not link those categories. This strategy allows us to work with the most reliable merge, but it comes at the cost of restricting the number of participating firms (i.e., 221 distinct firms and 805 firm-product categories). This complementary dataset allows us to introduce stricter fixed effects and verify the robustness of our main results.

2.3. Organizations and CEOs Details

We obtain the exact day on which firms' fiscal year end from Compustat and Global Compustat using the variable *apdedate*. This contrasts with the variable generally used to identify end of year date in Compustat, *datadate*. *Datadate* effectively identifies the last day of firms' end-of-year month, not the effective date. For example, in 2011 Apple Inc. *datadate* value is September 31st, but the firm effectively ended its fiscal year on September 24th, as recorded by *apdedate*. This distinction is important as many firms in our sample do not end their fiscal year on the last day of a month (130 firms in our sample). Given that we aggregate the data over a 30-day period, failing to use *apdedate* could impound noise in our key measures.

Then, we manually collect detailed organization structure data from Lexis Nexis Corporate Affiliations to evaluate the complexity of firms in the sample. This data offer unparallel visibility about the number of hierarchical layers in a firm, the relation among business units, as well as their respective function. Using these data, we obtain a measure of the number of firms' hierarchical layers as well as a measure of managers-to-subordinate ratio at a yearly frequency for the firms in our sample. This gives us a metric capturing the number of subordinates each senior manager (i.e., top layer) must supervise. Finally, we use the Nielsen data to measure the number of product categories firms produce every year, representing the breath of their operations. Table 1 reports our key summary statistics.

This data offers several benefits over the traditional measures of firm organizational structure in the current literature, which are generally obtained from Compustat segment data. First, Compustat segment data are often disconnected from firms' true operations (Price Water House Cooper, 2008), and firms have been known to game accounting rules by adjusting their organization structure to avoid reporting revenue metrics for sensitive divisions[4] (Georgiev, 2017). In contrast, Lexis Nexis collects firms' organization structure by having in-house specialists conduct periodic surveys with their partnered firms to augment publicly available information.

The three organizational measures provide distinct but complementary ways to capture firms' organizational complexity, strengthening our conclusions. Note that existing empirical works (Guadalupe and Wulf (2010), Bloom et al. (2010), Bloom et al. (2012)) have confirmed the validity of these proxies to capture firms' complexity. At last, the Nielsen data directly represent each individual product segment sold by firms in the sample, eliminating the risk that financial reporting gimmicks might obfuscate our measurements.

Finally, following the agency theories (Jensen and Meckling 1976; Jensen 1986) and role of downturns in disciplining managers (Schmalz and Zhuk 2019), we study how yearend overspending varies with a firm's free cash flow and excess liquidity. To capture moments when managers are less likely to experience acute monitoring from their superior in the use of their budget or when they would have easy access to additional resources once their annual budget is depleted, we use three complementary measures.

[4] Google reorganized into a conglomerate, Alphabet, to avoid the then newly implemented disclosure rules that would have required the revelation of sensitive information regarding some of their strategic units (e.g., Youtube) Source: https://www.marketwatch.com/story/the-sec-wants-to-know-why-google-doesnt-report-youtube-revenue-2018-02-26.

We find that yearend excess spendings are tempered in cases when upper managers have higher incentives to monitor their subordinates or when firms struggle to access additional capital (Table 7). This conclusion is supported by the negative and statistically significant coefficient for the interaction term Last Month$*$Financial Constraint.

2.4. Methodology

Our main empirical strategy consists of a panel dataset where the unit of observation is at the firm-month level. We also validate to robustness of our results by reproducing our main findings at the firm-month-product category level. We use the sharp discontinuity at the end of firms' fiscal year as the starting point of the panel construction. In our baseline specification, a month is a standardized unit of 30 days, when we aggregate the expenditure and the sales data. This ensures that some months do not mechanically receive a greater weight in the analysis, because calendar months have different length (i.e., 28,30, and 31 days)[5]. Thus, to generate the panel, we create increment of 30 days from apdedate, and combined observations in those time intervals for each firm in the sample. A similar exercise is done at the firm-product category level for the robustness sample.

Finally, firms do not directly report their annual advertising budgets, making it challenging to identify when managers deplete them. We obtain a coarse but direct measure of firms' budgeting cap, building on the survey evidence (Moorman (2021)) and our empirical results (Figure 2, Internet Appendix Table IA.1) documenting rigidity in firms' budgeting practices for advertising expenses. Precisely, we use the previous year's annual expenditures as our budget proxy.

3. Heuristic Budgeting Rules and Rationing

3.1. Resource Allocation

We begin our analysis by studying the effect of capital rationing on managers' expenditure with a graphical analysis. We find that at the exact moment when annual spendings exceed previously year's level, expenditures dramatically drop (Figure 7), and they remain low for the rest of the fiscal year, before reverting to average level (i.e., ~ 100/12) at the onset of the new fiscal year when the new budget gets

[5] Our results are also robust to simply using calendar months, but this is a less precise empirical strategy.

allocated. We then investigate what happens when rationing does not bind. When focusing on the subset of firms for which managers depleted their budgets at least once during the sample period, we find that expenditures spike by 31% on year-ends (Figure 8). To confirm that this pattern is not specific to firms that tend to deplete their budget, we show that the pattern persists when studying all the firms in the sample (Figure 8.2.). This suggests that this year-end overspending pattern is widespread, and it echoes findings from multiple other studies studying year-end patterns (e.g., Kinney et al. (1993), Callen (1996), Bartov (1993), Shin et al. (2002), Xu and Zwick (2022)). Ultimately, the high-frequency nature of our data combined with the sharp decline in expenditures happening at the very moment managers deplete their budget, as indicated by our proxy measure, sets a high bar and help mitigate the potential contribution of confounding factors in the graphical analysis.

To expand the intuition of graphical results, we turn to regression analyses. Table 2 confirms the unconditional year-end expenditure increase. The dependent variable is the proportion of the firms' annual budget spent on a specific month, in percentage points. The variable of interest is an indicator variable equal to 1 if the spendings fall on the last month of the firm's fiscal year, and 0 otherwise.

Panel A presents the results for data aggregated at the firm level. Column 1 shows that managers tend to drastically increase spendings on fiscal year-end, as shown by the positive and statistically significant coefficient on the term Year-End, with a t-statistic of 9.22.

Columns 2-4 gradually augment the specifications with month, year, firm and firm∗year fixed effects. In column 2, the month fixed effect absorbs seasonal patterns that affects firms in the consumer retail business in general (i.e., Halloween, Christmas), while the year fixed effect accounts for time series variation affecting all firms, such as variation in the business conditions and changes in consumer behavior regarding the potential of advertising at generating sales. In column 3, firm fixed effect absorbs firm-level advertising drivers that are constant during our sample period, such as firms' location, and firms' key industries. In column 4, we replace the firm and year fixed effects with firm∗fiscal year fixed effects. The inclusion of the firm∗year fixed effects accounts for the dynamic determinants of a firm capital budgeting strategies in a given year, such as variation in the firm's financial condition, the CEO's and CFO's budgeting expertise, the relation between the marketing division managers and upper management, and the division managers' incentive scheme. The coefficient on the indicator Last Month remains positive, statistically significant (t-statistic = 6.09), and economically important. The point estimate of 2.67 percentage points indicates that managers tend to spend a larger share of their annual budget toward the end of the year.

Panel B of Table 2 evaluates the robustness of the firm-level results, by investigate the same relation using the data aggregated at the firm and product category level. Column 1-4 mirror the set of fixed effects used in Panel A and presents unchanged conclusions. In Column 5, we leverage the added granularity of Panel B's data and include product category fixed effects, effectively controlling for time-invariant features of certain types of products, such as differences in competition intensity, and the efficiency of advertising at generating sales for each product group. At last, column 6 replaces all the previous fixed effects with product category∗month and product category∗fiscal year∗firm fixed effects. The inclusion of product category∗month fixed effects mute the role of specific seasonal patterns for each category of items sold (i.e., Halloween for candies, Christmas for toys), while the product category∗fiscal year∗firm fixed effects account for firms' specific product level decisions during the fiscal year. Ultimately, Panel B's results confirm our findings.

Then, we look at the effect of the upfront TV advertisings spendings for firms with end-of-year months happening during the upfront season. These managers have the unique ability to spread their leftover TV budget over the next upcoming year, by buying TV advertising slots of the highest quality—primetimes. Table 3 presents evidence consistent with these managers' unique opportunity to smooth their leftover funds throughout the upcoming year. Combined, the commonly rigid structure of budget cycles and the random arrival of investment opportunities appear to generate mismatches between the availability of and the need for funds.

In an effort to rule out seasonal patterns that could be firm specific, we design three additional tests. First, we use a subset of firms that change their fiscal year terminal month during the sample period. This allows us to respectively include firm*month and firm*product category*month fixed effects, effectively suppressing the role that a particular month would play for a firm, or a firm's product category, regardless of when their fiscal year ends (Internet Appendix Table IA.2). Second, using the same subsample, we implement a placebo test. Using firms' end-of-year month of the first part of the sample, we redo the analysis using the data of the second part. This forces the end-of-fiscal year to happen on a random month (Internet Appendix Table IA.3). Third, we show that our results are not driven by a "December effect", by excluding all firms ending their fiscal year on December 31st and then replicating the analysis (Internet Appendix Figure IA.1, Internet Appendix Table IA.4). These four tests suggest that seasonal patterns do not explain our documented dynamic.

Next, Table 4 presents evidence supporting our graphical interpretation of the role of capital rationing in mitigating year-end expenditures spikes on the intensive margin. The main variable of interest is the interaction term Last-Month∗Budget Depleted, where Budget Depleted is an indicator variable equal to 1 if the manager depleted his budgets before the end of the year, and 0 otherwise. Column 1 shows that once capital rationing binds, year-end expenditures are reduced by 46.1% (2.75%/5.10%-1) compared to other years, as shown by the negative coefficient (-2.75) and statistically significant coefficient on the term Last-Month∗Budget Depleted, with a t-statistic of -2.15. Column 2-4 then gradually introduce month, fiscal year, firm, and firm∗year fixed effects. Across all specifications, the economic magnitude of our coefficient of interest is stable and statistically significant. Column 1-4 of Panel B then replicate the results at the firm-product level sequentially introducing the same set of fixed effects. Column 5 adds product category fixed effects, and column 6 replaces all the previous fixed effects with their more restrictive versions, product category∗month and product category∗fiscal year∗firm fixed effects. The coefficient of the interaction term ranges from -2.76 to -2.60 across all specifications and is statistically significant at the 1% level (t-statistics are between -6.34 and -6.01). Note that in both panels, we test for the coefficient joint significance of the terms Last-Month and Last-Month∗Budget Depleted. We consistently find that capital rationing reduces spending toward the end of the year, and in most cases, it eliminates spikes.

To further investigate the role of budgets cap in mediating overspending, we focus on a subsample of the data that only includes observations during years in which firms do not deplete their budgets (Table

5). We then distinguish between two potential scenarios: (i) month during which firms run a budget surplus, when their remaining budget for the upcoming month exceeds the unconditional average of 8.33% (i.e., 100%/12), and (ii) when they have resources available, but not in excess (i.e., 0 < monthly available resource < 8.33%). We find that excess year-end spendings are concentrated in moments when firms run budgeting surpluses, as indicated by the positive and statistically significant coefficient of the interaction term Last Month∗Excess Budget (t-statistics between 3.57 and 4.09). In contrast, when firms have available funds but nothing in excess, the year-end allocation is equal or marginally smaller than any other months of the fiscal year, as shown by the small and statistically insignificant coefficient of the term Last Month (t-statistic between –6.99 and -4.75). This pattern is robust after including our entire set of fixed effects and is salient for both the firm- and product-level analyses.

Then, we investigate whether capital rationing impacts expenditures on the extensive margin (Table 6). The dependent variable is an indicator variable equal to 1 if the monthly allocation is smaller or equal to 8.33% (100% divided by 12 months) —the unconditional monthly budget share, and 0 otherwise. The variable of interest is an indicator variable equal to 1 once capital rationing binds for the fiscal year, and 0 otherwise. Using this specification, we find that managers are up to 16% (0.12/0.73) more likely to reduce expenditures below the unconditional average than when managers face capital rationing.

At the same time, we find that once managers deplete their budget, resource allocation becomes more binding in firms for which directly monitoring the additional expenses is more demanding, pointing to the role of organizational frictions in how firms set their allocation rules. Internet Appendix Table IA.5 shows that expenses in the months following budget depletion are more likely to be below the annual unconditional level (i.e., 8.33%) in complex firms (i.e., greater number of hierarchical layers, more product divisions, and a higher subordinates-to-executives ratio).

Finally, following the agency theories (Jensen and Meckling 1976; Jensen 1986) and role of downturn (Schmalz and Zhuk 2019) in disciplining managers, we study how yearend overspending varies with a firm's free cash flow and excess liquidity. To capture moments when managers are less likely to experience acute monitoring from their superior in the use of their budget or to have easy access to additional resources once their annual budget is depleted, we use three complementary measures. We find that year-end excess spendings are tempered in cases when upper managers have higher incentives to monitor their subordinates or when firms struggle to access additional capital (Table 7). This conclusion is supported by the negative and statistically significant coefficient for the interaction term Last Month∗Financial Constraint.

3.2. Performance

We now study how capital rationing helps the efficient allocation of resources. Our above results suggest that managers engage in soft capital rationing as described in Harris and Raviv (1996) and Holmstrom and Ricart i Costa (1986). The patterns presented in the previous section suggest that managers first allocate the bulk of their advertising budget during the upfront season over the year (i.e, 70% of the annual budget (Shapiro et al. 2021)), but that they keep some dry powder in case unexpected opportunities arise. Such a budget smoothing strategy is consistent with multiple existing theoretical models of resource allocation over the fiscal year (Liebman and Mahoney (2017); Xu and Zwick (2022)).

We start our analysis of this section with a graphical investigation. Figure 9 plots the impulse response function of advertising expenditure on firms' sales over time. On average, advertising expenditures conducted on non-terminal months of the fiscal year generate positive return on investment, albeit small. For the average dollar of advertising, firms generate $1.08 of sales in the six months following the expenditure. This magnitude is consistent with the general effect of advertising effort measured in Shapiro et al. (2021). However, advertising efforts conducted in the last month of the fiscal year do not produce positive return on investment on average, generating $0.17 of sales over the 6 months period following the expenditure, an 84% reduction in advertising efficacy.

Turning to our regression analysis, Panel A of Table 8 confirms the results of Figure 9 with our firm-level data. The dependent variable corresponds to the ratio of the firm's monthly sales divided by the fiscal year sales. There are two variables of interest: (i) Budget Share, which denotes the proportion of the annual budget spent during the month—the direct effect of advertising on sales, and (ii) the interaction term Last-Month∗Budget Share, which measures the different effect of advertising if spent on the last month of the fiscal year. As in prior analyses, column 1-4 sequentially enrich the models with month, fiscal year, firm, and firm∗year fixed effects.

