Customer Churn and Intangible Capital*

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Abstract

Intangible capital is a crucial and growing piece of firms' capital structure, but the multitude of distinct components are difficult to measure. We develop and make available several new firm-level metrics regarding a key component of intangible capital – firms' customer bases – using an increasingly common class of household transaction data. Linking household spending to customer-facing firms that make up over 30% of consumer spending, we show that churn in customer bases is associated with lower markups and market-to-book ratios and higher leverage. Churn is closely linked to firm-level volatility and risk, both cross-sectionally and over time. This new measure provides a clearer picture of firms' customer and brand capital than existing metrics like SG&A, R&D, or advertising expenditures and is also observable for private firms. We demonstrate that low levels of customer churn push firms away from neoclassical investment responsiveness and that low churn firms are better able to insulate organization capital from the risk of key talent flight.

JEL Classification: D22, E22, G32, L11

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1 Introduction

Intangible capital has become an increasingly important factor of production for many industries and has been put forth as one major factor driving increases in corporate concentration and markups over the past several decades.[1] Accordingly, this increase in the amount and scope of intangible capital has also driven changes in the exposure of firms to risk embodied in their intangible capital.

This growth has made the measurement of intangible capital more important when analyzing firm investment decisions, value, and risk exposure (see e.g., Peters and Taylor (2017), Eisfeldt et al. (2020)). Measurement is made more difficult by the fact that intangible capital is made up of a number of different components such as (1) technology/patents (see e.g., Kogan et al. (2017)), (2) customer base/branding (see e.g., Gourio and Rudanko (2014), Belo et al. (2019), Fornell et al. (2016)), (3) human-resource intangibles (see e.g., Eisfeldt and Papanikolaou (2013), Edmans (2011)), and (4) organizational design.[2]

Previous research has often relied on proxies of intangible capital such as capitalized SG&A or R&D spending (see Eisfeldt and Papanikolaou (2013) and Peters and Taylor (2017)) or 'residual methods' which attributes to intangibles all of the value that cannot be explained by tangible assets (see e.g., Ewens et al. (2020)). However, given the breadth of intangible capital, it's not always obvious how these imprecise metrics should be related to firm risk or decision-making. In this paper, we use new data regarding firms' customer bases to assist in prying open this black box and find an important component of intangible capital that has less ambiguous effects on both firm risk and firm behavior. Specifically, we measure the stability of a firm's customer base by directly observing levels of customer churn (i.e., turnover across years) using household financial transaction data. While we are not the first paper to suggest that stable customer bases are valued by firms, we are the first to directly measure customer retention and attrition across a wide range of firms using a flexible and adaptable measure.[3] This approach can be employed for both public and private firms, at high frequency and geographic granularity, and for firms without any intangible

[1] See work such as Crouzet and Eberly (2019), Eisfeldt and Papanikolaou (2014), Eisfeldt et al. (2020), Ewens et al. (2020), Belo et al. (2019), Sim et al. (2013), and Corrado et al. (2009).

[2] See e.g., Lev (2000), Lev and Radhakrishnan (2003) and Lev et al. (2009) for more on this decomposition.

[3] For instance, Belo et al. (2019), Fornell et al. (2016), Gourio and Rudanko (2014), and Morlacco and Zeke (2021) suggest that customer or brand capital can be a substantial portion of intangible value for some firms. Kleshchelski and Vincent (2009) show that firms limit price volatility due to sensitivity about customer attrition and turnover. Afrouzi et al. (2021) build a model of customer acquisition, customer demand, and market power.

assets (e.g., patents) on their balance sheet.

Unlike SG&A or R&D spending, customer churn is not a choice variable that a firm can entirely control but a direct measure of an outcome that is driven only partly by choices that a firm takes and partly by other firm, product, and geographic attributes. Just as patents can provide a realized measure of an important element of firm innovation, churn in customer bases provides a realized measure of another component of intangible capital that affects firm behavior.

In this paper, we demonstrate that household financial transaction data can create accurate customer-centric metrics that describe a wide range of firm-level attributes. This paper focuses primarily on one such metric, customer churn, but proposes, demonstrates, and makes available online others that can also be recreated using any household transaction database.[4]

While household financial transaction data has already proven invaluable to fields related to households and consumers, this paper shows that this class of data has substantial utility when applied to research regarding *firms*, as well. Across millions of households, we link transactions representing over 30% of household spending to firms in industries as diverse as retail, grocery, restaurants, aviation, utilities and telecom. Other customer-centric databases such as the Nielsen Consumer Panel cover a much narrower slice of consumer spending and also prohibit researchers from de-anonymizing retailer identities.[5]

We validate the observable trends in our household transaction data by benchmarking against authoritative public data sources like the U.S. Census retail sales report. We then push the data further, linking household transactions to firms and validating our firm-level matches against a range of data spanning firm-level revenues, prices, and geographic locations. Comparing financial and geographic characteristics for matched firms within our data to external sources, we demonstrate the household transaction database can provide an accurate picture of a firm's customer base. We can accurately predict firm revenue levels and growth when compared to Compustat and match the geographic spread of firms' establishments. Finally, we show that the average income of customer

[4]Numerous researchers in the United States and around the world have gained access to similar household financial transaction data and conduct research focusing mainly on questions relating to household decision-making. Some research utilizing financial transaction data has used sources from Mexico (Bachas et al., 2019), Singapore (Agarwal and Qian, 2014), Brazil (Medina, 2020), Turkey (Aydin, 2019), Germany (Baker et al., 2020), Iceland (Olafsson and Pagel, 2018), and the United States (e.g., Ganong and Noel (2019) and Balyuk and Williams (2021)).

[5]To our knowledge, Agarwal et al. (2020) and Klenow et al. (2020) are perhaps the only other papers that propose a similar approach. They demonstrate that disaggregated spending data can provide high quality signals about consumer demand, firm growth, and equity prices for consumer-facing firms.

bases predicts firm prices.

With this firm-linked financial transaction data, we build several measures of the churn in customer bases among hundreds of customer-facing firms. Our primary measure is the difference in individual customer spending shares among the customer base of firm f in year t and the customer base of firm f in year $t-1$. Other iterations of churn focus separately on intensive- or extensive-margin shifts in customer base growth. These measures are quite distinct from existing measures of intangible capital and are highly granular: they can be measured within the firm at a monthly and city level. The marketing literature has long discussed the importance of customer base churn, but data suitable for systematic firm-level analysis has been lacking.[6]

Using these novel measures of firm-level customer churn, we make two main contributions. First, we demonstrate that, consistent with theoretical evidence in Gilchrist et al. (2017) and Gourio and Rudanko (2014), churn is related to systematic risk and that firms without stable customer bases are more exposed to macroeconomic fluctuations. We focus on systematic risk, which despite being a central element in many models of asset pricing and corporate finance, the determinants of which are still understudied. Broadly, intangible capital is exposed to a different set of risks than physical capital. Unlike a machine or a plot of land, employees can abscond with ideas and human capital, patents can be found invalid, and customer bases can evaporate due to changing tastes or marketing blunders. We provide several pieces of evidence to support this linkage between systematic risk and churn.

