Extracting Consumer Demand: Credit Card Spending and Post-Earnings Returns*

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Abstract

Using proprietary individual transaction-level data from a large financial institution, this paper examines the information content of consumer (credit card) spending in explaining stock returns. After controlling for the quarterly earnings and sales surprises, we find a positive relation between the spending surprise on a firm's product during a fiscal quarter and the subsequent cumulative abnormal returns. One inter-quintile increase in the spending surprise leads to one percentage point increase in the 60-day post-earnings-announcement *CAR.* The predictive power is concentrated in firms with more sales from high-spending-capacity consumers, firms with a more diversified consumer base, and firms in consumer-oriented industries. Moreover, crecit card spending surprise predicts future earnings and sales surprises over the next four quarters. Further analysis suggests that our results are unlikely driven by information during the reporting lag period or other known factors that predict post-earnings returns. Our findings suggest that the disaggregated consumer spending provides a more accurate and persistent signal of consumer demand that is relevant to a firm's growth potential and stock pricing.

Keywords: return predictability, earnings announcement, consumer demand, credit cards, consumption

JEL Classification: D12, G14, H31

1. Introduction

Customers are 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 argument implies that observing purchases from end customers allows one to gauge a firm's consumer demand in a way potentially beyond what can be learned from the firm's financials. For example, consumer spending patterns could inform the level of current consumer demand as well as the persistence of consumer interest, both of which are relevant for projecting a firm's future cash flows. Despite its intuitive appeal, little research has been devoted to the information content of consumer demand in predicting stock returns.

One key challenge is to identify reliable measures of consumer demand. A few recent studies approach the question by using indirect indicators of consumer interest. For example, Huang (2016) uses customer ratings from Amazon.com as a proxy for perceived product quality, and finds the abnormal customer ratings positively predict the firm's revenue and subsequent abnormal returns. While focusing on a different question, Froot et al. (2016) also use consumer search patterns for retailers to deduce their spending inclination, which carry information about the firm's future sales growth and earnings surprises.

In this paper, we study whether consumer spending bears return predictability implications. Instead of inferring from consumer opinions or coarse indicators of consumer activity, we directly measure consumer demand by confirmed purchases from end customers. Specifically, we exploit a unique panel dataset of account-level credit card transactions in 2003 obtained from a large U.S. bank, and construct a spending surprise measure to capture consumer demand. In addition to the spending amount and merchant information, we also observe a rich array of consumer financial and demographic characteristics such as consumer credit score, age, and residence location, which facilitates our investigation into the source and mechanism of return predictability.

We propose two novel economic reasons why consumer spending contains value-relevant information that is incremental to publicly released accounting information. First, the earnings or sales reported by the firm may not accurately reflect actual purchases from end consumers, given that products go through various distribution layers before they reach the final clients. Products stored in retailers' warehouses, stuck in traffic, and sold to end customers are all recorded as sales on the firm's book, but they do not convey the same information about consumer demand. To better illustrate, we refer to the following example. By the end of February 2013, Leap Wireless International Inc., a prepaid carrier contracted to purchase iPhone from Apple, warned its investors that consumer demand for iPhones fell significantly short of its pre-committed level, leading to an expected loss (*The Wall Street Journal*, 27th Feb., 2013).[2] In this instance, the recorded revenue on Apple's book, which includes the committed iPhone purchase from Leap, fails to reflect the weak sales at Leap and thus exaggerates the true consumer interest.

Second, quantity of sales is not the only metric that matters. Buyer characteristics and composition offer another important signal to gauge the sustainability of consumer interest. The firm featuring a buyer group with greater purchase capacity presumably will remain competitive in the product market by attracting the same clientele in the future. Similarly, firms that tend to draw consumers from a wide range of demographics or geographic locations possess a stable consumer base, reflecting strong and sustainable consumer interest in the firm's product. Therefore, these firms will observe a more persistent revenue growth relative to the ones whose current buyer profile suggests weaker purchase capacity or arises from a concentrated clientele, even if they have the same level of current sales. The aggregate sales from the firm's financial report contain no information on their customer clientele, which is another source of incremental value provided by our micro-level spending dataset with consumer characteristics information.

Exploiting a novel dataset of a representative sample for more than 56,000 U.S. consumers from a large U.S. financial institution, we identify individual credit card spending in 812 US public firms during an eight-month period from 1st March to 31st October of 2003. Given the relatively short time series of our data, our empirical analysis rests on exploiting the consumer spending variation in the cross section.[3] For each fiscal quarter of a firm, we aggregate all credit card spending from its end customers, and construct a spending surprise measure as the deviation of a firm-quarter's total customer credit card spending from the industry average spending, scaled by the industry mean spending. We investigate the predictability of the consumer credit

[2] News source: http://www.wsj.com/articles/SB10001424127887323293704578330850401133588

[3] While our data only capture consumer 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 consumer spending, does not require a complete account of all spending by consumers. To the extent that the choice of consumer-spending instrument is plausibly exogenous to a firm's performance (i.e., consumers 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 consumer spending on a firm's products.

card spending surprise on a firm's cumulative abnormal stock returns around and after its earnings announcement. Quarterly earnings announcement is one of the most significant corporate information events when investors are presented with the firm's disclosure of its operating performance. Consequently, it serves as a natural setting for us to study the (incremental) value of direct consumer spending by controlling for the earnings and sales information released by the firm.

Credit cards play an important role in the study of consumer-spending behaviour since they represent the leading source of unsecured consumer credit in the US (Gross and Souleles, 2002; Japelli, Pischke and Souleles, 1998). From the 2004 Survey of Consumer Finances (SCF), more than 70 percent of households have at least one credit card. The median balance for those carrying a credit card balance was $2,200, and the mean was $5,100, which are large magnitudes relative to typical household balance sheets in 2004. As one of the largest consumer credit markets, US total revolving credit balances have exceed $925 billion, and the spending via general purpose credit card characterized 15 percent of the GDP in 2014.

We first show that the aggregated credit card spending during a given fiscal quarter strongly correlates with a firm's cash flows (sales and net income) for the same period, which provides a validation of our spending measure. More important, we find a significantly positive relation between the credit card spending surprise within a fiscal quarter and the firm's 60-day post-announcement cumulative abnormal return (*CAR*), after controlling for earnings and sales surprises. Consistent with prior studies on post-earnings-announcement returns (e.g., Livnat and Mendenhall, 2006), one inter-quintile increase in *QSUE* (Quintile of Standardized Unexpected Earnings) predicts 2.260 percentage points increase in the 60-day post-earnings announcement period. Turning to our main variable of interest, one inter-quintile increase in *QSUS* (Quintile of Standardized Unexpected Spending) is associated with 0.998 percentage point increase in 60-day post-announcement *CAR* (*CAR[+2,+61]*). This effect is statistically significant at one percent level and economically large. The magnitude is almost half the size of the post-earnings-announcement drift. Alternatively, it is equivalent to about 6.1 percent of the standard deviation of *CAR[+2,+61]*.

The evidence above confirms that spending by end customers provides incremental information about consumer demand than the aggregate sales or earnings reported by the firm. Next we utilize the consumer characteristics information to investigate the source of the return predictability. A firm with more revenue from high-spending-capacity consumers, or with a more diversified consumer base is associated with a sustainable consumer demand, leading to a higher return predictability from its spending surprise. Consumer credit quality, captured by *FICO score* or bank's *internal behavior score*, measures consumers' credit worthiness which to a large extent reflects their capacity to consume. Therefore, we define high spending capacity consumers as those with above-median *FICO score* or *internal behavior score* at the beginning of a quarter. Consistent with our hypothesis, we find that the return predictability is concentrated among firms with higher revenue proportions from high-spending-capacity consumers. To capture consumer base diversity, we construct HHI indexes regarding the distribution of the clientele in age or geographical region. Take the age distribution as an example. We first classify consumers as young, middle-aged, or old by their age; then for each firm-quarter, we calculate the credit card spending percentage from the three age groups respectively, and construct the *HHI age* as the sum of squared spending percentage from the three age groups. We then partition our sample by the median of HHI indexes in each quarter, and discover more significant post-earnings return predictability among firms with more diversified consumer bases (by age or geography).

The claim that direct consumer purchase conveys novel information has two further implications. First, the return predictability of spending surprise should be driven by consumer-oriented firms, whose end customer purchases are more closely linked with their cash flows. We define firms from Transportation & Public Utilities division, Retail Trade division, or Service division as consumer-oriented firms by their two-digit SIC code, and find a stronger effect of their spending surprise. Second, if the consumer spending is a more accurate and persistent indicator of a firm's growth potential, then we should expect the spending surprise to be predictive of the firm's future earnings and sales surprises. Consistent with this prediction, we document that our spending surprise measure predicts the firm's earnings and sales surprises in subsequent (four) quarters, after controlling for the contemporaneous earnings and sales surprises.

We consider several alternative explanations for our findings. One possible interpretation is that the direct consumer purchase within a fiscal quarter informs the firm's sales during the reporting lag (i.e., the time period after fiscal quarter end yet before earnings announcement date). According to this explanation, the true source of return predictability from the spending surprise within a fiscal quarter *t* may be attributable to its high correlation with the sales during the reporting lag, which is not yet covered in the firm's quarter *t* earnings announcement but will show up as part of the sales in a firm's earnings announcement in quarter $t+1$. To test this possibility, we use the total credit card spending during the reporting lag period for each firm-quarter to proxy for the reporting-lag sales. We do find an insignificant positive relation between spending surprise during the reporting lag period and the post-announcement *CAR*. Nevertheless, when we add the spending surprise within the fiscal quarter (i.e., our main explanatory variable) into the regression, the predictability of the spending surprise during the reporting lag period diminishes, while the coefficient associated with the within-quarter spending surprise remains significant with comparable magnitude as the main result.

We further investigate whether the return predictability documented in our paper is attributable to other confounding factors that explain post-earnings-announcement returns. Specifically, we consider three such factors, including earnings quality (e.g., Francis et al., 2007; Dechow, Ge, and Schrand, 2010; Hung, Li, and Wang, 2014), investor sophistication (Bartov, Radhakrishnan, and Krinsky, 2000), and investor inattention (Francis, Pagach, and Stephan, 1992; DellaVigna, and Pollet, 2009; Hirshleifer, Lim, and Teoh, 2009). We show that the return predictability of the spending surprise persists after controlling for earnings persistence and volatility, percentage of institutional ownership, or the number of concurrent earnings announcements.

To ensure the robustness of our results, we adopt alternative definitions of spending surprise, sales surprise, or earnings surprise and continue to find robust results. In addition, we employ altenrative benchmark return portfolios to calculate the buy-and-hold *CAR*s. The return predictability of spending surprise remains robust to various alternative *CAR* benchmarks.

This study is the first paper that links consumer spending to stock returns by exploiting granular consumer credit card transaction information. The unique transaction-level credit card spending dataset enables us to directly measure demand of end consumers and observe the firm's clientele composition, with which we trace out the sources and mechanisms of the return predictability. Our results are economically meaningful; we document substantial return and revenue predictability from the consumer spending surprise, after controlling for the firm's reported sales and earnings information.

We contribute to the stream of literature about the influence of consumer information on stock pricing. Huang (2016) posits that customer review serves as a direct measure of customer perceived product quality and predicts subsequent stock returns. Froot et al. (2016) use consumer search patterns on mobile devices to infer consumer purchase activity for 50 US retailers. Such consumer activity measure predicts the firms' future sales growth and earnings surprises. Ljungqvist and Qian (2016) document that short sellers use information about consumer demand to detect stock overvaluation. Several marketing and accounting studies also document that consumer satisfaction proves relevant for firm performance such as positively predicting stock returns (Fornell, et al., 2006; Aksoy, et al., 2008) and improving analyst recommendation (Luo, Homburg, and Wieseke, 2010). Compared to the previous studies, the use of micro-level credit card spending data allows for a more direct and accurate measure of consumer demand. Moreover, our results complement the previous studies by tracing out a novel economic mechanism underlying the return predictability of consumer demand information. We show that consumer spending is a more persistent signal of future firm performance than the accounting information reported by firms.

This paper is also broadly related to studies on determinants of stock return predictability in the cross section. In particular, there is a large literature on the slow diffusion of information following publicly announced earnings-related events, such as analysts' earnings forecasts (e.g., Elgers, Lo, and Pfeiffer, 2001) and earnings announcements (e.g., Bernard and Thomas, 1989, 1990). Extensive research documents investor's limited attention as a source of delayed reaction to information (e.g., DellaVigna, and Pollet, 2009; Hirshleifer, Lim, and Teoh, 2009). Cohen and Lou (2012) present evidence that complicated information processing for conglomerate firms slows down their price adjustment speed. While previous studies focus on the frictions in the information revelation, our results point to the role of consumer demand information in explaining the return predictability. We demonstrate that consumer spending, including the quantity of end customer purchase as well as consumer characteristics and composition, is pertinent to a firm's fundamentals. Such information is not easily observable by most market participants and will be revealed gradually over time.

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

2. Data and Methodology

We employ multiple datasets to construct our main sample. Specifically, we exploit a large, representative panel dataset of credit card transactions from a US bank to identify consumer spending for a given firm and the associated customer information. We also combine datasets from Compustat, CRSP, I/B/E/S, Thomson Reuters, Fama-French online data library, and DGTW online data library to obtain firm-level information.

2.1.Raw Data

2.1.1. Credit Card Spending Data

We utilize a proprietary dataset obtained from one of the leading banks issuing credit cards nationally in the United States to extract customer spending information. This bank has more than 5,000 banking centers across the nation, with more than 16,000 ATMs as well as call centers, online and mobile banking platforms as of 2013, and it attracts more than 20 percent of the US deposit. The entire dataset contains consumer financial transactions from 1st March to 31st October of 2003, including more than 120,000 accounts, which is a random, representative sample of the bank's customers. Similar to Agarwal, Liu, and Souleles (2007), the main unit of analysis is a credit card account, not an individual (who can hold multiple accounts); or in other words, we treat each account as an "individual consumer".[4] Throughout the paper, we will use "individual," "consumer," "customer," and "account" interchangeably.