The results in Panel A of Table 8 yield two conclusions. First, advertising expenditures have a positive effect on firms' sales, which is consistent with the general prescription of marketing research. Second, we find that advertising efforts done toward the end of the year result in substantially lower sales than in other periods of the year. The effect is statistically significant (t-statistical between -2.47 and -2.21), and it corresponds to a 62.5% decline in the average advertising dollar ability to generate sales (coefficient = 0.05). Panel B confirms our findings using the product level data. Merging the advertising data with the sales data comes with multiple practical challenges (Section 2.2), resulting in a limited subsample of our entire product level data[6]. However, this strategy allows us to replicate the firm-level analysis in column 1-4. Column 5 adds product category fixed effects, while column 6 replaces all previous fixed effects with our most restrictive specification by including product category∗month and product category∗fiscal year∗firm fixed effects. As a robustness test, we redo this analysis using an alternative definition for both our dependent variable and our variables of interest. Precisely, the dependent variable becomes the natural logarithm of firms' monthly sales plus one, and the variable of interest is the monthly advertising expenditures plus one. The results presented in Internet Appendix Table IA.6 confirm the findings in Table 8 for both the data aggregated at the firm and product levels, across all fixed effects specifications. While a recent literature criticizes the use of log plus 1 in regressions (e.g., Wardlaw et al. 2022), and instead suggests scaling left skewed variables as we do in our main specification, the results in Internet Appendix Table IA.6 help validate Table 8's interpretation.

Overall, this decline in performance is indicative of overinvestment, and capital budgeting practices can help explain why this might be the case. When left with an excess budget at the end of the year, managers usually face two options. They can either avoid spending their leftover budget, with the risk of receiving a smaller budget in the upcoming year (Moorman, (2021)) or losing the residual balance (Callen

[6] We have 38,100 observations in the product-level expenditure matched with sales dataset versus 299,718 in the complete product-level expenditure dataset.

et al. (1996); Liebman and Mahoney (2017)), or they can buy more remnant ads than they would otherwise, going down the quality ladder of opportunities in the process.

To confirm this reasoning, we investigate why year-end expenditures generate less sales. Table 9 considers two additional performance metrics: (i) the price of market penetration, (ii) and the price of viewer-hour. Panel A studies the price of market penetration, one of the key metrics utilized in marketing (Shapiro et al. (2021)) to evaluate ads' ability to reach target audiences. It measures how much firms must spend to reach their entire targeted population once during the month. A small number indicates that firms' ads are more effective at reaching firms' targeted audience. For both data aggregated at the firm and product levels, we find that year-end firms must spend \$4.53 million more to reach their population of potential viewers once per month (t-statistics = 2.58), a 39% decline in advertising expenses efficiency. Panel B studies the price that firms pay to promote their products to one viewer for one hour. A smaller number indicates that firms can reach out to a prospective client more efficiently. Again, we find robust and stable results, showing that on average firms spend \$0.74 more on year-end to advertise to one person per hour (t-statistics = 1.81), a 52% reduction in advertising efficacy.

Combined, these results indicate that on year-end, firms scramble to find way to quickly spend their budget. In the process, they select projects that are less efficient, and that generate less sales.

3.3. Projects Selection

Our analysis identifies three channels that help us understand what can mediate subpar project selection during year-end: (i) budget rationing, (ii) matching the arrival of investment opportunities with the availability of funds to managers, and (iii) monitoring.

4.3.1. Budget Rationing

In this section, we study the performance of expenditures once capital rationing binds to determine if this budgeting strategy helps mitigate poor resource allocation. While soft capital rationing constrains managers once it binds, it does not eliminate expenditures in those terminal months. Intuitively, it suggests that managers will then need to undergo stricter monitoring from their superior to receive approval for specific projects (Holmstrom and Ricart i Costa (1986), Harris and Raviv (1998), Malenko (2019)).

Table 10 studies year-end expenditure efficacy once rationing binds. For the firm-level and product-level data, Column 1-4 sequentially introduce our main fixed effects: month, year, firm, and firm∗year. For the product-level data, columns 5-6 then add the product category, the product category∗month, and the firm∗product category∗fiscal year fixed effects. Across all specifications, our coefficient of interest is associated with the interaction term Last Month∗Budget Share. When capital rationing binds, we find that year-end expenditures are as good as expenditures in any other month of the fiscal year, as our coefficient of interest is small or weekly positive (firm-level ranges from -0.00 to -0.02, product-level is 0.01) and our p-values are large (firm-level ranges from 0.983 to 0.803, product-level, 0.50 to 0.72).

While rationing mitigates overspending, we also find that the added rigidity likely induced by heightened monitoring impedes managers in taking unforeseen opportunities in the terminal months of the fiscal year. Internet Appendix Table IA.7 shows that, once budgets are depleted for the fiscal year, spendings become less sensitive to peers' spendings in the same product category, as illustrated by the negative and statistically significant coefficient of the interaction term Avg. Peers Spendings∗Budget Depleted.

We then ask why managers deplete their budget before the end of the year in the first place, given that they should expect facing heightened monitoring from their supervisors once capital rationing engages. Using the subset of the data including the month leading to early budget depletion, we find that the runup months' expenditure performance is markedly higher than during the same period when managers do not end up depleting their budget before the end of the year (Table 11). This suggests that capital rationing first helps mitigate the negative effect of overspending, and that once rationing engages, monitoring helps mitigate inefficient resource allocation.

3.3.2. Performance and Timing of Investment Opportunities

Second, to confirm that close-to-deadline projects' underperformance is linked to excessive spending relative to available investment options, we focus on a specific promotion channel in our sample: TV advertising. Primetime TV ads for the year are made available for booking during a fixed period between mid-May and the end of June (Shapiro et al. 2021), creating intra-year variation in investment opportunities for managers. Managers with end-of-year month falling in May or June can access a greater selection of investment opportunities and have the ability to smooth the leftover budget over the entire upcoming year when compared to peers. Our results suggest that year-end TV advertising expenditure spikes are concentrated among managers that cannot benefit from the upfront season to smooth the allocation of their leftover budget (Table 9) over the upcoming year. This relaxes managers' allocation constraints, improving resource allocation.

While it is challenging to directly assess the unique contribution of TV advertising on firms' sales because advertising strategies generally exploit a mix of communication channels (e.g., Television, radio, internet), we use TV advertising's unique performance metrics - the price of market penetration and the price of viewer-hour - to investigate the upfront season's effect on ads performance. Table 9 shows that, across all specifications, we find a negative coefficient for the interaction term (Last Month∗Upfront) that is significant at the 5% level, such that firms terminating their fiscal year during the upfront season select projects that are substantially better than their peers (β_2). At the same time, we fail to reject that the performance of year-end expenditures for the "upfront" firms is any different from those conducted during any other month of their fiscal year ($\beta_1 + \beta_2$).

Ultimately, these results suggest that, for managers rushed on year-end to spend their remaining budget, the limited menu of options likely forces them to go down the quality ladder of opportunities in the process, selecting projects that are worst at reaching their targeted audience for each invested dollar.

3.3.3. Monitoring: Incentives and Intensity

At last, we study the role of monitoring friction on wasteful expenditures. Large and complex firms are harder to manage, often overextending managers (Gabaix and Landier (2008)). This forces them to divide their limited attention across multiple projects and subordinates at once, reducing their monitoring capacity (Bolton and Dewatripont (1994), Aghion and Tirole (1997), Harris and Raviv (1998)). It is also posited that poor resource allocation is more likely when managers lack the proper incentives to exercise effort (Monsen et al. (1968), Kamerschen (1968)) or when they are distracted (Core, Holthausen, and Larcker (1999) and Shivdasani and Yermack (1999)). Our evidence supports both views.

Panel A of Table 12 shows that poor resource allocation appears to be concentrated in complex firms. To conduct this test, we use three metrics of organizational complexity to split our sample. First, we look at firms' hierarchy, the number of layers between the CEO and employees engaged in daily operations. A greater number suggests that it is harder for upper managers to directly monitor their lower rank subordinates. Second, we measure the number of product divisions that firms produce. This informs us about the number of distinct projects that CEOs must keep on their radar at once, dividing their focus. Finally, we measure the subordinates-to-manager ratio, by dividing the number of lower-level divisions and subsidiaries by the quantity of upper managers (hierarchical layer = 1). This gives a sense of upper managers' "team" size.

At the same time, busy CEOs with multiple external board appointments, CEOs approaching retirement, and CEOs with low insider ownership stakes appear to be culprit of the documented effect. Panel B of Table 12 shows that our results are concentrated in firms with CEOs that have limited time and incentives to monitor their subordinates.

Ultimately, results in this section highlight how capital rationing can complement direct monitoring when it comes to resource allocation.

4. Conclusion

This paper studies how capital budgeting tools can help improve resource allocation when managers are forced to delegate the execution of resource allocation to their subordinates. It is the first to offer project-level evidence on the role of heuristic capital budget rules and studies its effect on the efficient allocation of resources. In the process, it makes a step towards bettering our comprehension about which mechanisms are used by managers when monitoring is costly, and how it impacts resource allocation. While most prior work has focused on year-end patterns or how firms define their discount rate, our evidence highlights the equally important role of an alternative budgeting rule—rationing. We hope that the growing interest in constructing a more complete picture of firms' internal resource allocation method will continue to expand our understanding of this key area of research.

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FIGURE 1: The Importance of Advertising Expenditures for US Firms

Figure 1.1. plots the share of the advertising industry as a fraction of the total US capital expenditure over the period 2010-20219. To illustrate the relative importance of that industry, we also plot the share of the manufacturing industry as reported by the Census (NAICS code 31-33). Data measure the annual size of the advertising industry in the US is obtained from IBIS World (link: https://www.ibisworld.com/us/bed/total-advertising-expenditure/4118/). Data for the total US capital expenditure and the manufacturing industry capital expenditure are obtained from the 2010-2019 Capital Spending Report "Tables 2a. Total Capital Expenditures for Companies with Employees by Industry Sector" (link: https://www.census.gov/data/tables/time-series/econ/aces). Figure 1.2 and 1.3. respectively plots the relative importance of advertising expenditures to firms' capital expenditure and research and development, for both the firms in our sample and all firms included in Compustat. To avoid implementing filters based on firms with no R&D (xrd = 0) or no capital expenditures (capx = 0), we estimate the dollar of advertising per dollar of other expenditure in two steps. First, we measure the average ratio a as: ratio_CAPX = xad/(xad+capx) and then we backout our measure of interest from: ratio_CAPX/(1- ratio_CAPX). We use the same approach for research and development.

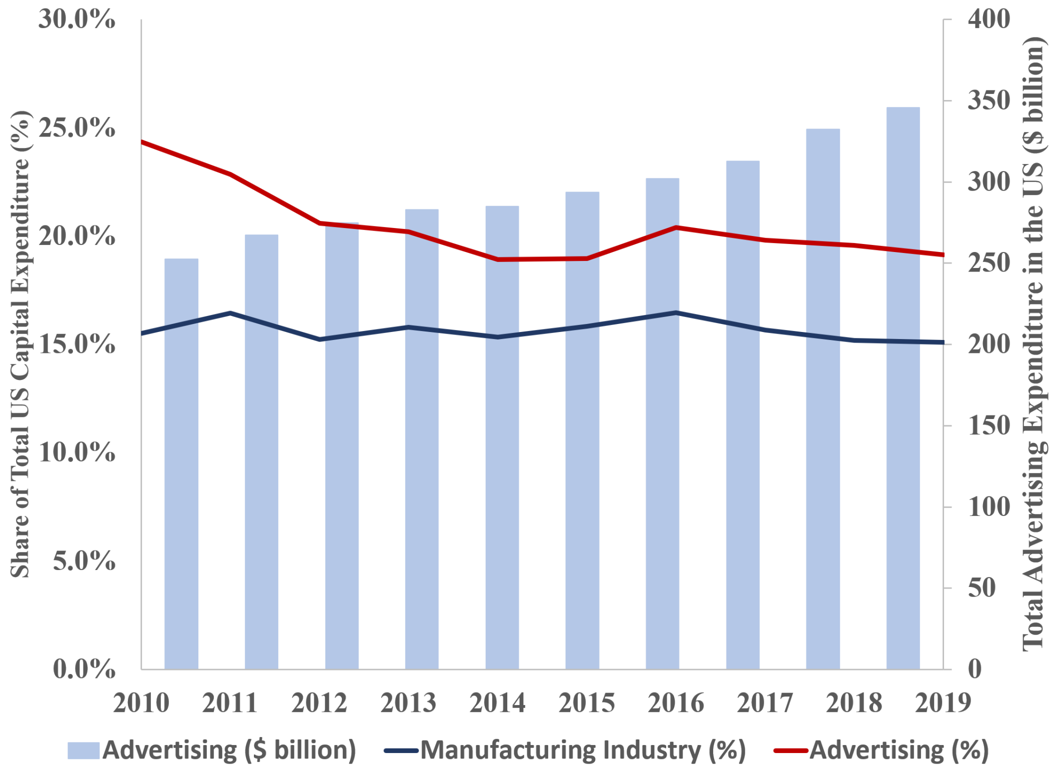

FIGURE 1.1: The economic Importance of the Advertising Industry in the US

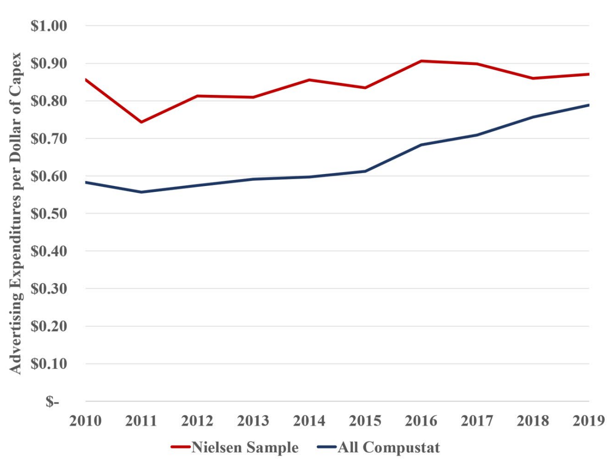

Figure 1.2.: Advertising vs. CAPEX

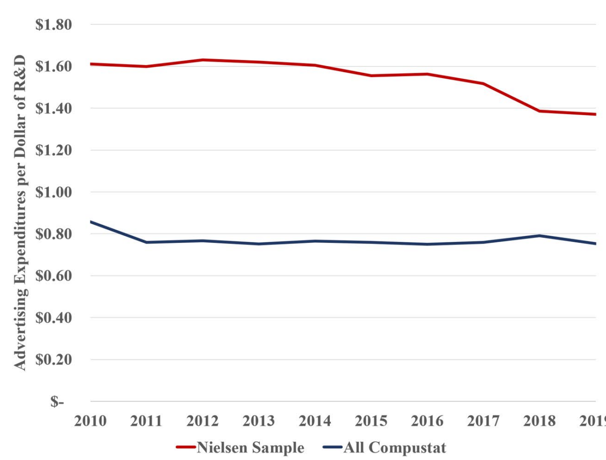

Figure 1.3. Advertising vs. R&D

FIGURE 2: Time Series Budget Dynamic

Figure 2.1. This figure presents the persistent of year-over-year advertising spendings in our sample. The solid red line indicates the 45-degree line. Figure 2.2. plots the average annual spending level over time in the sample.

