Disaggregated Sales and Stock Returns*

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Abstract

Using transaction-level credit card spending from a large US financial institution, we show that disaggregated sales provide accurate and persistent signals of customer demand relevant to a firm's stock pricing. After controlling for earnings and sales surprises, one inter-quintile increase in the adjusted customer spending during a firm's fiscal quarter leads to 1.5 percentage points increase in the 60-day post-earnings-announcement *CAR*. The predictability concentrates in consumer-oriented firms, especially those relying more on indirect sales distribution channels. We also find a stronger return response to spending from high *FICO* score, high liquidity, and loyal customers. The transmission speed of disaggregated sales information is slower than that of the earnings information, and small firms or firms far from their end customers exhibit a more delayed price response. Finally, the return implications of adjusted customer spending extend to firms along the production chain.

Keywords: return predictability, informed investors, disaggregated sales, customer demand, credit cards, consumption, household finance, financial institution, big data

JEL Classification: D12, G14, H31

1. Introduction

Customer demand is the source of a firm's cash flow. As Subrahmanyam and Titman (1999) describe, "a manager for a retailer such as JC Penney may obtain valuable information about the demand for the clothing line of a fledgling garment manufacturer." This highlights the value of observing customer purchase at the granular level. Indeed, investors have long recognized the importance of disaggregated sales information. With the rapid development of information collection technology in the recent decade, they have begun to access and exploit the availability of such data in their trading strategy. For example, hedge funds use satellite to obtain information on consumer traffic at retailers (*The Wall Street Journal*, 2016). There is also an increasing supply of data aggregation services that track and process individual consumers' purchase behavior.[1]

Why is such consumer spending information valuable, even though firms periodically disclose their sales? Being able to access timely sales information is obviously an important factor, but its value goes beyond that. Observing detailed information from customer purchases allows one to gauge demand for the firm's products in a way beyond what can be learned from the aggregate revenue measures.

The disclosed earnings or sales may not accurately reflect actual purchases from end customers, given that products go through various distribution layers before they reach the final clients. For example, confirmed sales to distributors may not accurately reflect true customer demand. In addition, buyer characteristics and spending patterns offer important signals to gauge the sustainability of customer interest, holding the level of sales constant. The firm featuring a buyer group with greater purchase capacity presumably will remain competitive in the product market by attracting the same customers (or clientele) in the future. Similarly, firms with loyal customers enjoy strong and sustainable consumer interest in the firm's product. Therefore, conditioning on the same level of aggregate sales, the unique information on customer clientele and characteristics provides complementary information to that contained in the aggregate sales from the firm's financial report.

Moreover, how stock prices incorporate the value-relevant information embedded in the disaggregated sales data remains an open question. While some informed investors have timely access to the proprietary information, their trading choices potentially suggest a nuanced price adjustment process. The extant literature documents that informed investors appear to wait for public

[1] Companies such as "Slice Intelligence" and "InfoScout" provide granular data that measure shoppers' purchase patterns. Other technology companies like "Mint" and "Betterment" are also actively collecting people's real-time bank account and credit card spending information (*The New York Times*, 2017). Data vendors like Acxiom, Datalogix, eBureau, Equifax, Experian, IRI all provide the granular consumer and (or) credit data (*Dummies.com*, "16 Major Data Vendors").

information disclosure, possibly to improve the precision of their trading signals (e.g., Katona, Painter, Patatoukas, and Zeng, 2019). Additionally, they tend to strategically choose trading venues to reduce price impact or add noise in trading to hide their private signals (Easley, O'Hara, and Srinivas, 1998; An, Ang, Bali, and Cakici, 2014; Yang and Zhu, 2019). These factors are further amplified by information or arbitrage frictions in the market, leading to slow price discovery with return predictability implications.

Despite the increasing popularity in exploiting disaggregated sales information by the investment profession, little research has investigated the return predictability implications of such information due to data limitations.[2] This paper attempts to fill the gap and test the hypotheses using direct measures of confirmed customer purchases. Specifically, we use a unique panel dataset of account-level credit card transactions, which not only allows us to observe the spending patterns and merchant information, but also a rich array of consumer financial and demographic characteristics. As a representative consumer spending instrument, credit cards play an important role in the study of consumer-spending behaviour (Gross and Souleles, 2002; Japelli, Pischke and Souleles, 1998).

The dataset contains a representative sample for more than 60,000 U.S. consumers from a major US bank, with which we identify individual credit card spending in a large sample of 858 US public firms from multiple industries from 1st March to 31st October of 2003. For each fiscal quarter of a firm, we aggregate all credit card spending from its customers, and construct an adjusted spending measure as the deviation of a firm's total customer credit card spending from the industry average spending, scaled by the firm's total sales in the same quarter. Despite the relatively short time series, our empirical analysis benefits from the granular administrative spending data with a higher signal-to-noise ratio and exploits variation of disaggregated sales in the cross-section.

We examine the predictability of the adjusted spending on a firm's cumulative abnormal stock return after its quarterly earnings announcement. As we conjecture earlier, trading of informed investors likely concentrates after the release of public signals (Katona, et al., 2019). In addition, high visibility and escalated trading activity typically associated with earnings announcements promote a stronger return predictability pattern during this period (Merton 1987; Gervais, Kaniel, and Mingelgrin, 2001; Kaniel, Ozoguz, Starks, 2012; Atilgan, 2014; An, et al., 2014). In our analysis, we focus on the returns during the post-announcement window to better isolate the effect of disaggregated sales.

[2] A few exceptions include Froot, Kang, Ozik, and Sadka (2017) and Huang (2018) that use novel but indirect proxies to measure customer perception and potential purchase behavior in a sample of firms.

We first show that the total credit card spending during a given fiscal quarter significantly correlates with a firm's cash flows (sales and net income) for the same period. More importantly, we find a significantly positive relation between the adjusted credit card spending within the firm's fiscal quarter and subsequent cumulative abnormal return (*CAR*), after controlling for contemporaneous earnings and sales surprises. Specifically, one inter-quintile increase in the adjusted spending is associated with 1.49 percentage points increase in 60-day post-announcement *CAR* (*CAR[+2,+61]*). This effect is statistically significant and economically large: the magnitude is more than half the size of the post-earnings-announcement drift (*PEAD*). We then verify the relevance of the credit card spending information in the cross-section: the predictive power of adjusted spending is stronger for the consumer-oriented firms, within which the effect is mainly driven by the firms that rely more on indirect distribution channels to sell products.

Next, we utilize the customer characteristics information in the credit card data to investigate the source of the return predictability associated with customer demand sustainability. High spending capacity customers and loyal customers are associated with more stable and persistent demand in the future, making their adjusted spending a more reliable signal of the firm's future cash flow.

Consumer credit quality, captured by *FICO* scores, measures consumers' creditworthiness which to a large extent reflects their capacity to consume. Individuals with greater access to credit are less sensitive to income or liquidity shocks, thus exhibit smoother consumption patterns. Similarly, we construct a *credit utilization* measure to capture the idea that a customer further away from binding credit constraints should have higher spending capacity than the ones that are more constrained. Consistent with the hypothesis, the return predictability is concentrated among sales from high *FICO score* and low *credit utilization rate* customers. Regarding customer loyalty, we also find a consistent result that the effect is mainly driven by the adjusted spending from *repeat* customers (who tend to repurchase from the same firm) and *loyal* customers (who tend to adhere to a few firms to buy a certain category of goods).

We discuss the role of information frictions in explaining the persistence of the return predictability. Value-relevant information would be incorporated into stock prices quickly unless there exist frictions that delay a speedy price adjustment. We find evidence that the customer spending information is incorporated into stock prices at a slower speed than the publicly disclosed earnings news. In addition, the price response to such information is slower for small firms and firms far from their end customers (i.e., firms that rely more on indirect sales distribution channels).

Next, we investigate broader return implications by incorporating the transmission of customer demand information from one firm to its economically linked firms. We find evidence of positive return predictability from the shocked customer firm's adjusted spending to the subsequent *CAR* of its supplier firms along the production chain, especially for the consumer-oriented firms.

Finally, we verify that the adjusted spending measure predicts the firm's earnings and sales surprises in the subsequent four quarters, after controlling for the contemporaneous earnings and sales surprises. We also perform a series of robustness checks on alternative explanations, sample selection, alternative variable specifications, and falsification tests.

We directly contribute to the rising literature on the influence of customer information on stock prices (Ittner and Larcker, 1998; Fornell, Mithas, Morgeson III, and Krishnan, 2006; Aksoy, Cooil, Groening, Keiningham, and Yalçın, 2008; Luo, Homburg, and Wieseke, 2010; Ljungqvist and Qian, 2016; Froot, Kang, Ozik, and Sadka, 2017; Huang, 2018). Compared with other papers from the literature, our study is the first that uses granular consumer information in the transactions of credit cards. The transaction-level credit card spending dataset enables us to directly observe confirmed purchases for each customer and more importantly characteristics of a firm's clientele, with which we trace out the sources of the return predictability associated with customer spending. Specifically, information on consumer credit quality and spending patterns offers important signals to gauge the sustainability of customer demand, which is unique from the credit card spending data. Additionally, by incorporating the return implications along the production chain for a broader set of firms, we allow a more comprehensive assessment of the economic significance of the disaggregated sales.

More broadly, the paper contributes to the informed investors literature, particularly on the source of their information and how they impound their signals into asset prices. Recent studies highlight the use of alternative data by sophisticated institutional investors (e.g., Gargano, Rossi, and Wermers, 2017; Katona, et al., 2019; Zhu, 2019). In addition, a large number of studies show various mechanisms through which informed investors trade on their private signals, for example through choices of trading signals, timing, or venue (Easley, O'Hara, and Scrinivas, 1998; Bali and Hovakimian, 2009; An, et al., 2014; Atilgan, 2014; Massa, Qian, Xu, and Zhang, 2015; Froot, et al., 2017; Yang and Zhu, 2019). Our results provide support, echoing the anecdotal evidence, that granular consumer spending information is engaged in informed trading. Our paper also complements the literature by showing that the disaggregated sales information mainly reveals after disclosure of public signals (likely due to informed investors' strategic choices), and when disaggregate sales contain more relevant private signals.

Our findings also relate to studies on predictable stock returns in the cross-section. There is a large literature on the slow diffusion of information following publicly announced earnings-related events, such as earnings announcements (Bernard and Thomas, 1989, 1990) and analysts' earnings forecasts (Elgers, Lo, and Pfeiffer Jr, 2001). We provide evidence consistent with the role of market frictions in explaining the return predictability of the disaggregated sales information. Moreover, our finding of a prominent effect in the post-earnings-announcement period is also consistent with the idea that in a stock market with incomplete information, positive shocks in the trading activity of the relevant stock further increase the stock visibility, which gives rise to a strong return predictability (Gervais, et al., 2001; Kaniel, et al., 2012).

The rest of the paper flows as follows: Section 2 describes the data and methodology; Sections 3 and 4 report main results and additional analysis respectively; and Section 5 concludes.

2. Data and Methodology

2.1. Raw Data

2.1.1. Credit Card Spending Data

We utilize a unique dataset obtained from one leading US bank issuing credit cards nationwide to measure disaggregated sales. This bank took more than 10 percent of all bank deposits in the US, with a retail consumer base of around 46 million as of 2016. The bank's customers are representative of the US consumer population (see also the description in Agarwal, Liu, and Souleles, 2007; Agarwal, Marwell, and McGranahan, 2017; Agarwal, Chomsisengphet, Meier, and Zou, 2020). The entire dataset contains more than 3 million financial transactions from 1st March to 31st October of 2003 for a random, representative sample of over 120,000 accounts of the bank's customers.

This dataset provides disaggregated transaction-level information about the individual's credit card spending, including the transaction amount, transaction date, and merchant name. Additionally, we observe monthly financial information regarding consumer credit (e.g., *FICO score*, *credit card balance*, *credit limit*), and a rich set of demographic information. Such customer characteristics serve as helpful tools in dissecting the source of information contained in customer spending. Compared to noisy public data, the proprietary signals from consumer spending have a higher signal-to-noise ratio, which allows us to obtain statistical power through variation in the cross-section despite the relatively short sample period.[3]

[3] While our data only capture customer spending through credit cards from one major financial institution, it is important to note that our identification strategy, one that exploits the cross-sectional variation in customer spending, does not require a complete account of all spending by customers. To the extent that the choice of customer-spending instrument is plausibly exogenous to a firm's performance (i.e., customers do not use specific credit cards from the financial institution in our sample to only purchase products from firms with high sales and earnings), spending aggregated from our dataset is an unbiased indicator of the overall customer spending on a firm's products. We verify this point by showing that for firm-quarters in our sample, the fraction of reported sales and the fraction of customer spending within industry have very similar distribution (Table IA1). Since only two percent (2,996)

Credit cards play an important role in consumer finances, facilitating studies of consumer-spending behavior (Gross and Souleles, 2002; Agarwal and Qian, 2014, 2017; Agarwal, Qian, and Zou, 2020). Credit cards, particularly bank cards (e.g., Visa, MasterCard, Discover, and Optima cards), represent the leading source of the unsecured consumer credit in the US (Japelli, et al., 1998). From the 2004 Survey of Consumer Finances (SCF), more than 70 percent of US households have at least one credit card. The median (mean) household credit card balance was $2,200 ($5,100), which is large in magnitude relative to typical household balance sheets in 2004. Around 50 percent of bank card holders still concentrate at least 90 percent of their total general-purpose balances on a single card. As one of the largest consumer credit markets, US' total revolving credit balances have exceeded $925 billion, and the spending via general-purpose credit card took up 15 percent of the GDP in 2014 (*Consumer Financial Protection Bureau*, 2015). In this paper, we investigate the return predictability from a firm's disaggregated sales; hence, we view credit card spending as an important source to measure customer demand for the firm's products.