This dataset provides disaggregated transaction-level information about the individual's credit card spending, including the transaction amount, transaction date, and merchant name. Merchant name is the key identifier we utilize to match customers with the corresponding public firms. Additionally, we observe monthly financial information regarding consumer credit (*FICO score* and *internal behavior score*), and a rich set of demographic information including age and property address (five-digit zip code, and state of residence). Such consumer characteristics serve as helpful tools in exploring the source of extra information from customer spending. [5]

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[4] There are three reasons for us to do account-level analysis. First, we want to use the credit card spending on firm products, and the credit card transactions happen at the account level. For example, an individual with two credit cards may use different cards to buy different firm products. Second, different credit card accounts of one individual may have different interest rates, credit lines, even different FICO scores and internal behavior scores, suggesting the bank treats different accounts differently. Third, we have some cases that only the account identifier is available but the individual identifier is missing. Therefore, to serve our research purpose, and also consider the data availability, we use credit card account as main unit of analysis from the consumer side, or in other words, we treat each credit card account as a different individual. In fact, most individuals in our credit card data only hold one account. There are only 2,573 accounts facing the situation that one individual holds more than one of the accounts, or missing individual identifier, which is a very small portion of the whole dataset (around 1.99 percent), and will not significantly affect any of our results.

[5] *Internal behavior score* is an internally generated score by the bank for each credit card holder; a higher behavior score means better behavior from credit card issuer's perspective.

Credit cards play an important role in consumer finances, facilitating studies of consumer-spending behavior (Gross and Souleles, 2002). 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, Pischke and Souleles, 1998). From the 2004 Survey of Consumer Finances (SCF), more than 70 percent of US households have at least one credit card. The median balance for those carrying a credit card balance was $2,200, and the mean was $5,100, which are large in magnitude relative to typical household balance sheets in 2004. From the 2015 CFPB (Consumer Financial Protection Bureau) report on consumer credit card market, about 63 percent of adult Americans have an open credit card (especially those with high *FICO scores*).[6] Around 50 percent of bank card holders still concentrate at least 90 percent of their total general purpose balances on a single card, which validates our account-level analysis.

As one of the largest consumer credit markets, US' total revolving credit balance has exceeded $925 billion, and the spending via general purpose credit card took up 15 percent of the GDP in 2014. Total consumer credit from credit card plans amounted to over $13 trillion in 2010, and over $11 trillion in 2014 (G.19 release from Federal Reserve Board of Governors). In this paper, we investigate the return predictability from a firm's consumer information; hence, we view credit card spending as an important source to extract the customer demand for a firm's products.

The credit card spending dataset offers several advantages compared to previous studies that rely on indirect proxies such as consumer opinion (Huang, 2016), consumer search pattern (Froot et al., 2016), or customer satisfaction index (e.g., Fornell, et al., 2006; Aksoy, et al., 2008). First, indirect proxies of consumer demand are invariably noisier and can even be biased. For example, self-reported opinions could give rise to selection bias (certain types of consumers are more likely self-report their opinions), response bias (the self-reported opinions could be inaccurate or untruthful), or opinion herding (consumers herd other's opinions when making comments while ignoring their own private signals (Bikhchandani, Hirshleifer, and Welch, 1992)). Since the spending transactions truthfully record the purchase behavior of credit card holders, biases stemming from self-reported data are less relevant. Second, in addition to the quantity of spending, the consumer composites offer equally informative implication for the sustainability of a firm's consumer demand. While such information is not available in customer reviews or

[6] http://files.consumerfinance.gov/f/201512_cfpb_report-the-consumer-credit-card-market.pdf

customer satisfaction survey, we are able to investigate them through consumer financial and demographic characteristics.

To establish the link between the consumers and public firms, we use the merchant names reported in credit card transaction record to identify the probable firms that a consumer has spent money with. Since we intend to identify "real" spending on firm products, we exclude obviously bank-admin related transactions such as late payment fee, cash advance fee, over limit fee, and financial charges. With this restriction, the remaining number of consumers is 129,277.

2.1.2. Firm-level Data

To fully capture the consumer spending, we restrict our study to firm-quarters with the whole fiscal quarters falling within the eight-month period (i.e., 1st March to 31st October in 2003). We obtain firm-quarter level information from CRSP, Compustat, and I/B/E/S. We use the quarterly earnings announcement date provided in Compustat. If the announcement date for a firm-quarter is not available in Compustat, we adopt the I/B/E/S date (conditional on availability). Since I/B/E/S tends to cover relatively large firms (Hong, Lim, and Stein, 2000), we use actual earnings per share from Compustat in our analysis.[7] Other firm characteristics including quarterly sales, net income, total asset, book value of equity, and the number of concurrent earnings announcements are obtained or constructed from Compustat. The number of analysts following is calculated based on I/B/E/S analyst forecasts data. Full company name, daily stock returns, price, the number of shares outstanding, and industry classification (four-digit SIC code) are obtained from CRSP. We calculate the percentage of institutional ownership from Thomson Reuters 13F.

The benchmark used to calculate abnormal returns in the main analysis is the Fama-French 6 Size×B/M portfolio returns. We also alternate to the 25 Size×B/M Fama-French portfolio returns, value-weighted market returns, or the 125 Size×B/M×Momentum DGTW portfolio returns (Daniel et al., 1997) as benchmarks for robustness checks. Daily portfolio returns and breakpoints for size and B/M ratio are obtained from Professor Kenneth French's data library, value-weighted market returns are drawn from CRSP, and the DGTW portfolio assignment as

[7] Only 64 percent firm-quarters in our final merged sample have active analyst forecasts within 90 days before earnings announcement date from I/B/E/S.

well as daily portfolio returns are obtained from Daniel, Grinblatt, Titman, and Wermers' website.[8]

2.2. Merged Final Sample and Summary Statistics

A key step for our sample construction is to match the public firms with the spending information of their customers. Since there is no unique identifier that directly connects the credit card spending data and the other datasets, we follow three steps below to establish the link between firms and consumers.

We start with the list of full company names from CRSP (as in 2003), which contains 6,940 firms.[9] In the first step, we extract all merchant names provided in the credit card transaction record, and match the 325,334 merchant names with the list of 6,940 firm names by their word similarity.[10] 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 three restrictions to reduce mismatching: (1) drop the merchants whose matching score is lower than 0.9; (2) drop the merchants whose credit card spending is less than $100 spending per month (i.e., with less than $800 total spending); (3) only keep those with matching scores no-lower than the fifth highest score among all the matched merchants for the this firm. After this step, we are left with 2,445 merchants (1,415 firms).

Next, we require the firms to have all relevant firm-level variables available, and only include the firm-quarters when the firm's whole fiscal quarter is within the eight-month sample period. We then aggregate all credit card spending for a firm within each fiscal quarter. For firm-

[8] http://alex2.umd.edu/wermers/ftpsite/Dgtw/coverpage.htm

[9] Firms may change names over time, therefore we drop firm names whose use ended before 2003, and started being used after 2003.

[10] This is an imperfect string match that does not require two names to be exactly the same. We use a user-written command "reclink" in STATA. This command can match between two string variables, and give a score ranging from 0 to 1 for the matching. A score of 1 means exactly match, and pairs of matching score lower than 0.6 are automatically dropped.

quarters with no credit card spending, we assign a spending amount of 0.[11] We end up with 1,421 firm-quarters (from 812 firms) in the final merged sample.

To the extent that customer spending provides additional information relevant to a firm's profitability and growth potential beyond the publicly available information, we hypothesize the unexpected part of the consumer spending, i.e., spending surprise, to be predictive of a firm's subsequent cumulative abnormal return (*CAR*). To adjust the different spending levels across products/firms, we construct our main measure of a firm's spending surprise during a fiscal quarter—*Standardized Unexpected Spending* (*SUS*)—as the deviation of total credit card spending from industry average spending, scaled by the industry mean spending:

$$SUS_{iknq} = \frac{Spending_{iknq} - Industry\ average\ spending_{kq}}{Industry\ average\ spending_{kq} + 1}$$

Where $Spending_{iknq}$ is the total credit card spending for firm *i* from industry *k* in the fiscal quarter *n*, with the fiscal quarter *n*'s ending month in the calendar quarter *q*. $Industry\ average\ spending_{kq}$ is the average credit card spending among all firms in our credit card data in the industry *k* during the calendar quarter *q*. Industry is defined by the two-digit SIC code. We divide by ($Industry\ average\ spending_{kq} + 1$) to account for zero values of the industry average spending. As mentioned in the previous literature (see, e.g., Kothari, 2001; Hirshleifer, Lim, and Teoh, 2009), the relation between the announcement abnormal returns and the earnings surprise is likely nonlinear. To avoid the possible non-linearity effect associated with our spending surprise measure, we sort *SUS* into five quintiles in each calendar quarter, and use the *QSUS* instead of raw *SUS* for our analysis. *QSUS* ranges from one to five from the bottom unexpected spending quintile (*QSUS*=1) to the top unexpected spending quintile (*QSUS*=5).

We focus on the period after the quarterly earnings announcement, which is arguably one of the most important information event concerning a publicly traded firm. More specifically, we investigate the predictability of the (credit card) spending surprise on firm-quarter's *CAR*s around and after the quarterly earnings announcement. Since the announcement period and the post-announcement period are usually separately investigated due to their different information

[11] Since all firms in our final matched sample do have some consumers buying their products at some time during the eight-month period, the zero-spending firm-quarter only happens when a firm has two fiscal quarters within our sample period, and one of the quarters has no credit card spending.

environments, we separately look at the *CAR*s during the three-day announcement period and the 60-day post-announcement period.[12] Following Hirshleifer, Lim, and Teoh (2009), we define *CAR*s as differences between the buy-and-hold returns of the announcing firm and the benchmark return. Returns from the matched Fama-French 6 size and book-to-market (B/M) portfolios are used as the benchmark for our main analysis. We accumulate the abnormal returns over the windows [-1, +1] or [+2, +61] in trading days relative to the announcement date:

$$CAR[-1,+1]_{in} = \prod_{k=t-1}^{t+1} (1 + R_{ik}) - \prod_{k=t-1}^{t+1} \left(1 + R_{pk}\right)$$

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

Where *t* is the earnings announcement date of firm *i* in fiscal quarter *n*; R_{ik} is the return of firm *i* on day *k* relative to earnings announcement day, and R_{pk} is the return of the matching size×B/M portfolio on day *k* 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 two trading days before the next quarter's earnings announcement date (i.e., till day -2 for the fiscal quarter *n+1*).

We require firm-quarters to have non-missing earnings announcement dates for both quarter *n* and quarter *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 firm-quarters to have available data to calculate size and book-to-market ratios.[13]

In the presence of known market reaction to earnings news during both the earnings announcement period (see, e.g., Ball and Brown, 1968) and the post-earnings-announcement

[12] Within a short window (usually 2 or 3 days) around the earnings announcement date, the financial information newly released by the earnings report induces large market reactions. Nevertheless during the post-announcement period, the information released from earnings report is considered stale, and shouldn't be able to predict any market reaction in an efficient market. Therefore studies usually separately investigate the market reaction for earnings announcement period and post-announcement period.

[13] Following the definitions from Professor French's online data library, *size (Market capitalization*) 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. Book-to-market ratio is calculated as: book equity for the fiscal year ending in calendar year *t-1*, divided by market equity at the end of December of *t-1*. *Book equity* 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, the redemption, liquidation, or par value (in that order) are used to estimate the book value of preferred stock.

period (known as Post-Earnings-Announcement-Drift, see, e.g., Bernard and Thomas, 1989), earnings surprise is an important piece of public 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: [14]

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

We also sort *SUEs* into five quintiles and use the *SUE* quintile (i.e., *QSUE*) as our control variable in the analysis. Similarly as before, *QSUE* ranges from one to five from the bottom unexpected earnings quintile (*QSUE*=1) to the top unexpected earnings quintile (*QSUE*=5).

To control for the information already reflected in company sales, 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:

$$SU\_Sale_{in} = \frac{Sale_{in} - Sale_{in-4}}{P_{in}}$$

We then sort *SU_Sale* into five quintiles and use the *QSU_Sale* instead of raw *SU_Sale* for our analysis. *QSU_Sale* ranges from one to five from the bottom unexpected sales quintile (*QSU_Sale*=1) to the top unexpected sales quintile (*QSU_Sale*=5).

Additionally, we control for other firm characteristics that are potentially related with *CARs*: firm size (market capitalization), book-to-market ratio, the number of analysts, and the reporting lag. Details of all variables are listed in Appendix A. Summary statistics for firms in our final merged sample (N=812) and all US firms (N=4,224) from 2003Q2 to 2003Q3 are reported in Panel A of Table 1.[15]

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[14] There is another widely used earnings surprise measure based on analyst forecast, which uses the analyst consensus forecast of *EPS* for the same quarter as the expected earnings. We do not adopt this measure in main analysis because only 64 percent firm-quarters in our sample are covered by analysts during the 90-day period before earnings announcement. We investigate the analyst forecast based *SUE* in the robustness test in Table 8, and our results still hold.

[15] 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 that the fiscal-quarter-end months fall into calendar quarter 2003Q2 and 2003Q3.

[Insert Table 1 about here]

The distribution of the quarterly consumer credit card spending for a given firm is highly skewed, with an average value of $14,406, and a median number of $2,000. The average daily credit card spending during the reporting lag for a firm-quarter is $178.

Compared to the full samle of all US firms, our sample includes firms with larger size, higher sales, net income, stock price, and institutional ownership, better analyst coverage, and less concurrent earnings announcements. These are arguably firms less subject to informational frictions in the capital market, which makes the return predictability documented in our paper likely an underestimate of the true effect. Consistently, we find that the average 60-day post-announcement cumulative abnormal return (*CAR[+2,+61]*) in our sample is about 1.43 percent lower than the full sample mean. On the other hand, the three-day announcement cumulative abnormal return (*CAR[-1,+1]*), earnings surprise (*SUE*), and sales surprise (*SU_Sale*) for both group of firms are not statistically distinguishable from zero.

Panel B of Table 1 provides the summary statistics of the demographic and financial information for customers in our final merged sample (N=56,559), in comparison with all credit card holders (N=129,277) from the bank's raw sample of credit card transactions. Compared to all credit card holders, consumers in our sample are slightly younger and less represented in the rural areas. In addition, they tend to have higher consumer credit (higher *FICO score* and *internal behavior score*) than the credit card holders as a whole. However, the differences are not economically large.