We find a strong positive relationship between churn and beta across all firms in the cross-section, within industries, and even within firms over time. OLS estimates imply that a firm in the 90th percentile of churn has CAPM beta of up to 0.4 higher than a firm in the 10th percentile. Checking for non-linearities, we sort firms into value-weighted portfolios based on churn and show that CAPM beta is monotonically increasing across them. We also use the COVID-19 pandemic as a laboratory to understand why churn is related to systematic risk. We show high churn firms were the hardest hit during the beginning of the COVID pandemic, even accounting for other measures of exposure to systematic risk, size, and seasonal patterns in spending across industries.

Finally, we present evidence on another channel which links churn to systematic risk through its

[6] For instance, Ascarza (2018) discusses the importance of targeting customers likely to churn. Lemmens and Gupta (2020) notes a range of approaches to enhance customer retention, while Kleshchelski and Vincent (2009) notes that firms are highly sensitive to customer churn when setting prices.

relationship to price adjustment. Kleshchelski and Vincent (2009) argue that the main reason firms don't adjust prices is because they are worried about losing customers and market share, a concern most salient to high churn firms with unstable customer bases. Previous work (eg. Weber (2014), Gilchrist et al. (2017)) argues that such firms are more exposed to systematic risk because of their inability to adjust prices in the face of downturns. Consistent with less price setting flexibility, we show that high churn firms have significantly less variability in profit margins over time.

In addition to churn being intimately associated with higher systematic risk, measuring churn directly helps to also clarify the separate impacts of different elements of intangible capital on firm-level risk. If increases in intangible capital are embedded in employees (e.g., employee training), firm-level risk may be elevated due to the potential for employees to take their human capital and exit the firm in order to start or join a competitor (see e.g., Eisfeldt and Papanikolaou (2013)). Crucially, this mechanism depends on the extent to which measured intangible capital is embodied in movable employees rather than specific to the firm (e.g., capitalized advertising, brand promotion, loyalty programs). Consequently, we find that there is no relationship between SG&A and systematic risk among low churn firms – among low churn firms, SG&A is transformed into capital/brand value rather than employee human capital. Among high churn firms, however, the relationship is monotonically increasing from low to high SG&A. In addition, among every tercile of organization capital, there is an increasing relationship between churn and risk.

Our second contribution is to provide empirical evidence that customer churn is highly predictive of a range of other firm-level decisions regarding markups and investment dynamics. In particular, we show evidence in support of models of customer frictions where a firm's customer base acts as a sticky state variable and adjust only slowly over time. These models act as one foundation for an adjustment cost model of firm investment and yield predictions that firms with lower levels of customer base churn will have higher rates of profitability, investment, and markups, but would respond more slowly to shocks their investment opportunity set over time (e.g., Christiano et al. (2005), Eberly et al. (2012)).[7]

[7]Our findings contribute to a larger debate on how firms acquire and extract value from their customer base over the business cycle. Dou et al. (2019) show that key talent drives customer capital and financial constraints may force this talent to leave in bad times. Gilchrist et al. (2017) show that firms build customer capital with low prices but charge high prices in bad times to maintain cashflows. On the other hand, Kim (2018) shows that firms decrease prices in bad times to boost cashflows. The divergences in findings may be caused by measurement issues – these papers are forced to measure customer bases indirectly.

In both the cross-section and within firm over time, we find that firms with lower levels of churn are able to charge higher markups and support higher valuations for similarly sized customer bases. Such relationships between lower churn and higher valuations (or market-to-book values) may underpin a recent drive among firms to shift towards subscription-based business models and loyalty programs that emphasize customer base stability. Moreover, controlling for other covariates and firm fixed effects, lower levels of customer churn significantly dampens the volatility of both profits and investment. We show that churn provides a clearer picture of the impacts of customer capital on investment dynamics than other proxies such as SG&A used in previous research (eg., Gourio and Rudanko (2014)).

The rest of the paper is organized as follows. Sections 2 and 3 describe our data, matching procedure, and validation exercises. Section 4 defines customer churn, illustrates some drivers of churn, and discusses customer churn as a component of intangible capital. Section 5 details the relationship between churn and firm-level volatility and risk and how churn covaries with firm characteristics and behavior. Section 6 concludes.

2 Data

2.1 Transaction-Level Linked-Account Data

Our data comes from a large online financial service provider that acts as an online aggregator of individuals' financial accounts. Online aggregation of financial accounts is a popular service that allows users to easily monitor financial activities from across multiple financial institutions using a single web-page or smart-phone app. Further, many large banks offer aggregation services as a feature within their own websites, potentially mitigating sample selection concerns in these situations.

Once a user initially signs up for the free service, they are typically given the opportunity to provide the service with user-names and passwords to financial accounts from any financial institution, though our particular data is limited to bank and credit card accounts. After signing up, the service automatically and regularly pulls data from the user's financial institutions. The data contains transaction-level data similar to those typically found on bank or credit card statements, containing the amount, date, and description of each transaction. The full dataset contains 2.7

million users from 2010 to 2015 and, though the sample grows slowly over time, there is very little attrition in our sample.

Recent work has utilized similar transaction-based sources to make inferences about the financial habits of the broader population. For instance, Baker (2018), and Kueng (2018) also utilize similar data from an online personal finance platform. They perform a multitude of validation tests comparing to data sources such as Census Retail Sales, home price data from Zillow, the Survey of Consumer Finance, and the Consumer Expenditure Survey. They find a close parallel between household-level financial behaviors and distributions in these sources relative to those found among users of the online platform.

Ganong and Noel (2019) and Olafsson and Pagel (2018) also perform validation exercises using different household transaction data taken from JPMorgan Chase and a financial services app covering the population of Iceland, respectively. Across a range of financial indicators, they find strong evidence of external validity of their results using their sample population. Such results point to the fact that, while these types of bank-derived sources will mechanically exclude financial activity by the unbanked, transaction-level financial data can produce accurate portrayals of aggregate economic activity and household behavior.

2.2 Matching Procedure

2.2.1 Transaction Description Cleaning

We begin our analysis by matching credit and debit card transactions that we observe to firms that we can then link to time-varying firm characteristics and financial performance. The initial universe of transaction descriptions is made up of about 25 million unique strings. This reflects not only a large number of unique firms, but also differences in description strings within firm driven by things like numeric transaction descriptions (e.g., 'txn: 491349'), establishment locations (e.g., 'walmart super center lancaster'), and how different credit and debit cards include or exclude punctuation.