The credit card spending dataset offers several advantages compared to previous studies that rely on indirect proxies such as customer review (Huang, 2018; Tang, 2018), customer search pattern (Froot, et al., 2017), satellite image (Zhu, 2019), or customer satisfaction index (e.g., Ittner and Larcker, 1998; Fornell, et al., 2006). First, indirect proxies of customer demand are invariably noisier and can even be biased. For example, self-reported opinions could give rise to selection bias, response bias, or opinion herding.[4] Since the spending transactions truthfully record the purchase behavior of credit card holders, our measure is not subject to biases stemming from self-reported data. Second and more importantly, in addition to the quantity of spending, tracing customer credit quality and shopping patterns from the credit card spending data reveals new insight on the sustainability of the firm's customer demand. Last but not the least, compared with the prior literature, we are able to identify a much larger sample of public firms (N=858) from multiple industries, which enables us to draw more generalizable implications.

To establish the link between customers and public firms, we use the merchant names reported in the credit card transaction record to identify the corresponding firms selling to retail customers. To

accounts in the whole dataset correspond to individuals with multiple credit card accounts with the bank, we will use "individual," "consumer," "customer," and "account" interchangeably. We also verify that excluding those multiple-account holders does not affect our results.

[4] Selection bias refers to the situation that certain types of consumers are more likely to self-report their opinions. Response bias refers to the situation that self-reported opinions could be inaccurate or untruthful. Opinion herding refers to the situation that consumers herd other's opinions when making comments while ignoring their own private signals.

identify "real" spending on firm products, we exclude bank fees items such as late payment fees, cash advance fees, over-limit fees, and financial charges. The dataset covers 129,277 retail customers.

2.1.2. Firm-level Data

Given the sample period of the credit card spending data, we restrict our study to firm-quarters with the whole fiscal quarters falling within the eight months (i.e., 1st March to 31st October in 2003). We obtain firm-quarter level information from CRSP, COMPUSTAT, and I/B/E/S. We mainly use the quarterly earnings announcement date provided in COMPUSTAT; if not available, we adopt the I/B/E/S date (conditional on availability). Actual earnings per share, and other firm characteristics including quarterly sales, net income, book value of equity, etc., are obtained or constructed from COMPUSTAT. The number of analysts following is calculated based on I/B/E/S analyst forecast data. Full company name, daily stock returns, price, the number of shares outstanding, and industry classification (four-digit SIC code) are obtained from CRSP. Finally, we obtain the production chain link information from the COMPUSTAT SEGMENT dataset. The benchmark used to calculate abnormal returns in the main analysis is the Fama-French 6 Size×B/M portfolio returns.

2.2. Merged Final Sample and Summary Statistics

A key step for our sample construction is to match the public firms with their customers. We follow three steps below to establish the link.

We start with the list of full company names from CRSP (as in 2003), which contains 6,940 firms.[5] First, we match the 325,334 merchant names from the credit card transaction record with the 6,940 firm names by their word similarity.[6] We keep merchant names that are successfully matched to only one company name. After this step, we are left with 120,274 merchant names (5,954 firms), and each merchant name is linked to one firm. Second, to ensure the accuracy of matching, we manually verify the matching for larger merchants (i.e., those with total customer spending ≥ $20,000 during the eight-month sample period). For the remaining pairs involving smaller merchants, we impose the following three restrictions to further reduce mismatching: (1) in case of no exact match in the company names, we drop the merchants whose matching scores are lower than 0.9; (2)

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[5] Firms may change names over time, therefore we drop the firm names which were stopped usage before 2003, or first used after 2003.

[6] We use a user-written command "reclink" in STATA, which performs comparison and matching based on the similarities of the input string variables. The algorithm generates a continuous matching score in the range of 0 and 1 (exact match), and produces a successful match when the names from the two data sources are similar (i.e., if the matching score is between 0.6 and 1).

among the remaining merchants, we drop the merchants whose customer credit card spending is less than \$100 spending per month (i.e., with less than \$800 total spending); (3) if still more than 5 merchants are matched to one firm, only keep those with matching scores no-lower than the fifth-highest score among all the matched merchants for the same firm. After this step, we are left with 2,445 merchants (1,415 firms).

We aggregate all credit card spending for a firm within each fiscal quarter. Due to the relatively short sample period for the credit card spending, we mainly exploit the cross-sectional variation in the customer purchase. To the extent that customer spending provides additional information relevant to a firm's profitability and growth potential beyond the current accounting information, we hypothesize the deviation of customer spending from the industry mean, to be predictive of a firm's subsequent cumulative abnormal return (*CAR*). As firms with larger sizes may naturally get a higher amount of credit card spending, we scale this measure by the firm's total sales in the same quarter. Specifically, the main measure of a firm's adjusted spending (*AdjSpend*) is constructed as below:

$$AdjSpend_{ikn} = \frac{Spending_{ikn} - Industry\ average\ spending_{ikn}}{Sale_{ikn} + 1}$$

Where $Spending_{ikn}$ is the total credit card spending in dollars for firm *i* from industry *k* in the fiscal quarter *n*. $Industry\ average\ spending_{ikn}$ is the average credit card spending for all firms in industry *k* during the same period.[7] Please refer to Appendix A in the Internet Appendix for detailed variable constructions. Following the literature convention, we sort *AdjSpend* into five quintiles in each calendar quarter, and use the *Q_AdjSpend* instead of raw *AdjSpend* for our analysis (see, e.g., Kothari, 2001; Hirshleifer, Lim, and Teoh, 2009). *Q_AdjSpend* ranges from the bottom adjusted spending quintile (*Q_AdjSpend*=1) to the top adjusted spending quintile (*Q_AdjSpend*=5).

The main dependent variable is the firm-quarter's cumulative abnormal return (*CAR*) in the 60-trading day period after the earnings announcement. Following Hirshleifer, Lim, and Teoh (2009), we define *CAR* as the difference between the buy-and-hold return of the announcing firm and return for respective benchmark portfolio: the matched Fama-French 6 Size×B/M portfolio. Specifically, we accumulate the abnormal returns over the window of [+2, +61] in trading days relative to the announcement date as:

[7] For example, if firm A's fiscal quarter 2 in 2003 is from 2003.04.01 to 2003.06.30, then the industry benchmark is the average credit card spending from all same-industry firms during 2003.04.01 to 2003.06.30. We divide by $(Sale_{ikn} + 1)$ to account for zero values of firm sales. There are only 7 firm-quarters with zero sales. We verity that constructing the adjusted spending measure as $AdjSpend_{ikn} = \frac{Spending_{ikn} - Industry\ average\ spending_{ikn}}{Sales_{ikn}}$ (i.e., drop the firm-quarters with 0 sales) generates very similar results for all the main analyses.

$$CAR[+2,+61]_{in} = \prod_{j=t+2}^{t+61}(1+R_{ij}) - \prod_{j=t+2}^{t+61}(1+R_{pj})$$

Where *t* is the earnings announcement date of firm *i* in fiscal quarter *n*; R_{ij} is the return of firm *i* on day *j* relative to earnings announcement day, and R_{pj} is the return of the matching size×B/M portfolio on day *j* relative to earnings announcement day. If the number of trading days between a firm's quarter *n* and quarter *n+1* earnings announcements is less than 60, we accumulate the post-announcement *CAR* till one trading day before the next quarter's earnings announcement date.

We require firms to have non-missing earnings announcement dates for both fiscal quarters *n* and *n+1*. We also require daily returns to be available in CRSP during the period. All *CAR*s are winsorized at the 1 and 99 percentiles in the final merged sample. Since we use the 6 Size×B/M portfolio return as the benchmark, we also require firms to have available data to calculate size and book-to-market ratios for both the current quarter, and for the month that the benchmark portfolio is formed.

In the presence of known market reaction to earnings news during the post-earnings-announcement period (known as *Post-Earnings-Announcement-Drift*, see, e.g., Bernard and Thomas, 1989), earnings surprise is an important piece of accounting information that we need to control for. We follow Livnat and Mendenhall (2006) and define the Standardized Unexpected Earnings (*SUE*) based on a rolling seasonal random walk model, as the deviation of earnings per share (*EPS*) from the *EPS* four quarters ago, scaled by price per share at the quarter-end:

$$SUE_{in} = \frac{EPS_{in} - EPS_{in-4}}{P_{in}}$$

We also sort *SUEs* into five quintiles and use the *SUE* quintile (i.e., *QSUE*) as our control variable in the analysis.

Since Jegadeesh and Livnat (2006) show that the firm's revenue surprise itself contains information, we also need to control for it. We constructed a *Standardized Unexpected Sales* (*SU_Sale*) measure following the *SUE* definition above. Specifically, we calculate the deviation of sales per share from the sales per share four quarters ago, scaled by the quarter-end price:

$$SU\_Sale_{in} = \frac{Sale\ per\ share_{in} - Sale\ per\ share_{in-4}}{P_{in}}$$

The *SU_Sale* is also sorted into five quintiles.

Additionally, we control for other firm characteristics that are potentially related to the post-announcement *CAR*: firm size (market capitalization), book-to-market ratio, the number of analysts, and the reporting lag for the current quarter. We end up with 1,510 firm-quarters (from 858 firms) that have all relevant firm-level information available in the final merged sample.

We compare firms in our final merged sample (N=858) and all US firms (N=4,488) from 2003Q2 to 2003Q3 in Panel A of Table 1.[8] The average (median) quarterly customer credit card spending for firms in the sample is $17,415 ($2,018). Compared to the full sample of US firms in CRSP in 2003, our sample includes firms with larger size and better analyst coverage. These are arguably firms less subject to informational frictions in the capital market, making the return predictability documented in our paper likely a conservative estimate of the value of disaggregate customer sales information. The average 60-day post-announcement cumulative abnormal return (*CAR[+2,+61]*) in our sample is about 1.33 percent lower than the mean in the full CRSP sample.[9]

[Insert Table 1 about here]

Panel B of Table 1 provides the summary statistics of the demographic and financial information for customers in our final merged sample (N=60,950), in comparison with all credit card holders (N=129,277) from the bank's raw sample. Though individuals in our sample tend to have higher consumer credit (higher *FICO score*) and lower credit utilization than all credit card holders, the differences are economically small.

We report the correlation matrix for selected variables in Panel C of Table 1. In general, there is a significantly positive correlation between the total credit card spending and the firm's reported sales (correlation=0.52) and net income (correlation=0.35). This provides reassuring evidence that customer spending, as captured by the credit card transactions, strongly correlates with the firm's cash flow. Turning to our main variable of interest (*AdjSpend*), we find that the correlation between *AdjSpend* and earnings surprise (*SUE*), and that between *AdjSpend* and sales surprise (*SU_Sale*) are both statistically insignificant and economically small. The low correlations indicate that *AdjSpend* serves more than just a re-interpretation of the contemporaneous accounting information known to predict a firm's subsequent financial and stock performance.

2.3. The Empirical Strategy

[8] The sample period for our credit card spending data is 1st March 2003 to 31st October 2003, and only a firm-quarter with the whole fiscal quarter falling into this eight-month period can be included in our final sample. Therefore, in our final sample, we only have firm-quarters fall into calendar quarter 2003Q2 and 2003Q3.

[9] In Section 4.2.1, we formally study the sample selection bias and find no evidence that the two groups of firms have distinct return responses to earnings surprises.

We examine the predictability of the adjusted spending on the post-announcement CAR, controlling for earnings surprise, sales surprise, and other firm-level characteristics. Specifically, we employ the following regression model:

$$CAR[+2,+61]_{ikn} = \beta Q\_AdjSpend_{ikn} + \theta QSUE_{ikn} + \varphi QSU\_Sale_{ikn} + \phi X_{ikn} + \delta_k + \upsilon_n + \epsilon_{ikn} \quad (1)$$

The dependent variable $CAR[+2,+61]_{ikn}$ represents the 60-day post-announcement *CAR* of firm *i* from industry *k* in fiscal quarter *n*. $Q\_AdjSpend_{ikn}$, $QSUE_{ikn}$, and QSU_Sale_{ikn} are quintile ranks of adjusted spending, earnings surprise, and sales surprise for firm *i* from industry *k* in fiscal quarter *n*, with quintile rankings based on independent sorts in the corresponding calendar quarter. X_{ikn} is a vector of firm-quarter level control variables including firm size, book-to-market ratio, the number of analysts following, and the length of reporting lag. δ_k represents a vector of industry fixed effects, and υ_n denotes the corresponding calendar year-quarter fixed effects.