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=0.37) and net income (correlation=0.30). This provides reassuring evidence that consumer spending, as captured in our credit card transactions dataset, captures information about a firm's cashflow.

Turning to our main variable of interest (*SUS*), we find that *SUS* significantly positively correlates with *SUE*, but the magnitude is small (0.09). In addition, the correlation between *SUS* and the sales surprise (*SU_Sale*) is -0.01 and statistically insignificant. Low correlations between the spending surprise and the earnings and sales surprise measures for the same quarter indicate that *SUS* serves more than just re-interpretation of the contemporaneous public information known to predict a firm's subsuequent financial and stock performance.

In summary, our final sample captures around 20 percent of firms in the CRSP-Compustat merged sample and contains around 44 percent credit card holders from the credit card transaction dataset. Compared to the CRSP universe, our sample includes larger and presumably more informationally-efficient firms, which implies that our findings likely provide a lower bound for the true effect. Consumers in our sample are economically not distinguishable from the other credit card holders in the raw data. Additionally, the significantly positive correlation between customer credit card spending and firm cash flows, together with the low correlations between three surprise measures, suggests that the spending surprise provides profit-relevant information independent of those contained in the company earnings or sales news (for the contemporaneous quarter).

2.3.The Empirical Strategy

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

$$CAR_{ikq} = \beta QSUS_{ikq} + \theta QSUE_{ikq} + \varphi QSU\_Sale_{ikq} + \phi X_{ikq} + \delta_k + \upsilon_q + \epsilon_{ikq} \tag{1}$$

The dependent variable CAR_{ikq} represents the three-day buy-and-hold Cumulative Abnormal Return (*CAR[-1,+1]*) or the 60-day post-announcement period (*CAR[+2,+61]*) of firm *i* from industry *k* with fiscal-quarter-end in calendar quarter *q*.[16] $QSUS_{ikq}$, $QSUE_{ikq}$, and QSU_Sale_{ikq} are quintile ranks of spending surprise (*QSUS*=1: bad consumption news; *QSUS*=5: good consumption news), earnings surprise (*QSUE*=1: bad earnings news; *QSUE*=5: good earnings news), and sales surprise (*QSU_Sale*=1: bad sales news; *QSU_Sale*=5: good sales news) for firm *i* from industry *k* whose fiscal-quarter ends in calendar quarter *q*. X_{ikq} is a vector of firm-level

[16] We do the analysis at calendar quarter level instead of fiscal quarter level for two reasons. First, our *SUS* measure is defined on a benchmark calculated at the calendar quarter level (industry average spending of firms with fiscal-quarter-end in the same calendar quarter). Second, for our heterogeneity analysis in next section, we need to partition firms into subsamples according to their firm characteristics or consumer characteristics. Since the same fiscal quarter may mean different calendar time for different firms, it is better to do all analysis at calendar quarter level, so that all firms are compared within similar time ranges.

control variables including firm size (market capitalization), 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_q denotes the year-quarter fixed effects. Details of variable definition and construction are reported in Appendix A.

We are particularly interested in the coefficient for *QSUS* (i.e., β). If disaggregated credit card spending provides additional information on a firm's growth potential, then the spending surprise should have a significant impact on the subsequent *CAR*, after controlling for other value-relevant public information. Specifically, a positive β is expected, meaning that good (positive) spending surprise leads to higher subsequent *CARs*, and that bad (negative) spending surprise leads to lower subsequent *CARs*, beyond the effect of earnings and sales surprises. While the spending surprise may also predict the three-day announcement return (i.e., *CAR[-1,+1]*), we expect the predictability to concentrate in the post-announcement *CAR* for two reasons. First, consumer spending is less salient than information from earnings report during the announcement period. Since investors have limited resources to obtain and process information (e.g., Hirshleifer, Lim, and Teoh, 2009), the effect of consumer information shall be more prounced during the post-announcement period. Second, consumer spending information is not immediately available to (most) investors. Most likely investors gradually obtain such information by observing the subsequent firm performance, paying attention to consumer-relevant information from varying sources, or having private access. These procedures take time, hence the price impact is more likely to manifest during the later time periods (i.e., the post-announcement period).

3. Main Results

*3.1.Consumer Spending and the Subsequent CAR*s

We begin by showing that disaggregated customer spending captures a firm's same-quarter cash flows. Specifically, we check the relation between the reported sales, net income, and consumers' total credit card spending within the same fiscal quarter. In columns 1 and 2 of Panel A, Table 2, we find significant positive correlation between firm sales and total consumer 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]

Before showing the return predictability of the spending surprise measure, we first check the effect of earnings surprise in columns 1 and 2 of Panel B, Table 2. Consistent with previous studies, earnings surprise generates significant predictability for both the announcement abnormal return (*CAR[-1,+1]*), and the post-announcement abnormal return (*CAR[+2,+61]*). Specifically, one inter-quintile increase in the earnings surprise (i.e., *QSUE*) is associated with 2.26 percentage points increase in the 60-day post-announcement *CAR* in our sample.[17]

The main thesis of this paper is that the spending surprise measure constructed from direct customer purchase conveys incremental information relevant to firm's future profitability. To investigate this central claim, we add our main variable of interest—the quintile of spending surprise (*QSUS*) into the regression. Consistent with our prediction, the spending surprise significantly positively predicts the 60-day post-announcement *CAR*, after controlling for earnings and sales surprises. As reported in column 4 of Table 2, one inter-quintile increase in *QSUS* leads to 0.998 percent increase in the 60-day post-announcement *CAR*, which is equivalent to around 6.1 percent of the standard deviation of *CAR[+2,+61]* in our sample, or equivalent to 42.2 percent of the earnings surprise effect.[18] The coefficient for the three-day announcement return is also positive, but is only statistically significant at the 10% level (coefficient=0.268; *p*value=0.060). This is also consistent with our conjecture that the consumer spending information mainly takes effect in the post-announcement period.

QSU_Sale is significantly positively related with the three-day announcement *CAR* (coefficient=0.699; *p*value=0.000) in column 3. However, it is not significantly related with 60-day post-announcement *CAR* (coefficient=-0.474; *p*value=0.278). This result seems to suggest that investors do exploit and respond to publicly available sales information immediately upon

[17] Our estimated predictability effect of the earnings surprise is similar as Livnat and Mendenhall (2006). In Livnat and Mendenhall (2006), the regression coefficient of 0.0521 for *Adjusted DSUE* (Adjusted Decile of *SUE*) in their Table 2 implies one inter-quintile increase in *SUE* predicts 1.12 percent in the post-announcement *CAR*, which is lower than the estimation in our sample. To account for the differences in sample and variable definitions and verify the robustness of our results, we extend the sample to all firm-quarters from 1987-2003 using our methodology. The estimated coefficient under our methodology is 0.056 for *Adjusted DSUE*, which is very close to the Livnat and Mendenhall (2006) estimation, and implies that one inter-quintile increase in *SUE* predicts 1.24 percent in the post-announcement *CAR*.

[18] The standard deviation of *CAR[+2,+61]* in sample is 16.27 percent.

its announcement. Moreover, the coefficient for the earnings surprise remains very similar after including the spending (and sales surprise) in the regression. This again suggests that the three surprise measures capture non-overlapping information.

3.2.Consumer Characteristics Information

Quantity of consumer spending is not the only metric that matters. Consumer characteristics, such as the purchase power of the customers, or the spread of consumer base, serve an equally important role in extracting the sustainability of a firm's customer demand. To shed light on this source of return predictability, we utilize consumers' financial and demographic characteristics observable in our proprietary credit card dataset. If consumer traits are another source of additional information regarding consumer demand sustainability, then the return predictability of spending surprise should be stronger for firms with more sustainable customer demand. The firm featuring a buyer group bringing high or stable cash flows presumably will attract the same clientele in the future, which bodes positively on its subsequent sales and returns.

3.2.1. Consumer Spending Capacity

Intuitively, a firm with more revenue from high-spending-capacity consumers has greater profit-generating potential. Hence we expect the return predictability of our spending surprise measure to concentrate among firms with larger proportion of revenues stemming from high-spending-capacity consumers. According to Agarwal and Qian (2014), individuals with greater access to credit exhibit smoother consumption patterns, especially in credit card spending, suggesting consumption from high-credit consumers to be more sustainable. Therefore, we adopt two measures of consumer credit quality—*FICO score* or *internal behavior score*— as proxies for their spending capacity, and separately check the effect of the spending surprise in two subsamples separated by the revenue proportion from high-spending capacity consumers.

We follow two steps to construct our subsamples. First, for each calendar quarter, we calculate the median *FICO score* or *internal behavior score* at the beginning of the respective fiscal quarter, and define high capacity consumers as individuals with higher-than-median quarter-beginning *FICO score* or *internal behavior score*.[19] In the second step, we calculate the percentage of spending from high-capacity consumers for each firm-quarter. Then we divide the subsamples by the median spending percentage from high-capacity customers, and report the regression results in Table 3. We also report the results for subsamples directly cut by the median number of high-spending-capacity consumers instead of their revenue proportion, and the results are similar to those in Table 3 (please refer to Internet Appendix Table IA1).

[Insert Table 3 about Here]

In Panel A of Table 3, high-capacity consumers are defined based on their quarter-beginning *FICO score*. Consistent with our prediction, spending surprise for firm-quarters with higher revenue proportion from high-FICO consumers exhibits stronger predictive power for post-announcement *CAR* (coefficient=1.540; *p*value=0.012). A similar pattern also shows in predicting the three-day announcement *CAR*: one inter-quintile increase in *QSUS* raises the *CAR[-1,+1]* by 0.634 percent more in high high-FICO spending firms than their low high-FICO spending counterparties. This difference in predictability is statistically significant, with a Chi-test statistic of 3.21 and a *p*value equal to 0.073.

In Panel B of Table 3, the quarter-beginning *internal behavior score* is used as the metric to define high-spending-capacity customers. Following a similar two-step procedure of subsample partition, we find similar results using the *internal behavior score* proxy. The predictability of spending surprise for the 60-day post-announcement *CAR* is statistically more significant for firm-quarters with more spending from high-behavior score consumers (coefficient=1.327; *p*value=0.031). A stronger return predictability of the high behavior-score subsample is also found during the three-day announcement period.

3.2.2. Consumer Base

Another dimension of a firm's consumer demand sustainability is its consumer base. On the one hand, firms with a diversified consumer base can better endure demand shocks, making consumer demand for these firms more sustainable. On the other hand, the consumer composite

[19] The respective fiscal quarter refers to the fiscal quarter with its quarter-end month fall into this calendar quarter. Note that even for the same firm in different fiscal quarters, its consumers could be different. Therefore for each fiscal quarter, we only consider the consumers that have purchased the firm's product within that quarter.

of firms with diversified consumer base is more complicated than their concentrated-consumer-base counterparties; hence the return predictability of the former, if any, may realize in a more gradual manner. We investigate a firm's customer base diversity from three perspectives: age diversity, regional diversity, and rural-urban diversity.

We follow the logic of the Herfindahl–Hirschman Index to construct measures for firm consumers' age and regional diversity. We use the age diversity as an example to illustrate our three-steps method. First, for each firm-quarter, we classify the consumers into three age groups according to the life-cycle pattern in Agarwal et al (2009): young (age <30), middle-age (30≤age<60), and old (age≥60). Then for each firm-quarter, we calculate the percentage of spending from consumers in the three groups, namely *spending percent_young*, *spending percent_middle*, and *spending percent_old* respectively. In the last step, we define the *HHI age* for firm *i* in fiscal quarter *n*, which falls into calendar quarter *q* as:

$$HHI\ age_{inq} = spending\ percent\_young_{inq}^2 + spending\ percent\_middle_{inq}^2 + spending\ percent\_old_{inq}^2$$

Since a higher HHI index represents higher consumer age concentration, we define firm-quarters with $HHI\ age$ lower than the quarter median as having a diversified consumer age structure. Regression results for firms with diversified or concentrated customer age are reported in Panel A of Table 4. As predicted, the spending surprise measure only statistically significantly predicts the 60-day post-announcement *CAR* in the subsample of firm-quarters with diversified consumer age (coefficient=1.843; *p*value=0.001). Additionally, we find the spending surprise is able to weakly predict the three-day announcement *CAR* for firms with concentrated customer age, but not for firms with age-diversified consumers. As we stated above, this could suggest that information (from customers) travels slower within complicated firms (i.e., firms with more diversified customer base).

[Insert Table 4 about Here]

The second dimension we investigate is the regional diversity of customers. We construct the *HHI region* index in a similar way as for age. First, we divide the resident state of consumers into five regions according to the 2000 US census: Midwest, Northeast, West, South, and others.

Then for each firm-quarter, we calculate the percentage of spending from consumers in the five regions, and construct the "Herfindahl–Hirschman Index" of region for firm i in fiscal quarter n, which ends in calendar quarter q as:

$$\begin{aligned} HHI\ region_{inq} &= spending\ percent\_midwest_{inq}^{2} + spending\ percent\_northeast_{inq}^{2} \\ &+ spending\ percent\_west_{inq}^{2} + spending\ percent\_south_{inq}^{2} \\ &+ spending\ percent\_other_{inq}^{2} \end{aligned}$$

In each calendar quarter, each firm's regional consumer bases are divided into diversified and concentrated according to the quarter median of $HHI\ region$, and regression results are reported in Panel B of Table 4. Similar to the age structure results, the spending surprise for firm-quarters with a diversified geographical distribution possesses higher return predictability for *CAR* during the post-announcement period: one quintile increase in *QSUS* leads to 1.917 percent increase in *CAR[+2,+61]* (*p*value=0.002), which is 1.719 percent higher than the effect for firms with regionally concentrated consumer base (Chi-test statistic=4.00; *p*value=0.046). Nevertheless, the predictability for the three-day announcement period is stronger among firms with a concentrated regional customer base.

Last but not least, we investigate the rural-urban diversity of the customer base. We define firm-quarters with higher-than-median rural spending percentage as having a diversified rural-urban consumer distribution. Regression results for subsamples defined along this dimension are reported in Panel C of Table 4. Again, we document that only the spending surprise in high rural demand subsample is statistically significant in predicting the 60-day post-announcement *CAR* (coefficient=1.853; *p*value=0.002). We also divide the subsamples based on the HHI indexes defined on the number of rural consumers (instead of spending percentage). Results are similar as what we found in Table 4, and we report them in Internet Appendix Table IA2.