Because we link transaction descriptions to particular firms, we are unable to utilize transactions without an associated merchant. For instance, ATM withdrawals, physical checks, and payment apps (e.g., Venmo or Paypal) will not be able to be matched to a merchant. This introduces some measurement error into our transaction-based pictures of firms. However, cash transactions are a fairly small and shrinking component of overall consumer spending and checks are most typically utilized for large financial payments like rent and car payments rather than for the retail goods and services purchases that we focus on.

Our first step is to reduce this count of unique strings by removing capitalization, numeric characters, punctuation, and common components (e.g., 'inc'). We are then left with approximately 1.5 million unique cleaned strings. Appendix Table A.1 displays some samples of the transaction descriptions in our dataset. For each of these unique cleaned descriptions, we display the number of times that transaction is observed in our data from 2010-2015, the average transaction amount, the fraction of transactions that are debited from an account (instead of credited), and the fraction of transactions that are similar to a previous transaction with that description within a user.

Some transactions are much more commonly observed than others. This reflects both the relative size of retailers but also the degree to which a given retailer has different descriptions for different locations or types of transactions. For instance, we estimate that Walmart Inc. (and its subsidiary Sam's Club) is associated with approximately 15,000 unique description strings that span different types of Walmart stores (e.g., 'Neighborhood Market', 'Super Center'), different locations, and differences in whether debit or credit cards were used.

2.2.2 Firm Selection and Matching

Given our sample of 1.5 million unique cleaned strings, we set out to develop a set of firm names to match with these strings. Our goal is to match our transaction data to all major firms that directly transact with households and for whom we have a relatively complete picture of revenue.

We start with Compustat and the universe of public firms in a set of industries that meet our criteria of being mostly consumer-facing. These industries include building materials and garden supply, general merchandise retailers, grocery stores, restaurants, hotels, personal and business services, utilities, home furnishings, apparel, communications, and airlines.[8] In addition, to supplement our set of public firms, we search the web for lists of large private firms in these sectors.

[8] These correspond to the two-digit SIC codes: 45, 48, 49, 52, 53, 54, 55, 56, 57, 58, 59, 70, 72, and 73. We end up excluding most gasoline stations as their revenue is typically combined with a large refiner or oil producer and thus, while the consumer-facing side is well observed, the consumer-facing business does not provide a good gauge of overall firm revenue or operations.

We find lists from sources such as Business Insider, Forbes, and Wikipedia that enumerate the largest firms and retailers in a range of categories. In total, firms in these industries cover trillions of dollars of revenue per year and represent a larger portion of GDP than manufacturing.

For each of these firms, we then manually search our database of unique transaction strings for transactions that mention the firm name precisely or a range of potential abbreviations and variants of a firm's name. Most firms have a multitude of distinct strings associated with them across different establishments, payment types, and brands (e.g., 'wal mart', 'walmart', 'wm super center', 'sams club', 'walmart sacramento', 'walmart joliet', etc.).

Using regular expressions to define our match criteria, our goal is to capture as many true positives as possible while not flagging excessive amounts of false positives. For instance, the term 'subway' will match sandwich purchases at a Subway restaurant but also transactions made at any number of public subway systems around the world or any of the hundreds of small businesses whose name includes the word 'subway'. For this reason, we also often employ limitations in our matching procedure based on retailer category (which is captured in our transaction database) as well as transaction sizes. As one example, when attempting to match Subway sandwich stores, we limit the retailer category of the transaction description to restaurants and the *average* transaction size for the transaction description to under 20 dollars.

Unfortunately, traditional machine learning algorithms are not well suited to the task of mapping these transaction descriptions to firms. Given the huge set of firms in the transaction data (everything from large national retailers to single-establishment stores), automated methods that rely on string-similarity measures tend to produce extremely high rates of false positives. Moreover, many firms' descriptions are dissimilar to their official firm name (e.g., 'tgt' may refer to 'Target Corporation'). For this reason, we mostly rely on manual inspection and experimentation to find descriptions that map to firms. In our entire sample of matched retailers, the mean number of unique text descriptions associated with a given retailer is 176 and the median number is 41.

After working through our sets of large public and private consumer-facing firms, we turn directly to the transaction data to fill in any potential holes in the data. We attempt to map any unmatched transaction descriptions within the most frequent 10,000 transaction descriptions. Generally, these descriptions refer to firms from an industry that we did not previously inspect. For instance, Lyft and Uber appear frequently in our data but are assigned a two-digit SIC industry of

41 (Local And Suburban Transit And Interurban Highway Passenger Transportation). Netflix similarly was not in one of our focused consumer facing industries according to our SIC classification (it is found with two-digit SIC of 78, which mostly contains movie producers).

Because some firms span a number of distinct brands, we must use data on subsidiaries to link brands to their parent company. For example, Yum! Brands is the corporation that owns brands like Taco Bell, Pizza Hut, and KFC. When households purchase food from one of these restaurants, their credit or debit transaction will list the merchant as 'Taco Bell' rather than 'Yum! Brands'. For the purposes of this paper's analysis, we collect household transactions across all of these brands to arrive at firm-level statistics. For future work, one benefit of this class of data is that revenue and customer information can be separately identified by brand within a parent firm.

2.2.3 Matched Firm Sample

In the end, we are able to match 428 public and 130 private firms within our sample window. While these firms constitute a small fraction of total firms, they are also by far the largest consumer facing firms in the economy. To illustrate this, we match our public firm data to Compustat and rank firms based on their total 2014 revenue. In all industries, the average firm in our matched dataset is large relative to the average firm in Compustat. In total, we are able to assign approximately 32% of total consumer spending in our dataset to a matched firm.[9]

For industries where we have extensive coverage, like airlines, general merchandise, and groceries, we are able to match all of the largest firms. In other industries we have only partial coverage of top firms. For example, we do not match to the Disney Corporation, one of the largest firms in the consumer telecom industry because generally households do not interact directly with the parent company itself (rather they interact through retailers of toys or movie theaters). Similarly, the International Game Technology company is one of the largest 'entertainment industry' firms, but it makes slot machines so has few direct transactions with households. Other firms in our partially covered industries transact mostly with businesses.

Table 1 provides some summary statistics regarding our matched firm-level data. In the first row, we see the median firm in our sample receives approximately $1.6M from the linked users in

[9]Appendix Table A.2 compares the numerical ranks (with one being the highest), and percentile ranks (with 100% being the highest) of the firms in our matched sample by industry.

our sample in a given quarter. Firm-level spending is skewed towards the largest firms, with the average firm receiving about \$8.4M. The largest single firm (Walmart) has approximately \$550M per quarter of observable revenue from our sample of users.

The second row in the table displays the fraction of firm's quarterly revenue that we observe among the users in our matched sample. We can only calculate this statistic for public firms with data available in Compustat. On average, we capture about 0.6% of a firm's quarterly revenue (median of 0.4%). There is substantial heterogeneity in the fraction of revenue that we observe in our data – the fraction may be impacted by the portion of a firm's revenue obtained from foreign consumers, whether a firm has substantial business-to-business revenue that is unobserved in our data, and if a firm has a large portion of transactions conducted with cash rather than credit or debit cards. In the third and fourth rows, we note the number of transactions as well as the number of unique users that we can link to a firm in a given quarter. In general, each firm-quarter observation receives tens of thousands of transactions in our data from tens of thousands of users.