We are particularly interested in the coefficient for *Q_AdjSpend* (i.e., β). If disaggregated sales provide additional information on a firm's growth potential, then the adjusted spending should have a significant positive impact on the subsequent post-announcement *CAR*, after controlling for other value-relevant accounting information.

3. Main Results

3.1. Information in Disaggregated Sales

We begin by showing that the disaggregated sales are pertinent to the firm's same-quarter cash flows. Specifically, we check the relation between the reported sales, net income, and total credit card spending within the same fiscal quarter. In columns (1) and (2) of Panel A, Table 2, we find a significant positive correlation between firm sales and total customer spending in the same fiscal quarter, with and without controlling for industry fixed effects. Similarly, total credit card spending is significantly positively associated with a firm's net income (columns (3)-(4)).

[Insert Table 2 about Here]

We then check the effect of earnings surprise in column (1) of Panel B, Table 2. Consistent with previous studies, earnings surprise generates significant predictability for the post-announcement abnormal return (*CAR[+2,+61]*). Specifically, one inter-quintile increase in the earnings surprise (i.e., *QSUE*) is associated with 2.34 percentage points increase in the 60-day post-announcement *CAR* in our sample.[10]

[10] This magnitude appears to be larger than those in previous studies: in comparison, the regression coefficient of 0.052 for *Adjusted DSUE* (Adjusted Decile of *SUE*) in Livnat and Mendenhall (2006) implies one inter-quintile

The main thesis of this paper is that the adjusted spending constructed from direct customer purchases conveys incremental information relevant to the firm's future profitability. To directly test this central claim, we add our main variable of interest—the quintile of adjusted spending (*Q_AdjSpend*) into the regression. Consistent with our prediction, the adjusted spending significantly positively predicts the subsequent *CAR*, after controlling for earnings and sales surprises. As reported in column (2) of Panel B, one inter-quintile increase in *Q_AdjSpend* leads to 1.49 percent increase in the 60-day post-announcement *CAR*, which is equivalent to around 9 percent of the standard deviation of *CAR[+2,+61]* in our sample, or 60 percent of the earnings surprise effect.[11] We also verify that compared with the 3-day announcement period and the 10-day period before the earnings announcement, the information in disaggregated sales mainly reveals during the post-announcement period.

QSU_Sale, however, is not significantly related with 60-day post-announcement *CAR* (coefficient=-0.320; *p*value=0.434). This result suggests that the customer spending does not merely mirror information in reported sales. Moreover, the fact that the coefficient for the earnings surprise remains very similar with or without the adjusted spending (and sales surprise) in the regression again suggests that the three measures capture independent information.

3.2. Consumer-oriented vs. Non-consumer-oriented Firms

The information implications of customer demand likely differ across firms. The customer spending by credit card holders should be more informative about revenue and growth potential for firms to whom sales to retail customers are more pertinent. Consumer-oriented firms' revenues heavily depend on the retail customers, whose disaggregated sales provide more (and accurate) private signals to the informed investors, hence the subsequent abnormal returns of these firms should be more responsive to adjusted spending from individual consumers.

We classify firms in our sample into consumer-oriented and non-consumer-oriented firms according to their two-digit SIC industries. Specifically, firms in our sample can be classified into 10 divisions according to their two-digit SIC industries: Transportation & Public Utilities; Retail Trade; Services; Agriculture, Forestry, & Fishing; Mining; Construction; Manufacturing; Wholesale Trade;

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increase in *SUE* predicts 1.12 percent increase in the post-announcement *CAR.* In Table IA8, we verify that this is not due to the methodology difference, nor sample selection issue arising from distinct characteristics of firms in our sample. Instead, the high *SUE* return predictability is common during 2003 Q2-Q3 for all firms.

[11] We have also estimated the post-announcement *CAR* effect for each quintile of *adjusted spending* separately, and find the effect of *adjusted spending* quintile to be monotonic.

Finance, Insurance, & Real Estate; and Public Administration.[12] Based on the nature of operations, firms from Transportation & Public Utilities division (two-digit SIC: 40-49), Retail Trade division (two-digit SIC: 52-59), or Service division (two-digit SIC: 70-89) are classified as consumer-oriented firms, and the remaining firms are classified as non-consumer-oriented firms. According to this classification, around half of the firms in our sample are consumer-oriented firms. The firm classification details are reported in Appendix B of the Internet Appendix.

Results reported in Panel A of Table 3 are in line with our prediction, that only the adjusted spending for consumer-oriented firms exhibits significant return predictability. Specifically, for consumer-oriented firms, one inter-quintile increase in *Q_AdjSpend* increases *CAR[+2,+61]* by 2.17 percent (*p*value=0.001), which is 1.35 percent higher than the effect for non-consumer-oriented firms (Chi-test statistic=3.24; *p*value=0.072).[13]

[Insert Table 3 about Here]

Moreover, even among the consumer-oriented firms, the informativeness of the disclosed aggregated sales on customer demand also varies. A common practice is that a firm can either sell directly to end customers (direct sales), or sell the products to other distributors or retailers (channel sales), or do both (Chiang, Chhajed, and Hess, 2003). When firms rely more on indirect distribution channels to sell products, the booked sales number does not necessarily signal end-customer demand, unless more information on the actual sales at the distributors or retailers is known. Consequently, credit card spending, which measures direct sales to end customers, will provide complementary information to aggregated firm sales.

We verify this point by further investigating the heterogeneous results by the firm's reliance on direct sales. According to the report on the retail industry from WFDSA (2019), over 60 percent of direct sales come from Wellness (33.2%) and Cosmetics & Personal care (31.2%) products; therefore we define a firm as relying more on direct sales if more than half of its disaggregated sales during our sample period is classified as Wellness or Cosmetics & Personal care-related spending (identified by the Merchant Category Code in the credit card transaction record).[14] Panel B of Table 3 shows that among the consumer-oriented firms, the predictive power of adjusted spending mainly come from

[12] The division classification is from:
http://mckimmoncenter.ncsu.edu/mckimmon/divisionUnits/ceus/sicCodePickList.jsp

[13] We have also investigated another criterion based on the fraction of sales to end customers out of the total sales—industries with median fraction of sales to consumers higher than the 50^{th} percentile among all industries in the sample are classified as consumer-oriented firms—and find a robust and consistent pattern (Table IA2).

[14] The WFDSA (2019) is available at: https://wfdsa.org/wp-content/uploads/2019/06/Product-Report-FINAL-v2.pdf. Appendix B in Internet Appendix lists the distribution of firms classified as relying more on direct sales in our sample.

firms relying less on direct sales, for which disaggregated sales to end customers are more useful to gauge consumer demand. A one inter-quintile increase in *Q_AdjSpend* increases *CAR[+2,+61]* by 2.02 percent (*p*value=0.006) for firms relying less on direct sales, compared with an effect of -1.22 (*p*value=0.820) for firms relying more on direct sales.[15]

3.3. Customer Characteristics Information

Why does disaggregated sales—measured from individual-level credit card spending—carry value relevant information about future demand? Besides providing a more accurate account of the sales number, perhaps a more important reason lies in the rich information about the sustainability of a firm's customer demand conveyed by the detailed customer characteristics. To investigate this idea, we utilize customers' characteristics and spending patterns observable in our proprietary credit card transaction dataset.

3.3.1. Customer Spending Capacity

Intuitively, high spending capacity customers have more stable spending patterns, and purchases from these customers are more likely to be repeated in the future.[16] High spending capacity customers have greater revenue-generating potential for a firm, therefore, the observed effect in the main finding should mostly come from sales generated by high spending capacity consumers. We propose several measures to capture high spending capacity consumers.

According to Agarwal and Qian (2014), individuals with greater access to credit are less sensitive to income or liquidity shocks thus exhibit smoother consumption patterns, especially in credit card spending. Hence, we employ consumer credit quality as one proxy for spending capacity and expect the return predictability of the adjusted spending to mostly derive from high credit quality customers. We adopt a commonly used credit score—*FICO score* — as a proxy for their spending

[15] To better understand this result, we compare the key firm characteristics between firms relying more and less on direct sales, and find they have similar size, institutional ownership, analyst coverage, stock turnover, Amihud illiquidity (Amihud, 2002), and idiosyncratic volatility (Ang, Hodrick, Xing, and Zhang, 2006) by the end of 2002, suggesting that the differential return response to adjusted spending is unlikely driven by firm characteristics that cause the same piece of information to be incorporated into prices at different rates. Furthermore, consistent with our story, we document a stronger predictive power of sales surprise quintile from the firms relying more on direct sales, which contains more customer demand information.

[16] We verify this point by showing that the *high spending capacity* customers, based on our measures below, are significantly more likely than *low spending capacity* customers to be *repeat customers*. Moreover, conditional on repurchase transactions, the total repurchase amount for each *repeat customer* is also higher for *high spending capacity* customers (Table IA3).

capacity, and decompose the total credit card spending into the amount from customer groups with high and low spending capacity.

We follow two steps to implement the decomposition. First, for each quarter, we get the quarter-beginning *FICO score* for each customer, and define high capacity customers as individuals with no lower than 740 quarter-beginning *FICO score*.[17] In the second step, we compute the spending amount from *high FICO* customers and *low FICO* customers for each firm-quarter respectively. Then for spending from each group of customers, we calculate the adjusted spending as its deviation from industry average spending, scaled by the firm's total sales in the same quarter; and sort the adjusted spending into quintiles. We include the quintiles of adjusted spending for both groups of customers in the regression, and report the results in column (1) of Panel A, Table 4.

[Insert Table 4 about Here]

Consistent with our prediction, adjusted spending from *high FICO* customers exhibits strong predictive power during the 60-day post-announcement period (coefficient=2.619; *p*value<0.001), compared with the small and insignificant effect from *low FICO* customers' adjusted spending (coefficient=-0.502; *p*value=0.533).

Our second measure is based on the idea that the liquidity status of a consumer speaks to his or her spending capacity. To measure the liquidity status, we create a *credit utilization* measure for each customer-quarter as the total credit card balance in the quarter-beginning month divided by the same-month credit limit. A lower level of *credit utilization* corresponds to more available liquidity and better spending capacity, and we use 30% as the cutoff value.[18] As reported in column (2) of Panel A, Table 4, we find the predictive power concentrates in the adjusted spending from consumers utilizing less than 30 percent of their credit limit.

We also use the *internal behavior score* and *delinquency* status as corroborative measures for customer credit quality and liquidity status respectively, and find similar results. For brevity, we focus on the *FICO score* and *credit utilization* measures in the main text, and leave the other two measures results to the Internet Appendix (Table IA4).

3.3.2. Customer Loyalty

[17] Individuals with *FICO score* $\geqslant$740 are considered to have excellent credit quality (*Credit.org*, "What is a Good Credit Score?"). The sample median *FICO score* of the consumers is also around 740.

[18] Financial experts and credit score rating institutes usually suggest credit card holders to keep credit utilization below 30 percent in order to maintain a good credit score. 30 percent is the average utilization rate for Americans (*Self.inc*, "Everything you need to know about credit utilization"), which also corresponds to our sample mean.

Customer loyalty is another important indicator of persistent customer demand (Bronnenberg, Dubé, and Gentzkow, 2012). We should expect the adjusted spending from loyal customers to be more predictive of the firm's future return. In Panel B of Table 4, we investigated two customer loyalty measures: *repeat customers* and *loyal customers*. Please refer to Appendix A in the Internet Appendix for detailed variable constructions.

Repeat customers are those who have ever purchased more than once from the same firm. The regression results suggest that one inter-quintile increase in their adjusted spending leads to 1.49 percent increase in 60-day post-announcement *CAR* (*p*value=0.002), compared with 0.57 percent (*p*value=0.464) for that from *non-repeat customers* (column (1)). A *loyal customer* is defined as someone who intends to adhere to one or a few merchants to purchase a given type of goods. As reported in column (2) of Panel B, Table 4, we find the predictive power for 60-day post-announcement *CAR* is stronger for *loyal customers* (coefficient = 1.989; *p*value=0.013) than *switching customers* (coefficient = -0.231; *p*value=0.838).

We also investigate the information in customer characteristics using customer composition as another metric. Firms with a diversified customer base can better endure demand shocks, leading to a more stable (projected) customer demand. We indeed find supportive evidence, and detailed results are reported in Table IA5 of the Internet Appendix.