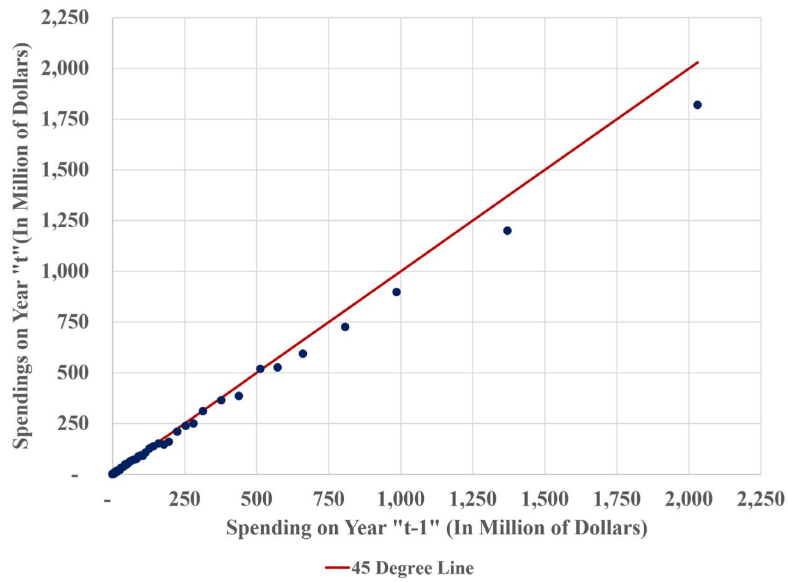

Figure 2.1. Persistency of Year Over Year Spendings

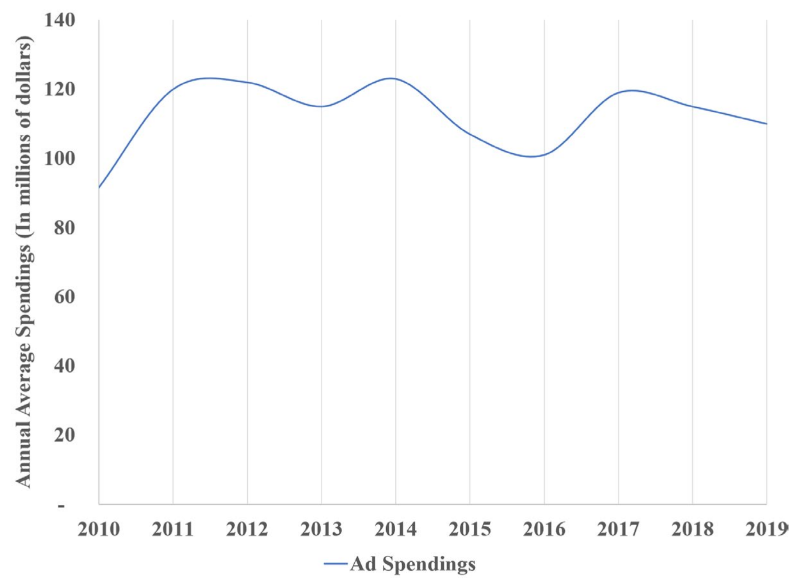

Figure 2.2. Average Annual Spending Over Time

FIGURE 3: Yearend Month and Sample Properties

Figure 3.2. shows the number of firm-year observations that have the end-of-year month on a specific month. The number 1 on the x-axis indicates January, and number 12 denotes *December.* Between January and November, we observe 1,603 distinct firm-year observations, while we have 1,891 observations for the month of December alone. Figure 3.1. counts the number of end-of-year months for each product category in the sample. For example, a value of 2 indicates that firms engage in that product category with have the last month on the fiscal year on two distinct months in the sample (e.g., June and August).

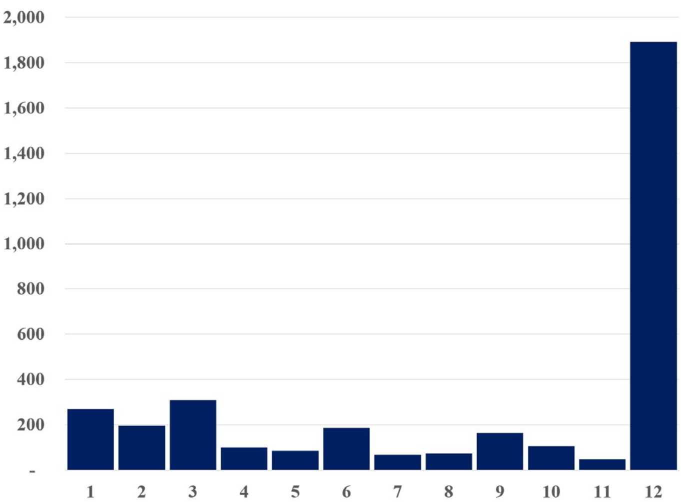

Figure 3.1. Number of Firm-Year Ending on Months of the Calendar Year

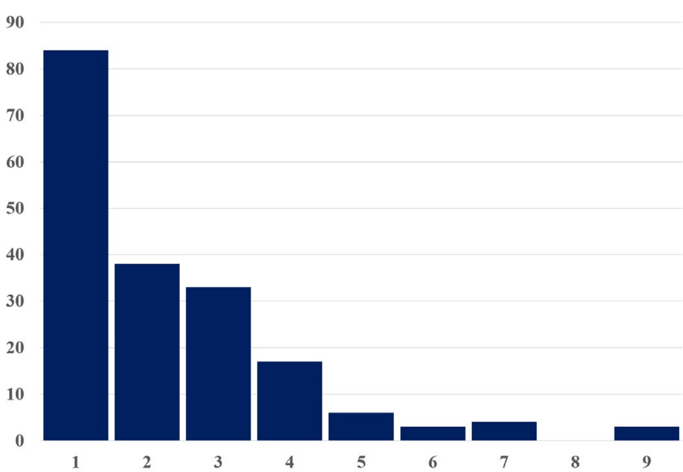

Figure 3.2. Number of End of Year Month Per Product Category

FIGURE 4: Product Categories Frequency

Figure 4.1. shows the distinct number of product categories that have a firm with an end-of-year month on that specific month. Number 1 indicates January, and number 12 shows *December*. Figures 4.2 and 4.3 respectively show the histogram of the number of product category per firms account for all categories that firms are selling and including only the product category that represent 5% of the firms advertising expenditure.

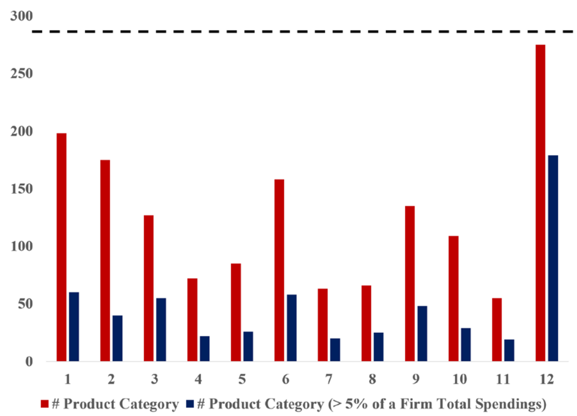

Figure 4.1. Number of Distinct Product Category Associated with EOY Month (287 total)

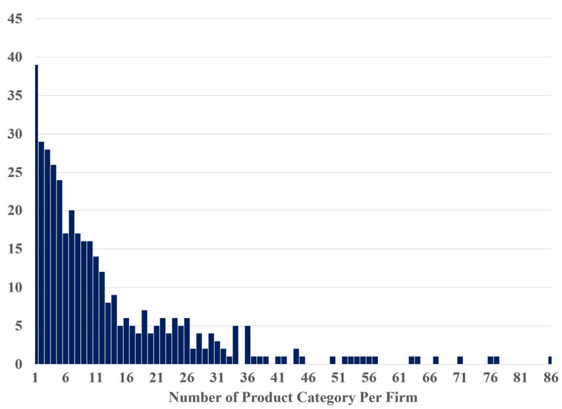

Figure 4.2. Product Categories Per Firms

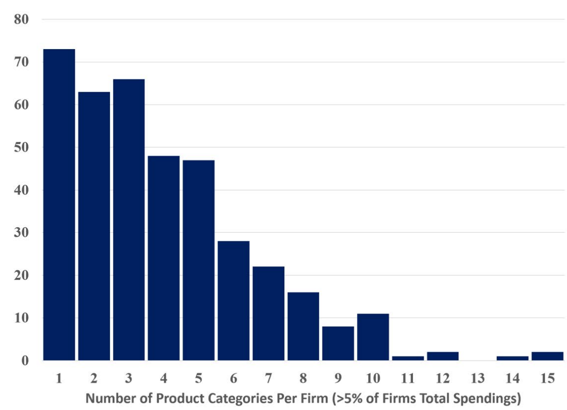

Figure 4.3. Product Categories Per Firms (>5%)

FIGURE 5: E-Commerce Retail Sales as a Percent of Total Retail Sales

The figure plots the share of e-commerce retail sales over the period 2010-2019. Data is obtained from the Federal Reserve Economic Data of Saint-Louis (FRED), using the data code: ECOMPCTSA.

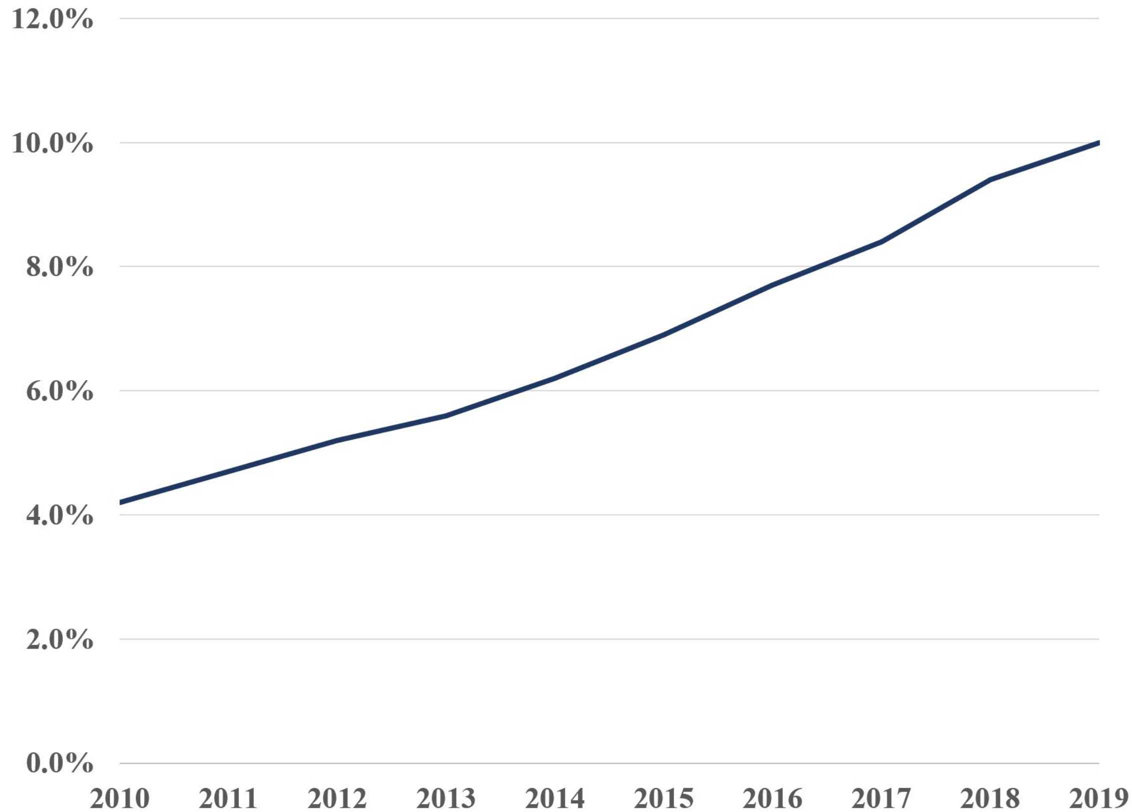

FIGURE 6 Advertising Mix over the Fiscal Year

Figure 6.1. plots the share of each advertising medium used by firms over the average fiscal year, showing the relative importance and stability of firms advertising preferences. Figure 6.2. shows the deviation from the annual mean for each advertising medium.

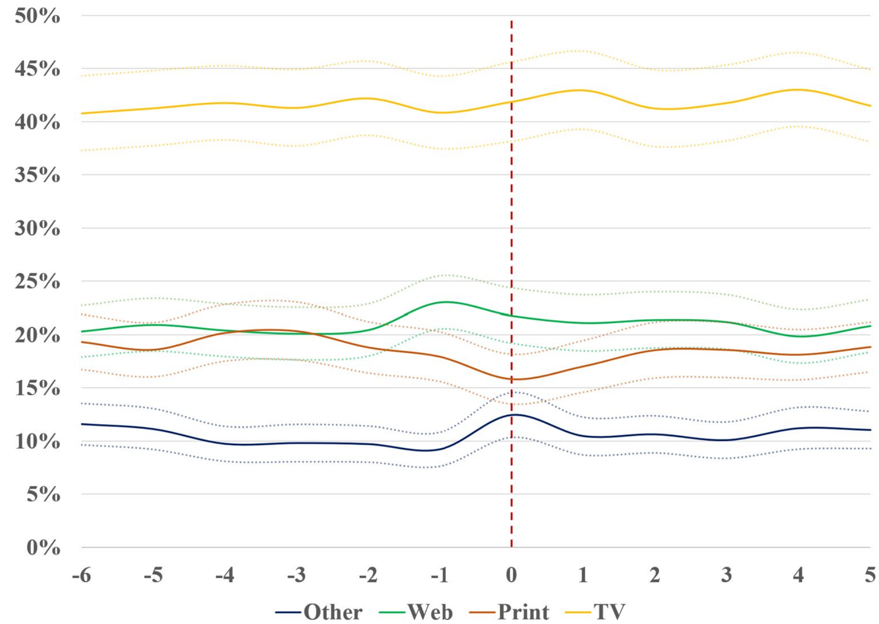

FIGURE 6.1: Share of Firms' Advertising Portfolio

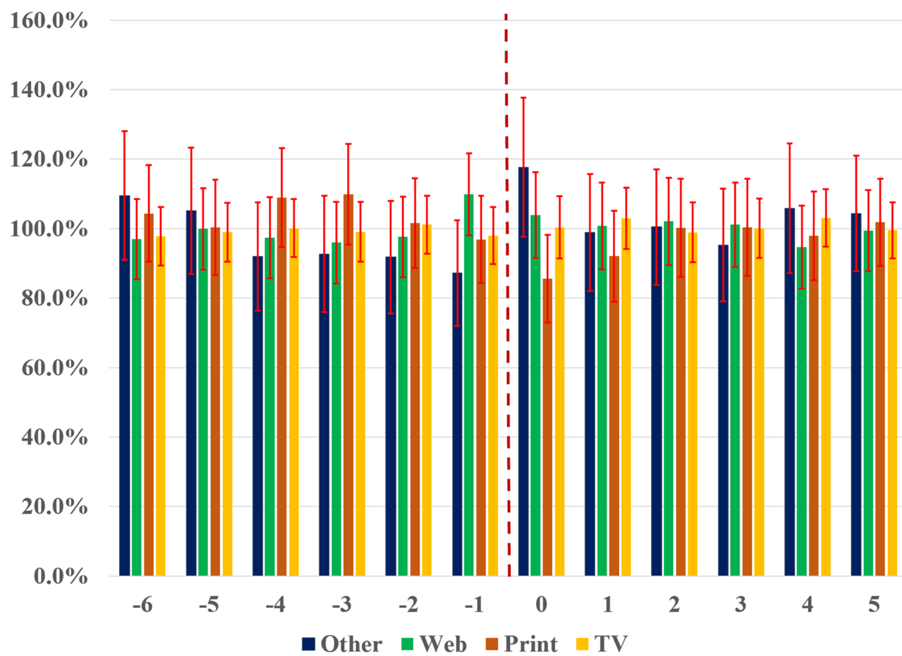

FIGURE 6.2: Deviation from Annual Mean per Advertising Type

FIGURE 7: Binding "Budgets" and End-of-Year Expenses

Figure 7.1. to 7.4. respectively plot the effect of busting last year spending level before a given month, on the following months spending levels. The red bands denote the 95th percentile confidence interval for errors clustered at the firm level.