We think that this matching procedure suffices for illustrating the benefits of better understanding customer churn and similarities across firms. Given the amount of research that focuses solely on publicly traded firms, a limitation to large firms is not necessarily an impediment to inference regarding important drivers of firm behavior, in general. However, for researchers interested in more fully mapping out networks of competition, entry and exit, or private firms, it may be necessary to expand the matched sample. With additional work, it is possible for researchers to substantially increase the number of matches to smaller firms within the categories that we already focus on (e.g., smaller independent restaurants and retailers). Moreover, the procedure can be easily extended to similar household financial transaction datasets that have longer time horizons, allowing for a more thorough analysis of shifts in customer bases within a firm over time.

While our data appears to provide a high quality picture of the customer bases and disaggregated revenue of the firms in our sample, we are limited in our analysis to a set of large consumer-facing firms. In principle, other sectors such as manufacturing or service firms selling primarily to businesses may face similar impacts from customer churn. However, customer dynamics may be different in these sectors owing to generally higher transaction amounts and more complex contracts and sales terms than among firms selling direct-to-consumer.

3 Validation of Firm Matching and Transaction Data

In this section, we provide evidence that our transaction data provides a meaningful view of both consumer spending in general and also of individual firm characteristics. In particular, we examine whether our linked transaction-firm data can accurately describe the sources of firms' revenue, the geographic distribution of retailers' activity, and provide a proxy for firm price levels.

3.1 Transaction Data Validation

Our sample is not drawn from a random sample of the population, but it appears to be widely representative with some exceptions. Relative to other FinTech data providers with products aimed at narrower slices of the population (e.g., lower income households or households interested in peer-to-peer lending), this data is sourced from a much broader range of households. This database is also used in Baugh et al. (2018) and Baugh and Correia (2022) where the authors illustrate that the income distribution of users in the sample is comparable to that of the U.S., with substantial deviations only in the lowest income bins (e.g., households earning under $10,000 per year; see Appendix Figure A.1). We also find that users in our sample are well dispersed geographically in the United States, though we have higher concentrations of users in the states of California, New York, and Texas relative to true population distributions. However, dropping members from any given state or the top and bottom income deciles does not substantially impact our results.

One challenge of working with aggregator data is determining the accuracy of key variables, such as income and consumption. Our ability to correctly measure income depends on whether a user has linked the bank account that receives their direct deposit paychecks. If we observe no income in linked checking accounts, it is impossible for us to determine whether the user truly has zero income or is simply receiving income in an unlinked account. To mitigate this concern, restrict our analysis to the subset of users for whom we observe over $500 of income flowing to their checking accounts. Further, similar to Baker (2018), we compare household spending in our dataset with the U.S. Census monthly retail trade report in the categories of general merchandise, groceries, restaurants, and gas. Spending for both data sources is scaled to the value of 1 in January of 2011. As shown in Figure A.2, the spending patterns in our sample closely mirror the monthly retail trade report for the given categories. The correlation between the aggregator data to the monthly retail trade report averages 89% across the four categories, with the highest correlation of 96% occurring in the category of general merchandise.

3.2 Firm Matching Validation

3.2.1 Customer Characteristics and Revenue

Our first firm matching validation test is to directly compare the official revenue data to the spending that we observe at that firm for the subset of public firms in our sample (428 of 558 firms).

We match total aggregated consumer spending for public firms in our sample to their quarterly Compustat revenue data from 2010 to 2015. Given that our cleaned sample contains approximately 1.7 million users, out of a total U.S. adult population of 245 million (as of 2014), we would expect that the spending we observe would make up approximately 0.7% of revenue that these firms report if all firm revenue was obtained directly from consumers located in the United States. For firms in our matched sample, we observe an average of 0.6% of quarterly revenue (and a median of 0.4%), reflecting the fact that firms in our sample obtain a portion of their revenue from sources that we do not observe such as consumers overseas or from other businesses.

In Figure 1, we plot both levels and changes in logged spending against levels and changes in logged Compustat revenue. While the absolute levels are different owing to the fact that we observe only a fraction of individuals in the economy, we find a strong correlation between our own spending data and the revenue reported by public firms in relative terms. We do a good job of matching relative sizes of firms as well as the within-firm quarter-to-quarter growth dynamics over time. Our measure achieves higher rates of correlation and fit when restricting to firms that do not have sizable operations overseas. In addition, we see closer correlations when we exclude firms that have larger fractions of business-to-business revenue.

3.2.2 Geographic Locations - Chain Store Guides

We also test whether the geographical distribution of stores and firm-level revenue in our data matches the empirical distribution of their stores. To do this, we utilize data from Chain Store Guide (CSG) database, which tracks the physical locations of retailer branches for a wide range of large regional or national chains. In addition, they include some characteristics about the types of establishments, size of stores, and branch number. We collect CSG data from the entirety of our sample period (2010-2015).

We are able to match 58 firms from the CSG database to our sample of firms. We then construct two measures of firm geographic dispersion from our transaction data. First, we simply calculate the fraction of consumer spending that we observe from users in a given state at a particular firm for each year in our sample.

$$FracSpend_{ist} = \frac{\sum_i spending_{irst}}{\sum_i \sum_s spending_{irst}}$$

Where i indexes users, r indexes retailers, s indexes states (and Washington DC), and t represents a calendar year.

We would not necessarily expect a perfect one-to-one relationship between these measures for each retailer. Especially for the fraction of spending we observe, since we do not have establishment-level sales data. While a state may have 10% of a retailer's physical stores, those stores may account for 15% of that retailer's national sales. However, on average we would expect a strong relationship between these measures.

As a second geographic metric, using the transaction-level description strings, we are able to pick out transactions at particular retailers' locations. For instance, a transaction may be labeled as 'McDonalds (Store #391)' rather than simply as 'McDonalds'. We utilize this to construct a measure of the fraction of a retailer's locations in a state each year. We also construct the analog to this variable from the CSG data: the fraction of stores in a given state for a firm-year observation.

In Figure 2, we display bin-scatter plots of these measures across all state-years in our sample. In the top row, we plot the relationship between the two store level measures (fraction of stores by state-year-retailer in our transaction data against fraction of stores by state-year-retailer in the CSG data). The right panel censors the plot to better highlight the fit among the smaller states. The bottom row displays the relationships between the fraction of spending that we observe for a retailer in a state-year against the fraction of stores from the CSG data in a state-year.[10] Across all specifications, there is a strong positive relationship between the geographic distribution of spending in the CSG data and in our transaction data.

[10] Appendix Figure A.3 breaks down these comparisons by state. In all cases, we see a strong relationship that lies quite close to the 45-degree line, suggesting that we are getting an accurate and unbiased sample of the geographic distribution of spending, on average.