Taken together, results from Table 3 and Table 4 demonstrate another source of additional information from direct consumer spending: consumer spending capacity and customer base embedded in the direct customer purchase is informative on a firm's (future) profitability. Specifically, our findings suggest that the spending surprise predicts the 60-day post-announcement *CAR* more strongly among firms with a higher revenue proportion from high-spending-capacity consumers (i.e., more spending from consumers with higher *FICO score* or *internal behavior score*), or diversified consumer base (i.e., higher age, regional, or rural-urban diversity in spending).

3.3. Further Implications

3.3.1. Informativeness of Consumer Spending

Though we claim that consumer credit card spending is helpful in extracting a firm's customer demand, its implication is not equally strong among all firms. To be precise, the direct customer purchase should be more informative if it is more closely linked with a firm's cash flow and growth potential. Consumer-oriented firms' revenues heavily depend on their end customers, hence a natural prediction is that the consumer spending surprise should be more informative for consumer-oriented firms, generating a stronger relation between the customer spending surprise and post-announcement *CAR*.

We classify firms in our sample into consumer-oriented and non-consumer-oriented firms according to their two-digit industries. Specifically, we classify industries 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) as consumer-oriented, and the remaining industries as non-consumer-oriented. The division and industry definition is from McKimmon Center of NCSU, and the detailed firm and industry assignment in our sample are reported in Appendix B. [20] According to this classification, around half of the firms in our sample are consumer-oriented. Regression results for consumer-oriented and non-consumer-oriented firms are reported in Table 5.

[Insert Table 5 about Here]

Results are in line with our predictions, that only the consumer spending surprise for consumer-oriented firms exhibits significant return predictability. Specifically, for consumer-oriented firms, one inter-quintile increase in *QSUS* increases *CAR[+2,+61]* by 1.757 percent (*p*value=0.001), which is 1.458 percent higher than their counterparties in the non-consumer-oriented industries (Chi-test statistic=5.60; *p*value=0.018) .

[20] http://mckimmoncenter.ncsu.edu/mckimmon/divisionUnits/ceus/sicCodePickList.jsp

3.3.2. Predictability of Future Earnings and Sales Surprises

One further implication lies in that the information content of the spending surprise measure should manifest itself in the firm's future cash flows. To test this hypothesis, we investigate whether the spending surprise in quarter *t* predicts the earnings or sales surprise in subsequent quarters, controlling for the earnings and sales news in quarter *t*.

In columns 1-2 of of Table 6, we replace the dependent variables with the earnings surprises in the next quarter (i.e., quarter *t+1*) and four quarters ahead (i.e., quarter *t+4*) respectively. Consistent with Bernard and Thomas (1990), we find a positive relation between earnings surprise in quarter *t* and the earnings surprises in the subsequent three quarters, and a negative relation between earnings surprise in quarter *t* and the earnings surprise in quarter *t+4*.[21] More important, after controlling for the effect of earnings surprise and sales surprise in quarter *t*, the spending surprise in quarter *t* still significantly positively predict the future earnings surprises (coefficient=0.052 for quarter *t+1*, and coefficient=0.060 for quarter *t+4*).

[Insert Table 6 about Here]

Similarly, we use the sales surprises in quarter *t+1* and *t+4* as dependent variables, and report the regression results in columns 3-4 of Table 6 respectively. Also consistent with our hypothesis, the consumer spending surprise positively predicts future sales surprise, after controlling for the effect of current sales and earnings news. Our findings in Table 6 are consistent with Huang (2016) in the sense that abnormal customer information captures new information in cash flows. Nevertheless, our tests differentiate from Huang's in that he uses the abnormal customer rating, which is immediately available by the fiscal-quarter end, to predict the earnings and revenue surprises for the same fiscal quarter which comes after the reporting lag. In contrast, we employ the spending surprise in the current quarter to predict the surprises of cash flows in future quarters, which better illustrates the idea that direct consumer spending contains relevant information about a firm's future profitability.

4. Additional Analysis

[21] To save space, we omit the results for quarters *t+2* and *t+3*. The spending surprise can also significantly positively predict the earnings surprises in quarter *t+2* (coefficient=0.047) and quarter *t+3* (coefficient=0.068).

4.1.Alternative Explanations

In the previous sections, we aim to deliver three points: (1) customer spending surprise within a fiscal quarter conveys additional value-relevant information about a firm's profitability and growth potential; (2) the information is attributable to two reasons: direct customer spending is a more precise measure of consumer demand, and the embedded consumer composition information is relevant to the consumer demand sustainability; and (3) the consumer spending surprise is more informative for consumer-oriented firms, and it is also predictive of future earnings and sales surprises. Next, we study alternative explanations for the positive relation between the spending surprise and subsequent *CAR*s (especially post-announcement *CAR*).

4.1.1. Sales during Reporting Lag

There is a time lag between the fiscal quarter end and the earnings announcement date (i.e., the reporting lag), and sales during the reporting lag is not covered by the current earnings report. As a result, it is possible that the true source of the return predictability of the spending surprise within a fiscal quarter in fact stems from its correlation with the sales during the reporting lag.

To investigate this alternative mechanism, we use the (credit card) spending during the reporting lag period to proxy for the corporate sales during that period, and include this variable in the regression. Since the reporting lag varies in length for different firm-quarters, we define the Standardized Unexpected Spending during the reporting lag (i.e., *QSUS (reporting lag)*) based on the daily average customer spending for a firm-quarter during the reporting lag. Detailed variable construction can be found in Appendix A.

In columns 1-2 of Panel A, Table 7, we focus on the effect of the spending surprise during the reporting lag: while it positively predicts subsequent *CAR*s, the effect is statistically insignificant. One inter-quintile increase in the spending surprise during the reporting lag is associated with 0.618 percent increase in the post-announcement *CAR* as reported in column (2) (*p*value=0.140).

Next, we add the spending surprise within the fiscal quarter (i.e, *QSUS*) into the regression (columns 3-4). The evidence strongly supports our information story instead of the alternative explanation. After including *QSUS* into the regression, the coefficient for the spending surprise during the reporting lag decreases to 0.188 for the 60-day post-announcement *CAR*, and even becomes negative for the three-day announcement *CAR*. By contrast, the predictive power of

QSUS on the post-announcement *CAR* remains statistically significant and economically large (coefficient=0.907; *p*value=0.039). Compared to the main result in Table 2, the magnitude of the predictability associated with *QSUS* barely changes after including the spending surprise during the reporting lag period in the regression. This suggests that the sales information during the reporting lag unlikely explains the return predictability that we document in the main analysis.[22]

[Insert Table 7 about Here]

4.1.2. Three Known Factors Associated with Post-announcement *CAR*

Earnings surprise is known to be positively related with the post-announcement *CAR*, and the Post-Earnings-Announcement-Drift (*PEAD*) is one of the most persistent anomalies in the US stock market (e.g., Fama, 1998). Although we have controlled for the earnings surprise in all analysis, there is a comprehensive stream of studies showing that the same level of earnings surprise could lead to different levels of the post-announcement *CAR*s. Three widely known factors associated with heterogeneous *PEAD* include earnings quality, investor sophistication, and investor inattention.

Previous research documents a stronger *PEAD* among firms with lower earnings quality because of its association with high information uncertainty (Francis et al., 2007; Hung, Li, and Wang, 2014). In addition, Froot et al. (2016) find that managers use their private information about consumer demand to manage their earnings (quality). Therefore, we study whether the significant predictive power of the spending surprise on the post-announcement *CAR* in our setting is attributable to various earnings properties. Following Hirshleifer, Lim, and Teoh (2009), we add two earnings properties into the regression: earnings persistence and earnings volatility. We define earnings persistence as the regression coefficient of the quarterly earnings

[22] According to Table 1, the average reporting lag for a firm is around 30 days in our sample, while a fiscal quarter usually lasts for three months. One might be concerned that the low predictive power of spending surprise during reporting lag is due to the short time period of collecting spending information. To alleviate this concern, we further extend the after-fiscal-end period to the time after fiscal-quarter end until day +61 relative to the earnings announcement date. We get the daily average customer spending for firm-quarters during this period, and construct a *QSUS (fiscal end, +61]* measure accordingly. We run the horse run test for this measure, and find similar results as in Panel A of Table 6: the regression coefficient for *QSUS (fiscal end, +61]* when *QSUS* is not added is 0.851, and it diminishes to 0.286 after adding spending surprise within the fiscal quarter. The coefficient for *QSUS*, instead, increases 1.162. However, since this identification requires the whole period between fiscal-quarter end to 61 trading days after earnings announcement date to be within our eight-month sample period, we are left with 488 observations and the power of estimation is sacrificed to a large extend.

per share on the earnings per share four quarters ago during the past four years, which is a proxy for earnings quality (Dechow, Ge, and Schrand, 2010). We calculate the earnings volatility as the standard deviation, during the preceding four years, of the difference between the quarterly earnings and the earnings per share four quarters ago. Detailed variable construction is reported in Appendix A.

As reported in columns 1-2 of Panel B, Table 7, despite the significant effects of earnings property measures on subsequent *CARs*, the coefficients for the spending surprise remain significantly positive. One inter-quintile increase in *QSUS* is associated with 0.742 percent increase in post-announcement *CAR* (*p*value=0.019), and 0.381 percent increase in three-day announcement *CAR* (*p*value=0.008), after the additional control of earnings properties.

In addition to earnings quality, investor sophistication is also found associated with *PEAD*. Institutional investors are generally more sophisticated in processing financial information, inducing a more prompt price response to earnings news (Bartov, Radhakrishnan, and Krinsky, 2000). To study this alternative, we obtain the institutional ownership information for each firm-quarter from Thomson Reuters 13F and control for the percentage of *institutional ownership* in columns 3-4 of Panel B, Table 7. Consistent with prior studies, the effect of earnings news on post-announcement *CAR* is lower among firms with more sophisticated investors (i.e., higher institutional ownership). More important, including institutional ownership as another control does not change the effect of the spending surprise (coefficient=0.996; *p*value=0.003 for the 60-day post-announcement *CAR;* coefficient=0.258, *p*value =0.079 for the three-day announcement *CAR*).

Moreover, investors only have limited cognitive resources to collect and process information. Therefore when investors are distracted to other concurrent events, they will be less attentive to a particular firm's financial report, which leads to a greater delay in the price response to its earnings news (Francis, Pagach, and Stephan, 1992; DellaVigna, and Pollet, 2009; Hirshleifer, Lim, and Teoh, 2009). We follow Hirshleifer, Lim, and Teoh (2009) and use the number of concurrent earnings announcements to proxy for investor distraction. We find that the coefficients of *QSUS* do not change significantly after adding the number of concurrent earnings announcements as control (coefficient=0.991, *p*value=0.003 for the post-announcement *CAR*; coefficient=0.272, *p*value=0.053 for the three-day announcement *CAR*).

4.2. Robustness Tests

We conduct several tests to ensure the robustness of our main results. First, we want to show that the effect of spending surprise is robust regarding alternative specifications of spending surprise, sales surprise, and earnings surprise. Second, we illustrate that changing the benchmark for calculating *CAR*s does not erode the return predictability of spending surprise.

4.2.1. Alternative Definitions of Spending, Sales, and Earnings Surprise

Although we have differenced out the industry average spending when constructing the spending surprise measure, there could still be concerns for the correlation between firm size and the *SUS*. For example, it is possible that larger firms within each industry will always generate higher-than-average credit card spending, thus always stay in the top quintile of *SUS*. We address this concern by revising the spending surprise definition—we scale the deviation of a firm's total credit card spending from the industry mean spending by its total asset. Specifically, we define an SUS_asset measure as:

$$SUS\_asset_{iknq} = \frac{Spending_{iknq} - Industry\ average\ spending_{kq}}{Total\ asset_{iknq}}$$

Similar to all the surprise measures, we sort SUS_asset into quintiles in each fiscal quarter and use *QSUS_asset* as the main independent variable in the regression. Results in Table 8, Panel A show an even greater predictability for the post-announcement *CAR* (coefficient=1.560; *p*value=0.001).

In our main analysis, we define the sales surprise on a time series basis following the seasonal random walk model. As an alternative, we re-define the sales surprise by exploiting the cross-sectional variation. Specifically, we define a $SU\_Sale\_industry$ as:

$$SU\_Sale\_industry_{iknq} = \frac{Sale_{iknq} - Industry\ average\ sale_{kq}}{Industry\ average\ sale_{kq}}$$

We add the quintile of this industry-level sales surprise into the regression, and report the results in columns 3-4 of Panel A, Table 8. We find that the effect of our main explanatory variable *QSUS* remains robust to the revised sales surprise measure (coefficient=0.944, *p*value=0.004 for the post-announcement *CAR*; coefficient=0.261, *p*value=0.072 for the three-day announcement *CAR*).

We also consider another widely used measure of earnings surprise—the Standardized Unexpected Earnings based on analyst forecast (*SUE_af*). According to the comparison in Livnat and Mendenhall (2006), the earnings surprise based on analyst forecasts and time-series models may capture different forms of mispricing. To control for the information contained in the analyst forecast based earnings surprise, we define *SUE_af* for a firm-quarter as the deviation of its *EPS* from the median analyst forecast within 90 days prior to the earnings announcement:

$$SUE\_af_{in} = \frac{EPS_{in} - EPS\_AF_{in}}{P_{in}}$$

Since only 64 percent of the firm-quarters in our sample are covered by analyst(s) during the 90-day pre-announcement period, the number of observations for the regression using analyst forecast based *SUE* declines to 910 (columns 5-6 of Table 8, Panel A). However, the predictability of the spending surprise for the post-announcement *CAR* is still economically large and statistically highly significant (coefficient=1.468; *p*value=0.001).[23]

4.2.2. Alternative Benchmarks for *CAR*s

In this subsection, we employ three other return benchmarks used in previous studies—Fama-French 25 size×B/M portfolio returns, value-weighted market return, and 125 size×B/M×Momentum DGTW portfolio return—to calculate the respective buy-and-hold *CAR*s (Hirshleifer, Lim, and Teoh, 2009; Hung, Li, and Wang, 2014). Regression results under the alternative benchmarks are reported in Panel B of Table 8.

Regardless of the return benchmarks, our documented return predictability for the post-announcement *CAR* preserves. The coefficient for the post-announcement *CAR* is highly statistically significant and ranges from 0.753-1.011, the magtude of which is similar as our main result.