3.4. The Role of the Information Environment in Explaining the Return Predictability

While modern technology makes it possible for investors to access alternative data like the credit card spending that we study in the paper, any value-relevant information would be incorporated into stock prices immediately unless there are frictions that delay a speedy price adjustment. In this aspect, we conduct additional tests and find evidence of slow adjustment of such information into stock prices, especially when impediments to efficient information transmission are greater. Specifically, we hypothesize that the publicly disclosed information (i.e., earnings surprise) shall be reflected in stock prices faster than the customer spending information. In Panel A of Figure 1, we trace the price adjustment speed in response to *SUE* and *adjusted spending* quintiles during the [-1, +61] trading day period (or until one day before the next earnings announcement date, whichever is earlier), by plotting the effect on *CAR* at event time *t* as a fraction of the total effect on *CAR* over the entire trading period. We find that at every time point, the percentage of adjustment is higher for the publicly disclosed *SUE* information, than the *adjusted spending* information.

[Insert Figure 1 about Here]

Furthermore, consistent with existing literature, we find the price adjustment process in response to customer spending information is relatively slower for the subsample of firms with plausibly higher information frictions: in Panel B, we find the price adjustment percentage of *adjusted spending* information is always higher for larger firms at any time point compared to smaller firms. Moreover, the transmission speed of customer demand information shall also differ depending on how far the firm is from its ultimate customers. Specifically, information embedded in the disaggregated sales shall transmit faster for firms closer to their end customers, and we find a consistent result that firms further away from their end customers (i.e., the firms relying less on direct sales) experience a slower transmission of the disaggregated sales information (Panel C).

3.5. Return Implications along the Production Chain

Finally, we consider return implications by incorporating the transmission of customer demand information from one firm to a broader set of economically linked firms (Cohen and Frazzini, 2008; Menzly and Ozbas, 2010; Albuquerque, Ramadorai, and Watugala, 2015). Due to the interconnections between firms and sectors, microeconomic shocks may propagate throughout the economy instead of remaining in the origination place (Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi, 2012). Consequently, an accurate measure of disaggregated sales for a firm also informs us of (persistent) demand shocks along its production chain. A high level of stable demand for a firm's goods transmits to its supplier firms due to the firm's positive demand for the intermediate goods from its suppliers; whereas the transmission from the supplier firm's goods demand to the customer firms is less obvious. In our setting, we then expect a positive return predictability to occur in the direction from the shocked customer firms' adjusted spending to the subsequent *CAR* of the supplier firms along the production chain. Moreover, as we argue that the disaggregated sales offer more accurate customer demand information for consumer-oriented firms, the cross return implication along the production chain should also be more pronounced for the consumer-oriented firms.

To investigate this hypothesis, we first employ the customer-supplier relationship in 2003 constructed by Cen, Maydew, Zhang, and Zuo (2017) based on COMPUSTAT Segment Customer file. For each customer firm-quarter in our sample, we compute its supplier firms' *CAR*s in the subsequent month following its earnings announcement day. Based on the identified customer-supplier pairs from the same dataset, we construct the customer firms' *CAR*s in the subsequent month for each supplier-quarter in sample in a similar way. We test whether the adjusted spending from firms in our sample predicts their supplier or customer firms' subsequent *CAR*s.

In Panel A of Table 5, we investigate the predictive power from customer firms (in our sample) to their supplier firms. In column (1), we show that one inter-quintile increase in adjusted spending of customer firms leads to a 0.43 percentage points increase in supplier firms' *CAR* in the subsequent month. Columns (2)-(3) show that the predictive power is mainly driven by consumer-oriented customer firms: one inter-quintile increase in their adjusted spending leads to 0.72 percentage points increase in supplier firms' subsequent *CAR* (*p*value=0.059), and the effect is economically sizable. On the other hand, the predictive power for supplier firms' return is statistically indistinguishable from zero for the non-consumer-oriented customer firms. This pattern stays robust when we further add the earnings surprise quintile from customer firms as a control.

[Insert Table 5 about Here]

In Panel B of Table 5, we investigate the predictive power in the opposite direction, i.e., from supplier firms to customer firms. Consistent with the prediction, there is no significant relationship between the supplier firms' adjusted spending and the customer firms' subsequent *CAR*.

4. Additional Analysis

4.1. Predicting Future Earnings and Sales Surprises

The information content of the adjusted spending is not only relevant in predicting returns, but should also manifest itself in the firm's future cash flows. To test this hypothesis, we investigate whether the adjusted spending in quarter *n* predicts the earnings or sales surprise in the subsequent quarters, controlling for the earnings and sales news in the current quarter *n*. We find consistent results (reported in Table IA6): after controlling for the effect of earnings surprise and sales surprise in quarter *n*, the adjusted spending in quarter *n* still significantly positively predicts the earnings surprises and sales surprises to up to 4 quarters in the future.

4.2. Alternative Explanations

We then show that the positive relationship between the adjusted spending and the post-announcement *CAR* is not driven by potential confounding factors that lead to *PEAD*, including earnings quality (Hung, Li, and Wang, 2014), investor sophistication (Bartov, Radhakrishnan, and Krinsky, 2000), and investor inattention (DellaVigna and Pollet, 2009; Hirshleifer, Lim, and Teoh, 2009). Specifically, in Table IA7 of the Internet Appendix, we show that after additionally controlling for the earnings quality (proxy by *earnings persistence* and *earnings volatility*), investor sophistication (proxy by *institutional ownership*), or investor inattention (proxy by *number of concurrent earnings announcements*), the effect of adjusted spending stays strong and robust. Our main result is also robust to another proxy for earnings quality: the *discretionary accrual* as the regression residual of the Modified Jones Model (Dechow, Sloan, and Sweeney, 1995).

We have also accounted for additional candidates of omitted variables by including selling, general, and administrative expenses (SG&A), R&D expenses, capital expenditures, operating cash flows, as well as an indicator of "early announcement risk" as control variables in the regression (Savor and Wilson, 2016). The effect of adjusted spending remains robust.

4.3. Robustness Tests

4.2.1. Potential Sample Selection Concerns

Our main analysis is based on 858 firms that can be matched to the merchants in the credit card data. If our sample firms differ from a typical CRSP company in ways that affect their return dynamics (especially during the post-earnings announcement period), then our interpretation of the documented return predictability may be specific to this subsample. In response, we show that the return predictability of earnings surprise on post-announcement *CAR* is similar for firms in our sample and other CRSP firms not in the sample, during the extended period of 1980-2003, both within our sample period and outside the sample period (Table IA8).

4.2.2. Alternative Specifications

It is possible that the adjusted spending measure simply captures the cross-sectional variation within an industry that the sales and earnings surprises defined under the seasonal random walk model do not capture. To tackle this problem, we construct two alternative measures for sales and earnings surprises that adjust for the cross-sectional variation within the industry, and still find robust results (Columns (1)-(2) of Table IA9). Columns (3)-(4) of Panel A, Table IA9 show that our results are also robust when we use analyst forecast-based earnings surprise (*SUE_af*), or when we scale the customer spending deviation from industry average by the same quarter's total asset to construct the adjusted spending measure. In unreported results, we have investigated two other proxies of *SUE*: the *SUE* defined in Anderson, Reeb, and Zhao (2012) and the three-day announcement *CAR*. We continue to find significant return predictability of adjusted spending.

The main result remains qualitatively and quantitatively similar under alternative benchmark portfolio returns in calculating *CAR* (Panel B of Table IA9), and alternative industry classifications (Panel C of Table IA9). Lastly, we show that the statistical significance of our main findings remain the same under the bootstrap standard error estimation (Table IA10).

4.2.3. Account for Industry-level Variations

Since the adjusted spending measure mainly exploits the within industry variation, one might worry that the number of firms in some industries is too small. We address this concern by excluding industries with a small number of firms and find a robust effect of adjusted spending (Panel A, Table IA11). Moreover, the results are robust when we further control for within-industry size difference of firms (Panel B, Table IA11). Lastly, we control for the industry average *CAR* during the [+2,+61] trading day period after each firm-quarter's earnings announcement in the regression, and the result stays robust (Panel C, Table IA11).

4.2.4. Falsification Test

Finally, we show that the effect of the adjusted spending is unlikely due to a spurious relationship. We randomly assign the adjusted spending to an arbitrarily chosen firm-quarter and re-run the main regression for 100 times, and the regression coefficients for the randomly assigned *Q_AdjSpend* is never significantly positive at 5% level (see Figure IA1).

5. Conclusion

In this paper, we investigate the information contained in the disaggregated sales from the firm's retail customers. Using a large panel dataset on credit card transactions, we find that credit card adjusted spending on a firm's products within a fiscal quarter positively predicts the subsequent stock abnormal return. After controlling for the earnings and sales surprises, one inter-quintile increase in the adjusted spending generates 1.49 percentage points increase in the 60-day post-announcement *CAR* (*CAR[+2,+61]*). The predictive power is stronger among the consumer-oriented firms, especially those relying more on indirect sales distribution channels. To explain the source of the incremental information, we find the customer traits are helpful in gauging the sustainability of future customer demand for the firm's products. Specifically, we document a stronger predictive power of the adjusted spending from high spending capacity customers and loyal customers.

Moreover, we find a slower transmission speed for the disaggregated sales information compared to the public earnings information; and it is even slower for the smaller firms and firms further away from their end customers. The ability of customer firms' adjusted spending to predict their suppliers' subsequent *CAR*s further supports the idea that disaggregated sales convey value-relevant customer demand information and carry return implications to a broader set of firms.

Overall, findings in our study provide direct evidence that consumer spending serves as a valuable source of information to extract a firm's customer demand. To the extent that sophisticated investors have access to the information, the strong return implications documented in the paper offer new evidence on informed trading. Our paper also complements the informed investor literature by showing that the disaggregated sales information mainly reveals after disclosure of public signals (likely due to informed investors' strategic choices), and when disaggregate sales contain more relevant private signals.

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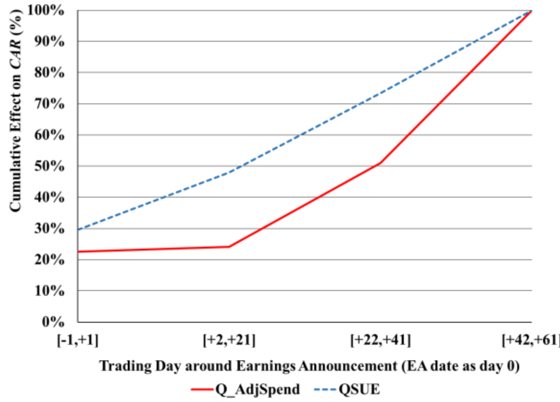
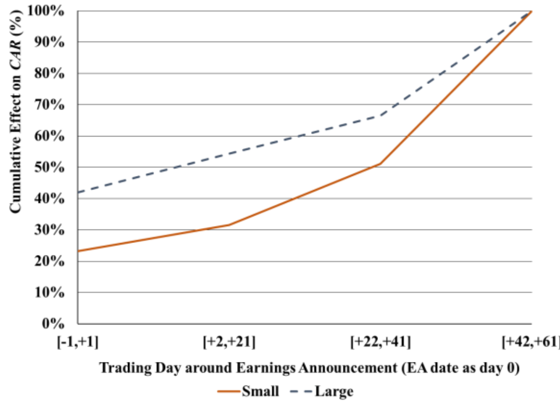
Figure 1. Cumulative Predictive Power in Return

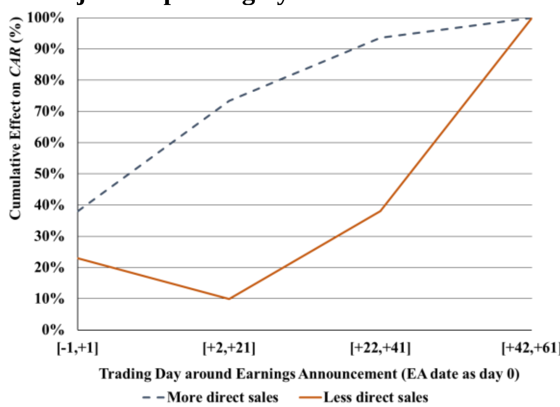
Panel A. Cumulative effect of earnings surprise and adjusted spending



Panel B. Cumulative effect of adjusted spending by size



Panel C. Cumulative effect of adjusted spending by distribution of sales



Note. This figure plots the cumulative effect of adjusted spending and *SUE* on *CAR* at event time *t* as a fraction of the total effect on *CAR* during the [-1, +61] trading day period around earnings announcement, with time *t* being the first and every 20 trading day after the earnings announcement. Panel A plots the cumulative effect of adjusted spending quintile and *SUE* quintile on *CAR* from the full sample. Panel B plots the cumulative effect of adjusted spending quintile on *CAR* from subsamples split by Fama-French median size breakpoint. Panel C plots the cumulative effect of adjusted spending quintile on *CAR* from subsamples split by distribution of sales. For detailed variable definitions and constructions, please see Appendix A in the Internet Appendix.