3.2.3 Customer Income and Firm-Level Prices

Another aspect of firm customer bases that can be easily surmised from transaction-level data is that of the average income of any given consumer-facing firm. We construct a quarterly index of the average user income of a store's clients, weighted by the amount they spend at that retailer:

$$Quality_{rt} = \frac{\sum_i spending_{irt} * income_{it}}{\sum_i spending_{irt}}$$

Where r identifies a retailer, i indexes users, and t refers to a calendar year. Firms in our sample exhibit large differences in this measure, aligning well with an ex-ante notion of the firm's quality. This measure correlates strongly with other indicators of retailer quality and prices. From Yelp.com, we are able to obtain indicators of how expensive the average product at a particular firm is for about two thirds of our sample of firms. For each matched firm, we record a rating between $ and $$$$ that indicates low to high prices, respectively. We regress our measure of firm quality on indicators for these price rankings and report the results in Table 2.

Unsurprisingly, we find that firms that have higher income customer bases in our data tend to be those selling higher priced goods, on average. This is both true overall and in all subcategories of firm that we examine. For instance, relative to the average customer of the lowest priced restaurants ($), the average customer of the highest priced restaurants in our sample ($$$$) tends to have a $24,016 higher annual income.

4 Measuring Customer Base Churn

We now turn to our transaction-based measure of churn within a firm's customer base. Broadly, we claim that customer base attributes attainable from transaction data can add significantly to the understanding of firms and cross-sectional heterogeneity among firms. For consumer-facing firms, our measure of churn offers a more fundamental window into the consumer attachment to firms and a clearer metric of an important element of intangible capital.[11]

We measure customer base churn as the dissimilarity between the customer base of firm f in year t and the customer base of firm f in year $t - k$, weighted by customer spending at that firm.

[11]The firm-specific measures used in this paper, along with other firm customer base data, are available on the authors websites.

We define $s_{f,i,t}$ as the share of firm f's revenue in our matched sample that comes from customer i in year t. This definition implies that $s_{f,i,t} \in [0,1]$ and $\sum_i s_{f,i,t} = 1$ for all f and t:

$$Churn_{f,t-k} = \left(\sum_i |s_{f,i,t} - s_{f,i,t-k}| \right) / (2) \tag{1}$$

where the sum $\sum_i |s_{f,i,t} - s_{f,i,t-k}|$ is taken over all customers that shop at firm f in *either* year t or year $t-k$. In words, churn is the difference in spending shares coming from each customer i between years t and $t-k$. The way it is defined, $\sum_i |s_{f,i,t} - s_{f,i,t-k}|$ can vary between zero and two. A value of zero would imply constant revenue shares, and a constant customer base between years t and $t-k$, while a value of two implies a completely different customer base. We divide this by 2 so churn is normalized to values between 0 and 1.[12]

In this calculation, we require that customers are observed in our data in both years so that our measure of churn is not conflating attrition from our sample with attrition from a customer base. The sample has very low attrition; re-computing our churn measure without this restriction has a correlation of approximately 0.98 with the restricted measure that we utilize.

In the Appendix, we discuss the robustness of this measure to variants which focus on particular aspects of customer churn. For instance, we develop two metrics that more specifically track the extensive margin adjustment of the customer base: the fraction of spending sourced from new customers in a given year and the fraction of spending from the previous year conducted by customers that left the customer base in the current year. Both variants are highly correlated with our baseline measure, with correlation coefficients of 0.91 and 0.81, respectively. We also construct measures restricting to particular sets of customers or adjust for the extent by which spending per customer increases proportionally. Finally, we construct measures of customer loyalty derived from the frequency of purchases at a particular store relative to all spending within a category. All measures are highly correlated with one another and our main results are robust to using alternative definitions of churn.

[12] In Appendix Figure A.4, we plot histograms of this measure across all firms for $k = [1,4]$. As one would expect, churn increases over time. That is, the customer base of a firm at time t is more similar to the customer base of that firm at time $t-1$ than at time $t-4$. There is substantial spread among firms at all horizons: at the most extreme, about 10% of firms see 90% of their revenue coming from new customers.

4.1 Drivers of Customer Base Churn

Figure 3 highlights the fact that much of the variation in rates of customer churn is driven by systematic differences across industries. Firms in industries like Utilities, Telecom, and Groceries tend to have highly persistent customer base distributions. In contrast, the customers in industries such as Hotels, Car Rentals, and Clothing retailers tend to be much less persistent across years. Some of this variation is driven by the nature of contracts and competition within these industries. For instance, an individual likely only has a customer relationship with a single electricity provider, and this likely stays constant over time until a major move. Similarly, households tend to gravitate to a single local grocery store to a larger extent than they do for other retail stores. Consequently, churn tends to be fairly consistent within firms over time. For instance, regressing churn on lagged churn yields a coefficient of 0.85 and a correlation coefficient of 0.84.

Similarly, some customer churn may be driven by factors such as regional concentration among retailers, firm-specific loyalty programs, or contractual agreements. For instance, if a retailer has no local competition in a retail category, it may be difficult for customers to patronize competitors, even if they would so desire. Moreover, long-term contracts increase switching costs and likely dampen churn in customer bases as well as the marginal impact of local competition.

Figure 4 plots within-city churn against local categorical sales shares for two groups of firms. In each group, we find that increases in local competition predict increases in local churn in customer bases.[13] We see, however, notable differences between two categories of retailers: one composed of firms who generally have longer-term contracts (Utilities and Telecom firms) and the other composed of firms that who interact with customers through one-off purchases (Restaurants, Convenience Stores, General Merchandise, Groceries, and Entertainment). For 'Regular Purchase' firms, cities in which a firm tends to have fewer major competitors see much lower levels of churn. In contrast, for 'Long-term Contract' firms, the local sales shares have substantially smaller impacts. That is, even with ample local competition, customers are often locked into a given firm for a number of years through contractual provisions.

[13] Local spending shares are defined as $\frac{Spending_{icjt}}{\sum Spending_{cjt}}$ where i indexes firms, c indexes categories of spending, j indexes cities, and t indexes years. In Appendix Table A.3, we show the association between levels of local categorical spending share and churn, conditional on a range of fixed effects. Higher levels of local categorical sales dominance tend to drive significantly lower levels of customer churn. Moreover, this local sales dominance produces large increases in R^2.

While firms exhibit large differences in their average levels of customer churn when compared to each other, substantial changes in firm-level churn can take place over time within a firm. JC Penny provides one case study of how measured customer churn can be affected by corporate decision-making and customer-facing policies. After declines in sales growth in previous years and a campaign by activist investor Bill Ackman, Ron Johnson was appointed as CEO in 2011. Johnson spearheaded a drastic change in pricing at the retailer in Q1 2012, doing away with most of the "sale" and coupon-based pricing and instituting consistent low prices across the store, mirroring the approach at Johnson's former employer, Apple. JC Penney's customer base reacted strongly and negatively to this change, increasing turnover substantially in the ensuing years.