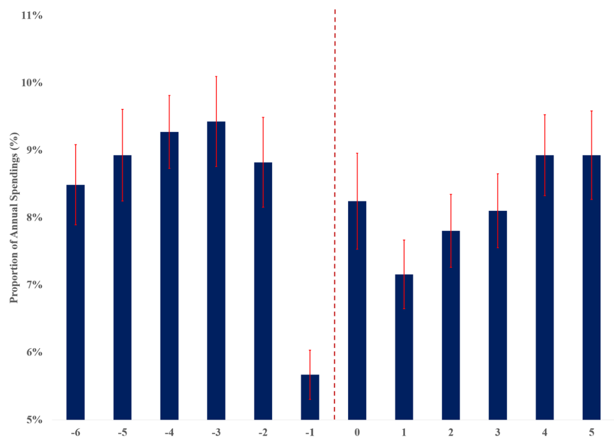

Figure 7.1: By Month 12

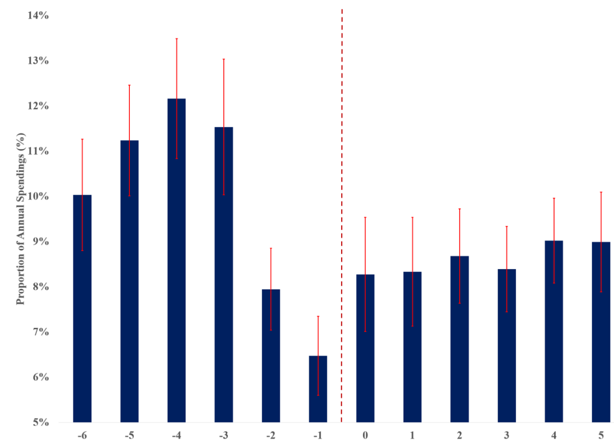

Figure 7.2: By Month 11

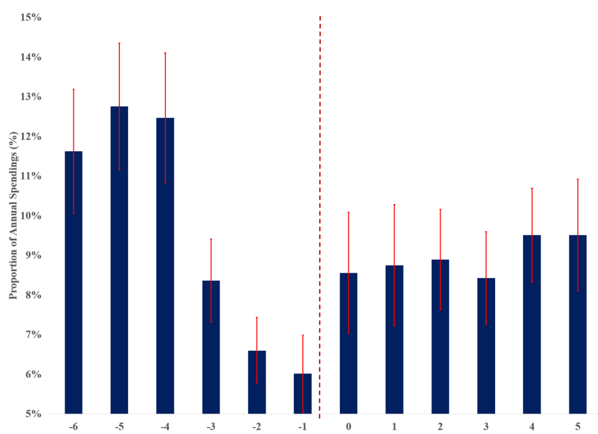

Figure 7.3: By Month 10

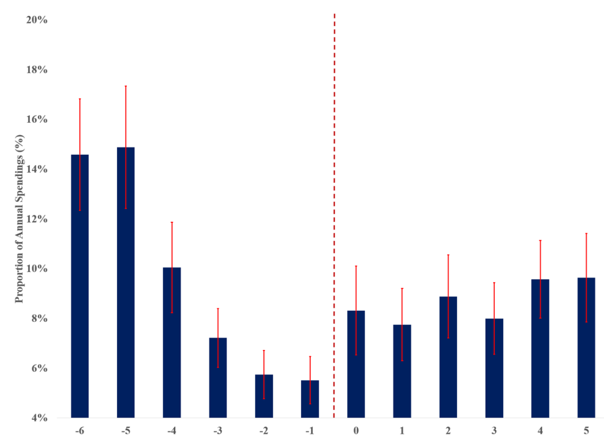

Figure 7.4: By Month 9

FIGURE 8: Firms' Monthly Spendings Over the Fiscal Year

Figure 8.1. plots the monthly proportion of firms' annual spendings done around the end of firms' fiscal year, measured for all the public firms in our sample (347) using ad spending data from Nielsen AdIntel from 2010 to 2019. Months ranked 0 denotes the first month of the fiscal year, whereas month number -1 indicates the last month of the fiscal year. The red bands denote the 95th percentile confidences interval for errors clustered at the firm level. Figure 8.2. plots the same pattern for firms that depleted their budget at least once during the sample. Figure 8.3. and 8.4., respectively plots the average patterns over the fiscal year for firms' sales and products' price.

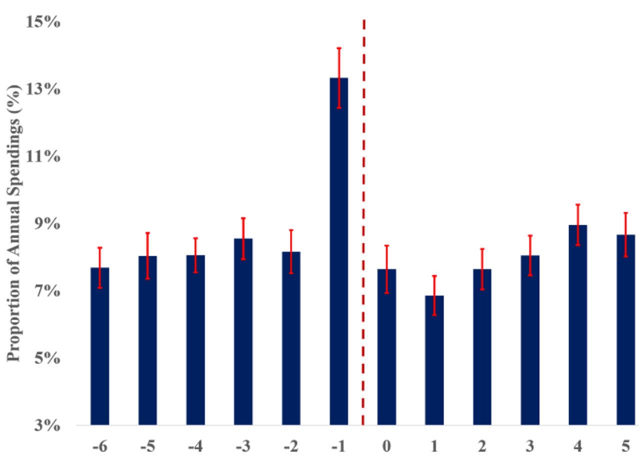

Figure 8.1: Year-End Spendings (All firms)

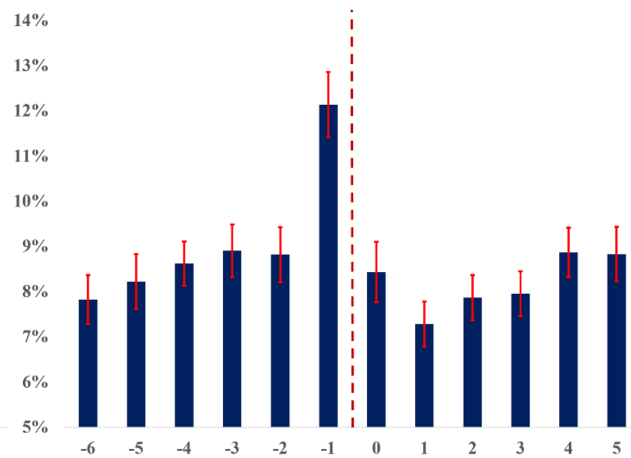

Figure 4.2: Year-End Spendings (Depleted Budget Once)

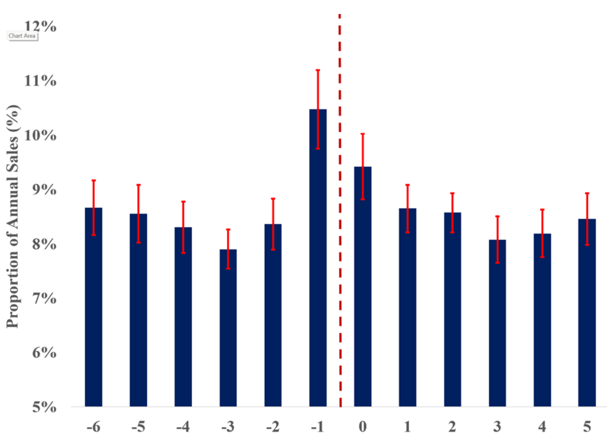

Figure 4.3: Firms' Sales

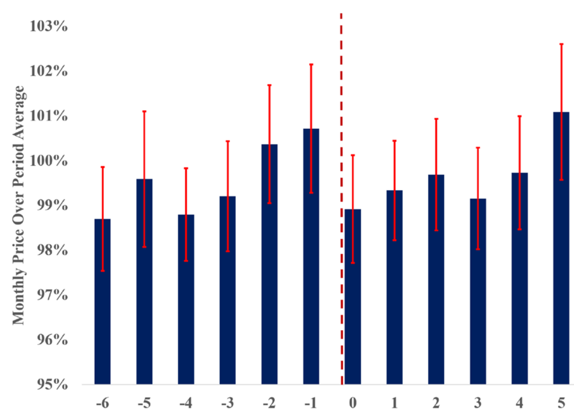

Figure 4.4: Firm's Prices

FIGURE 9: Advertising to Sales Impulse Response Function

The figure 9 plot firms' the impulse response function of advertising spendings on sales over the first 5 months after the firms spent the money on advertising. For the average dollars spend on advertising, it takes up to 3 months to obtain a positive return on investment (RIO). For the average dollar spent on the end-of-year month, it is never achieved.

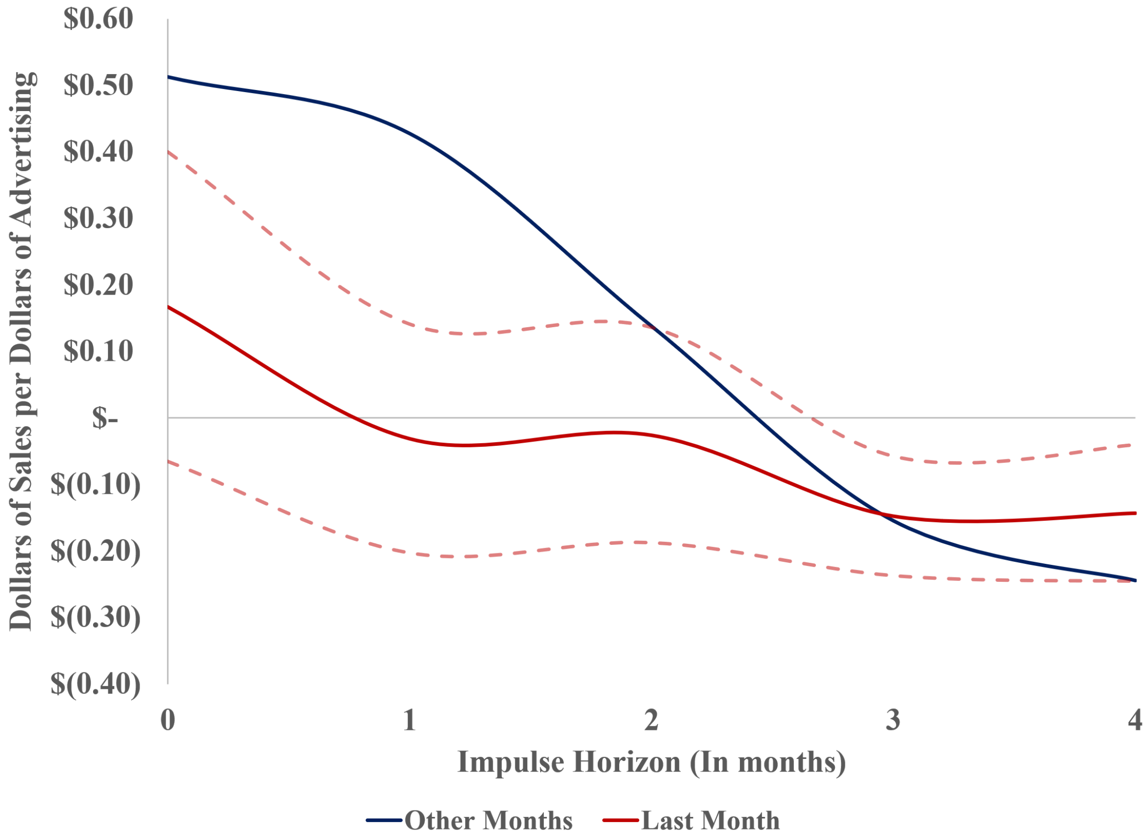

TABLE 1: Summary Statistics

Panel A: Firms						
Variable	**Mean**	**25th Pct.**	**Median**	**75th Pct.**	**Std. Dev.**	**No. Obs.**
No. of Product Categories	9.45	3.00	6.00	13.00	9.54	3,175
No. of Hierarchical Layers	2.38	1.00	2.00	3.00	1.25	3,175
Firm Size	8.55	7.30	8.47	9.94	2.03	3,175
Monthly Share of Annual Sales (%)	8.47	5.96	7.72	9.51	8.16	23,352
Monthly Share of Annual Advertising Spendings (%)	8.65	1.10	6.38	10.47	12.32	35,250
TV Advertising Share of Monthly Ads (%)	41.99	0.00	42.68	80.08	38.66	29,686
Web Advertising Share of Month Ads (%)	20.56	0.06	2.18	19.95	34.34	29,686
Print Media Share of Monthly Ads (%)	18.51	0.00	0.24	24.43	30.29	29,686
Other Mediums Share of Month Ads (%)	10.74	0.00	0.66	5.63	24.70	29,686