Table 1. Summary Statistics

Panel A: Firm characteristics

	Firms in sample			All firms			
	Mean	SD	Median	Mean	SD	Median	Difference in means
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Total credit card spending ($)	17,415	103,672	2,018				
Adjusted Spending (AdjSpend)	-231	1,603	-22				
CAR[+2,+61] (%)	2.65	16.08	0.00	3.98	18.14	0.63	-1.33**
SUE	0.03	0.52	0.00	0.08	4.33	0.00	-0.05
SU_Sale	-0.01	0.25	0.01	-0.01	0.33	0.01	-0.003
Sales ($million)	929	4,147	97	517	2,548	46.33	412***
Net income ($million)	53.00	290.56	2.43	26.25	183.87	0.99	26.75***
Market capitalization ($million)	3,862	19,293	368	2,102	12,259	220	1,761***
Book equity ($million)	1,907	8,193	185	1,131	5,190	112	776***
Number of analysts	3.95	5.45	1.50	2.72	4.41	1.00	1.23***
Number of firms	858			4,488			

Panel B: Customer characteristics

	Customers in sample			All credit card holders			
	Mean	SD	Median	Mean	SD	Median	Difference in means
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FICO score	722	82	733	711	81	723	11.09***
Credit utilization	0.30	0.31	0.17	0.34	0.43	0.20	-0.04***
Number of individuals	60,950			129,277			

Panel C: Correlation matrix

variables	sales	net income	total credit card spending	AdjSpend	SUE	SU_Sale
	(1)	(2)	(3)	(4)	(5)	(6)
Sales	1.00					
Net income	0.81***	1.00				
Total credit card spending	0.52***	0.35***	1.00			
AdjSpend	0.03	0.02	0.06**	1.00		
SUE	-0.01	-0.004	0.001	-0.04	1.00	
SU_Sale	0.04	0.03	0.02	0.02	-0.10***	1.00

Note. This table provides summary statistics of firm characteristics, consumer demographics, and correlation matrix between selected variables. Panel A reports firm characteristics for firms in our main sample, and all firms within the calendar quarter 2003Q2 to 2003Q3. All firm characteristics are measured quarterly and reported at the firm level. Panel B reports the financial characteristics of firms' customers in our final sample, and all credit card holders within our sample period (i.e., 1st March 2003 to 31st October 2003). All customer characteristics are measured monthly, and reported at the individual level. Panel C reports the correlation matrix between selected variables. For detailed variable definitions and constructions, please see Appendix A in the Internet Appendix. Differences in means of each variable are reported in column (7) of Panel A and Panel B. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table 2. Information in Disaggregated Sales

Panel A: Relation between firm sales, net income, and total credit card spending

	Sales ($thousand)		Net income ($thousand)	
	(1)	(2)	(3)	(4)
Total credit card spending	22.791***	25.096***	1.135***	1.239***
	(23.69)	(4.98)	(14.43)	(3.57)
Constant	531,432***	506,914***	31,911***	31,081***
	(4.21)	(5.28)	(3.09)	(4.13)
Industry FE	N	Y	N	Y
Year-quarter FE	Y	Y	Y	Y
Observations	1,510	1,510	1,510	1,510
R-squared	0.27	0.45	0.12	0.27

Panel B: Effect of adjusted spending on post-announcement *CAR*

	CAR[+2,+61]	
	(1)	(2)
Q_AdjSpend		1.490***
		(3.72)
QSUE	2.343***	2.465***
	(4.68)	(4.80)
QSU_Sale		-0.320
		(-0.79)
Log (size)	-1.151**	-1.640***
	(-2.59)	(-3.64)
B/M	-0.043	-0.067
	(-0.77)	(-1.23)
Log (number of analyst +1)	0.417	0.230
	(0.40)	(0.21)
Reporting lag	-0.068	-0.072
	(-1.36)	(-1.48)
Constant	4.421	3.772
	(1.62)	(1.30)
Industry FE	Y	Y
Year-quarter FE	Y	Y
Observations	1,472	1,472
R-squared	0.12	0.13

Note. This table investigates the information in disaggregated sales. Columns (1) and (2) of Panel A present the correlation between the firm's quarterly net income (in thousands of US dollars) and total credit card spending (in US dollar). Columns (3) and (4) present the correlation between the firms' quarterly sales (in thousands of US dollars) and total credit card spending. Industry fixed effect is included, and standard errors are clustered at the two-digit industry level in columns (2) and (4). Year-quarter fixed effect is controlled in all columns. Panel B shows the effect of adjusted spending on the 60-day post-announcement *CAR* (*CAR[+2,+61]*). Column (1) presents the response of *CAR[+2,+61]* to *Standardized Unexpected Earnings* quintile. Column (2) reports the effect of *Adjusted Spending* quintile on *CAR[+2,+61]*, controlling for earnings surprise and sales surprise quintiles (*QSUE* and *QSU_Sale*). Quintile ranking of *AdjSpend*, *SUE*, and *SU_Sale* are all based on independent sorts in each calendar quarter. For detailed variable definitions and constructions, please see Appendix A in the Internet Appendix. All *CAR*s are measured in percentage. Industry and year-quarter fixed effects are included, and standard errors are clustered at the two-digit industry level. t-statistics are reported in parentheses. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table 3. Consumer-oriented vs. Non-consumer-oriented Firms

Panel A: Consumer-oriented vs. non-consumer-oriented industries

	CAR[+2,+61]	
	Consumer-oriented firms (1)	Non-consumer-oriented firms (2)
Q_AdjSpend	2.173***	0.826
	(3.65)	(1.66)
QSUE	2.308***	2.839***
	(4.91)	(3.20)
QSU_Sale	-0.287	-0.633
	(-0.69)	(-0.93)
Firm characteristics controls	Y	Y
Industry FE	Y	Y
Year-quarter FE	Y	Y
Observations	752	720
R-squared	0.11	0.16

Panel B: Within consumer-oriented industries: by distribution of sales

	CAR[+2,+61]	
	Firms relying less on direct sales (1)	Firms relying more on direct sales (2)
Q_AdjSpend	2.018***	-1.218
	(3.03)	(-0.23)
QSUE	2.088***	4.499
	(4.66)	(0.84)
QSU_Sale	-0.501	2.379
	(-1.03)	(0.39)
Firm characteristics controls	Y	Y
Industry FE	Y	Y
Year-quarter FE	Y	Y
Observations	696	56
R-squared	0.12	0.30

Note. This table presents the informativeness of the adjusted spending across firms. Firms from Transportation & Public Utilities division (2-digit SIC: 40-49), Retail Trade division (two-digit SIC: 52-59), and Service division (two-digit SIC: 70-89) are defined as consumer-oriented firms; and firms from the rest sectors are defined as non-consumer-oriented firms. Panel A reports the average effect in consumer-oriented firms (column (1)) and non-consumer-oriented firms (columns (2)) respectively. Panel B reports the average effect from firms relying less on direct sales (column (1)) and more on direct sales (column (2)) among the consumer-oriented firms, respectively. We classify a firm as relying more on direct sales if its customer sales during the whole sample period mainly come from Wellness or Cosmetics & Personal care category. For detailed variable definitions and constructions, please see Appendix A in the Internet Appendix; for detailed firm classifications, please see Appendix B in the Internet Appendix. Industry and year-quarter fixed effects are included. All *CAR*s are measured in percentage. Coefficients for other control variables and constant term are omitted. Standard errors are clustered at the two-digit industry level. t-statistics are reported in parentheses. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table 4. Heterogeneity by Customer Characteristics

Panel A: By customer spending capacity

	CAR[+2,+61]	
	FICO score	Credit utilization
	(1)	(2)
Q_AdjSpend_high spending capacity	2.619***	1.538**
	(3.99)	(2.05)
Q_AdjSpend_low spending capacity	-0.502	0.471
	(-0.63)	(0.52)
Surprise controls	Y	Y
Firm characteristics controls	Y	Y
Industry FE	Y	Y
Year-quarter FE	Y	Y
Observations	1,392	1,438
R-squared	0.12	0.12

Panel B: By customer loyalty

	CAR[+2,+61]	
	Repeat customers	Loyal customers
	(1)	(2)
Q_AdjSpend_high loyalty	1.485***	1.989**
	(3.31)	(2.57)
Q_AdjSpend_low loyalty	0.565	-0.231
	(0.74)	(-0.21)
Surprise controls	Y	Y
Firm characteristics controls	Y	Y
Industry FE	Y	Y
Year-quarter FE	Y	Y
Observations	1,439	1,439
R-squared	0.12	0.12

Note. This table presents the return predictability of the adjusted spending from firm-quarter's customer groups with different characteristics. Panel A reports the effect of adjusted spending from customers with high and low spending capacity separately. We define high spending capacity customers as individuals with quarter-beginning *FICO score* no lower than 740 (column (1)) or quarter-beginning *credit utilization* no higher than 30 percent (column (2)). *Q_AdjSpend_high spending capacity* is the quintile of adjusted spending from high spending capacity customers. *Q_AdjSpend_low spending capacity* is the quintile of adjusted spending from low spending capacity customers. Panel B reports the effect of adjusted spending from customers with high and low loyalty separately. We define high loyalty customers as *repeat customers* (column (1)) or *loyal customers* (column (2)). *Q_AdjSpend_high loyalty* is the quintile of adjusted spending from high loyalty customers. *Q_AdjSpend_low loyalty* is the quintile of adjusted spending from low loyalty customers. For detailed variable definitions and constructions, please see Appendix A in the Internet Appendix. All *CAR*s are measured in percentage. Coefficients for other control variables and constant term are omitted. Industry and year-quarter fixed effects are included. Standard errors are clustered at the two-digit industry level. t-statistics are reported in parentheses. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table 5. Predictive Power along the Production Chain

Panel A: Customer → supplier

	One-month supplier firm's *CAR* following customer firm's earnings announcement		
	All customer firms	Consumer-oriented customer firms	Non-consumer-oriented customer firms
	(1)	(2)	(3)
Q_AdjSpend_customer	0.426	0.721*	-1.723
	(1.02)	(1.91)	(-0.91)
Customer Industry FE	Y	Y	Y
Year-quarter FE	Y	Y	Y
Observations	1,019	654	365
R-squared	0.06	0.04	0.09

Panel B: Supplier → customer

	One-month customer firm's *CAR* following supplier firm's earnings announcement		
	All supplier firms	Consumer-oriented supplier firms	Non-consumer-oriented supplier firms
	(1)	(2)	(3)
Q_AdjSpend_supplier	-0.205	0.290	-0.361
	(-0.52)	(0.28)	(-0.90)
Supplier Industry FE	Y	Y	Y
Year-quarter FE	Y	Y	Y
Observations	426	123	303
R-squared	0.08	0.02	0.10

Note. This table presents the return predictability of the adjusted spending along the production chain. In Panel A, we test the predictive power of customer firms' adjusted spending quintile on their supplier firms' *CAR* in the subsequent month following the customer firms' earnings announcement. Column (1) reports the average effect for all customer firms in the sample. Column (2) reports the effect of adjusted spending from consumer-oriented customer firms. Column (3) reports the effect of adjusted spending from non-consumer-oriented customer firms.. In Panel B, we test the predictive power of supplier firms' adjusted spending quintile on their customer firms' *CAR* in the subsequent month following the supplier firms' earnings announcement. Column (1) reports the average effect for all supplier firms in the sample. Column (2) reports the effect of adjusted spending from consumer-oriented supplier firms. Column (3) reports the effect of adjusted spending from non-consumer-oriented supplier firms. All *CAR*s are measured in percentage. For detailed variable definitions and constructions, please see Appendix A in the Internet Appendix. Year-quarter fixed effects are included. Panel A controls for customer firm industry fixed effect, and cluster standard errors at the customer firm level. Panel B controls for supplier firm industry fixed effect, and cluster standard errors at the supplier firm level. t-statistics are reported in parentheses. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

INTERNET APPENDIX
for

Disaggregated Sales and Stock Returns

Appendix A: Variable Definitions and Constructions

1. Cumulative Abnormal Returns:

CAR[+2,+61] is the percentage buy-and-hold cumulative abnormal return over 60 trading days after the quarterly earnings announcement. It is constructed based on the six size×B/M Fama-French portfolio benchmark. Specifically, we define the buy-and-hold *CAR* following Hirshleifer, Lim, and Teoh (2009).

$$CAR[+2,+61]_{in} = \prod_{j=t+2}^{t+61}\left(1+R_{ij}\right) - \prod_{j=t+2}^{t+61}\left(1+R_{pj}\right)$$

Where *t* is the earnings announcement date of firm *i* in fiscal quarter *n*; R_{ij} is the return of firm *i* on day *j* relative to the announcement day, and R_{pj} is the return of the matching size×B/M portfolio on day *j*. We use the nearest subsequent trading day if the earnings announcement date is a non-trading day. We accumulate the abnormal return till one day before the next earnings announcement date, if the number of trading days between two consecutive earnings announcements is less than 60 days. We require the number of days between two earnings announcement dates to be longer than 30 days but shorter than 365 days, and the number of days during reporting lag (the time after fiscal quarter end date but before earnings announcement day) to be longer than 0 day but shorter than 365 days.