Last but not least, we show that the effect of the spending surprise is unlikely due to a spurious relation. We randomly match the spending surprise with an arbitrarily chosen firm-quarter and re-run the main analysis as in Table 2. We repeat this exercise for 100 times, and the

[23] In unreported results, we also use the three-day announcement *CAR* to proxy for earnings surprise, and continue to find significant predictability for the 60-day post announcement *CAR*, no matter using the raw three-day *CAR* (coefficient=0.924; *p*value=0.007), or quintile of the three-day *CAR* (coefficient=0.926; *p*value=0.008).

regression coefficients for the randomly assigned *QSUS* are all statistically indistinguishable from zero (see Figure IA1 in Internet Appendix).

5. Conclusion

In this paper, we investigate the information content in the (credit card) spending from a firm's end consumers. Using a large proprietary panel dataset on credit card transactions, we find that credit card spending surprise on a firm's products within a fiscal quarter positively predicts subsequent stock abnormal returns. After controlling for the earnings and sales surprises, we find that one inter-quintile increase in the spending surprise generates 0.998 percentage point increase in the 60-day post-announcement *CAR* (*CAR[+2,+61]*). We propose two economic reasons to explain the incremental return predictability: consumer spending measures the customer demand more precisely, and the consumer composition information is relevant to the sustainability of consumer demand. Consistent with our conjecture, investigation into customer characteristics shows that the effect of the spending surprise concentrates among firms with more purchase from high-spending-capacity customers, or firms with a more diversified consumer base. We further show that the return predictability of credit card spending surprise is driven by consumer-oriented firms, to whom such direct purchase is more informative. The ability of spending surprise to predict future earnings and sales surprises further supports the idea that direct customer purchase conveys value-relevant information.

Taken together, findings in our study provide novel evidence that direct customer spending serves as a valuable source of information to extract a firm's overall consumer demand. We highlight the additional predictive power of customer spending surprise, above and beyond the publicly disclosed information. Investors and analysts could exert effort to discover and utilize such information (either on actual spending or on consumer composition), which could be helpful in investment decision making.

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Appendix A. Variable Definitions and Constructions

1. Cumulative Abnormal Returns:

CAR is the percentage buy-and-hold cumulative abnormal return over a specified event window around 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).

$$CAR[-1,+1]_{in} = \prod_{k=t-1}^{t+1}(1+R_{ik}) - \prod_{k=t-1}^{t+1}(1+R_{pk})$$

$$CAR[+2,+61]_{in} = \prod_{k=t+2}^{t+61}(1+R_{ik}) - \prod_{k=t+2}^{t+61}(1+R_{pk})$$

Where *t* is the earnings announcement date of firm *i* in fiscal quarter *n*; R_{ik} is the return of firm *i* on day *k* relative to the announcement day, and R_{pk} is the return of the matching size×B/M portfolio on day *k*. We use the nearest subsequent trading day if the earnings announcement 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. Market equity (size) is price times shares outstanding; and the book-to-market ratio used to form portfolios in June of year *t* is book equity for the fiscal year ending in calendar year *t-1*, divided by market equity at the end of December of *t-1*. All definitions follow that provided in Professor Kenneth French's website.[24] 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.[25]

For the robustness check in Panel B of Table 8, we replace the benchmark portfolio return (i.e., R_{pk}) with 25 size×B/M Fama-French portfolio return, value-weighted market return, or 125 size×B/M×Momentum DGTW portfolio return respectively.[26]

2. Standardized Unexpected Variables:

2.1. Standardized Unexpected Spendings

Standardized Unexpected Spending (SUS) is a firm-quarter's consumer credit card spending surprise. We define this variable using industry average spending as benchmark. Specifically,

$$SUS_{iknq} = \frac{Spending_{iknq} - Industry\ average\ spending_{kq}}{Industry\ average\ spending_{kq} + 1}$$

[24] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/variable_definitions.html
[25] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[26] http://alex2.umd.edu/wermers/ftpsite/Dgtw/coverpage.htm

Where $Spending_{iknq}$ is the aggregated credit card spending for firm *i* from industry *k* within fiscal quarter *n*, and the fiscal quarter n's ending month is in calendar quarter q; and $Industry\ average\ spending_{kq}$ is the industry average credit card spending for industry *k* in calendar quarter *q*. Industry is defined based on the two-digit SIC code. We scale by $Industry\ average\ spending_{kq} + 1$ to account for zero industry average spending cases. We calculate the industry average spending at the calendar quarter level because the same fiscal quarter for different firms corresponds to a different calendar quarter.

Quintile of Standardized Unexpected Spending (QSUS) is the quintile of *SUS* sorted by every calendar quarter. *QSUS* ranges from the bottom unexpected spending quintile (*QSUS*=1) to the top unexpected spending quintile (*QSUS*=5).

SUS (reporting lag) is a firm-quarter's customer credit card spending surprise during the reporting lag period. Specifically,

$$SUS_{iknq} = \frac{Daily\ total\ credit\ card\ spending\ \ in\ reporting\ lag_{iknq} - Industry\ average\ daily\ spending\ in\ reporting\ lag_{kq}}{Industry\ average\ daily\ spending\ in\ reporting\ lag_{kq} + 1}$$

Where $Daily\ total\ credit\ card\ spending\ in\ reporting\ lag_{iknq}$ is the daily average aggregated credit card spending for firm *i* from industry *k* during the reporting lag of fiscal quarter *n*, and the fiscal quarter *n*'s ending month is in calendar quarter q. We use the daily average instead of total spending during the reporting lag period because firms' reporting lags vary in length. $Industry\ average\ daily\ spending\ in\ reporting\ lag_{kq}$ is the industry average daily credit card spending during the reporting lag period for industry *k* in calendar quarter *q*.

QSUS (reporting lag) is the quintile of *SUS (reporting lag)* sorted by every calendar quarter. *QSUS (reporting lag)* ranges from the bottom unexpected spending quintile within the reporting lag period (*QSUS (reporting lag)* =1) to the top unexpected spending quintile within the reporting lag period (*QSUS (reporting lag)* =5).

SUS_asset is the deviation of a firm-quarter's total credit card spending from the industry mean credit card spending, scaled by total asset. Specifically,

$$SUS\_asset_{iknq} = \frac{Spending_{iknq} - Industry\ average\ spending_{kq}}{Total\ asset_{iknq}}$$

Where $Total\ asset_{iknq}$ is the value of total asset for firm *i* from industry *k* within fiscal quarter *n*, and the fiscal quarter *n*'s ending month is in calendar quarter *q*; and other variables are defined as above.

QSUS_asset is the quintile of *SUS_asset* sorted by every calendar quarter. *QSUS_asset* ranges from the bottom unexpected spending quintile (*QSUS_asset*=1) to the top unexpected spending quintile (*QSUS_asset*=5).

2.2. Standardized Unexpected Earnings

Standardized Unexpected Earnings (SUE) is 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).

SUE_af is the analyst forecast-based Standardized Unexpected Earnings following Livnat and Mendenhall (2006). Specifically,

$$SUE\_af_{in} = \frac{EPS_{in} - EPS\_AF_{in}}{P_{in}}$$

Where EPS_AF_{in} is the median of earning forecasts reported to I/B/E/S in the 90 days prior to the earnings announcement. We only consider the most recent forecast for each analyst.

QSUE_af is the quintile of *SUE_af* sorted by every calendar quarter. *QSUE_af* ranges from the bottom unexpected earnings quintile (*QSUE_af*=1) to the top unexpected earnings quintile (*QSUE_af*=5).

2.3. Standardized Unexpected Sales

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

$$SU\_Sale_{in} = \frac{Sale_{in} - Sale_{in-4}}{P_{in}}$$

Where $Sale_{in}$ 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 common shares used to calculate diluted *EPS*; otherwise we use the 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).

SU_Sale_industry is the deviation of a firm-quarter's reported sales from the industry mean sales, scaled by industry mean sales. Specifically,

$$SU\_Sale\_industry_{iknq} = \frac{Sale_{iknq} - Industry\ average\ sale_{kq}}{Industry\ average\ sale_{kq}}$$

Where $Sale_{iknq}$ is the number of total sales for firm *i* from industry *k* within fiscal quarter *n*, and the fiscal quarter *n*'s ending month is in calendar quarter *q*; and $Industry\ average\ sale_{kq}$ is the industry average total sales for industry *k* in calendar quarter *q*. Industry is based on the two-digit SIC code.

QSU_Sale_industry is the quintile of *SU_Sale_industry* sorted by every calendar quarter. *QSU_Sale_industry* ranges from the bottom industry-level unexpected sales quintile (*QSU_Sale_industry*=1) to the top industry-level unexpected sales quintile (*QSU_Sale_industry*=5).

3. Consumer Characteristics:

Total credit card spending is defined as 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).

Daily total credit card spending in reporting lag is the amount of daily average customer credit card spending during the reporting lag period (the time period after fiscal quarter end to one trading day before the quarterly earnings announcement). Specifically,

$$Daily\ total\ credit\ card\ spending\ in\ reporting\ lag = \frac{total\ credit\ card\ spending\ during\ (fiscal\ quarter\ end\ date, -1)}{the\ trading\ day\ before\ earnings\ annuncement\ date - fiscal\ quarter\ end\ date - 1}.$$

Age measures the age of an individual in 2003.

Rural is a dummy variable equal to one if the consumer is from rural area. We define a zip-code area as rural if more than half (i.e., >50%) of the population in this zip-code area are defined as rural population by US census.[27]

FICO score is consumer's FICO score, which measures consumer's credit risk.

Internal behavior score is an internal-generated credit quality score for a credit card holder; a higher internal behavior score indicates better credit quality from credit card issuer's perspective.

HHI Index of spending measures the diversity of spending from different customer groups.

[27] https://www.census.gov/geo/maps-data/data/ua_rel_download.html

Specifically, for age diversity, we define three age groups: young (age<30), middle-age (30≤age<60), and old (age ≥60). For each firm-quarter, we calculate the percentage of spending from the three age groups, then calculate *HHI Index of spending for age* as:

$$HHI\ age_{inq} = spending\ percent\_young_{inq}^2 + spending\ percent\_middle_{inq}^2 + spending\ percent\_old_{inq}^2$$

Where $spending\ percent\_young_{inq}$, $spending\ percent\_middle_{inq}$, and $spending\ percent\_old_{inq}$ are percentages of spending from young, middle-age, and old consumers for firm *i* in fiscal quarter *n* respectively, and the ending month of fiscal quarter *n* is in calendar quarter *q*.

For regional diversity, we define five regional groups according to the 2000 US census: midwest, northeast, west, south, and other.[28] Similarly, for each firm-quarter, we calculate the percentage of spending from the five regional groups, then calculate *HHI Index of spending for region* as:

$$HHI\ region_{inq} = spending\ percent\_midwest_{inq}^2 + spending\ percent\_northeast_{inq}^2 + spending\ percent\_west_{inq}^2 + spending\ percent\_south_{inq}^2 + spending\ percent\_other_{inq}^2$$

Where $spending\ percent\_midwest_{inq}$, $spending\ percent\_northeast_{inq}$, $spending\ percent\_west_{inq}$, $spending\ percent\_south_{inq}$, and $spending\ percent\_other_{inq}$ are percentages of spending from respective regional groups for firm *i* in fiscal quarter *n*, and the ending month of fiscal quarter *n* is in calendar quarter *q*.

In Table A1 and Table A2 for Internet Appendix, we define the HHI Indexes using percentage of consumers from different age or regional groups. For example:

$$HHI\ age\ (number\ of\ consumer)_{inq} = percent\_young_{inq}^2 + percent\_middle_{inq}^2 + percent\_old_{inq}^2$$

Where $percent\_young_{inq}$, $percent\_middle_{inq}$, and $percent\_old_{inq}$ are percentages of young, middle-age, and old consumers for firm *i* in fiscal quarter *n* respectively, and the ending month of fiscal quarter *n* is in calendar quarter *q*. $HHI\ region\ (number\ of\ consumer)$ is defined in a similar way.

4. Firm Characteristics:

Sale 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*).

[28] http://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf. We use the 2000 Census because our credit card data sample period is in 2003. States or districts that are not included in 2000 Census (three possible reasons: existing states or district not included in 2000 Census, miscoding of state/district information in credit card data, or missing information for state/district) are classified as "other."

Market capitalization 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. ***Log(size)*** is the log of market capitalization (in millions) at the end of prior June.

Book equity 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*** is the book-to-market ratio, calculated as: book equity for the fiscal year ending in calendar year *t-1*, divided by market equity at the end of December of *t-1*.

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 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.

Total asset is the amount of total asset, measured in millions of US dollars.

Earnings persistence is defined as the coefficient estimation of quarterly *EPS* regressed on the *EPS* in the same quarter last year for US firms. Specifically for each firm i, we run the following regression using earnings data from past four years:

$$EPS_{in} = \alpha_i + \beta_i EPS_{in-4} + \varepsilon_{in-4}$$

And β_i is the earnings persistence for firm i. At least four observations are required for running the regression.

Earnings volatility is the standard deviation during the preceding four years for the deviations of quarterly earnings from one-year-ago earnings. At least four observations are required for calculating earnings volatility.

Institutional ownership is the proportion of shares outstanding held by institutional investors at the ending month of a fiscal quarter.

Number of concurrent earnings announcements is the total number of earnings announcements on the same announcement date for a firm-quarter.