TABLE 2: Last Month of Fiscal Year Effects

This table studies how deadlines impact firms' resource allocation over the fiscal year, by estimating the proportion of firms' annual spending done during the last month of the period using an OLS regression. The dependent variable is $\text{Spendings}_{i,t} = \frac{Monthly\ Spending_{i,t}}{Fiscal\ Year\ Spending_{i,y}}$, or $\text{Spendings}_{i,k,t} = \frac{Monthly\ Spending_{i,k,t}}{Fiscal\ Year\ Spending_{i,k,y}}$ for firm "i" in product category "k" on month "t" in Panel A and B respectively. The first variable of interest L*ast Month*$_{i,t}$ is a binary indicator that equals 1 if it is the last month of the firms' fiscal year, and 0 otherwise. Variable definitions appear in Appendix 1. The *t*-statistics (in parenthesis) are based on standard errors that are heteroskedasticity consistent and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Panel A: Firm-Level	$\text{Spendings}_{i,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
(β_1) Last $\text{Month}_{i,t}$	3.78***	2.80***	2.74***	2.67***		
	(9.22)	(6.42)	(6.22)	(6.09)		
R^2	0.01	0.01	0.03	0.07		
F-Statistics	84.93	41.21	38.66	37.08		
No. Obs.	35,250	35,250	35,250	35,250		
Panel B: Product-Level	$\text{Spendings}_{i,k,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
(β_1) Last $\text{Month}_{i,t}$	2.94***	2.60***	2.54***	2.52***	2.74***	2.70***
	(10.83)	(8.99)	(8.75)	(8.70)	(10.08)	(9.92)
R^2	0.00	0.00	0.01	0.02	0.04	0.11
F-Statistics	117.35	80.79	76.60	75.61	101.56	98.33
No. Obs.	299,718	299,718	299,718	299,718	299,614	299,610
Month FE	No	Yes	Yes	Yes	Yes	No
Fiscal Year FE	No	Yes	Yes	No	No	No
Firm FE	No	No	Yes	No	No	No
Firm*Fiscal Year FE	No	No	No	Yes	Yes	No
Product Category FE	No	No	No	No	Yes	No
Product Category*Month FE	No	No	No	No	No	Yes
Product Category*Fiscal Year*Firm FE	No	No	No	No	No	Yes

TABLE 3: Last Month of Fiscal Year Effects and the Upfronts Season

This table studies how each dollar of advertising spendings spent in the last month of the fiscal year generates in terms in sales using an OLS regression. The dependent variable is variable of interest is $\text{TV Spendings}_{i,t} = \frac{Monthly\ TV\ Spending_{i,t}}{Fiscal\ Year\ TV\ Spending_{i,y}}$, or $\text{TV Spendings}_{i,k,t} = \frac{TV\ Monthly\ Spending_{i,k,t}}{Fiscal\ Year\ TV\ Spending_{i,k,y}}$ in Panel A and B respectively. The first variable of interest is the L*ast Month*$_{i,t}$, defined as a binary indicator that equals 1 if it is the last month of the firms' fiscal year, and 0 otherwise. The second variable of interest is Upfront Season, an indicator variable if the firm's fiscal year ends in May or June, and 0 otherwise. Variable definitions appear in Appendix 1. The *t*-statistics (in parenthesis) are based on standard errors that are heteroskedasticity consistent and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Panel A: Product-Level	$\text{TV Spendings}_{i,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
(β_1) Last $\text{Month}_{i,t}$	3.67***	2.16***	2.09***	2.09***		
	(6.07)	(3.25)	(3.12)	(3.14)		
(β_3) Last $\text{Month}_{i,t}$ * Upfront $\text{Season}_{i,y}$	-4.69***	-3.18**	-3.24**	-3.12**		
	(-3.41)	(-2.33)	(-2.40)	(-2.30)		
(β_3) Upfront $\text{Season}_{i,y}$	0.45***	0.32**				
	(3.52)	(2.50)				
$\boldsymbol{\beta_1 + \beta_2}$	-1.02	-1.02	-1.14	-1.02		
R^2	0.01	0.01	0.03	0.08		
F-Statistics	13.20	4.20	5.47	5.42		
No. Obs.	25,974	25,974	25,974	25,974		
Panel B: Product-Level	$\text{TV Spendings}_{i,k,t}$					
	(1)	(1)	(1)	(1)	(1)	(1)
(β_1) Last $\text{Month}_{i,t}$	4.29***	2.60***	2.54***	2.53***	2.95***	2.90***
	(8.60)	(4.81)	(4.69)	(4.67)	(5.59)	(5.36)
(β_3) Last $\text{Month}_{i,t}$ * Upfront $\text{Season}_{i,y}$	-3.95***	-2.15*	-2.21*	-2.18*	-2.71**	-2.40**
	(-3.48)	(-1.79)	(-1.96)	(-1.93)	(-2.35)	(-2.11)
(β_3) Upfront $\text{Season}_{i,y}$	0.44***	0.28***				
	(4.40)	(2.64)				
$\boldsymbol{\beta_1 + \beta_2}$	0.34	0.45	0.33	0.35	0.23	0.50
R^2	0.00	0.01	0.01	0.03	0.08	0.14
F-Statistics	27.90	9.17	11.02	10.93	15.91	14.78
No. Obs.	109,308	109,308	109,308	109,308	109,205	109,205
Month FE	No	Yes	Yes	Yes	Yes	No
Fiscal Year FE	No	Yes	Yes	No	No	No
Firm FE	No	No	Yes	No	No	No
Firm*Fiscal Year FE	No	No	No	Yes	Yes	No
Product Category FE	No	No	No	No	Yes	No
Product Category*Month FE	No	No	No	No	No	Yes
Product Category*Fiscal Year*Firm FE	No	No	No	No	No	Yes

TABLE 4: Last Month of Fiscal Year Effects – When First Spend All the Budget

This table studies how deadlines impact firms' resource allocation over the fiscal year, by estimating the proportion of firms' annual spending done during the last month of the period using an OLS regression. The dependent variable is $\text{Spendings}_{\text{i,t}} = \frac{Monthly\ Spending_{i,t}}{Fiscal\ Year\ Spending_{i,y}}$, or $\text{Spendings}_{\text{i,k,t}} = \frac{Monthly\ Spending_{i,k,t}}{Fiscal\ Year\ Spending_{i,k,y}}$ in Panel A and B respectively. The first variable of interest L*ast Month*$_{\text{i,t}}$ is a binary indicator that equals 1 if it is the last month of the firms' fiscal year, and 0 otherwise. The second variable of interest, Budget Depleted, is an indicator variable equal to 1 if the firms has spent more or as much of their last year spending level on month "t", and 0 otherwise. Variable definitions appear in Appendix 1. The *t*-statistics (in parenthesis) are based on standard errors that are heteroskedasticity consistent and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Panel A: Firm-Level	$\text{Spendings}_{\text{i,t}}$					
	(1)	(2)	(3)	(4)	(5)	(6)
(β_1) Last Month$_{i,\text{t}}$	6.62***	5.38***	5.31***	5.10***		
	(4.54)	(3.54)	(3.49)	(3.35)		
(β_2) Last Month$_{i,\text{t}}$ * Budget Depleted$_{\text{i,t}}$	-3.26**	-2.92*	-2.91*	-2.75*		
	(-2.15)	(-1.91)	(-1.91)	(-1.80)		
(β_3) Budget Depleted$_{i,\text{t}}$	0.38***	0.35***				
	(3.01)	(2.77)				
$\boldsymbol{\beta_1 + \beta_2 = 0}$	3.37***	2.46***	2.40***	2.35***		
R^2	0.01	0.01	0.03	0.07		
F-Statistics	30.48	14.93	19.45	18.63		
No. Obs.	35,250	35,250	35,250	35,250		
Panel B: Product-Level	$\text{Spendings}_{\text{i,k,t}}$					
	(1)	(2)	(3)	(4)	(5)	(6)
(β_1) Last Month$_{i,\text{t}}$	3.59***	3.25***	3.20***	3.18***	3.37***	3.33***
	(11.78)	(10.13)	(9.89)	(9.84)	(10.91)	(10.69)
(β_2) Last Month$_{i,\text{t}}$ * Budget Depleted$_{i,\text{t}}$	-2.76***	-2.74***	-2.75***	-2.76***	-2.64***	-2.60***
	(-6.33)	(-6.34)	(-6.28)	(-6.29)	(-6.11)	(-6.01)
(β_3) Budget Depleted$_{i,\text{t}}$	0.47***	0.46***	0.60***			
	(5.25)	(5.23)	(6.64)			
$\boldsymbol{\beta_1 + \beta_2 = 0}$	0.86**	0 .54	0.47	0.45	0.75**	0.75**
R^2	0.00	0.00	0.01	0.02	0.04	0.11
F-Statistics	53.11	43.28	43.83	49.89	59.65	57.24
No. Obs.	299,718	299,718	299,718	299,718	299,614	299,610
Month FE	No	Yes	Yes	Yes	Yes	No
Fiscal Year FE	No	Yes	Yes	No	No	No
Firm FE	No	No	Yes	No	No	No
Firm*Fiscal Year FE	No	No	No	Yes	Yes	No
Product Category*Month FE	No	No	No	No	Yes	No
Product Category*Month*Firm FE	No	No	No	No	No	Yes
Product Category*Fiscal Year*Firm FE	No	No	No	No	No	Yes

TABLE 5: Last Month of Fiscal Year Effects – When Firms Have Excess Budget

This table studies how deadlines impact firms' resource allocation over the fiscal year, by estimating the proportion of firms' annual spending done during the last month of the period using an OLS regression. For the analysis, we use the subsample of the data in which firms do not deplete their budget during the fiscal year. The dependent variable is $\text{Spendings}_{i,t} = \frac{Monthly\ Spending_{i,t}}{Fiscal\ Year\ Spending_{i,y}}$, or $\text{Spendings}_{i,k,t} = \frac{Monthly\ Spending_{i,k,t}}{Fiscal\ Year\ Spending_{i,k,y}}$ in Panel A and B respectively. The first variable of interest *Last Month*$_{i,t}$ is a binary indicator that equals 1 if it is the last month of the firms' fiscal year, and 0 otherwise. The second variable of interest, Excess Budget, is an indicator variable equal to 1 if the firms remaining budget for the rest of the fiscal year is greater than 1/12 for each of the remaining month on "t", and 0 otherwise. For example, on month 10, if the firm has spent less than 1-10/12, the indicator variable would be equal to 1. Variable definitions appear in Appendix 1. The *t*-statistics (in parenthesis) are based on standard errors that are heteroskedasticity consistent and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Panel A: Firm-Level	$\text{Spendings}_{i,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
(β_1) Last $\text{Month}_{i,t}$	-1.79***	-2.84***	-3.00***	-3.07***		
	(-4.75)	(-6.61)	(-6.86)	(-6.99)		
(β_2) Last $\text{Month}_{i,t}$ * Excess $\text{Budget}_{i,t}$	5.16***	5.18***	5.73***	6.00***		
	(3.57)	(3.57)	(3.90)	(4.09)		
(β_3) Excess $\text{Budget}_{i,t}$	0.75**	0.60**	0.76*	-0.34		
	(2.55)	(2.04)	(1.95)	(-0.57)		
R^2	0.00	0.01	0.03	0.07		
F-Statistics	12.53	18.28	18.08	16.56		
No. Obs.	22,752	22,752	22,705	22,224		
Panel B: Product-Level	$\text{Spendings}_{i,k,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
(β_1) Last $\text{Month}_{i,t}$	-0.06	-0.42	-0.52*	-0.53*	-0.21	-0.25
	(-0.20)	(-1.35)	(-1.66)	(-1.69)	(-0.71)	(-0.83)
(β_2) Last $\text{Month}_{i,t}$ * Excess $\text{Budget}_{i,t}$	3.55***	3.71***	4.05***	4.09***	3.69***	3.82***
	(3.76)	(3.92)	(4.30)	(4.38)	(4.06)	(4.19)
(β_3) $Excess\ Budget_{i,t}$	0.03	-0.10	-0.07	-0.58	-0.89**	-0.87**
	(0.17)	(-0.46)	(-0.24)	(-1.31)	(-2.41)	(-2.25)
R^2	0.00	0.00	0.01	0.02	0.05	0.11
F-Statistics	7.20	5.49	6.52	6.64	7.46	7.70
No. Obs.	205,481	205,481	205,455	205,307	205,201	202,050
Month FE	No	Yes	Yes	Yes	Yes	No
Fiscal Year FE	No	Yes	Yes	No	No	No
Firm FE	No	No	Yes	No	No	No
Firm*Fiscal Year FE	No	No	No	Yes	Yes	No
Product Category*Month FE	No	No	No	No	Yes	No
Product Category*Month*Firm FE	No	No	No	No	No	Yes
Product Category*Fiscal Year*Firm FE	No	No	No	No	No	Yes

TABLE 6: Expenditure Extensive Margin and Capital Rationing

This table studies how budgeting limits impact resources allocation using an OLS regression. The dependent variable is an indicator variable equal to 1 if the monthly allocation is below the unconditional average (100%/12), and 0 otherwise. The first variable of interest Depleted $Budget_{i,t}$ is a binary indicator equals 1 if it the firm has already spend more than last year expenditure on month "t", and 0 otherwise. Variable definitions appear in Appendix 1. The *t*-statistics (in parenthesis) are based on standard errors that are heteroskedasticity consistent and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

	Expenditure $Below\ Average_{i,t} = 1$						
	Firm-Level				**Product-Level**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(β_1) Depleted $Budget_{i,t}$	0.03*	0.04**	0.06***	0.12***	0.03***	0.02***	0.02***
	(1.77)	(2.30)	(3.03)	(5.76)	(3.28)	(2.61)	(2.74)
R^2	0.02	0.06	0.07	0.15	0.03	0.08	0.22
F-Statistics	3.14	5.29	9.19	33.19	10.75	6.82	7.49
No. Obs.	35,250	35,250	35,250	35,250	299,718	299,614	299,610
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	No
Fiscal Year FE	No	Yes	Yes	No	No	No	No
Firm FE	No	No	Yes	No	No	No	No
Firm*Fiscal Year FE	No	No	No	Yes	Yes	Yes	No
Product Category*Month FE	No	No	No	No	Yes	No	No
Product Category*Month*Firm FE	No	No	No	No	No	No	Yes
Product Category*Fiscal Year*Firm FE	No	No	No	No	No	No	Yes

TABLE 7: Free Cash Flow, Excess Cash, and Financial Constraint

This table studies how deadlines impact firms' resource allocation over the fiscal year, by estimating the proportion of firms' annual spending done during the last month of the period using an OLS regression. The dependent variable is $\text{Spendings}_{\text{i,t}} = \frac{Monthly\ Spending_{i,t}}{Fiscal\ Year\ Spending_{i,y}}$, or $\text{Spendings}_{\text{i,k,t}} = \frac{Monthly\ Spending_{i,k,t}}{Fiscal\ Year\ Spending_{i,k,y}}$ in Panel A and B respectively. The first variable of interest L*ast Month*$_{\text{i,t}}$ is a binary indicator that equals 1 if it is the last month of the firms' fiscal year, and 0 otherwise. The second variable of interest, Financial Constraint, measures three distinct measure of financial constraint and surpluses: (1) an indicator variable equal to 1 if the Handlock and Pierce index is below the median, (2) an indicator variable equal to 1 if the firms cash/at is below the sample median, and (3) and indicator variable equal to 1 of the firm free cash flows (OANCF/AT) is below the sample median. Variable definitions appear in Appendix 1. The *t*-statistics (in parenthesis) are based on standard errors that are heteroskedasticity consistent and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