Each stock is matched with one of the six size×B/M portfolios formed at the end of June each year. The *size* and *B/M* ratio for each stock used to match with the Fama-French portfolio are constructed in the same way as the Fama-French portfolio breakpoints. Specifically, *market equity* (or *size*) for a stock used to match with Fama-French portfolio in year *y* is the share price (CRSP variable *prc*) times shares outstanding (CRSP variable *shrout*) in the end of June of year *y*. The *book-to-market* ratio for a stock used to match with the Fama-French portfolio in June of year *y* is the *book equity* for the last fiscal year-end in *y-1*, divided by the *market equity* at the end of December of *y-1*. *Book equity* is the book value of stockholders' equity, plus balance sheet deferred taxes and investment tax credit (if available), minus the book value of preferred stock. Depending on availability, the redemption, liquidation, or par value (in that order) is used to estimate the book value of preferred stock. All definitions follow Kenneth French's website. The breakpoints of the six size×B/M portfolios, and the daily benchmark returns of the six portfolios are also obtained from Professor Kenneth French's data library.

2. Adjusted Spending, Earnings Surprise, and Sales Surprise:

Adjusted Spending (*AdjSpend****)*** is a firm-quarter's industry-adjusted customer credit card spending. Specifically,

$$AdjSpend_{ikn} = \frac{Spending_{ikn} - Industry\ average\ spending_{ikn}}{Sale_{ikn}+1}$$

Where $Spending_{ikn}$ is the aggregated credit card spending in dollar for firm *i* from industry *k* within fiscal quarter *n*; and $Industry\ average\ spending_{ikn}$ is the average credit card spending for all firms in industry *k* during the same period. Industry is defined based on the two-digit SIC code. $Sale_{ikn}$ is the total sales in millions of dollars for firm *i* from industry *k* within the fiscal quarter *n*. We scale by ($Sale_{ikn}+1$) to account for zero sales cases.

Quintile of Adjusted Spending (*Q_AdjSpend****)*** is the quintile of *AdjSpend* sorted by every calendar quarter. *Q_AdjSpend* ranges from the bottom adjusted spending quintile (*Q_AdjSpend*=1) to the top adjusted spending quintile (*Q_AdjSpend*=5).

When we test the heterogeneity by customer spending capacity and customer loyalty (Table 4), we decompose the total credit card spending into spending from customer groups split by customer characteristics, and construct adjusted spending for different customer groups separately. For example,

$$AdjSpend\_high\ spending\ capacity_{ikn} = \frac{Spending\ from\ high\ capacity\ customers_{ikn} - Industry\ average\ spending_{ikn}}{Sale_{ikn}+1}$$

Standardized Unexpected Earnings (SUE) is the standardized earnings surprise based on a rolling seasonal random walk (SRW) model following Livnat and Mendenhall (2006). Specifically,

$$SUE_{in} = \frac{EPS_{in} - EPS_{in-4}}{P_{in}}$$

Where EPS_{in} is the primary Earnings Per Share before extraordinary items for firm *i* in fiscal quarter *n*, and P_{in} is the price per share for firm *i* at the end of quarter *n*. EPS_{in} and P_{in} are unadjusted for stock splits, but EPS_{in-4} is adjusted for any stock splits and stock dividends during the period {n−4, n}. If most analyst forecasts of *EPS* for a firm-quarter are based on diluted *EPS*, we use COMPUSTAT's diluted *EPS* figures; otherwise we use basic primary *EPS*.

Quintile of Standardized Unexpected Earning (QSUE) is the quintile of *SUE* sorted by every calendar quarter. *QSUE* ranges from the bottom unexpected earnings quintile (*QSUE*=1) to the top unexpected earnings quintile (*QSUE*=5).

Standardized Unexpected Sales (SU_Sale) is the standardized sales surprise based on a rolling seasonal random walk (SRW) model. Specifically,

$$SU\_Sale_{in} = \frac{Sale\ per\ share_{in} - Sale\ per\ share_{in-4}}{P_{in}}$$

Where $Sale\ per\ share_{in}$ is sales per share for firm *i* in fiscal quarter *n*, and P_{in} is the price per share for firm *i* at the end of quarter *n*. Sales per share is calculated by dividing quarterly sales by the number of common shares used to calculate *EPS*. If most analyst forecasts of *EPS* for a firm-quarter are based on diluted *EPS*, we divide the sales by the number of common shares used to calculate diluted *EPS*; otherwise we use the number of common shares used to calculate primary *EPS*.

Quintile of Standardized Unexpected Sales (QSU_Sale) is the quintile of *SU_Sale* sorted by every calendar quarter. *QSU_Sale* ranges from the bottom unexpected sales quintile (*QSU_Sale*=1) to the top unexpected sales quintile (*QSU_Sale*=5).

3. Customer Characteristics:

Total credit card spending is the amount of total credit card spending within a fiscal quarter aggregated from credit card transactions, measured in US dollars. We only include firm-quarters that the whole fiscal-quarters are within our sample period (i.e., 1st March 2003 to 31st October 2003).

FICO score is the customer's FICO score, which measures his or her credit quality. Individuals with no lower than 740 quarter-beginning *FICO score* are defined as ***high FICO*** (hence *high spending capacity*) customers.

Credit utilization is the fraction of the total credit card balance out of the same-month credit limit. For individual *l* in month *t*, $credit\ utilization_{lt} = \frac{total\ credit\ card\ balance_{lt}}{credit\ limit_{lt}}$. Individuals with quarter-beginning *credit utilization* no higher than 30 percent are defined as ***low credit utilization*** (hence *high spending capacity*) customers.

Repeat customer is the individual who has ever purchased more than once from the same firm.

Loyal customer is the customer who intends to adhere to one or a few merchants to purchase a given category of goods. First, we exploit the goods type information from the Merchant Category Code in the credit card transaction record and divide the goods into nine categories: travel, transportation, supermarket, entertainment, apparel, dining, durable, service, and others. Second, for individual *l*, we calculate the *loyalty ratio* for goods category *c* = total number of category *c* goods purchases / total number of merchants that category *c* goods are purchased from during the whole sample period. We define a customer *l* as a loyal customer for a goods category *c* if the $loyalty\ ratio_{lc}$ is no lower than the median *loyalty ratio* for goods category *c*. Then for each merchant, if it sells goods from more than one category, we identify its major type of goods sold as the category with the largest fraction of purchase counts during the whole sample period. For a firm (mostly) selling goods category *c*, its loyal customers are the loyal customers for goods category *c*.

4. Firm Characteristics:

Sales is the total quarterly sales in millions of US dollars (COMPUSTAT variable *saleq*).

Net income is the total net income in millions of US dollars (COMPUSTAT variable *niq*).

Stock price is the quarterly close price, measured in US dollars (CRSP variable *prc*).

Market capitalization for a fiscal quarter is defined as the product of the share price (CRSP variable *prc*) and the total number of shares outstanding (CRSP variable *shrout*) reported in millions in fiscal quarter-end month. ***Log(size)*** is the log of market capitalization (in millions).

Book equity for a fiscal quarter is a firm's book value of equity constructed from COMPUSTAT data. It is the book value of stockholders' equity, plus balance sheet deferred taxes and investment tax credit (if available), minus the book value of preferred stock. Depending on availability, we use the redemption, liquidation, or par value (in that order) to estimate the book value of preferred stock. ***B/M*** for a fiscal quarter is the book-to-market ratio, calculated as book equity for the fiscal quarter end, divided by market equity at fiscal quarter-end month.

Number of analysts is the number of (active) analysts that have made forecasts within 90 days of the earnings announcement date. Firm-quarters with no analyst forecast during this period are assigned with 0 for this variable. ***Log(number of analyst + 1)*** is the log of the number of analysts that have made forecasts within 90 days before the quarterly earnings announcement date.

Reporting lag is the number of days between the fiscal-quarter end date and the earnings announcement date.

Consumer-oriented firms are firms from Transportation & Public Utilities division (two-digit SIC: 40-49), Retail Trade division (two-digit SIC: 52-59), or Service division (two-digit SIC: 70-89). The rest firms are classified as ***non-consumer-oriented firms***. Please see Appendix B for the detailed classification.

Firms relying more on direct sales are the firms with more than half of the disaggregated sales during our sample period is classified as Wellness or Cosmetics & Personal care-related spending (identified by the Merchant Category Code in the credit card transaction record). The rest firms are classified as ***firms relying less on direct sales***. Please see Appendix B for the detailed classification.

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Appendix B: Firm Classifications

We classify firms from Transportation & Public Utilities division (two-digit SIC: 40-49), Retail Trade division (two-digit SIC: 52-59), and Service division (two-digit SIC: 70-89) as consumer-oriented firms, and the rest firms as non-consumer-oriented firms. The division classification is from McKimmon Center of NCSU.

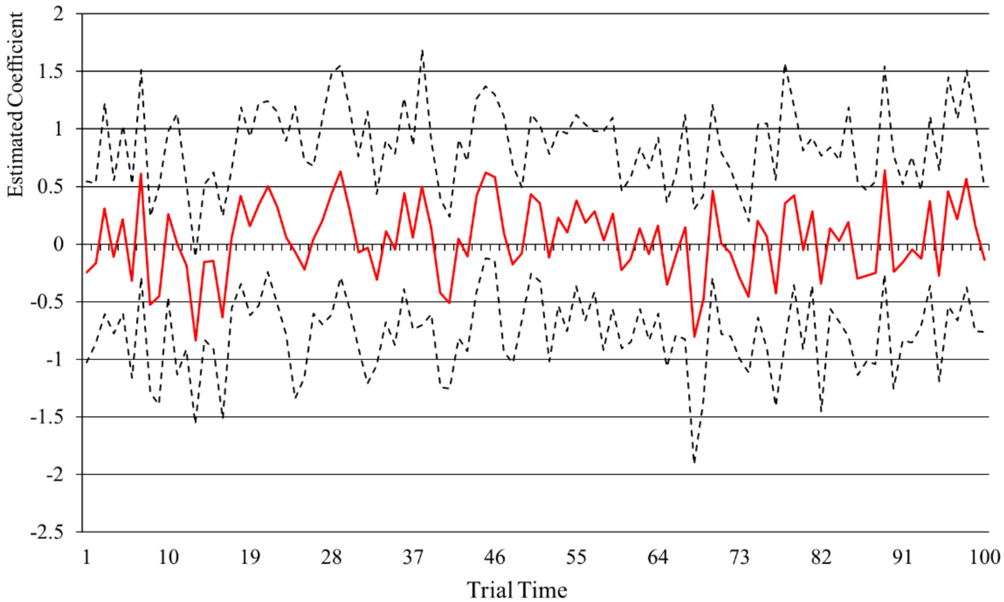
We define the firms' reliance on direct sales based on the type of goods or services they mainly sell. According to the report on the retail industry from WFDSA (2019), over 60 percent of direct sales come from two product categories: Wellness (33.2%) and Cosmetics & Personal care (31.2%). Therefore, we define a firm as relying more on direct sales if more than half of its disaggregated sales during our sample period is classified as Wellness or Cosmetics & Personal care-related spending (identified by the Merchant Category Code in the credit card transaction record); and the rest firms are classified as relying less on direct sales.