In Figure 5, we show the rate of quarter-on-quarter customer churn for JC Penney during our sample window normalized by average churn for that quarter within the 1-digit SIC industry. The red vertical line denotes the timing of the change in pricing policy. We see a large and persistent increase in churn, approximately 1.5 standard deviations, following this change. This shift, the largest quarterly change in churn for JC Penney during our sample period, is driven mostly by increases in the attrition of existing customers.

4.2 Customer Bases as a Component of Intangible Capital

Many papers have discussed the rise in intangible capital over the past decades and how this rise can lead economists and policymakers to mis-measure things like productivity growth, competition, and markups.[14] The overall stock of intangible capital held by a firm is often measured by means of acquisition premia (e.g., Ewens et al. (2020)) or through a perpetual inventory method which aggregates flows of SG&A or R&D spending (e.g., Eisfeldt et al. (2020)).

However, intangible capital is not an undifferentiated concept: it reflects an amalgamation of a number of components such as R&D and patent holdings, advertising or brand capital, knowledge capital held by workers, and business practices such as software utilization or novel supply chains, customer capital, and organization capital. Independent measurement of these pieces is important as they may not be highly correlated with one another (or even positively correlated). While overall productivity may hinge on aggregate intangible capital, other elements of firm-level risk

[14] A small sample of papers include: Crouzet and Eberly (2019), Eisfeldt and Papanikolaou (2014), Eisfeldt et al. (2020), Ewens et al. (2020), Belo et al. (2019), Sim et al. (2013), Corrado et al. (2009).

or decision-making may depend on only a subset of these types. Therefore, utilizing aggregate intangible capital may yield biased estimates when examining the impacts on firm-level outcomes.

As a stark example, Figure 6 displays the correlation between firm-year intangibles proxies and our measure of firm-level customer churn. Splitting our sample into retail and non-retail firms, a clear picture emerges: the relationship between customer churn and SG&A (or advertising expenditures) is negative for non-retail firms but highly positive for retail firms. Other work (e.g., De Loecker et al. (2020), Traina (2021), and Ayyagari et al. (2019)) has discussed in aggregate whether SG&A can be treated as an intangible investment or as a marginal operating expense, but here we see variation in SG&A's relationship with customer attachment cross-sectionally. Using advertising expenses or SG&A as a proxy for customer attachment or brand capital will lead researchers to substantially different conclusions in different industries. Our measure of customer churn speaks directly to this element of intangible capital: higher levels of customer attachment to a firm and/or brand manifest in lower levels of churn within a firm's customer base.

Table 3 highlights an association between customer churn and some customer-related intangible capital both within and across firms and industries, controlling for firm size. For instance, Columns 1 and 2 examine the relationship between customer churn and firms' book-to-market ratios, finding that firms with lower levels of churn command higher market values relative to their book value. Columns 3 and 4 find that brand value is highly correlated with levels of customer churn. Columns 5 and 6 show how average market value per customer of a firm is related to differences in average churn across firms. A one standard deviation decrease in churn is associated with an increase in per-customer market value of 25-40%, an effect that persists even after additionally controlling for markups and brand value.[15]

Finally, in Columns 7 and 8, we note that lower levels of churn are also associated with higher markups. Overall, lower churn in a firm's customer base tends to manifest as a more valuable customer base. The ability to retain customers, as measured by churn, can allow firms to increase margins and profits, yielding higher market values and lower book-to-market levels.

[15]Values calculated by Brand Finance's Brandirectory which looks at components such as emotional connection, financial performance and sustainability and then applies royalty rates to calculate a capitalized brand value. Appendix Figure A.5 displays the relationship between brand value rankings and churn across a range of industry categories. Markup data are obtained from Loualiche (Forthcoming) who calculates markups using the method in De Loecker et al. (2020). Number of customers for a firm is estimated by first calculating average spending per customer at a firm in our data, then dividing total firm sales (from Compustat) by that average customer spending.

Beyond firm values and markups, customer churn is also correlated with a firm's capital structure. In particular, leverage has been previously been noted to be negatively correlated with various metrics of intangible asset intensity across firms (see e.g., Crouzet and Eberly (2019) and Caglio et al. (2021)). This may be driven by the fact that intangible capital, unlike physical capital, cannot be used as collateral for asset-backed borrowing.[16] Indeed, in Table 4, we find that high churn firms tend to hold much less cash and are much more highly levered than low churn firms. This dynamic holds even when controlling for other proxies for intangible capital like levels of SG&A or R&D within a firm.

5 Customer Churn and Firm Risk

Churn in firm-level customer bases over time is a key metric with which to assess customer-facing firms. Higher levels of churn in customer bases can be a source of risk and volatility across firms who rely on such customers for their sales. To demonstrate this, we run the following regression:

$$Outcome_{i,t} = \alpha + \beta Churn_{i,(t-1,t)} + \gamma ln(Revenue_{i,t-1}) + \text{FE} + \epsilon_{i,t} \tag{2}$$

where $Churn_{i,(t-1,t)}$ is measured based on each year's customer base, relative to the previous year's customer base, $Revenue_{i,t-1}$ is the firm's total revenue in Compustat last year, and FE represent industry- or firm-level fixed effects. In terms of outcomes, we focus on CAPM beta and idiosyncratic stock volatility, but find similar results using total stock volatility or revenue volatility.

Column 1 in Table 5 shows a strong positive correlation between our measure of churn and CAPM beta. In terms of magnitudes, the point estimate implies that a firm in the 90th percentile of churn (0.87) has a 0.39 higher CAPM beta than a firm in the 10th percentile (0.30). Columns 2-3 show that including fixed effects for 2-digit SIC industries or Hoberg and Phillips (2010)-50 industries shrinks the point estimate by about 50%, but the relationship between churn and CAPM beta remains statistically significant.

[16]Recently, however, firms have begun to use the strength of their customer base as a source of collateral. For example, during the COVID-19 outbreak, airlines borrowed billions of dollars against their loyalty programs to fund operating losses.

Column 4 shows that the relationship between churn and CAPM beta survives including firm-level fixed effects. This is a high bar, as we only have 4 years of data for each firm. Finally, columns 5-8 show the results for idiosyncratic volatility, which mirror those for CAPM beta. Overall, our results suggest that firms which have more churn in their customer bases are riskier and more volatile than other firms and that changes in churn over time predict changes in risk and volatility within a firm.