	$\text{Spendings}_{\text{i,t}}$					
	Below Median Hadlock-Pierce Index		**Below Median Firm Cash**		**Below Median Free Cash Flow**	
	Firm-Level	Product-Level	Firm-Level	Product-Level	Firm-Level	Product-Level
	(1)	(2)	(3)	(4)	(5)	(6)
(β_1) Last $\text{Month}_{\text{i,t}}$	3.59***	3.18***	4.18***	3.34***	4.42***	3.44***
	(5.43)	(8.94)	(6.08)	(9.08)	(6.87)	(8.74)
(β_2) Last Month $*$ Financial $\text{Constraint}_{\text{i,y}}$	-1.77**	-0.90*	-3.10***	-1.26**	-3.74***	-1.56***
	(-2.19)	(-1.72)	(-3.69)	(-2.45)	(-4.42)	(-2.92)
(β_3) Financial $\text{Constraint}_{i,y}$	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.
Month FE	Yes	No	Yes	No	Yes	No
Firm*Fiscal Year FE	Yes	No	Yes	No	Yes	No
Product Category*Month FE	No	Yes	No	Yes	No	Yes
Product Category*Fiscal Year*Firm FE	No	Yes	No	Yes	No	Yes
R^2	0.07	0.11	0.07	0.11	0.07	0.11
F-Statistics	19.04	54.95	20.06	55.13	23.97	50.37
No. Obs.	35,250	299,610	35,250	299,610	35,250	299,610

TABLE 8: Firms' Monthly Sales and the Advertising Efficiency

This table studies how each dollar of advertising spendings spent in the last month of the fiscal year generates in terms in sales using an OLS regression. The dependent variable is $Sales_{i,t}=\frac{Monthly\ Sales_{i,t}}{Fiscal\ Year\ Sales_{i,y}}$, or $Sales_{i,k,t}=\frac{Monthly\ Sales_{i,t}}{Fiscal\ Year\ Sales_{i,y}}$ in Panel A and B respectively. The first variable of interest is the *Last Month*$_{i,t}$, defined as a binary indicator that equals 1 if it is the last month of the firms' fiscal year, and 0 otherwise. The second variable of interest is $\text{Spendings}_{i,t} = \frac{Monthly\ Spending_{i,t}}{Fiscal\ Year\ Spending_{i,y}}$, or $\text{Spendings}_{i,k,t} = \frac{Monthly\ Spending_{i,k,t}}{Fiscal\ Year\ Spending_{i,k,y}}$ in Panel A and B respectively. Variable definitions appear in Appendix 1. The *t*-statistics (in parenthesis) are based on standard errors that are heteroskedasticity consistent and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Panel A: Firm Level	$\text{Sales}_{i,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
(β_1) Last Month$_{i,t}$	1.96***	0.94**	0.95**	0.97**		
	(5.13)	(2.14)	(2.14)	(2.19)		
(β_2) Last Month$_{i,t}$ * $Spending_{i,t}$	-0.05**	-0.05**	-0.05**	-0.05**		
	(-2.21)	(-2.47)	(-2.35)	(-2.44)		
(β_3) $Spending_{i,t}$	0.07***	0.07***	0.07***	0.08***		
	(5.28)	(5.32)	(5.22)	(5.46)		
R^2	0.02	0.02	0.05	0.10		
F-Statistics	7.14	4.86	4.62	4.87		
No. Obs.	21,294	21,294	21,294	21,294		
Panel B: Product Level	$\text{Sales}_{i,k,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
(β_1) Last Month$_{i,t}$	1.27***	0.56**	0.54**	0.54**	0.83***	0.87***
	(5.68)	(2.12)	(2.03)	(2.06)	(2.97)	(3.10)
(β_2) Last Month$_{i,t}$ * $Spending_{i,k,t}$	-0.02*	-0.02**	-0.02*	-0.02*	-0.02**	-0.02**
	(-1.96)	(-2.11)	(-1.73)	(-1.75)	(-2.35)	(-2.58)
(β_3) $Spending_{i,k,t}$	0.04***	0.04***	0.03***	0.03***	0.02***	0.03***
	(5.92)	(5.90)	(5.66)	(5.71)	(4.24)	(4.29)
R^2	0.01	0.02	0.04	0.06	0.18	0.21
F-Statistics	10.39	7.68	7.24	7.31	5.26	5.03
No. Obs.	38,100	38,100	38,100	38,100	38,044	38,044
Controls	$Spending_{i,[\mathbf{k}],t-1}$, $Spending_{i,[\mathbf{k}]t-2}$, $Spending_{i,[\mathbf{k}],t-3}$, $Spending_{i,[\mathbf{k}],t-4}$, $Spending_{i,[\mathbf{k}],t-5}$, $Spending_{i,[\mathbf{k}],t-6}$					
Month FE	No	Yes	Yes	Yes	Yes	No
Fiscal Year FE	No	Yes	Yes	No	No	No
Firm FE	No	No	Yes	No	No	No
Firm*Fiscal Year FE	No	No	No	Yes	Yes	No
Product Category FE	No	No	No	No	Yes	No
Product Category*Month FE	No	No	No	No	No	Yes
Product Category*Fiscal Year*Firm FE	No	No	No	No	No	Yes

TABLE 9: Upfront Season and Quality

This table studies how ads aired in a month perform in terms of reaching its target audience using an OLS regression. Panel A: The dependent variable, *Price of Market Penetration,* measures the dollar amount that firms must spend to reach the entire market once during the month (i.e., $\frac{TV\ Advertising\ Spendings\ (\$\ mil.)_{i,[k],t}}{Total\ Viewers\ Reached_{i,[k],t}/Universe\ of\ Viewiers_{i,[k],t}}$, divided by the total number of viewers that the firms could have reach at a given point (i.e., universal estimates). The method is borrowed from Shapiro et al. (2021) (See the technical note). Panel B: the dependent variable, *Price per viewer-Hour*, measures the dollar amount to reach 1 million viewers for one hour (i.e., $\frac{TV\ Advertising\ Spendings_{i,[k],t}}{Total\ Viewers\ Reached_{i,[k],t} * Total\ Ads\ Hours\ Aired_{i,[k],t}/1{,}000{,}000}$). Both variables of interest are winsorized at the 1st and 99th percentile. The first variable of interest is the L*ast Month*$_{i,t}$, defined as a binary indicator that equals 1 if it is the last month of the firms' fiscal year, and 0 otherwise. The second variable of interest is Upfront Season, an indicator variable if the firm's fiscal year ends in May or June, and 0 otherwise. Variable definitions appear in Appendix 1. The *t*-statistics (in parenthesis) are based on standard errors that are heteroskedasticity consistent and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Panel A: Market Penetration	*Price of Market Penetration*$_{i,[k],t}$				
	Firm-Level		Product-Level		
	(1)	(2)	(3)	(4)	(5)
(β_1) Last Month$_{i,t}$	6.99***	4.53**	1.78*	1.82*	2.41**
	(4.42)	(2.58)	(1.91)	(1.79)	(2.44)
(β_3) Last Month$_{i,t}$ * Upfront Season$_{i,y}$	-7.26***	-4.24*	-4.13**	-3.35*	-3.80*
	(-3.22)	(-1.69)	(-2.57)	(-1.77)	(-1.82)
(β_3) Upfront Season$_{i,y}$	1.01		-9.90***		
	(0.24)		(-2.73)		
$\boldsymbol{\beta_1 + \beta_2}$	-0.27	0.29	-2.35*	-1.53	-1.39
R^2	0.00	0.29	0.01	0.37	0.52
F-Statistics	6.54	3.34	8.97	1.97	3.12
No. Obs.	16,885	16,720	55022	54608	53150
Panel B: Viewer-Hour	*Price per viewier − hour*$_{i,[k],t}$				
	Firm-Level		Product-Level		
	(1)	(2)	(3)	(4)	(5)
(β_1) Last Month$_{i,t}$	1.12***	0.74*	0.57***	0.35***	0.39***
	(3.38)	(1.81)	(5.36)	(2.88)	(3.18)
(β_3) Last Month$_{i,t}$ * Upfront Season$_{i,y}$	-1.41***	-0.98*	-0.46***	-0.44*	-0.52*
	(-3.09)	(-1.73)	(-2.77)	(-1.95)	(-1.95)
(β_3) Upfront Season$_{i,y}$	-0.14		-0.75**		
	(-0.31)		(-2.28)		
$\boldsymbol{\beta_1 + \beta_2}$	-.29	-.25	-0.11	-0.09	-0.13
R^2	0.00	0.24	0.00	0.31	0.53
F-Statistics	4.34	1.79	11.07	4.16	5.05
No. Obs.	16,885	16,720	55022	54608	53150
Month FE	No	Yes	No	No	No
Fiscal Year FE	No	No	No	No	No
Firm FE	No	No	No	No	No
Firm*Fiscal Year FE	No	Yes	No	Yes	No
Product Category FE	No	No	No	No	No
Product Category*Month FE	No	No	No	Yes	Yes
Product Category*Fiscal Year*Firm FE	No	No	No	No	Yes

TABLE 10: Year-End Performance when Rationing Binds

This table studies how each dollar of advertising spendings spent in the last month of the fiscal year generates in terms in sales using an OLS regression for the subsample of firm-year during which managers deplete their budget before yearend. The dependent variable is $Sales_{i,t}$=$\frac{Monthly\ Sales_{i,t}}{Fiscal\ Year\ Sales_{i,y}}$, or *Monthly* $Sales_{i,t}$=$\frac{Monthly\ Sales_{i,t}}{Fiscal\ Year\ Sales_{i,y}}$ in Panel A and B respectively. The first variable of interest is the L*ast Month*$_{i,t}$, defined as a binary indicator that equals 1 if it is the last month of the firms' fiscal year, and 0 otherwise. The second variable of interest is $\text{Spendings}_{i,t} = \frac{Monthly\ Spending_{i,t}}{Fiscal\ Year\ Spending_{i,y}}$, or $\text{Spendings}_{i,k,t} = \frac{Monthly\ Spending_{i,k,t}}{Fiscal\ Year\ Spending_{i,k,y}}$ in Panel A and B respectively. Variable definitions appear in Appendix 1. The *t*-statistics (in parenthesis) are based on standard errors that are heteroskedasticity consistent and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Panel A: Firm-Level	$\text{Sales}_{i,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
(β_1) Last $\text{Month}_{i,t}$	1.33*	0.49	0.78	0.75		
	(1.76)	(0.63)	(0.97)	(0.95)		
(β_2) Last $\text{Month}_{i,t}$ * $Spending_{i,t}$	-0.00	-0.00	-0.02	-0.02		
	(-0.02)	(-0.05)	(-0.25)	(-0.21)		
(β_3) $Spending_{i,t}$	0.10***	0.10***	0.10***	0.11***		
	(3.49)	(3.55)	(3.59)	(3.77)		
R^2	0.03	0.04	0.10	0.11		
F-Statistics	3.26	2.41	2.40	2.65		
No. Obs.	4,860	4,860	4,860	4,860		
Panel B: Product-Level	$\text{Sales}_{i,k,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
(β_1) Last $\text{Month}_{i,t}$	0.85***	0.03	0.05	0.05	0.35	0.33
	(3.02)	(0.08)	(0.13)	(0.14)	(0.77)	(0.70)
(β_2) Last $\text{Month}_{i,t}$ * $Spending_{i,k,t}$	0.01	0.01	0.01	0.01	0.01	0.01
	(0.65)	(0.61)	(0.67)	(0.68)	(0.36)	(0.49)
(β_3) $Spending_{i,k,t}$	0.03***	0.03***	0.03***	0.03***	0.01*	0.02**
	(3.05)	(3.07)	(3.09)	(3.10)	(1.89)	(2.11)
R^2	0.02	0.02	0.06	0.07	0.28	0.33
F-Statistics	4.74	3.44	3.45	3.51	2.49	3.04
No. Obs.	8,784	8,784	8,784	8,784	8,577	8,577
Controls	$Spending_{i,[\mathbf{k}],t-1}$, $Spending_{i,[\mathbf{k}]t-2}$, $Spending_{i,[\mathbf{k}],t-3}$, $Spending_{i,[\mathbf{k}],t-4}$, $Spending_{i,[\mathbf{k}],t-5}$, $Spending_{i,[\mathbf{k}],t-6}$					
Month FE	No	Yes	No	No	Yes	No
Fiscal Year FE	No	No	No	No	No	No
Firm FE	No	No	No	No	No	No
Firm*Fiscal Year FE	No	Yes	No	No	Yes	No
Product Category*Month FE	No	No	No	No	No	No
Product Category*Month*Firm FE	No	No	Yes	No	No	Yes
Product Category*Fiscal Year*Firm FE	No	No	Yes	No	No	Yes

TABLE 11: Why Do Firms Bust the Budget?

This table studies how each dollar of advertising spendings spent in the last month of the fiscal year generates in terms in sales using an OLS regression during the latter part of the sample. The dependent variable is $Sales_{i,t}=\frac{Monthly\ Sales_{i,t}}{Fiscal\ Year\ Sales_{i,y}}$,. The first variable of interest is the *Runup Months*$_{i,t}$, defined as a binary indicator that equals 1 if the month is before the manager depleted its annual budget, and 0 otherwise. The second variable of interest is $\text{Spendings}_{i,t} = \frac{Monthly\ Spending_{i,t}}{Fiscal\ Year\ Spending_{i,y}}$. Variable definitions appear in Appendix 1. The *t*-statistics (in parenthesis) are based on standard errors that are heteroskedasticity consistent and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

	$\text{Sales}_{i,t}$			
	(1)	(2)	(3)	(4)
(β_1) Runup $\text{Months}_{i,t}$	-1.00***	-0.87**	-0.78**	-0.63
	(-2.74)	(-2.26)	(-2.07)	(-1.09)
(β_2) $Runup\ Months_{i,t} * Spendings_{i,t}$	0.06*	0.07*	0.06*	0.07**
	(1.67)	(1.96)	(1.91)	(2.19)
(β_3) $Spendings_{i,t}$	0.04***	0.03**	0.03**	0.03**
	(3.09)	(2.57)	(2.33)	(2.43)
Month FE	No	Yes	Yes	Yes
Fiscal Year FE	No	Yes	Yes	No
Firm FE	No	No	Yes	No
Firm*Fiscal Year FE	No	No	No	Yes
R^2	0.01	0.03	0.09	0.17
F-Statistics	3.12	2.54	2.16	2.20
No. Obs.	11,154	11,154	11,154	11,154