Appendix B. Firm Classification

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, and specific classification is reported in the table below.[29]

2-digit SIC Code	Industry	Division	Number of Firms	Percent	Consumer Oriented
40	Railroad Transportation	Transportation & Public Utilities	3	0.37	YES
42	Trucking & Warehousing	Transportation & Public Utilities	4	0.49	YES
44	Water Transportation	Transportation & Public Utilities	5	0.62	YES
45	Transportation by Air	Transportation & Public Utilities	11	1.35	YES
46	Pipelines, Except Natural Gas	Transportation & Public Utilities	2	0.25	YES
47	Transportation Services	Transportation & Public Utilities	1	0.12	YES
48	Communications	Transportation & Public Utilities	22	2.71	YES
49	Electric, Gas, & Sanitary Services	Transportation & Public Utilities	32	3.94	YES
52	Building Materials & Gardening Supplies	Retail Trade	4	0.49	YES
53	General Merchandise Stores	Retail Trade	16	1.97	YES
54	Food Stores	Retail Trade	9	1.11	YES
55	Automotive Dealers & Service Stations	Retail Trade	8	0.99	YES
56	Apparel & Accessory Stores	Retail Trade	29	3.57	YES
57	Furniture & Home furnishings Stores	Retail Trade	13	1.60	YES
58	Eating & Drinking Places	Retail Trade	31	3.82	YES
59	Miscellaneous Retail	Retail Trade	48	5.91	YES
70	Hotels & Other Lodging Places	Services	6	0.74	YES
72	Personal Services	Services	6	0.74	YES
73	Business Services	Services	85	10.47	YES
75	Auto Repair, Services, & Parking	Services	6	0.74	YES
78	Motion Pictures	Services	7	0.86	YES
79	Amusement & Recreation Services	Services	11	1.35	YES
80	Health Services	Services	15	1.85	YES
82	Educational Services	Services	3	0.37	YES
83	Social Services	Services	1	0.12	YES

[29]http://mckimmoncenter.ncsu.edu/mckimmon/divisionUnits/ceus/sicCodePickList.jsp

87	Engineering & Management Services	Services	19	2.34	YES
89	Services, Not Elsewhere Classified	Services	1	0.12	YES
Total			398	49.01	
01	Agricultural Production - Crops	Agriculture, Forestry, & Fishing	2	0.25	
10	Metal, Mining	Mining	6	0.74	NO
13	Oil & Gas Extraction	Mining	15	1.85	NO
14	Nonmetallic Minerals, Except Fuels	Mining	1	0.12	NO
15	General Building Contractors	Construction	3	0.37	NO
16	Heavy Construction, Except Building	Construction	5	0.62	NO
17	Special Trade Contractors	Construction	4	0.49	NO
20	Food & Kindred Products	Manufacturing	19	2.34	NO
22	Textile Mill Products	Manufacturing	3	0.37	NO
23	Apparel & Other Textile Products	Manufacturing	8	0.99	NO
24	Lumber & Wood Products	Manufacturing	4	0.49	NO
25	Furniture & Fixtures	Manufacturing	6	0.74	NO
26	Paper & Allied Products	Manufacturing	4	0.49	NO
27	Printing & Publishing	Manufacturing	16	1.97	NO
28	Chemical & Allied Products	Manufacturing	29	3.57	NO
29	Petroleum & Coal Products	Manufacturing	11	1.35	NO
30	Rubber & Miscellaneous Plastics Products	Manufacturing	4	0.49	NO
31	Leather & Leather Products	Manufacturing	6	0.74	NO
32	Stone, Clay, & Glass Products	Manufacturing	4	0.49	NO
33	Primary Metal Industries	Manufacturing	10	1.23	NO
34	Fabricated Metal Products	Manufacturing	9	1.11	NO
35	Industrial Machinery & Equipment	Manufacturing	32	3.94	NO
36	Electronic & Other Electric Equipment	Manufacturing	55	6.77	NO
37	Transportation Equipment	Manufacturing	11	1.35	NO
38	Instruments & Related Products	Manufacturing	27	3.33	NO
39	Miscellaneous Manufacturing Industries	Manufacturing	7	0.86	NO
50	Wholesale Trade - Durable Goods	Wholesale Trade	21	2.59	NO
51	Wholesale Trade - Nondurable Goods	Wholesale Trade	11	1.35	NO
60	Depository Institutions	Finance, Insurance, & Real Estate	3	0.37	NO

61	Nondepository Institutions	Finance, Insurance, & Real Estate	10	1.23	NO
62	Security & Commodity Brokers	Finance, Insurance, & Real Estate	8	0.99	NO
63	Insurance Carriers	Finance, Insurance, & Real Estate	28	3.45	NO
64	Insurance Agents, Brokers, & Service	Finance, Insurance, & Real Estate	1	0.12	NO
65	Real Estate	Finance, Insurance, & Real Estate	7	0.86	NO
67	Holding & Other Investment Offices	Finance, Insurance, & Real Estate	23	2.83	NO
95	Environmental Quality & Housing	Public Administration	1	0.12	NO
Total			414	50.99	NO

Table 1. Summary Statistics

Panel A: Firm characteristics

	Firms in sample			All firms			
	Mean	Std. dev.	Median	Mean	Std. dev.	Median	Difference in means (1) – (4)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Standardized Unexpected Spending (SUS)	-0.04	1.69	-0.54				
total credit card spending ($)	14,406	68,570	2,000				
daily total credit card spending in reporting lag ($)	178	938	15				
CAR[-1,+1] (%)	0.23	5.97	0.18	0.19	6.60	-0.05	0.04
CAR[+2,+61] (%)	2.75	16.27	-0.00	4.18	18.62	0.74	-1.43**
Standardized Unexpected Earnings (SUE)	0.01	0.11	0.00	0.02	0.46	0.00	-0.01
Standardized Unexpected Sales (SU_Sale)	-0.01	0.23	0.01	-0.01	0.28	0.01	-0.01
Earnings Per Share (EPS, $)	0.21	0.51	0.15	0.12	0.70	0.07	0.09***
sale ($million)	840	3,587	96	486	2,280	46	354***
net income ($million)	48.17	278.05	2.33	25.74	181.10	1.07	22.43***
stock price ($)	20.62	32.54	15.03	16.27	23.07	10.82	4.36***
market capitalization ($million)	3,382	17,113	311	1,934	11,461	192	1448***
book equity ($million)	1,711	7,564	182	1,069	4,918	116	642***
number of analysts	3.94	5.45	1.50	2.71	4.36	1.00	1.23***
reporting lag (day)	30.44	11.69	28.50	32.73	12.19	30.50	-2.29***
total asset ($million)	5,932	46,073	371	4,465	38,475	239	1467***
earnings persistence	0.32	0.54	0.21	0.22	0.58	0.12	0.09***
earnings volatility	401.23	11,244.46	0.25	273.80	7,892.45	0.28	127.43
number of concurrent earnings announcements	213	141	202	231	157	211	-18***
institutional ownership	0.41	0.34	0.40	0.35	0.33	0.27	0.06***
Number of firms	812			4,224			

Panel B: Consumer characteristics

	Consumers in sample			All credit card holders			
	Mean	Std. dev.	Median	Mean	Std. dev.	Median	Difference in means (1) – (4)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Age	44.94	15.04	44.00	46.53	15.34	45.00	-1.59***
rural	0.11	0.32	0.00	0.13	0.33	0.00	-0.01***
FICO score	722	83	733	711	81	723	11***
internal behavior score	658	144	712	623	168	693	35***
Number of individuals	56,599			129,277			

Panel C: Correlation matrix

variables	Sale	net income	total credit card spending	EPS	SUS	SUE	SU_Sale	CAR[-1,+1]	CAR[+2,+61]
sale	1.00								
net income	0.83***	1.00							
total credit card spending	0.37***	0.30***	1.00						
EPS	0.19***	0.23***	0.07**	1.00					
SUS	0.22***	0.21***	0.31***	0.05*	1.00				
SUE	-0.003	0.001	0.03	0.10***	0.09***	1.00			
SU_Sale	0.04	0.03	0.01	0.10***	-0.01	0.06**	1.00		
CAR[-1,+1]	-0.004	0.004	-0.02	0.08***	-0.02	0.06**	0.12***	1.00	
CAR[+2,+61]	-0.02	-0.03	0.00	-0.08***	0.05*	0.16***	0.04	0.06**	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 included in our main sample, and all firms within calendar quarter 2003Q2 to 2003Q3. All firm characteristics are measured quarterly, and reported at firm level. Panel B reports demographic and financial information of firm 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 individual level. Panel C reports the correlation matrix between selected variables. *SUS* (Standardized Unexpected Spending) is the constructed spending surprise measure. *Total credit card spending* is the amount of total customer credit card spending within a fiscal quarter, measured in US dollars. We only include firm-quarters that the whole fiscal-quarter is within our sample period. *Daily total credit card spending in reporting lag* is the amount of average customer credit card spending for one day during the reporting lag (the time period after fiscal quarter end to one trading day before quarterly earnings announcement). *CAR[-1,+1]* is the buy-and-hold three-day cumulative abnormal return around the quarterly earnings announcement date, measured in percentage. *CAR[+2,+61]* is the buy-and-hold 60-day cumulative abnormal return after the quarterly earnings announcement, measured in percentage. *Standardized Unexpected Earnings (SUE)* is the standardized unexpected earnings. *Standardized Unexpected Sales (SU_Sale)* is the standardized unexpected sales. *Earnings Per Share (EPS)* is the earnings per share excluding extraordinary items (if most analyst forecasts of earnings per share are based on diluted *EPS*, we use the Compustat's diluted *EPS* figure; otherwise we use the basic *EPS* figure), measured in US dollar. *sale* is the amount of quarterly sales, measured in millions of US dollars. *Net income* is the total net income in millions of US dollars. *Stock price* is firm's quarterly closing price, measured in US dollars. *Market capitalization* is the amount of market capitalization, measured in millions of US dollars. *Book equity* is the amount of book equity, measured in millions of US dollars. *Number of analysts* is 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 earnings announcement date. *Total asset* is the amount of total asset, measured in millions of US dollars. *Earnings persistence* measures the autocorrelation of earnings per share. *Earnings volatility* measures the volatility of earnings per share. *Number of concurrent earnings announcements* is the total number of earnings announcements on the same announcement date for a firm-quarter. *Institutional ownership* is the proportion of shares outstanding held by institutional investors for a firm-quarter. *age* measures the age of an individual in 2003. *rural* is a dummy variable equal to one if an individual is from rural area defined by US census. *FICO score* is consumer's FICO score. *Internal behavior score* is an internal-generated score for a credit card holder, quantifying customer's credit quality; a higher internal behavior score indicates better customer credit quality from credit card issuer's perspective. For detailed variable definitions and constructions, please see Appendix A. 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 Consumer Spending Surprise

Panel A. Relation between firm sale, net income, and total credit card spending

	Sale ($thousand)		Net income ($thousand)	
	(1)	(2)	(3)	(4)
Total credit card spending	19.174***	22.192**	1.178***	1.440*
	(15.11)	(2.25)	(11.74)	(1.96)
Constant	571,015.014***	536,487.896***	30,858.034***	27,873.596**
	(4.31)	(3.43)	(2.95)	(2.31)
Industry FE	N	Y	N	Y
Year-quarter FE	Y	Y	Y	Y
Observations	1,421	1,421	1,421	1,421
R-squared	0.14	0.33	0.09	0.25

Panel B. Relation between *CAR*s and Standardized Unexpected Spending

	(1)	(2)	(3)	(4)
	CAR[-1,+1]	CAR[+2,+61]	CAR[-1,+1]	CAR[+2,+61]
QSUS			0.268*	0.998***
			(1.91)	(3.14)
QSUE	0.985***	2.260***	0.864***	2.364***
	(6.63)	(4.57)	(5.89)	(4.60)
QSU_Sale			0.699***	-0.474
			(3.96)	(-1.09)
Log (size)	-0.040	-1.011**	-0.141	-1.158***
	(-0.27)	(-2.35)	(-0.94)	(-2.78)
B/M	0.012	-0.039	0.005	-0.047
	(0.82)	(-0.86)	(0.35)	(-1.08)
Log (number of analyst +1)	0.317	0.108	0.346	-0.002
	(0.96)	(0.10)	(1.06)	(-0.00)
Reporting lag	-0.021	-0.065	-0.022	-0.067
	(-1.19)	(-1.41)	(-1.26)	(-1.48)
Constant	-2.247**	4.234	-4.181***	3.395
	(-2.11)	(1.63)	(-4.00)	(1.16)
Industry FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	1,415	1,415	1,415	1,415
R-squared	0.09	0.13	0.07	0.13

Note. This table presents the relation between the firm's aggregated consumer credit card spending within a fiscal quarter, and its reported cash flows (sales and net income) in Panel A; and the effect of the consumer spending surprise on subsequent *CAR*s in Panel B. In columns (1) and (2) of Panel A, we present the correlation between 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 firms' quarterly sales (in thousands of US dollars) and credit card-aggregated 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 are controlled in all columns. In Panel B, we show the effect of spending surprise constructed from credit card spending. Columns (1) and (2) present the response of three-day announcement return (*CAR[-1,+1]*) and 60-day post-announcement cumulative abnormal return (*CAR[+2,+61]*) to *Standardized Unexpected Earnings* quintiles (*QSUE*; *QSUE*=1: bad earnings news, *QSUE*=5: good earnings news). Columns (3) and (4) reports the effect of *Standardized Unexpected Spending* quintiles (*QSUS*; *QSUS*=1: bad spending news; *QSUS*=5: good spending news) for *CAR[-1,+1]* and *CAR[+2,+61]*, controlling for earnings surprise (*QSUE*) and sales surprise (*QSU_Sale*; *QSU_Sale*=1: bad sales news; *QSU_Sale*=5: good sales news). Quintile ranking of *SUS*, *SUE*, and *SU_Sale* are all based on independent sorts in each calendar quarter. *Log(size)* is the log of market capitalization (in millions) at the end of prior June. *B/M* is the book-to-market ratio (calculated as: book equity for the fiscal year ending in calendar year *t-1*, divided by market equity at the end of December of *t-1*). *Log(number of analyst + 1)* is the log of number of analysts that have made forecasts within 90 days before the quarterly earnings announcement date. We use *Log(number of analyst + 1)* to include zero-analyst cases. *Reporting lag* is the number of days between the fiscal-quarter end date and earnings announcement date. For detailed variable definitions and constructions, please see Appendix A. 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. Heterogeneity by Consumer Spending Capacity

Panel A. High *FICO score* as high spending capacity

	More spending from High FICO score consumers		Less spending from high FICO score consumers	
	CAR[-1,+1]	CAR[+2,+61]	CAR[-1,+1]	CAR[+2,+61]
	(1)	(2)	(3)	(4)
QSUS	0.546**	1.540**	-0.088	0.243
	(2.18)	(2.60)	(-0.39)	(0.29)
QSUE	0.714***	1.607*	0.974***	2.394***
	(2.95)	(1.89)	(3.00)	(3.70)
QSU_Sale	0.491*	0.024	0.985**	-0.171
	(1.85)	(0.03)	(2.64)	(-0.30)
Constant	-5.129***	-5.030	-3.437*	11.501**
	(-2.75)	(-1.21)	(-1.92)	(2.10)
Controls	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	662	662	661	661
R-squared	0.11	0.14	0.13	0.19