While these results suggest a strong relationship between customer churn and firm volatility, two potential issues arise from Equation 2. First, this estimation approach may be masking a potential non-linear or non-monotonic relationship between churn and risk. Second, because observations are equally weighted, the estimates may be heavily influenced by small firms. To rule out these issues, we form value-weighted portfolios of firms based on the churn in their customer base and test the relationship between average churn and firm-level equity price volatility between 2010 and 2019. In Appendix Table A.4, we find that CAPM betas monotonically increase from low churn to high churn portfolios but that the positive relationship between churn and CAPM beta is mostly coming from the extreme portfolios.[17]

Finally, in the appendix, we provide another link between churn and systematic risk through its relationship to price adjustment. This is motivated by Kleshchelski and Vincent (2009), who argue that the main reason firms don't adjust prices is because they are worried about losing customers and market share. It seems natural that high churn firms would be the most sensitive to this concern as their customers exhibit the least attachment to the firm. This concern may expose high churn firms to more systematic risk because such firms might be unable to adjust prices in the face of economic downturns (Weber (2014), Gilchrist et al. (2017)). While we cannot directly observe firms' prices, we compute firm-level standard deviation of various margin measures between 2010 and 2019 and run a regression of margin volatility on churn in Appendix Table A.5. In each case, we find a negative relationship between churn and margin variability, which survives including category fixed effects (though significance is sometimes marginal given we have only around 300 observations).

[17]Another concern is that these results are driven by the relationship between firm size and churn. To rule this out, we perform a double sort, first forming 3 groups based on a firm's total revenue in the previous year and then forming 3 sub-groups based on churn. Appendix Table A.6 shows that the monotonic increasing relationship between churn and CAPM beta holds within each tercile of firm revenue.

5.1 Firm-Specific Revenue Declines During COVID-19

COVID-19 presented an opportunity to perform an out of sample test of how having low customer-base attachment (high churn) can drive demand-side risk for firms. Baker et al. (2021) noted that the tendency for households to visit new retailers declines as income declines. This may manifest during a recession with households retrenching into their usual retailers and restaurants and not trying out somewhere they have not visited before. These firms may also lack the ability to adjust prices as freely during downturns to retain customers and marketshare (Weber (2014))

To test this effect, we examine whether firms relying on a steady stream of new customers (i.e., high churn) are more strongly impacted by the recent COVID-19 outbreak and recession.

During March 2020, city and state governments began unprecedented efforts to halt the spread of COVID-19 by dramatically limiting the ability of retail businesses to remain open and to operate normally. Many businesses were virtually halted or else mandated to operate only remotely. For instance, restaurants were often required to allow only take-out or delivery orders, and many other retail establishments were forced to operate only online, using delivery services or curbside pickup.

In Table 6, we utilize data from the SafeGraph Data Consortium to examine the impact of these events on consumer spending at a range of retail establishments and how these changes in spending are linked to rates of churn measured at those retailers in earlier years. SafeGraph uses data from a range of debit cards to track aggregated levels of daily consumer spending across merchants. We use daily spending data from January 2019 through the end of March 2020 and can observe hundreds of millions of transactions at retailers linked to our measure of customer churn.

Column 1 shows that firms, on average, saw 30% reductions in customer spending during March 2020 as compared to March 2019. In Column 2, we see that firms with high levels of customer churn (estimated using the 2010-2015 data) saw much larger declines in customer traffic and spending than those with low levels of churn: a firm in the top quartile of churn saw a decline in spending about three times larger than those in the bottom quartile. In Column 3, we retain a strong negative impact of churn above and beyond controls for firm-level equity betas and firm size interacted with indicators for March 2020.

While there are substantial concerns about differential treatment across different sectors of the economy during COVID (e.g., some types of retailers faced more legal restrictions than others), these correlations between revenue declines and customer churn are not driven by differences across industries. Using both industry and industry by month fixed effects in columns 4 and 5, we see that the effect persists with a similar magnitude. That is, even controlling for the average industry-level decline in consumer spending during March 2020, high churn firms still tended to see declines in consumer spending substantially greater than among low churn firms in the same sector.

5.2 Churn and Organization Capital

Separately identifying customer attachment as a component of intangible capital can not only make inferences regarding risk and customer capital clearer, but can also clarify the impacts of other elements of intangible capital within a firm. For example, consider the model in Eisfeldt and Papanikolaou (2013). Firm i's output at time t, $y_{i,t}$, is a function of its initial endowment of physical capital K_i and organization capital O_i. Specifically:

$$y_{i,t} = \theta_t K_i + \theta_t e^{\epsilon_i} O_i \tag{3}$$

where θ_t is a disembodied technology shock that affects both forms of capital and follows a geometric random walk.

In this model, higher levels of organization capital make a firm riskier both in terms of total stock return volatility and CAPM beta. Organization capital is a source of risk because firm i's efficiency in using O_i, ϵ_i, is set to the level of aggregate efficiency, x_t, at the time the firm is founded. Efficiency follows a random walk, so if x_t becomes sufficiently high, it is attractive for employees to start a new firm. O_i is specific to employees, not the firm, so they can take the stock of O_i with them and use it more efficiently in the new firm. As a result, x_t shocks become a source of risk for firms, where exposure is proportional to the level of organization capital. Sun and Xiaolan (2019), using capitalized R&D expenditures to proxy for intangible capital, is among the other models that have embedded intangible capital in firms' employees.

Our prior is that there are multiple types of organization capital that have different implications for firm riskiness. One way to formalize this thinking is to modify the baseline model of Eisfeldt and Papanikolaou (2013), splitting organization capital into two components: (1) $O_i^{employees}$ which employees can take with them if they start a new firm and (2) O_i^{brand} which is specific to the firm and thus cannot be absconded with by the employees.

In our proposed modification, $O_i = O_i^{employees} + O_i^{brand}$, so it is possibles for firms to have high O_i, but not be very risky. Specifically, higher levels of O_i^{brand} do not expose firms to more x_t risk. We believe firms with low churn have relatively more of their organization capital in brand value, while firms with high churn have more of their organization capital accrue to their employees.

To test our hypothesis regarding different types of organization capital, each month we perform a 3×3 sort on churn and (Organization capital)/(Total book assets plus organization capital), hereafter OK/AT. Organization capital is measured by capitalizing SG&A in a perpetual inventory method (see e.g., Eisfeldt and Papanikolaou (2013), Eisfeldt and Papanikolaou (2014), Eisfeldt et al. (2020)).[18] To this end, we first sort firms into 3 terciles of churn. Then, within each of these 3 buckets, we form 3 sub-terciles based on OK/AT. To reduce the influence of small firms, within each month, observations are value-weighted within each of the 9 portfolios.

Table 7 contains the results. Consistent with our prior, we see that there is a monotonic increasing relationship between OK/AT and CAPM beta among high churn firms, but the relationship is essentially flat among low churn firms. We believe that this is because if a firm has both low churn, but high organization capital, SG&A is accruing to the firm through the creation of brand capital. The fact that this type of organization capital is sticky means that these firms are not riskier than low churn firms with less organization capital.