2-digit SIC code	Industry	Division	No. of firms in division	Fraction of firms with high reliance on direct sales (%)
Consumer-oriented				
40	Railroad Transportation	Transportation & Public Utilities	87	5
42	Trucking & Warehousing			
44	Water Transportation			
45	Transportation by Air			
46	Pipelines, Except Natural Gas			
47	Transportation Services			
48	Communications			
49	Electric, Gas, & Sanitary Services			
52	Building Materials & Gardening Supplies	Retail Trade	173	8
53	General Merchandise Stores			
54	Food Stores			
55	Automotive Dealers & Service Stations			
56	Apparel & Accessory Stores			
57	Furniture & Home furnishings Stores			
58	Eating & Drinking Places			
59	Miscellaneous Retail			
70	Hotels & Other Lodging Places	Services	172	8
72	Personal Services			
73	Business Services			
75	Auto Repair, Services, & Parking			
78	Motion Pictures			

79	Amusement & Recreation Services			
80	Health Services			
82	Educational Services			
83	Social Services			
87	Engineering & Management Services			
89	Services, Not Elsewhere Classified			
Sub total			432	7
Non-consumer-oriented				
01	Agricultural Production - Crops	Agriculture, Forestry, & Fishing	2	0
10	Metal, Mining	Mining	21	0
12	Coal Mining			
13	Oil & Gas Extraction			
14	Nonmetallic Minerals, Except Fuels			
15	General Building Contractors	Construction	12	0
16	Heavy Construction, Except Building			
17	Special Trade Contractors			
20	Food & Kindred Products	Manufacturing	276	6
22	Textile Mill Products			
23	Apparel & Other Textile Products			
24	Lumber & Wood Products			
25	Furniture & Fixtures			
26	Paper & Allied Products			
27	Printing & Publishing			
28	Chemical & Allied Products			
29	Petroleum & Coal Products			
30	Rubber & Miscellaneous Plastics Products			
31	Leather & Leather Products			
32	Stone, Clay, & Glass Products			
33	Primary Metal Industries			
34	Fabricated Metal Products			
35	Industrial Machinery & Equipment			
36	Electronic & Other Electric Equipment			

37	Transportation Equipment			
38	Instruments & Related Products			
39	Miscellaneous Manufacturing Industries			
50	Wholesale Trade - Durable Goods	Wholesale Trade	34	0
51	Wholesale Trade - Nondurable Goods			
60	Depository Institutions	Finance, Insurance, & Real Estate	80	4
61	Nondepository Institutions			
62	Security & Commodity Brokers			
63	Insurance Carriers			
64	Insurance Agents, Brokers, & Service			
65	Real Estate			
67	Holding & Other Investment Offices			
95	Environmental Quality & Housing	Public Administration	1	0
Sub total			426	5
Total			858	6

Figure IA1. Random Match between Adjusted Spending and Firm-quarters



Note. This figure plots the coefficients and 95% confidence intervals for *Q_AdjSpend* from the main regression, when the *Q_AdjSpend* is randomly assigned to an arbitrary firm-quarter in the sample. The random match is replicated for 100 times. The horizontal axis is the time of the random match, and the vertical axis is the magnitude of the regression coefficient for *Q_AdjSpend*. For detailed variable definitions and constructions, please see Appendix A in the Internet Appendix.

Table IA1. Aggregated Sales and Credit Card Spending within Industry

Panel A. Distribution of the difference: sales fraction – spending fraction within industry

Mean	Std. dev.	25 percentile	Median	75 percentile
(1)	(2)	(3)	(4)	(5)
0.000	0.147	-0.026	-0.003	0.012

Panel B. Exclude firm-quarters with |sales fraction – spending fraction|>10%

	CAR[+2,+61]
	(1)
Q_AdjSpend	1.778***
	(3.94)
QSUE	2.648***
	(4.65)
QSU_Sale	-0.128
	(-0.32)
Firm characteristics controls	Y
Industry FE	Y
Year-quarter FE	Y
Observations	1,184
R-squared	0.14

Note. This table investigates the difference between firm-quarters' sales fraction and customer spending faction within industry in our sample. S*ales fraction* is the firm-quarter's reported sales scaled by total reported sales from all same-industry firms in the same calendar quarter in our sample. S*pending fraction* is the firm-quarter's customer credit card spending scaled by total customer credit card spending from all same-industry firms in the same calendar quarter in our sample. In Panel A, we report the distribution of the difference between *sales fraction* and *spending fraction*. In Panel B, we estimate our main result after excluding firm-quarters with over 10 percent of difference in *sales fraction* and *spending fraction*. All *CAR*s are measured in percentage. Coefficients for other control variables and constant term are omitted. For detailed variable definitions and constructions, please see Appendix A in the Internet Appendix. Industry and year-quarter fixed effects are included. Standard errors are clustered at the two-digit industry level. t-statistics are reported in parentheses. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table IA2. Heterogeneous Effect by Fraction of Sales to Consumers

	CAR[+2,+61]	
	High fraction of sales to consumers	Low fraction of sales to consumers
	(1)	(2)
Q_AdjSpend	1.739***	0.737
	(3.80)	(0.93)
QSUE	2.866***	1.861**
	(4.44)	(2.61)
QSU_Sale	-0.772	0.284
	(-1.60)	(0.45)
Firm characteristics controls	Y	Y
Industry FE	Y	Y
Year-quarter FE	Y	Y
Observations	888	584
R-squared	0.15	0.12

Note. This table presents the heterogeneous effect under an alternative classification criterion for consumer-oriented firms. We report the average effect in consumer-oriented firms (column (1)) and non-consumer-oriented firms (columns (2)) under the alternative definition respectively. Specifically, we compute the fraction of credit card sales out of the reported sales for each firm quarter. Firms in industries with median fraction of sales to consumers higher than the 50th percentile among all industries in the sample are classified as consumer-oriented firms, and firms in the rest industries as non-consumer-oriented firms. For other detailed variable definitions and constructions, please see Appendix A in the Internet Appendix. Industry and year-quarter fixed effects are included. All *CAR*s are measured in percentage. Coefficients for other control variables and constant term are omitted. Standard errors are clustered at the two-digit industry level. t-statistics are reported in parentheses. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table IA3. Do Customer Spending Capacity Measures Predict Future Purchases?

	Repeat customer (dummy)		Repeat purchase amount ($)	
	FICO score	Credit utilization	FICO score	Credit utilization
	(1)	(2)	(3)	(4)
High spending capacity	0.046***	0.019***	25.527***	6.159**
	(22.33)	(8.86)	(7.17)	(2.47)
Firm FE	Y	Y	Y	Y
Observations	331,241	340,930	141,176	144,337
R-squared	0.09	0.09	0.17	0.17

Note. This table investigates the relation between customer spending capacity proxies and repeat purchase behaviors. Each customer in the sample is classified as with *high spending capacity* or *low spending capacity* according to the spending capacity characteristics (sample-beginning *FICO score* and *credit utilization*). *Repeat customer* for a firm is the individual who has purchased more than once from this firm. *Repeat purchase amount* for a firm is the total dollar amount for the repurchase transactions at the firm from each *repeat customer*. Columns (1)-(2) report the extensive margin effect; and columns (3)-(4) report the intensive margin effect. *High spending capacity* is a dummy equal to 1 for customers with high spending capacity. For detailed variable definitions and constructions, please see Appendix A in the Internet Appendix. Firm fixed effect is included, and standard errors are clustered at the firm level. Coefficients for the constant term are omitted. t-statistics are reported in parentheses. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table IA4. Heterogeneity by Customer Spending Capacity (Alternative Measures)

	CAR[+2,+61]	
	Behavior score	Delinquency
	(1)	(2)
Q_AdjSpend_high spending capacity	1.509**	1.483***
	(2.11)	(3.48)
Q_AdjSpend_low spending capacity	0.747	0.376
	(0.86)	(0.37)
Surprise controls	Y	Y
Firm characteristics controls	Y	Y
Industry FE	Y	Y
Year-quarter FE	Y	Y
Observations	1,438	1,439
R-squared	0.12	0.12

Note. This table presents the return predictability of the adjusted spending from the firm's customer groups with high and low spending capacity separately, under two alternative measures of consumer credit and liquidity status. We define high-spending-capacity customers as individuals with top tercile quarter-beginning *internal behavior score* (column (1)), or the individual who has never been delinquent during the whole sample period (column (2)). *Internal behavior score* is an internal-generated credit quality score for a credit card holder; a higher *internal behavior score* indicates better credit quality. Total credit card spending in each firm-quarter is decomposed into the amount from high spending capacity customers and low spending capacity customers respectively. *Q_AdjSpend_high spending capacity* is the quintile of adjusted spending from high spending capacity customers. *Q_AdjSpend_low spending capacity* is the quintile of adjusted spending from low spending capacity customers. All *CAR*s are measured in percentage. Coefficients for other control variables and constant term are omitted. For detailed variable definitions and constructions, please see Appendix A in the Internet Appendix. Industry and year-quarter fixed effects are included. Standard errors are clustered at the two-digit industry level. t-statistics are reported in parentheses. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table IA5. Heterogeneity by Customer Base

Panel A. Customer age diversity

	CAR[+2,+61]	
	High age diversity	Low age diversity
	(1)	(2)
Q_AdjSpend	2.324***	0.794
	(2.91)	(0.98)
QSUE	2.228***	2.526***
	(3.18)	(3.16)
QSU_Sale	-0.866	0.033
	(-1.55)	(0.05)
Firm characteristics controls	Y	Y
Industry FE	Y	Y
Year-quarter FE	Y	Y
Observations	717	714
R-squared	0.17	0.17

Panel B. Customer regional diversity

	CAR[+2,+61]	
	High regional diversity	Low regional diversity
	(1)	(2)
Q_AdjSpend	2.370***	0.819
	(3.25)	(1.22)
QSUE	1.858***	3.026***
	(3.13)	(3.94)
QSU_Sale	-0.710	-0.079
	(-1.25)	(-0.13)
Firm characteristics controls	Y	Y
Industry FE	Y	Y
Year-quarter FE	Y	Y
Observations	716	716
R-squared	0.17	0.17

Panel C. Rural-urban diversity

	CAR[+2,+61]	
	High rural-urban diversity	Low rural-urban diversity
	(1)	(2)
Q_AdjSpend	2.329***	0.668
	(3.09)	(0.69)
QSUE	1.547**	3.183***
	(2.20)	(4.01)
QSU_Sale	-0.364	-0.222
	(-0.75)	(-0.33)
Firm characteristics controls	Y	Y
Industry FE	Y	Y
Year-quarter FE	Y	Y
Observations	714	712
R-squared	0.15	0.18

Note. This table presents the heterogeneous return predictability of the adjusted spending by the firm's customer base diversity. Panel A investigates the heterogeneity by the firm's customer age diversity. Firm-quarters with lower-than-median *HHI age* from three age groups (i.e., young (age<30), middle-age (30≤age<60), and old (age≥60)) are defined as diversified. Column (1) reports the regression results for firm-quarters with consumption from diversified customer age groups; and column (2) reports the regression results for firm-quarters with consumption from concentrated customer age groups. Panel B reports the heterogeneity by customer regional diversity. Firm-quarters with lower-than-median *HHI region* from five regional groups (i.e., Midwest, Northeast, West, South, and other) are defined as diversified. Column (1) reports the regression results for firm-quarters with regionally diversified consumption; and column (2) reports the regression results for firm-quarters with regionally concentrated consumption. Panel C reports the heterogeneity by customer rural-urban diversity. Firm-quarters with lower-than-median *HHI rural-urban* from rural and urban customers are defined as diversified. Column (1) reports the regression results for firm-quarters with diversified rural-urban consumption; and column (2) reports the regression results for firm-quarters with concentrated rural-urban consumption. Quintile ranking of *AdjSpend*, *SUE*, and *SU_Sale* are all based on independent sorts in each calendar quarter. All *CAR*s are measured in percentage. Coefficients for other control variables and constant term are omitted. For detailed variable definitions and constructions, please see Appendix A in the Internet Appendix. Industry and year-quarter fixed effects are included. Standard errors are clustered at the two-digit industry level. t-statistics are reported in parentheses. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table IA6. Predicting Future Earnings and Sales Surprises

	QSUE in quarter		*QSU_Sale* in quarter	
	n+1	*n*+4	*n*+1	*n*+4
	(1)	(2)	(3)	(4)
Q_AdjSpend	0.026	0.085**	0.058**	0.067**
	(0.82)	(2.34)	(2.11)	(2.17)
QSUE	0.328***	-0.158***	-0.044*	-0.043
	(9.60)	(-3.62)	(-1.91)	(-1.45)
QSU_Sale	0.025	0.003	0.617***	0.024
	(1.08)	(0.08)	(22.62)	(0.56)
Firm characteristics controls	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	1,482	1,404	1,482	1,404
R-squared	0.24	0.14	0.45	0.16

Note. This table presents the predictability of the firm's adjusted spending on its future earnings and sales surprises. We construct earnings surprise (sales surprise) in future quarters as the change of *EPS* (*Sales per share*) scaled by price in quarter *n* to avoid the contamination of changing price caused by adjusted spending. For example, the *SUE* in quarter *n*+1 is $SUE_{\mathrm{in}+1} = \frac{EPS_{\mathrm{in}+1} - EPS_{\mathrm{in}-3}}{P_{\mathrm{in}}}$. Columns (1)–(2) report the predictive power of adjusted spending quintiles in quarter *n* for earnings surprise quintiles in quarter *n+1* and *n+4* respectively. Columns (3)-(4) report the predictive power of adjusted spending quintiles in quarter *n* for sales surprise quintiles in quarter *n+1* and *n+4* respectively. *Q_AdjSpend* is quintiles of adjusted spending. *QSUE* is quintile of earnings surprise. *QSU_Sale* is quintile of sales surprise. Quintile ranking of *AdjSpend*, *SUE*, and *SU_Sale* are all based on independent sorts in each calendar quarter. All *CAR*s are measured in percentage. Coefficients for other control variables and constant term are omitted. For detailed variable definitions and constructions, please see Appendix A in the Internet Appendix. Industry and year-quarter fixed effects are included. Standard errors are clustered at the two-digit industry level. t-statistics are reported in parentheses. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table IA7. Alternative Explanations