Panel B. High *internal behavior score* as high spending capacity

	More spending from high behaviour score consumers		Less spending from high behaviour score consumers	
	CAR[-1,+1]	CAR[+2,+61]	CAR[-1,+1]	CAR[+2,+61]
	(1)	(2)	(3)	(4)
QSUS	0.515*	1.327**	-0.072	1.111
	(1.84)	(2.18)	(-0.29)	(1.50)
QSUE	1.199***	1.646**	0.523**	2.757***
	(5.33)	(2.21)	(2.49)	(3.34)
QSU_Sale	0.864***	0.219	0.601**	-0.530
	(3.32)	(0.32)	(2.24)	(-0.94)
Constant	-8.191***	7.485	0.027	-2.005
	(-4.10)	(1.66)	(0.02)	(-0.45)
Controls	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	673	673	674	674
R-squared	0.17	0.17	0.09	0.17

Note. This table presents the return predictability of the spending surprise by the firm's customer spending capacity. We adopt two measures of consumer credit to proxy for customer spending capacity. In Panel A, we define high spending-capacity customers as consumers with higher-than-median quarter-beginning *FICO score*. Columns (1)-(2) presents the regression results for firm-quarters with higher-than-median percentage of total consumer spending coming from high-FICO consumers; and columns (3)-(4) reports results for the rest firm-quarters. In Panel B, we define high spending-capacity customers as consumers with higher-than-median quarter-beginning *internal behavior score*. Columns (1)-(2) presents the regression results for firm-quarters with higher-than-median percentage of total consumer spending comes from high-behavior consumers; and columns (3)-(4) reports results for the rest firm-quarters. *QSUS* is quintile of spending surprise (*QSUS*=1: bad spending news; *QSUS*=5: good spending news). *QSUE* is quintile of earnings surprise (*QSUE*=1: bad earnings news, *QSUE*=5: good earnings news). *QSU_Sale* is quintile of sales surprise (*QSU_Sale*=1: bad sales news; *QSU_Sale*=5: good sales news). Quintile ranking of *SUS*, *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 are omitted. For detailed variable definitions and constructions, please see Appendix A. 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 4. Heterogeneity by Consumer Base

Panel A. Consumer age diversity

	High age diversity		Low age diversity	
	(1)	(2)	(3)	(4)
	CAR[-1,+1]	CAR[+2,+61]	CAR[-1,+1]	CAR[+2,+61]
QSUS	-0.117	1.843***	0.458*	0.747
	(-0.57)	(3.67)	(1.80)	(0.99)
QSUE	0.506*	1.618**	1.299***	2.713***
	(1.91)	(2.49)	(5.05)	(3.31)
QSU_Sale	0.554**	-0.915	0.901***	-0.252
	(2.24)	(-1.34)	(2.97)	(-0.34)
Constant	-3.603**	2.292	-4.777**	6.035
	(-2.10)	(0.39)	(-2.25)	(1.35)
Controls	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	683	683	688	688
R-squared	0.11	0.16	0.15	0.17

Panel B. Consumer regional diversity

	High regional diversity		Low regional diversity	
	(1)	(2)	(3)	(4)
	CAR[-1,+1]	CAR[+2,+61]	CAR[-1,+1]	CAR[+2,+61]
QSUS	0.182	1.917***	0.600**	0.198
	(0.78)	(3.17)	(2.55)	(0.38)
QSUE	0.506	1.339*	1.115***	2.237***
	(1.65)	(1.96)	(5.13)	(3.22)
QSU_Sale	0.571**	-0.687	0.732***	-0.004
	(2.53)	(-0.98)	(3.02)	(-0.01)
Constant	-3.551**	3.252	-5.773***	9.387**
	(-2.31)	(0.58)	(-3.08)	(2.01)
Controls	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	661	661	666	666
R-squared	0.10	0.18	0.15	0.15

Panel C. Rural-urban diversity

	High rural consumption		Low rural consumption	
	(1)	(2)	(3)	(4)
	CAR[-1,+1]	CAR[+2,+61]	CAR[-1,+1]	CAR[+2,+61]
QSUS	-0.060	1.853***	0.391	0.565
	(-0.31)	(3.28)	(1.46)	(0.77)
QSUE	0.666***	1.360*	0.932***	2.743***
	(2.73)	(1.90)	(3.76)	(3.54)
QSU_Sale	0.544**	-0.765	0.892***	0.012
	(2.58)	(-1.15)	(3.00)	(0.02)
Constant	-3.835***	7.061	-4.946**	0.793
	(-2.67)	(1.45)	(-2.04)	(0.16)
Controls	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	663	663	715	715
R-squared	0.12	0.16	0.14	0.18

Note. This table presents the return predictability of the spending surprise by the firm's consumer base diversity. In Panel A, we investigate the heterogeneity by the firm's consumer 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. Columns (1) and (2) report the regression results for firms with consumers diversified in age; and columns (3) and (4) report the regression results for firms with consumers concentrated in age. In Panel B, we report the heterogeneity by regional diversity. Firm-quarters with lower-than-median *HHI region* for a firm-quarter from five regional groups (i.e., Midwest, Northeast, West, South, and other) are defined as diversified. Columns (1) and (2) report the regression results for firm-quarters with regionally diversified consumers; and columns (3) and (4) report the regression results for firms with regionally concentrated consumers. In Panel C, we report the heterogeneity by rural-urban diversity. Firm-quarters with higher-than-median rural consumption percentage are defined as having higher rural-urban diversity. Columns (1)-(2) report the regression results for firm-quarters with high rural consumption; and columns (3) and (4) report the regression results for firm-quarters with low rural consumption. *QSUS* is quintile of spending surprise (*QSUS*=1: bad spending news; *QSUS*=5: good spending news). *QSUE* is quintile of earnings surprise (*QSUE*=1: bad earnings news, *QSUE*=5: good earnings news). *QSU_Sale* is quintile of sales surprise (*QSU_Sale*=1: bad sales news; *QSU_Sale*=5: good sales news). Quintile ranking of *SUS*, *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 are omitted. For detailed variable definitions and constructions, please see Appendix A. 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. Informativeness of Consumer Spending: Consumer-oriented Firms

	Consumer-oriented Firms		Non-consumer-oriented Firms	
	(1)	(2)	(3)	(4)
	CAR[-1,+1]	CAR[+2,+61]	CAR[-1,+1]	CAR[+2,+61]
QSUS	0.239	1.757***	0.297	0.299
	(1.31)	(3.92)	(1.48)	(0.66)
QSUE	0.855***	1.908***	0.924***	3.066***
	(3.89)	(4.25)	(4.11)	(3.68)
QSU_Sale	1.005***	-0.119	0.377	-1.095
	(3.76)	(-0.26)	(1.66)	(-1.60)
Constant	-3.585**	0.108	-4.837***	6.844
	(-2.24)	(0.02)	(-3.72)	(1.60)
Controls	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	704	704	711	711
R-squared	0.09	0.11	0.10	0.16

Note. This table presents the heterogeneity in informativeness of the consumer credit card spending. 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; firms from the rest sectors are defined as non-consumer-oriented firms. Detailed firm assignment can be found in Appendix B. Columns (1) and (2) in Panel B report the regression results for consumer-oriented firms. Columns (3) and (4) in Panel B report the regression results for non-consumer-oriented firms. *QSUS* is quintile of spending surprise (*QSUS*=1: bad spending news; *QSUS*=5: good spending news). *QSUE* is quintile of earnings surprise (*QSUE*=1: bad earnings news, *QSUE*=5: good earnings news). *QSU_Sale* is quintile of sales surprise (*QSU_Sale*=1: bad sales news; *QSU_Sale*=5: good sales news). Quintile ranking of *SUS, 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 are omitted. For detailed variable definitions and constructions, please see Appendix A. 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 6. Predicting Future Earnings and Sales Surprises

	Future *QSUE* in quarter		Future *QSU_Sale* in quarter	
	t+1	*t*+4	*t*+1	*t*+4
	(1)	(2)	(3)	(4)
QSUS	0.052*	0.060**	0.039*	0.025
	(1.76)	(2.43)	(1.70)	(0.87)
QSUE	0.305***	-0.162***	-0.059**	-0.056
	(9.73)	(-3.56)	(-2.62)	(-1.64)
QSU_Sale	0.027	0.007	0.624***	0.034
	(1.12)	(0.20)	(21.13)	(0.68)
Constant	2.218***	3.310***	1.272***	2.913***
	(8.81)	(14.55)	(6.45)	(9.31)
Controls	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	1,412	1,342	1,412	1,343
R-squared	0.22	0.13	0.46	0.15

Note. This table presents the predictability of the consumer credit card spending surprise in future earnings and sales surprises. Columns (1) and (2) report the regression results when dependent variables are quintile of earnings surprises in quarter *t+1* and quarter *t+4* respectively. Columns (3) and (4) report the regression results when dependent variables are quintile of sales surprises in quarter *t+1* and quarter *t+4* respectively. *QSUS* is quintile of spending surprise (*QSUS*=1: bad spending news; *QSUS*=5: good spending news). *QSUE* is quintile of earnings surprise (*QSUE*=1: bad earnings news, *QSUE*=5: good earnings news). QSU_Sale is quintile of sales surprise (*QSU_Sale*=1: bad sales news; *QSU_Sale*=5: good sales news). Quintile ranking of *SUS*, *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 are omitted. For detailed variable definitions and constructions, please see Appendix A. 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 7. Alternative Explanations

Panel A. Sales during reporting lag

	(1)	(2)	(3)	(4)
	CAR[-1,+1]	CAR[+2,+61]	CAR[-1,+1]	CAR[+2,+61]
QSUS			0.286	0.907**
			(1.67)	(2.11)
QSUS (reporting lag)	0.098	0.618	-0.037	0.188
	(0.58)	(1.50)	(-0.18)	(0.36)
QSUE	0.857***	2.330***	0.866***	2.357***
	(5.80)	(4.52)	(5.82)	(4.57)
QSU_Sale	0.695***	-0.492	0.700***	-0.477
	(3.98)	(-1.14)	(3.98)	(-1.10)
Constant	-3.824***	4.368	-4.162***	3.297
	(-3.95)	(1.39)	(-4.08)	(1.09)
Controls	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	1,415	1,415	1,415	1,415
R-squared	0.09	0.13	0.09	0.13

Panel B. Earnings property, investor sophistication, or investor distraction

	Earnings property		Institutional ownership		Investor distraction	
	(1)	(2)	(3)	(4)	(5)	(6)
	CAR[-1,+1]	CAR[+2,+61]	CAR[-1,+1]	CAR[+2,+61]	CAR[-1,+1]	CAR[+2,+61]
QSUS	0.381***	0.742**	0.258*	0.996***	0.272*	0.991***
	(2.77)	(2.40)	(1.79)	(3.11)	(1.97)	(3.11)
QSUE	0.934***	1.837***	0.865***	2.304***	0.858***	2.374***
	(5.80)	(2.87)	(6.03)	(4.56)	(5.94)	(4.59)
QSU_Sale	0.543***	-0.333	0.697***	-0.470	0.701***	-0.476
	(3.09)	(-0.65)	(3.97)	(-1.06)	(3.99)	(-1.09)
Earnings persistece	0.809**	-2.944**				
	(2.10)	(-2.47)				
Earnings volatility	-0.000***	-0.000***				
	(-4.76)	(-13.49)				
Institutional ownership			0.215	-4.102**		
			(0.32)	(-2.26)		
Number of concurrent earnings announcements					-0.001	0.002
					(-0.94)	(0.42)
Constant	-5.038***	-3.881	-4.171***	4.010	-3.756***	2.723
	(-4.91)	(-1.15)	(-3.89)	(1.35)	(-3.48)	(0.83)
Controls	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y	Y	Y
Observations	1,167	1,167	1,408	1,408	1,415	1,415
R-squared	0.10	0.15	0.09	0.13	0.09	0.13

Note. This table presents the test results of alternative explanations for the predictive power of customer spending surprise. In Panel A, we investigate the alternative that the predictability of customer spending surprise works through its correlation with sales during reporting lag. In columns (1) and (2), we use the quintile of daily Standardized Unexpected Spending (*QSUS (reporting lag)*) during the reporting lag (the period after fiscal quarter end date to one day before earnings announcement date) in the regression. In columns (3) and (4), we add the quintile of Standardized Unexpected Spending within the fiscal quarter (*QSUS*) into the regression. In Panel B, we control for three factors associated with the Post-Earnings-Announcement-Drift: earnings property (quality), institutional ownership, and investor distraction. In columns (1) and (2), we add two earnings properties—*earnings persistence* and *earnings volatility*—in regression as controls. In columns (3) and (4), we add firm-quarter's percentage of institutional ownership (*institutional ownership*) in regression. In columns (5) and (6), we add the number of concurrent earnings announcements on the same date (*number of concurrent earnings announcements*) for a firm-quarter in regression. *QSUS (reporting lag)* is quintile of spending surprise based on daily credit card spending during the reporting lag (*QSUS (reporting lag)*=1: low spending surprise during reporting lag; *QSUS (reporting lag)*=5: high spending surprise during reporting lag). *QSUS* is quintile of spending surprise within a fiscal quarter (*QSUS*=1: bad spending news within fiscal quarter; *QSUS*=5: good spending news within fiscal quarter). *QSUE* is quintile of earnings surprise (*QSUE*=1: bad earnings news, *QSUE*=5: good earnings news). *QSU_Sale* is quintile of sales surprise (*QSU_Sale*=1: bad sales news; *QSU_Sale*=5: good sales news). Quintile ranking of *SUS*, *daily SUS (fiscal end, -1)*, *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 are omitted. For detailed variable definitions and constructions, please see Appendix A. 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 8. Robustness Tests