TABLE 12: The Effect of Firm Complexity and Distracted Managers

This table studies how each dollar of advertising spendings spent in the last month of the fiscal year generates in terms in sales using an OLS regression. The dependent variable is $Sales_{i,t}=\frac{Monthly\ Sales_{i,t}}{Fiscal\ Year\ Sales_{i,y}}$. The first variable of interest is the L*ast Month*$_{i,t}$, defined as a binary indicator that equals 1 if it is the last month of the firms' fiscal year, and 0 otherwise. The dependent variable is $\text{Spendings}_{i,t} = \frac{Monthly\ Spending_{i,t}}{Fiscal\ Year\ Spending_{i,y}}$. Panel A, investigate the effect of firm complexity using three metrics: (1) Hierarchical layers counts the total number of layers between the CEO and the lowest unit in the firm, (2) Product Divisions counts the number of distinct product category produced, and (3) flatness counts the number of subordinate units for each upper-level manager (first hierarchical layer). In Panel B, we study the role of CEOs' distraction using three metrics: (1) an indicator variable equal to 1 if the CEO has external board seats, (2) an indicator variable is the CEO is within 5 years from the average CEOs' retirement age in execucomp, and (3) CEOs' insider ownership. Variable definitions appear in Appendix 1. The *t*-statistics (in parenthesis) are based on standard errors that are heteroskedasticity consistent and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Panel A: Complex Firms	$Sales_{i,t}$					
	No. Hierarchical Layers		**No. of Product Divisions**		**Firm Flatness**	
	No. Layers Below Median	No. Layers Above Median	No. Divisions Below Median	No. Divisions Above Median	Flatness Below Median	Flatness Above Median
	(1)	(2)	(3)	(4)	(5)	(6)
(β_1) Last Month$_{i,t}$	1.18**	0.65	1.34**	1.33*	0.98	0.91
	(2.13)	(0.85)	(2.21)	(1.88)	(1.53)	(1.50)
(β_2) Last Month$_{i,t}$ * $Spending_{i,t}$	-0.03	-0.09***	-0.03	-0.14***	-0.02	-0.07***
	(-1.09)	(-2.77)	(-1.06)	(-2.76)	(-0.53)	(-3.01)
(β_3) $Spending_{i,t}$	0.07***	0.09***	0.06***	0.16***	0.08***	0.07***
	(4.58)	(3.26)	(4.19)	(3.67)	(4.49)	(3.31)
R^2	0.10	0.10	0.10	0.10	0.11	0.10
F-Statistics	4.56	3.81	4.80	3.20	5.11	2.66
No. Obs.	12,618	10,572	11,688	11,502	10,986	12,204
Panel B: Distracted CEOs	$Sales_{i,t}$					
	Busy CEOs		**CEOs Close to Retirement**		**CEO Ownership**	
	No External Board Seat	At least 1 External Board Seat	CEO is close to retirement	CEO is not close to retirement	Insider Ownership Above Median	Insider Ownership Below Median
	(1)	(2)	(3)	(4)	(5)	(6)
(β_1) Last Month$_{i,t}$	0.48	1.31***	2.64***	0.40	1.09*	1.26**
	(0.59)	(2.69)	(2.72)	(0.88)	(1.79)	(2.00)
(β_2) Last Month$_{i,t}$ * $Spending_{i,t}$	-0.04	-0.07**	-0.05	-0.06***	-0.02	-0.16***
	(-1.26)	(-2.28)	(-0.86)	(-3.14)	(-0.76)	(-3.29)
(β_3) $Spending_{i,t}$	0.06***	0.09***	0.09***	0.07***	0.05***	0.16***
	(3.34)	(4.53)	(3.34)	(4.99)	(4.35)	(3.69)
R^2	0.09	0.10	0.12	0.09	0.10	0.11
F-Statistics	3.50	3.54	3.45	4.61	3.54	2.64
No. Obs.	8,058	13,236	5,622	15,672	13,152	8,142
Controls	$Spending_{i,t-1}$, $Spending_{i,t-2}$, $Spending_{i,t-3}$, $Spending_{i,t-4}$, $Spending_{i,t-5}$, $Spending_{i,t-6}$					
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Appendix 1: Variables Description

Dependent Variables	Definition
$\text{Expenditure Below Average}_{i,t}$	Binary variable equal to 1 if the monthly allocation is below the unconditional average (100%/12), and 0 otherwise.
$\text{Price of Market Penetration}_{i,[\mathbf{k}],t}$	$\frac{\text{TV Advertising Spendings}_{i,[k],t}/1{,}000{,}000}{\text{Total Viewers Reached}_{i,[k],t}/\text{Universe of Viewiers}_{i,[k],t}}$, winsorized at the 1st and 99th percentile.
$\text{Price per viewier} - \text{hour}_{i,[\mathbf{k}],t}$	$\frac{\text{TV Advertising Spendings}_{i,[k],t}}{\text{Total Viewers Reached}_{i,[k],t} * \text{Total Ads Hours Aired}_{i,[k],t}}$, winsorized at the 1st and 99th percentile.
$\text{Sales}_{i,t}$	$\frac{\text{Monthly Sales}_{i,t}}{\text{Fiscal Year Sales}_{i,y}}$, for firm "i" on month "t".
$\text{Sales}_{i,k,t}$	$\frac{\text{Monthly Sales}_{i,k,t}}{\text{Fiscal Year Sales}_{i,k,y}}$, for firm "i" in product category "k" on month "t".
$\text{Spendings}_{i,t}$	$\frac{\text{Monthly Spending}_{i,t}}{\text{Fiscal Year Spending}_{i,y}}$, for firm "i" on month "t".
$\text{Spendings}_{i,k,t}$	$\frac{\text{Monthly Spending}_{i,k,t}}{\text{Fiscal Year Spending}_{i,k,y}}$, for firm "i" in product category "k" on month "t".
$\text{TV Spendings}_{i,t}$	$\frac{\text{Monthly TV Spending}_{i,t}}{\text{Fiscal Year TV Spending}_{i,y}}$, for firm "i" on month "t".
$\text{TV Spendings}_{i,k,t}$	$\frac{\text{TV Monthly Spending}_{i,k,t}}{\text{Fiscal Year TV Spending}_{i,k,y}}$, for firm "i" in product category "k" on month "t".
Variable of Interest	
$\text{Avg. Peers Spendings}_{i,k,t}$	The average of firm's "i" peers spendings in product category "k" on month "t".
$\text{Budget Depleted}_{i,t}$	A binary variable equal to 1 if the firms has spent more or as much of their last year spending level on month "t", and 0 otherwise.
Busy CEOs	A binary variable equal to 1 if the CEO has external board seats, and 0 otherwise.
$\text{Capital Rationing}_{i,t}$	A binary variable equal to 1 if the firm engaged in capital rationing on that year, and 0 otherwise. A firm is said to engaged in capital rationing if monthly expenses are below 8.33% (100%/12) in the month(s) following the moment the firm spent more than its last year level.
CEOs Close to Retirement	A binary variable is the CEO is within 5 years from the average CEOs' retirement age in Compustat (62), and 0 otherwise.
CEO Ownership	Share of the firm owned by the CEO in Execucomp (shrown_tot_pct).
$\text{Excess Budget}_{i,t}$	A binary variable equal to 1 if the firms remaining budget for the rest of the fiscal year is greater than 1/12 for each of the remaining month on "t", and 0 otherwise. For example, on month 10, if the firm has spent less than 1-10/12, the indicator variable would be equal to 1.
Firm Cash	Che/at
Firm Flatness	Counts the average number of subordinate units for each upper-level manager (first hierarchical layer).
Free Cash Flow	OANCF/at
Hadlock-Pierce Index	-0.737*size+0.043*size*size-0.04*age, where size is the natural logarithm of total asset (at), and age from the first year the firm appears in Compustat as min(age,30).
$\text{Last Month}_{i,t}$	A binary indicator that equals 1 if it is the last month of the firms' fiscal year, and 0 otherwise.
No. Hierarchical Layers	Counts the total number of layers between the CEO and the lowest unit in the firm in the Lexis Nexis dataset.
No. of Product Divisions	Counts the number of distinct product category produced in the Nielsen dataset.
$\text{Runup Months}_{i,t}$	Aa binary indicator that equals 1 in the month leading to budget depletion, and 0 otherwise.
$\text{Upfront Season}_{i,y}$	A binary variable if the firm's fiscal year ends in May or June, the upfront season, and 0 otherwise.

INTERNET APPENDIX

On a Spending Spree:
The Real Effects of Heuristics in Managerial Budgets

PAUL H. DÉCAIRE AND DENIS SOSYURA

INTERNET APPENDIX FIGURE IA.1

Firms' Monthly Spendings Over the Fiscal Year – Without the "December Effect"

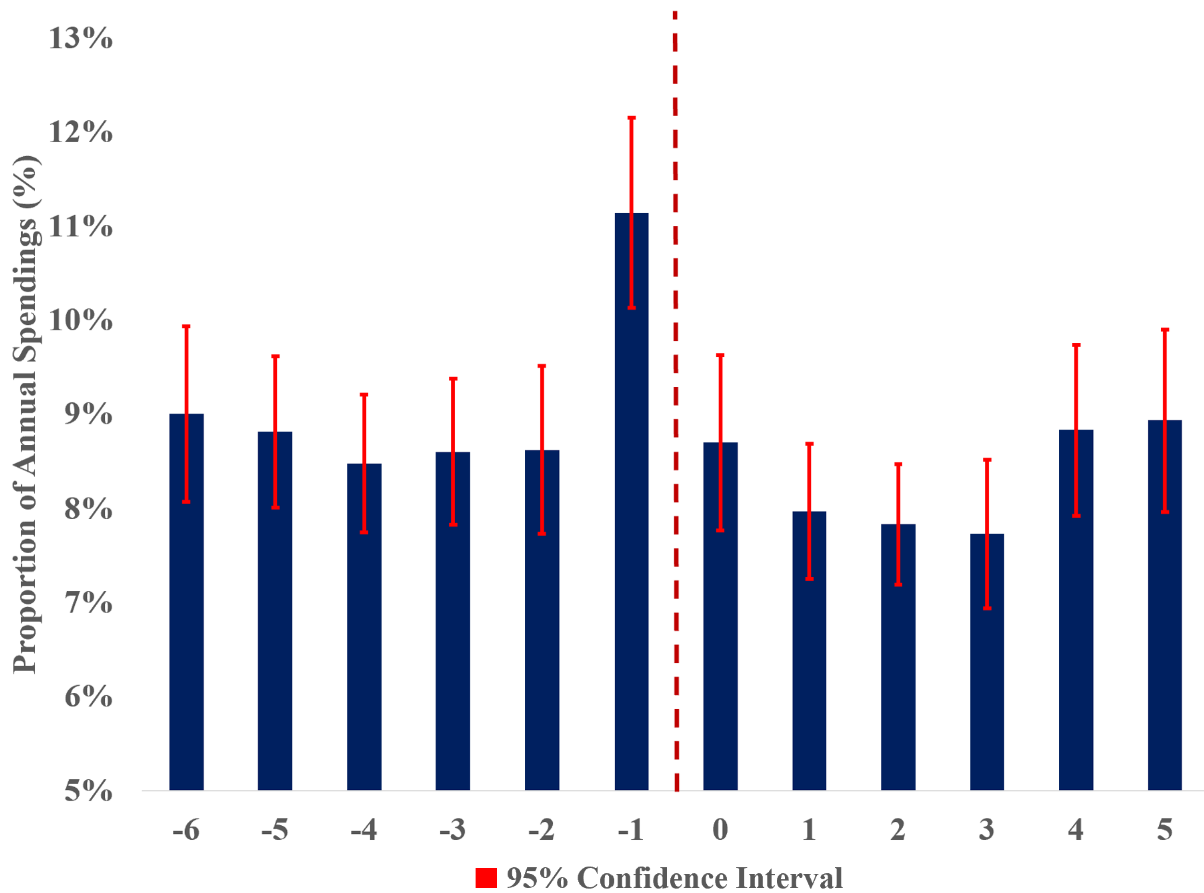

Figure IA.1: The Fiscal Year Last Month Effect on Firms' Spendings – Without the "December Effect"

The figure plots the monthly proportion of firms' annual spendings done around the end of firms' fiscal year, excluding firms for which the end of the fiscal year occurs during the month of December. We use ad spending data from Nielsen AdIntel from 2010 to 2019. Months ranked 0 denotes the first month of the fiscal year, whereas month number -1 indicates the last month of the fiscal year. The red bands denote the 95th percentile confidences interval for errors clustered at the firm level.

INTERNET APPENDIX TABLE IA.1: Firms' Year-Over-Year Spending Dynamics

This table studies how deadlines impact firms' resource allocation over the fiscal year, by estimating the proportion of firms' annual spending done during the last month of the period using an OLS regression. The dependent variable is *Spendings* which measure the firms' proportion of the fiscal year annual spending done in a given month aggregated at the firm level (i.e., $\text{Spendings}_{\text{i,y}} = \mathit{Fiscal\,Year\,Spending}_{i,y}$). The t-statistics (in parenthesis) are based on standard errors that are heteroskedasticity consistent and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

	Fiscal Year $\text{Spendings}_{\text{i,y}}$					
	(1)	(2)	(3)	(4)	(5)	(6)
(β_1) Fiscal Year $\text{Spendings}_{\text{i,y}-1}$	0.96***	0.96***	0.97***	0.97***	0.96***	0.96***
	(73.55)	(73.32)	(78.95)	(78.62)	(71.80)	(71.58)
(β_2) Fiscal Year $\text{Sales}_{\text{i,y}}$	6,914.76**	2,093.22	5,515.11**	2,358.69	6,758.38**	3,701.62
	(2.50)	(0.67)	(2.24)	(0.83)	(2.49)	(1.30)
(β_3) Fiscal Year $\text{Sales}_{\text{i,y}-1}$		5,019.31*		3,284.62		3,182.44
		(1.81)		(1.20)		(1.29)
(β_4) Time Trend_y					-6,419,099.17***	-6,407,444.43***
					(-6.15)	(-6.14)
Year FE	No	No	Yes	Yes	No	No
R^2	0.88	0.88	0.89	0.89	0.88	0.88
F-Statistics	3,906.74	2,670.76	4,276.26	2,955.54	2,823.16	2,164.00
No. Obs.	2,795	2,795	2,795	2,795	2,795	2,795

INTERNET APPENDIX TABLE IA.2: Last Month of Fiscal Year Effects – Only Firms That Change EOY Fiscal Month and Additional FE

This table studies how deadlines impact firms' resource allocation over the fiscal year, by estimating the proportion of firms' annual spending done during the last month of the period using an OLS regression and only firms that changed the last month of their fiscal year. The dependent variable is $\text{Spendings}_{\text{i,t}} = \frac{Monthly\ Spending_{i,t}}{Fiscal\ Year\ Spending_{i,y}}$, or $\text{Spendings}_{\text{i,k,t}} = \frac{Monthly\ Spending_{i,k,t}}{Fiscal\ Year\ Spending_{i,k,y}}$ in Panel A and B respectively. The first variable of interest *Last Month*$_{\text{i,t}}$ is a binary indicator that equals 1 if it is the last month of the firms' fiscal year, and 0 otherwise. Variable definitions and sample selection criteria appear in Appendixes 1 and 2, respectively. The *t*-statistics (in parenthesis) are based on standard errors that are heteroskedasticity consistent and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Panel A: Firm-Level	$\text{Spendings}_{\text{i,t}}$					
	(1)	(2)	(3)	(4)	(5)	(6)
(β_1) Last $\text{Month}_{i,\text{t}}$	5.17***	3.50***	3.45***	4.06***		
	(4.93)	(3.45)	(3.40)	(4.17)		
R^2	0.01	0.04	0.06	0.27		
F-Statistics	24.29	11.90	11.53	17.39		
No. Obs.	6,318	6,318	6,318	6,306		
Panel B: Product-Level	$\text{Spendings}_{\text{i,k,t}}$					
	(1)	(2)	(3)	(4)	(5)	(6)
(β_1) Last $\text{Month}_{i,\text{t}}$	3.48***	2.79***	2.76***	3.25***	3.18***	3.22***
	(4.78)	(4.41)	(4.28)	(5.34)	(5.29)	(5.25)
R^2	0.00	0.01	0.01	0.05	0.12	0.32
F-Statistics	22.81	19.42	18.33	28.54	28.04	27.59
No. Obs.	52,758	52,758	52,758	52,750	52,589	50,283
Month FE	No	Yes	Yes	No	No	No
Fiscal Year FE	No	Yes	Yes	No	No	No
Firm FE	No	No	Yes	No	No	No
Firm*Fiscal Year FE	No	No	No	Yes	Yes	No
Firm*Month FE	**No**	**No**	**No**	**Yes**	**Yes**	**No**
Product Category*Month FE	No	No	No	No	Yes	No
Product Category*Month*Firm FE	No	No	No	No	No	Yes
Product Category*Fiscal Year*Firm FE	No	No	No	No	No	Yes