	CAR[+2,+61]		
	Earnings quality (1)	Institutional ownership (2)	Investor distraction (3)
Q_AdjSpend	1.309***	1.615***	1.490***
	(3.04)	(4.06)	(3.71)
QSUE	2.567***	2.418***	2.462***
	(4.96)	(4.78)	(4.73)
QSU_Sale	-0.339	-0.322	-0.316
	(-0.84)	(-0.78)	(-0.77)
Earnings persistence	-2.963***		
	(-2.83)		
Earnings volatility	-0.000***		
	(-11.35)		
Institutional ownership		-3.839**	
		(2.08)	
Number of concurrent EA			-0.001
			(-0.15)
Firm characteristics controls	Y	Y	Y
Industry FE	Y	Y	Y
Year-quarter FE	Y	Y	Y
Observations	1,415	1,465	1,472
R-squared	0.14	0.13	0.13

Note. This table presents the test results for alternative explanations by controlling for three factors associated with the *Post-Earnings-Announcement-Drift*: earnings quality, institutional ownership, and investor distraction. Column (1) adds two earnings properties—*earnings persistence* and *earnings volatility*—as additional controls. *Earnings persistence* is the coefficient estimation of quarterly *EPS* regressed on the *EPS* in the same quarter last year (using the past four years of data to run the regression). *Earnings volatility* is the standard deviation during the preceding four years for the deviations of quarterly earnings from one-year-ago earnings. Column (2) adds firm-quarter's percentage of institutional ownership (*institutional ownership*) by the ending month of each fiscal quarter as additional control. Column (3) adds the number of concurrent earnings announcements on the same date (*number of concurrent EA*) for a firm-quarter as an additional control. Quintile ranking of *AdjSpend*, *SUE*, and *SU_Sale* are all based on independent sorts in each calendar quarter. All *CAR*s are measured in percentage. Coefficients for other control variables and constant term are omitted. For detailed variable definitions and constructions, please see Appendix A in the Internet Appendix. Industry and year-quarter fixed effects are included. Standard errors are clustered at the two-digit industry level. t-statistics are reported in parentheses. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table IA8. Post-announcement Return Predictability of Earnings Surprise

Panel A. Firms in sample vs. firms not in sample, 1980-2003

	All firms (1)	Firms in sample (2)	Firms not in sample (3)	Difference (2)-(3) (4)
↑ in *CAR[+2,+61]* when 1 inter-quintile ↑ in *SUE*	1.3%	1.4%	1.3%	0.1%

Panel B. Sample period (2003 Q2-Q3) vs. other period, 1980-2003

↑in *CAR[+2,+61]* when 1 inter-quintile ↑ in *SUE*		All firms (1)	Firms in sample (2)	Firms not in sample (3)	Difference (2)-(3) (4)
(a)	During 2003Q2-Q3	2.3%	2.7%	2.2%	0.5%
(b)	During other time in 1980-2003	1.2%	1.3%	1.2%	0.1%
Difference (a)-(b)		1.1%***	1.4%**	1.0%***	0.4%

Note. This table presents the return predictability of the earnings surprise during the 60-day post-announcement period. In Panel A, we extend the time period to all quarters in 1980-2003, and check the return predictability of *SUE* for firms in sample and firms not in sample separately. In Panel B, we further divide the time period into sample period (2003 Q2-Q3) and other period, and check the return predictability of *SUE* for firms in sample and firms not in the sample during the two periods separately. Column (1) reports the effects for all firms together; columns (2) and (3) report the effects for firms in sample and not in sample respectively; and column (4) report the difference in effects between firms in sample and firms not in the sample. *QSUE* is quintile of earnings surprise (*QSUE*=1: bad earnings news, *QSUE*=5: good earnings news). Quintile ranking of *SUE* is based on independent sorts in each calendar quarter. For detailed variable definitions and constructions, please see Appendix A in the Internet Appendix. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table IA9. Robustness Tests

Panel A. Alternative definitions of sales surprise, earnings surprise, and adjusted spending

	CAR[+2,+61]			
	Industry-adjusted sales and earnings	Change in sales and earnings proportion in industry	Analyst forecast based *SUE*	Asset-scaled adjusted spending
	(1)	(2)	(3)	(4)
Q_AdjSpend	1.253***	1.345***	2.373***	
	(2.99)	(3.27)	(4.16)	
Q_AdjSpend_asset				1.656***
				(4.74)
Q_AdjEarning	0.707			
	(1.27)			
Q_ChgEarningProp		-0.033		
		(-0.05)		
QSUE_af			0.266	
			(0.53)	
QSUE				2.469***
				(4.78)
Q_AdjSale	0.322			
	(0.31)			
Q_ChgSaleProp		0.281		
		(0.70)		
QSU_Sale			-0.199	-0.267
			(-0.34)	(-0.65)
Firm characteristics controls	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	1,472	1,472	959	1,472
R-squared	0.11	0.11	0.16	0.13

Panel B. Alternative benchmarks for *CAR*s

	CAR[+2,+61]		
	25 size × B/M Fama-French portfolio return	Value-weighted market return	125 size × B/M × Momentum DGTW portfolio return
	(1)	(2)	(3)
Q_AdjSpend	1.407***	1.572***	0.871**
	(3.56)	(3.93)	(2.57)
QSUE	2.336***	2.367***	2.653***
	(4.34)	(4.57)	(4.97)
QSU_Sale	-0.205	-0.350	-0.016
	(-0.50)	(-0.85)	(-0.04)
Firm characteristics controls	Y	Y	Y
Industry FE	Y	Y	Y
Year-quarter FE	Y	Y	Y
Observations	1,471	1,486	1,306
R-squared	0.11	0.16	0.13

Panel C. Alternative industry classifications

	CAR[+2,+61]	
	Fama-French 48 industry (2)	3-digit NAICS industry
	(1)	(2)
Q_AdjSpend	1.483***	1.538***
	(2.90)	(3.57)
QSUE	2.392***	2.291***
	(6.00)	(3.43)
QSU_Sale	-0.268	-0.287
	(-0.69)	(-0.62)
Firm characteristics controls	Y	Y
Industry FE	Y	Y
Year-quarter FE	Y	Y
Observations	1,461	1,457
R-squared	0.12	0.13

Note. This table presents three sets of robustness tests. In panel A, we consider alternative specifications regarding sales surprise, earnings surprise, and adjusted spending. In column (1), we replace quintile of sales (earnings) surprise with quintile of industry-adjusted sales (earnings): *Q_AdjSale* (*Q_AdjEarning*), where $AdjSale_{ikn} = \frac{Sale_{ikn} - Industry\ average\ sale_{ikn}}{Sale_{ikn}+1}$, and $AdjEarning_{ikn} = \frac{NI_{ikn} - Industry\ average\ NI_{ikn}}{NI_{ikn}+1}$. In column (2), we replace quintile of sales (earnings) surprise with quintile of change in sales (earnings) as a fraction of the industry's total sales (earnings) from the same quarter of last year: *Q_ChgSaleProp* (*Q_ChgEarningProp*), where $ChgSaleProp_{ikn} = \frac{Sales_{ikn}}{Industry\ total\ sales_{kn}} - \frac{Sales_{ikn-4}}{Industry\ total\ sales_{kn-4}}$, and $ChgEarningProp_{ikn} = \frac{NI_{ikn}}{Industry\ total\ NI_{kn}} - \frac{NI_{ikn-4}}{Industry\ total\ NI_{kn-4}}$. In column (3), we replace *QSUE* with analyst forecast based earnings surprise: *QSUE_af*, where $SUE\_af_{in} = \frac{EPS_{in} - EPS\_AF_{in}}{P_{in}}$, and EPS_AF_{in} is the median of analysts' most recent earnings forecasts reported to I/B/E/S in the 90 days before the earnings announcement day. In column (4), we define the adjusted customer spending as $AdjSpend\_asset_{ikn} = \frac{Spending_{ikn} - Industry\ average\ spending_{ikn}}{Total\ asset_{ikn}}$, and investigate the effect of *Q_AdjSpend_asset*. In Panel B, we replicate the main results in Table 2 using three alternative benchmark portfolio returns to calculate *CAR*. Columns (1)-(3) use the benchmark returns as 25 size×B/M Fama-French portfolio returns, value-weighted market returns, and 125 size×B/M×Momentum DGTW portfolio returns respectively (Daniel, Grinblatt, Titman, and Wermers, 1997; Wermers, 2004). In Panel C, we replicate the main results in Table 2 using two alternative industry classifications: Fama-French 48 industry (column (1)) and 3-digit NAICS industry (column (2)). Industry and year-quarter fixed effects are included. Coefficients for other control variables and constant term are omitted. Standard errors are clustered at the two-digit industry level. t-statistics are reported in parentheses. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table IA10. Bootstrap Standard Error Estimation

	CAR[+2,+61]
	(1)
Q_AdjSpend	1.490***
	(3.73)
QSUE	2.465***
	(4.80)
QSU_Sale	-0.320
	(-0.78)
Firm characteristics controls	Y
Industry FE	Y
Year-quarter FE	Y
Observations	1,472
R-squared	0.13

Note. This table presents the effect of adjusted spending on subsequent *CAR* when standard errors for regression are estimated by bootstrapping for 500 times. Quintile ranking of *AdjSpend*, *SUE*, and *SU_Sale* are all based on independent sorts in each calendar quarter. For detailed variable definitions and constructions, please see Appendix A in the Internet Appendix. All *CAR*s are measured in percentage. Coefficients for other control variables and constant term are omitted. Industry and year-quarter fixed effects are included, and standard errors are generated by bootstrap. t-statistics are reported in parentheses. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

Table IA11. Account for Industry-level Variations

Panel A. Exclude industries with less than N firms

	CAR[+2,+61]			
	N=3	N=5	N=10	N=20
	(1)	(2)	(3)	(4)
Q_AdjSpend	1.522***	1.464***	1.681***	1.575***
	(3.77)	(3.67)	(4.72)	(4.08)
QSUE	2.470***	2.534***	2.535***	2.361***
	(4.81)	(4.87)	(4.80)	(3.99)
QSU_Sale	-0.305	-0.245	-0.260	-0.623
	(-0.75)	(-0.61)	(-0.66)	(-1.62)
Firm characteristics controls	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	1,453	1,402	1,196	887
R-squared	0.12	0.12	0.12	0.11

Panel B: Control for firm size within industry

	CAR[+2,+61]	
	(1)	(2)
Q_AdjSpend	1.488***	
	(3.74)	
Q_ResSpend		1.291***
		(3.78)
QSUE	2.466***	2.414***
	(4.83)	(4.65)
QSU_Sale	-0.320	-0.283
	(-0.79)	(-0.70)
IndRank_size	0.005	
	(0.06)	
Firm characteristics controls	Y	Y
Industry FE	Y	Y
Year-quarter FE	Y	Y
Observations	1,472	1,472
R-squared	0.13	0.13

Panel C. Control for industry average *CAR*[+2,+61]

	CAR[+2,+61]
	(1)
Q_AdjSpend	1.460***
	(3.67)
QSUE	2.490***
	(4.90)
QSU_Sale	-0.248
	(-0.59)
Industry Average CAR[+2,+61]	0.927***
	(6.55)
Firm characteristics controls	Y
Industry FE	Y
Year-quarter FE	Y
Observations	1,472
R-squared	0.16

Note. This table presents the effect of adjusted spending on post-announcement *CAR* after accounting for industry-level variations. Panel A excludes industries with less than X firms, with X being 3, 5, 10 or 20 in columns (1)-(4). Panel B controls for within-industry size difference of firms. Column (1) additionally controls for the rank of quarter-end firm size within the industry (*IndRank_size*) for each quarter in the regression. Column (2) replaces the quintile of *adjusted spending* with the quintile of a *residualized spending* measure orthogonal to the firm size. Specifically, we regress the deviation of customer spending from industry mean (i.e., the numerator for *AdjSpend* measure) on the quarter-end *size* for each firm-quarter and take the regression residual as *residualized spending.* Panel C includes the industry average *CAR* during the [+2,+61] trading day period after each firm-quarter's earnings announcement in the regression. Quintile ranking of *AdjSpend*, *residualized spending*, *SUE*, and *SU_Sale* are all based on independent sorts in each calendar quarter. For detailed variable definitions and constructions, please see Appendix A in the Internet Appendix. All *CAR*s are measured in percentage. Coefficients for other control variables and constant term are omitted. Industry and year-quarter fixed effects are included, and standard errors are clustered at the two-digit industry level. t-statistics are reported in parentheses. *** indicates significant at 1 percent, ** indicates significant at 5 percent, and * indicates significant at 10 percent respectively.

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