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

	Asset-scaled *SUS*		Industry-level *Su_Sale*		Analyst forecast based *SUE*	
	(1)	(2)	(3)	(4)	(5)	(6)
	CAR[-1,+1]	CAR[+2,+61]	CAR[-1,+1]	CAR[+2,+61]	CAR[-1,+1]	CAR[+2,+61]
QSUS			0.261*	0.944***	0.140	1.468***
			(1.83)	(3.00)	(0.70)	(3.56)
QSUS_asset	0.225	1.560***				
	(1.20)	(3.49)				
QSUE	0.866***	2.388***	0.870***	2.405***		
	(5.95)	(4.59)	(6.03)	(4.68)		
QSUE_af					1.426***	0.221
					(6.97)	(0.43)
QSU_Sale	0.702***	-0.446	0.683***	-0.598	0.348*	-0.122
	(4.04)	(-1.02)	(4.00)	(-1.40)	(1.83)	(-0.23)
QSU_Sale_industry			0.214	1.630		
			(0.69)	(1.45)		
Constant	-3.895***	3.786	-4.089***	4.097	-5.795***	9.551**
	(-3.73)	(1.34)	(-3.69)	(1.40)	(-4.23)	(2.58)
Controls	Y	Y	Y	Y		
Industry FE	Y	Y	Y	Y		
Year-quarter FE	Y	Y	Y	Y		
Observations	1,415	1,415	1,415	1,415	910	910
R-squared	0.09	0.13	0.09	0.13	0.12	0.15

Panel B. Alternative benchmarks for CARs

	25 size ×B/M Fama-French portfolio return		Value-weighted market return		125 size ×B/M ×Momentum DGTW portfolio return	
	(1)	(2)	(3)	(4)	(5)	(6)
	CAR[-1,+1]	CAR[+2,+61]	CAR[-1,+1]	CAR[+2,+61]	CAR[-1,+1]	CAR[+2,+61]
QSUS	0.255*	1.011***	0.249*	0.970***	0.206	0.753**
	(1.79)	(3.20)	(1.79)	-3.06	(1.44)	(2.25)
QSUE	0.872***	2.243***	0.874***	2.243***	1.056***	2.620***
	(5.93)	(4.19)	(5.70)	-4.19	(6.64)	(4.59)
QSU_Sale	0.679***	-0.348	0.718***	-0.518	0.649***	-0.179
	(3.87)	(-0.80)	(4.02)	-1.15	(3.71)	(-0.39)
Constant	-4.381***	-3.380	-3.895***	16.695***	-4.764***	-6.693*
	(-4.28)	(-1.12)	(-3.79)	(5.98)	(-4.97)	(-1.81)
Controls	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y	Y	Y
Observations	1,415	1,415	1,415	1,415	1,264	1,264
R-squared	0.09	0.12	0.09	0.16	0.10	0.13

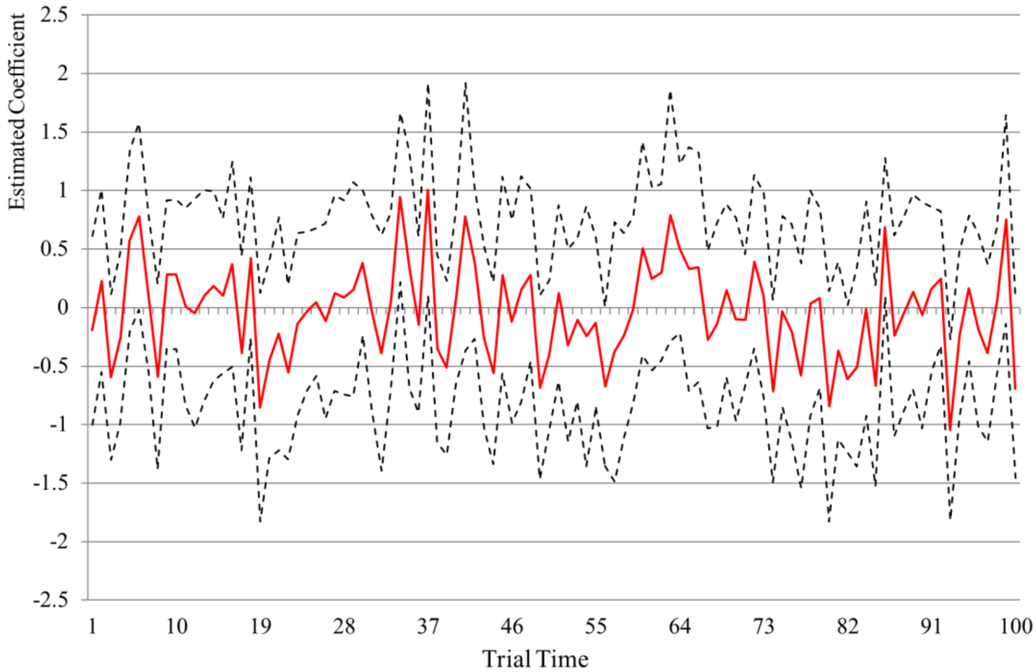
Note. This table presents two sets of robustness tests. In panel A, we consider alternative specifications regarding spending surprise, sales surprise, and earnings surprise. In columns (1) and (2), we replace *QSUS* with an asset-scaled specification for spending surprise measure: *QSUS_asset*. In columns (3) and (4), we add a sales surprise measure defined based on industry benchmark: *QSU_Sale_industry*. In columns (5) and (6), we replace *QSUE* with analyst forecast based earnings surprise: *QSUE_af*. In Panel B, we replicate the main results in Table 2 using three alternative benchmark portfolios to calculate *CAR*s. In columns (1) and (2), we use 25 size×B/M Fama-French portfolio returns as benchmark returns. In columns (3) and (4), we use value-weighted market return as benchmark return. In columns (5) and (6), we use 125 size×B/M×Momentum DGTW portfolio returns as benchmark returns. *QSUS* is quintile of spending surprise (*QSUS*=1: bad spending news; *QSUS*=5: good spending news). *QSUS_asset* is quintile of asset-scaled spending surprise. *QSUE* is quintile of seasonal random walk based earnings surprise (*QSUE*=1: bad earnings news, *QSUE*=5: good earnings news). *QSUE_af* is quintile of analyst forecast based earnings surprise. *QSU_Sale* is quintile of sales surprise (*QSU_Sale*=1: bad sales news; *QSU_Sale*=5: good sales news). *QSU_Sale_industry* is quintile of industry-level sales surprise (*QSU_Sale_industry*=1: bad sales news compared to industry mean sales; *QSU_Sale_industry*=5: good sales news compared to industry mean sales). Quintile ranking of *SUS*, *SUS_asset*, *SUE*, *SUE_af*, *SU_Sale*, and *SU_Sale_industry* are all based on independent sorts in each calendar quarter. All *CAR*s are measured in percentage. Coefficients for other control variables are omitted. For detailed variable definitions and constructions, please see Appendix A. 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.

INTERNET APPENDIX
FOR

Extracting Consumer Demand:
Credit Card Spending and Post-Earnings Returns

(Not Intended for Publication)

Figure IA1: Random Match between Spending Surprise and Firms



Note. This figure plots the coefficients and 95% confidence intervals for *QSUS* from regression equation (1), when the *QSUS* is randomly matched with any arbitrary firm-quarter in sample, and *CAR[+2,+61]* is used as dependent variable. The random match is replicated for 100 times. The horizontal axis is the time of random match, and the vertical axis is the magnitude of regression coefficient for *QSUS*. For detailed variable definitions and constructions, please see Appendix A.

Table IA1. Consumer Spending Capacity Subsamples by Number of Consumers

Panel A. High *FICO score* as high spending capacity

	More High FICO score consumers		Less high FICO score consumers	
	CAR[-1,+1]	CAR[+2,+61]	CAR[-1,+1]	CAR[+2,+61]
	(1)	(2)	(3)	(4)
QSUS	0.246	1.327**	0.097	0.420
	(1.11)	(2.12)	(0.46)	(0.61)
QSUE	0.474*	1.914***	1.202***	1.821***
	(1.99)	(2.87)	(4.76)	(2.91)
QSU_Sale	0.668**	-0.252	0.707**	0.145
	(2.33)	(-0.33)	(2.42)	(0.25)
Constant	-5.005**	-5.487	-4.044***	13.094**
	(-2.63)	(-1.34)	(3.22)	(2.21)
Controls	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	666	666	665	665
R-squared	0.10	0.14	0.16	0.18

Panel B. High *internal behavior score* as high spending capacity

	More high behaviour score consumers		Less high behaviour score consumers	
	CAR[-1,+1]	CAR[+2,+61]	CAR[-1,+1]	CAR[+2,+61]
	(1)	(2)	(3)	(4)
QSUS	0.402	1.476**	0.092	0.759
	(1.60)	(2.49)	(0.43)	(1.03)
QSUE	1.022***	1.610**	0.707***	2.391***
	(4.80)	(2.56)	(2.78)	(2.70)
QSU_Sale	1.057***	-0.357	0.506*	-0.370
	(4.30)	(-0.59)	(1.86)	(-0.58)
Constant	-7.742***	10.072**	-1.700	0.857
	(-3.36)	(2.21)	(-1.07)	(0.19)
Controls	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	676	676	679	679
R-squared	0.15	0.16	0.11	0.17

Note. This table presents the return predictability of the spending surprise by the firm's customer spending capacity defined on number of consumers in different consumer groups. We adopt two measures of consumer credit to proxy for customer spending capacity. In Panel A, we define high spending-capacity customers as consumers with higher-than-median quarter-beginning *FICO score*. Columns (1)-(2) presents the regression results for firm-quarters with higher-than-median percentage of high-FICO consumers; and columns (3)-(4) reports results for the rest firm-quarters. In Panel B, we define high spending-capacity customers as consumers with higher-than-median quarter-beginning *internal behavior score*. Columns (1)-(2) presents the regression results for firm-quarters with higher-than-median percentage of high-behavior consumers; and columns (3)-(4) reports results for the rest firm-quarters. *QSUS* is quintile of spending surprise (*QSUS*=1: bad spending news; *QSUS*=5: good spending news). *QSUE* is quintile of earnings surprise (*QSUE*=1: bad earnings news, *QSUE*=5: good earnings news). *QSU_Sale* is quintile of sales surprise (*QSU_Sale*=1: bad sales news; *QSU_Sale*=5: good sales news). Quintile ranking of *SUS*, *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 are omitted. For detailed variable definitions and constructions, please see Appendix A. 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. Consumer Base Subsamples by Number of Consumers

Panel A. Consumer age diversity

	High age diversity		Low age diversity	
	(1)	(2)	(3)	(4)
	CAR[-1,+1]	CAR[+2,+61]	CAR[-1,+1]	CAR[+2,+61]
QSUS	-0.269	1.213***	0.691***	1.377**
	(-1.38)	(2.99)	(2.79)	(2.01)
QSUE	0.528**	1.879***	1.197***	2.329**
	(2.30)	(3.38)	(4.75)	(2.60)
QSU_Sale	0.540**	-0.341	0.862***	-0.554
	(2.42)	(-0.50)	(3.18)	(-0.74)
Constant	-3.789***	0.503	-4.390**	6.356
	(-2.74)	(0.09)	(-2.13)	(1.44)
Controls	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	685	685	689	689
R-squared	0.08	0.17	0.19	0.15

Panel B. Consumer regional diversity

	High regional diversity		Low regional diversity	
	(1)	(2)	(3)	(4)
	CAR[-1,+1]	CAR[+2,+61]	CAR[-1,+1]	CAR[+2,+61]
QSUS	0.202	1.993***	0.288	-0.191
	(1.03)	(3.38)	(1.21)	(-0.33)
QSUE	0.559*	1.445**	0.999***	1.988***
	(1.98)	(2.27)	(4.94)	(2.90)
QSU_Sale	0.743***	-1.105*	0.627***	0.364
	(3.26)	(-1.77)	(2.71)	(0.57)
Constant	-4.429***	6.599	-4.456**	5.722
	(-3.20)	(1.16)	(-2.11)	(1.02)
Controls	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	651	651	680	680
R-squared	0.11	0.17	0.13	0.16

Panel C. Rural-urban diversity				
	More rural consumers		Less rural consumers	
	(1)	(2)	(3)	(4)
	CAR[-1,+1]	CAR[+2,+61]	CAR[-1,+1]	CAR[+2,+61]
QSUS	-0.011	1.839***	0.348	0.521
	(-0.06)	(3.38)	(1.34)	(0.65)
QSUE	0.756***	1.475**	0.829***	2.094***
	(2.76)	(2.07)	(3.57)	(3.01)
QSU_Sale	0.621**	-0.605	0.945***	0.267
	(2.60)	(-1.00)	(3.24)	(0.41)
Constant	-4.329***	5.358	-5.562**	2.353
	(-2.72)	(1.19)	(-2.16)	(0.41)
Controls	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	657	657	667	667
R-squared	0.13	0.16	0.14	0.18

Note. This table presents the return predictability of the spending surprise by the firm's consumer base diversity defined on number of consumers in different consumer groups. In Panel A, we investigate the heterogeneity by firm's consumer age diversity. Firm-quarters with lower-than-median *HHI age* defined on number of consumers from three age groups (i.e., young (age<30), middle-age (30≤age<60), and old (age≥60)) are defined as diversified. Columns (1) and (2) report the regression results for firms with consumers diversified in age; and columns (3) and (4) report the regression results for firms with consumers concentrated in age. In Panel B, we report the heterogeneity by regional diversity. Firm-quarters with lower-than-median *HHI region* defined on number of consumers for a firm-quarter from five region groups (i.e., Midwest, Northeast, West, South, and other) are defined as diversified. Columns (1) and (2) report the regression results for firm-quarters with regionally diversified consumers; and columns (3) and (4) report the regression results for firms with regionally concentrated consumers. In Panel C, we report the heterogeneity by rural-urban diversity. Because most credit card holders are from urban areas, firm-quarters with higher-than-median rural consumer percentage are defined as having higher rural-urban diversity. Columns (1)-(2) report the regression results for firm-quarters with more rural consumers; and columns (3) and (4) report the regression results for firm-quarters with less rural consumers. *QSUS* is quintile of spending surprise (*QSUS*=1: bad spending news; *QSUS*=5: good spending news). *QSUE* is quintile of earnings surprise (*QSUE*=1: bad earnings news, *QSUE*=5: good earnings news). *QSU_Sale* is quintile of sales surprise (*QSU_Sale*=1: bad sales news; *QSU_Sale*=5: good sales news). Quintile ranking of *SUS*, *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 are omitted. For detailed variable definitions and constructions, please see Appendix A. 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.