INTERNET APPENDIX TABLE IA.3: Placebo – Using Previous Last Month of Fiscal Year Effects (67 distinct firms)

This table studies how deadlines impact firms' resource allocation over the fiscal year, by estimating the proportion of firms' annual spending done during the last month of the period using an OLS regression using a subsample of firms that changed the last month of their fiscal year. The dependent variable is $\text{Spendings}_{\text{i,t}} = \frac{Monthly\ Spending_{i,t}}{Fiscal\ Year\ Spending_{i,y}}$, or $\text{Spendings}_{\text{i,k,t}} = \frac{Monthly\ Spending_{i,k,t}}{Fiscal\ Year\ Spending_{i,k,y}}$ in Panel A and B respectively. The first variable of interest L*ast Month*$_{\text{i,t}}$ is a binary indicator that equals 1 if it is the last month of the firms' fiscal year, and 0 otherwise. Variable definitions and sample selection criteria appear in Appendixes 1 and 2, respectively. The *t*-statistics (in parenthesis) are based on standard errors that are heteroskedasticity consistent and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Panel A: Firm-Level	$\text{Spendings}_{\text{i,t}}$					
	(1)	(2)	(3)	(4)	(5)	(6)
(β_1) Last $\text{Month}_{i,\text{t}}$	-0.46	-0.08	0.02	-0.01		
	(-0.48)	(-0.05)	(0.02)	(-0.01)		
R^2	0.00	0.03	0.05	0.08		
F-Statistics	0.23	0.00	0.00	0.00		
No. Obs.	3,492	3,492	3,492	3,492		
Panel B: Product-Level	$\text{Spendings}_{\text{i,k,t}}$					
	(1)	(2)	(3)	(4)	(5)	(6)
(β_1) Last $\text{Month}_{i,\text{t}}$	0.16	0.16	0.16	0.49	0.53	0.66
	51.96	41.64	42.91	34.28	38.54	51.30
R^2	0.00	0.00	0.01	0.01	0.12	0.18
F-Statistics	0.05	0.05	0.03	0.03	0.23	0.15
No. Obs.	27,246	27,246	27,246	27,246	26,939	26,937
Month FE	No	Yes	Yes	Yes	Yes	No
Fiscal Year FE	No	Yes	Yes	No	No	No
Firm FE	No	No	Yes	No	No	No
Firm*Fiscal Year FE	No	No	No	Yes	Yes	No
Product Category FE	No	No	No	No	Yes	No
Product Category*Month FE	No	No	No	No	No	Yes
Product Category*Fiscal Year*Firm FE	No	No	No	No	No	Yes

INTERNET APPENDIX TABLE IA.4: Last Month of Fiscal Year Effects – No December Effect

This table studies how deadlines impact firms' resource allocation over the fiscal year, by estimating the proportion of firms' annual spending done during the last month of the period using an OLS regression. Excluding all firms with yearend falling in December. The dependent variable is $\text{Spendings}_{\text{i,t}} = \frac{Monthly\ Spending_{i,t}}{Fiscal\ Year\ Spending_{i,y}}$, or $\text{Spendings}_{\text{i,k,t}} = \frac{Monthly\ Spending_{i,k,t}}{Fiscal\ Year\ Spending_{i,k,y}}$ in Panel A and B respectively. The first variable of interest L*ast Month*$_{\text{i,t}}$ is a binary indicator that equals 1 if it is the last month of the firms' fiscal year, and 0 otherwise. Variable definitions and sample selection criteria appear in Appendixes 1 and 2, respectively. The *t*-statistics (in parenthesis) are based on standard errors that are heteroskedasticity consistent and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Panel A: Firm-Level	$\text{Spendings}_{\text{i,t}}$					
	(1)	(2)	(3)	(4)	(5)	(6)
(β_1) Last $\text{Month}_{i,\text{t}}$	2.55***	2.69***	2.66***	2.63***		
	(4.49)	(4.75)	(4.64)	(4.65)		
R^2	0.00	0.01	0.04	0.07		
F-Statistics	20.13	22.59	21.54	21.59		
No. Obs.	16,314	16,314	16,314	16,314		
Panel B: Product-Level	$\text{Spendings}_{\text{i,k,t}}$					
	(1)	(2)	(3)	(4)	(5)	(6)
(β_1) Last $\text{Month}_{i,\text{k,t}}$	2.73***	2.83***	2.83***	2.82***	3.08***	3.03***
	(6.68)	(6.72)	(6.72)	(6.71)	(7.80)	(7.73)
R^2	0.00	0.00	0.01	0.02	0.06	0.12
F-Statistics	44.58	45.18	45.21	45.03	60.86	59.73
No. Obs.	138,756	138,756	138,756	138,756	138,647	138,643
Month FE	No	Yes	Yes	Yes	Yes	No
Fiscal Year FE	No	Yes	Yes	No	No	No
Firm FE	No	No	Yes	No	No	No
Firm*Fiscal Year FE	No	No	No	Yes	Yes	No
Product Category FE	No	No	No	No	Yes	No
Product Category*Month FE	No	No	No	No	No	Yes
Product Category*Fiscal Year*Firm FE	No	No	No	No	No	Yes

INTERNET APPENDIX TABLE IA.5: Who Engages in Capital Rationing?

This table shows which type of organization is more likely to engage in credit rationing using a Probit regression. There are 4 measures of organization complexity. First, there is the number of *Hierarchical Layers* measured as the number of layers that separate the CEO from the operating units as reported in the Lexis Nexis data. Second, *Flatness* of the firms, measures the number of units that are not direct reports to the CEO as reported in the Lexis Nexis data (scaled by 100). Third, *Number of Divisions,* measures the number of distinct business segment the firm engage in using Compustat data. Fourth, *Firm size,* is a measure of the firm's total assets. The dependent variable is *Capital Rationing* which is an indicator variable equal to 1 if the firm engaged in capital rationing on that year, and 0 otherwise. A firm is said to engaged in capital rationing if monthly expenses are below 8.33% (100%/12) in the month(s) following the moment the firm spent more than its last year level. The *t*-statistics (in parenthesis) are based on standard errors that are heteroskedasticity consistent and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

	Resource Allocation Binds When Budget is $\text{Busted}_{i,t}$ = 1					
	Flatness		Number of Product Divisions		Hierarchical Layers	
	(1)	(2)	(3)	(4)	(5)	(6)
(β_1) Capital $\text{Rationing}_{i,t}$	0.06***	0.13***	0.03	0.11***	-0.02	0.04
	(3.69)	(6.14)	(1.36)	(3.71)	(-0.59)	(0.92)
(β_2) Capital $\text{Rationing}_{i,t}$ * Complex $\text{Firm}_{i,t}$	0.32***	0.31**	0.44**	0.41*	0.04***	0.04***
	(3.39)	(2.51)	(2.35)	(1.92)	(3.00)	(2.76)
(β_3) Complex $\text{Firm}_{i,t}$	-0.11***		-0.28***		-0.02***	
	(-3.66)		(-7.47)		(-5.02)	
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Fiscal Year FE	No	No	No	No	No	No
Firm FE	No	No	No	No	No	No
Firm*Fiscal Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.01	0.15	0.02	0.15	0.02	0.15
F-Statistics	16.37	27.75	24.45	24.30	15.41	26.32
No. Obs.	38,100	38,100	38,100	38,100	38,100	38,100

INTERNET APPENDIX TABLE IA.6: Firms' Monthly Sales and the Expenses Efficiency – Natural Logarithm Version

This table studies how each dollar of advertising spendings spent in the last month of the fiscal year generates in terms in sales using an OLS regression. The dependent variable is $Sales_{i,t=}$ $\ln(1 + Monthly\ Sales_{i,t})$, or $Monthly\ Sales_{i,t=}\ln(1 + Monthly\ Sales_{i,k,t})$ in Panel A and B respectively. The first variable of interest is the L*ast Month*$_{i,t}$, defined as a binary indicator that equals 1 if it is the last month of the firms' fiscal year, and 0 otherwise. The second variable of interest is $\text{Spendings}_{i,t} = \ln(1 + Monthly\ Spendings_{i,t})$, or $\text{Spendings}_{i,k,t} == \ln(1 + Monthly\ Spendings_{i,k,t})$ in Panel A and B respectively. Variable definitions and sample selection criteria appear in Appendix 2 and Table A.2, respectively. The *t*-statistics (in parenthesis) are based on standard errors that are heteroskedasticity consistent and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Panel A: Firm Level	$\ln(1 + \text{Sales}_{i,t})$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(β_1) Last $\text{Month}_{i,t}$		0.93***	0.81***	0.57***	0.47***		
		(4.53)	(4.09)	(5.64)	(4.65)		
(β_2) Last $\text{Month}_{i,t}$ * $\ln(1 + \text{Spendings}_{i,t})$		-0.05***	-0.05***	-0.03***	-0.02***		
		(-3.09)	(-3.11)	(-4.69)	(-3.62)		
(β_3) $\ln(1 + \text{Spendings}_{i,t})$	0.33***	0.33***	0.33***	0.20***	0.22***		
	(11.09)	(11.39)	(11.36)	(13.42)	(15.19)		
R^2	0.11	0.11	0.12	0.86	0.91		
F-Statistics	40.10	35.24	35.24	32.49	47.85		
No. Obs.	24,336	24,336	24,336	24,336	24,336		
Panel B: Product Level	$\ln(1 + \text{Sales}_{i,k,t})$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(β_1) Last $\text{Month}_{i,k,t}$		0.84***	0.71***	0.46***	0.46***	0.55***	0.53***
		(6.15)	(6.17)	(5.54)	(5.50)	(5.93)	(6.34)
(β_2) Last $\text{Month}_{i,k,t}$ * $\ln(1 + \text{Spendings}_{i,k,t})$		-0.05***	-0.05***	-0.02**	-0.02**	-0.02**	-0.02***
		(-3.67)	(-3.79)	(-2.46)	(-2.46)	(-2.42)	(-3.14)
(β_3) $\ln(1 + \text{Spendings}_{i,k,t})$	0.21***	0.21***	0.21***	0.15***	0.15***	0.15***	0.13***
	(15.84)	(16.03)	(15.83)	(13.87)	(13.94)	(14.71)	(13.48)
R^2	0.16	0.16	0.16	0.49	0.53	0.66	0.89
F-Statistics	51.96	41.64	42.91	34.28	38.54	51.30	35.36
No. Obs.	48,984	48,984	48,984	48,984	48,984	48,972	48,972
Controls	$(\boldsymbol{\beta_4})$ $\ln(1 + \text{Ad Spendings}_{i,[\mathbf{k}],t-1})$, $(\boldsymbol{\beta_5})$ $\ln(1 + \text{Ad Spendings}_{i,[\mathbf{k}],t-2})$, $(\boldsymbol{\beta_6})$ $\ln(1 + \text{Ad Spendings}_{i,[\mathbf{k}],t-3})$, $(\boldsymbol{\beta_7})$ $\ln(1 + \text{Ad Spendings}_{i,[\mathbf{k}],t-4})$, $(\boldsymbol{\beta_8})$ $\ln(1 + \text{Ad Spendings}_{i,[\mathbf{k}],t-5})$, $(\boldsymbol{\beta_9})$ $\ln(1 + \text{Ad Spendings}_{i,[\mathbf{k}],t-6})$						
Month FE	No	No	Yes	Yes	Yes	Yes	No
Fiscal Year FE	No	No	Yes	Yes	No	No	No
Firm FE	No	No	No	Yes	No	No	No
Firm*Fiscal Year FE	No	No	No	No	Yes	Yes	No
Product Category FE	No	No	No	No	No	Yes	No
Product Category*Month FE	No	No	No	No	No	No	Yes
Product Category*Fiscal Year*Firm FE	No	No	No	No	No	No	Yes

INTERNET APPENDIX TABLE IA.7: Binding Budgets and Investment Sensitivity

This table studies how deadlines impact firms' resource allocation over the fiscal year, by estimating the proportion of firms' annual spending done during the last month of the period using an OLS regression. The dependent variable is $\text{Spendings}_{i,k,t} = \frac{Monthly\ Spending_{i,k,t}}{Fiscal\ Year\ Spending_{i,k,y}}$. The first variable of interest Avg. Peers $\text{Spendings}_{i,k,t}$ measure the average of firm's "i" peers spendings to product category "k" on month "t". The second variable of interest, *Budget Depleted*$_{i,t}$, is an indicator variable equal to 1 if the firms has spent more or as much of their last year spending level on month "t", and 0 otherwise. Variable definitions and sample selection criteria appear in Appendixes 1 and 2, respectively. The *t*-statistics (in parenthesis) are based on standard errors that are heteroskedasticity consistent and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

	$\text{Spendings}_{i,k,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
(β_1) Avg. $Peers\ Spendings_{i,k,t}$	0.17***	0.16***	0.15***	0.15***	0.05***	0.06***
	(15.83)	(15.43)	(14.00)	(13.99)	(5.60)	(6.12)
(β_2) Avg. $Peers\ Spendings_{i,k,t}$ * $Budget\ Depleted_{i,t}$	-0.06***	-0.06***	-0.05***	-0.06***	-0.07***	-0.08***
	(-3.09)	(-3.15)	(-2.98)	(-3.10)	(-3.92)	(-4.37)
(β_3) $Budget\ Depleted_{i,t}$	0.23	-0.12	-0.11	-0.25	-0.08	-0.03
	(1.30)	(-0.71)	(-0.56)	(-1.10)	(-0.35)	(-0.13)
$\boldsymbol{\beta_1 + \beta_2}$	0.11***	0.10***	0.10***	0.09***	-0.02	-0.02
Month FE	No	Yes	Yes	Yes	Yes	No
Fiscal Year FE	No	Yes	Yes	No	No	No
Firm FE	No	No	Yes	No	No	No
Firm*Fiscal Year FE	No	No	No	Yes	Yes	No
Product Category FE	No	No	No	No	Yes	No
Product Category*Month FE	No	No	No	No	No	Yes
Product Category*Fiscal Year*Firm FE	No	No	No	No	No	Yes
R^2	0.01	0.01	0.01	0.02	0.04	0.11
F-Statistics	94.12	88.08	72.64	72.21	11.83	14.04
No. Obs.	263,326	263,326	263,323	263,321	263,312	262,610