The opposite is true for the firms with high organization capital and high churn: their investments in intangible capital (i.e., SG&A) are accruing to employees. Because employees can leave the firm at any time, this stock of organization capital makes these firms riskier.[19]

5.3 Customer Churn and Firm-level Investment

Beyond a relationship with firm risk, we seek to apply our measure of customer churn to a framework that highlights the importance of this specific component of intangible capital and produces predictions for firms' investment behavior. Capital and labor adjustment cost models have been extended to feature customer frictions (i.e., accounting for customer attachment or loyalty) when

[18]We obtain data on organization capital scaled by total assets from the authors' GitHub repository. Following Eisfeldt et al. (2020), we remove all observations were OK/AT is 0 because SG&A is missing/zero in Compustat, or where OK/AT is less than zero because book assets are less than zero.

[19]Appendix Table A.7 performs a triple sort on size, churn and OK/AT to rule out that these results are driven by size. The relationship between OK/AT and CAPM beta is strongest among high churn firms in each firm size bin.

shifting across firms or products. In such models, customer bases act as state variables and thus can affect the rate of return on any given investment. As laid out in Christiano et al. (2005), these investment adjustment costs can take the form:

$$k_{t+1} = (1-\delta)k_t + F(i_t, i_{t-1}) \tag{4}$$

$$F(i_t, i_{t-1}) = \left(1 - S\left(\frac{i_t}{i_{t-1}}\right)\right) i_t \tag{5}$$

where each period a share δ of capital depreciates and firms purchase investment goods, i_t, to increase the capital stock. The function $F(i_t, i_{t-1})$ describes how current and past investment is transformed into installed capital that can be utilized by the firm in the next period. The convex function $S\left(\frac{i_t}{i_{t-1}}\right)$ penalizes deviations from the prior level of investment, with $S(1) = 0$.

These adjustment costs shift firms' responses to investment opportunities away from a frictionless benchmark. In the limit, without frictions, markups and profits are zero and Tobin's q is equal to one (where market value is equal to book value and the marginal dollar of investment will not affect the value of the firm). In a framework that features customer or product frictions, firms with a higher degree of customer stickiness can be expected to have higher levels of markups and higher market-to-book value (Q), consistent with our findings in Table 3. Firms with high levels of customer attachment (and low customer churn), are able to extract value from their customers over time after initial investments in customer acquisition.

Moreover, such low-churn or low-friction firms are predicted to feature an investment profile that is smoother over time (see Eberly et al. (2012)). Customer base adjustment frictions lead these firms to adjust more slowly to new investment opportunities, resulting in weaker investment responses to changes in Tobin's Q. High churn firms would be predicted to more closely approximate the frictionless benchmark in a neoclassical model wherein increases in firm productivity drive immediate increases in firm investment.

Gourio and Rudanko (2014) pursue this general line of reasoning, building a model of product market competition that features customer attachment driven by frictions in search that prevent customers from costlessly shifting between firms. This model results in sticky customer bases and generates the empirical implications for firm-level characteristics and behavior as described above. They use SG&A spending to proxy for levels of frictions that will generate more stable customer bases for some industries than others.

Our measures of firm-level customer churn can be seen as identifying heterogeneity in the function $S(\cdot)$ across firms, as some customer bases are more difficult to adjust than others. They are also consistent with identifying time-series variation in $S(\cdot)$, as e.g., it may be more costly to adjust a customer base during a recession when people are hesitant to try new firms/products.

Table 4 explicitly tests these theoretical predictions using our measure of customer churn, controlling for time and firm or industry fixed effects as well as firm size (as proxied by sales). Following results in Table 3, in Column 3 we note that firms with low levels of customer churn do tend to also have high market-to-book values relative to other firms in their industries. Consistent with more responsive investment rates in the model, we find that customer churn is a strong predictor of more volatile investment rates over time within a firm in Column 4.

We then examine whether customer churn is associated with differences in firms' responses to Q shocks and whether these predictions hold for SG&A as well. That is, we test whether the neoclassical model, in which firm investment responds immediately to changes in productivity, is a weaker fit for firms with high levels of customer attachment (and low customer churn). Explicitly required for SG&A to perform well as a proxy for customer capital is that SG&A is highly linked to firms or industries that have high barriers/frictions in their markets.

In Column 5, we show that firms with low levels of SG&A do appear to be more like 'classical' no-adjustment-cost firms who respond more strongly to shocks to Q than firms with higher levels of SG&A spending. In Column 6, we repeat this regression, restricting the sample solely to firms in the retail sector (SIC-1 code of 5). Here, the coefficient on SG&A switches sign and is significantly different than zero, producing an effect opposite to our prediction. We assert that this change in sign is not due to this conceptual model failing among such firms, but because SG&A is not a good predictor of customer stickiness within the retail industry. Firms in this industry with the highest levels of customer attachment tend to be those that actually spend only small amounts on SG&A, as seen in Figure 6.

Finally, Columns 7 and 8 include an interaction of lagged Q with an indicator for a firm having higher than median levels of annual customer churn alongside the low SG&A indicator. Here, the interaction terms on the high churn are highly significant and of the predicted sign when examining all firms and when restricting to retailers. High churn firms tend to respond about 50% more strongly to changes in Q than do low churn firms. Moreover, controlling for firm-level churn renders the coefficients on the SG&A interaction term near-zero in magnitude and statistically insignificant.

In short, our measure of customer churn consistently demonstrates the impacts of firm-level customer search frictions and provides further empirical support for an adjustment cost model proposed by Christiano et al. (2005). Moreover, we find that using SG&A yields substantially biased estimates of the effects of customer capital on firm markups and investment behavior.

6 Conclusion

With the importance of intangible capital among firms growing substantially in the past few decades, it is imperative to have metrics that clearly identify its components. These measures can help to illustrate the drivers of heterogeneity across industries and firms when it comes to risk, investment, and markups. Intangible capital is generally described as an amalgamation of a number of components such as brand or customer capital, organization capital, business practices, and applied R&D/patent activity but is often measured in an undifferentiated manner.

Using credit and debit card transaction data, this paper demonstrates that it is possible to construct accurate pictures of firm characteristics at a highly granular level for both public and private customer-facing firms. We use this data to develop measures of firm-specific churn in customer bases that vary over time and aims to provide a tool to disentangle important elements of intangible capital across firms.

Customer churn is important for understanding both firm financial and economic outcomes. Churn correlates highly with a range of metrics of firm-level risk and volatility and outperforms typical measures in predicting revenue declines during the COVID-19 pandemic. We demonstrate that churn uniquely captures elements of customer and organization capital that are unobserved when using a proxy like SG&A spending, better explaining cross-sectional variation in markups, investment behavior, and equity returns.

In addition, this paper highlights the broader potential for further customer centric measures to be constructed with household transaction data for use by policymakers and researchers, making several firm-level measures available on the authors' websites. Researchers can construct these types of indicators using an increasingly accessible class of financial transaction data that has been popularized in fields like household finance and macroeconomics. We would encourage other researchers in areas that focus on firm behavior and asset prices to leverage transaction data in order to answer questions regarding consumer-facing firms.

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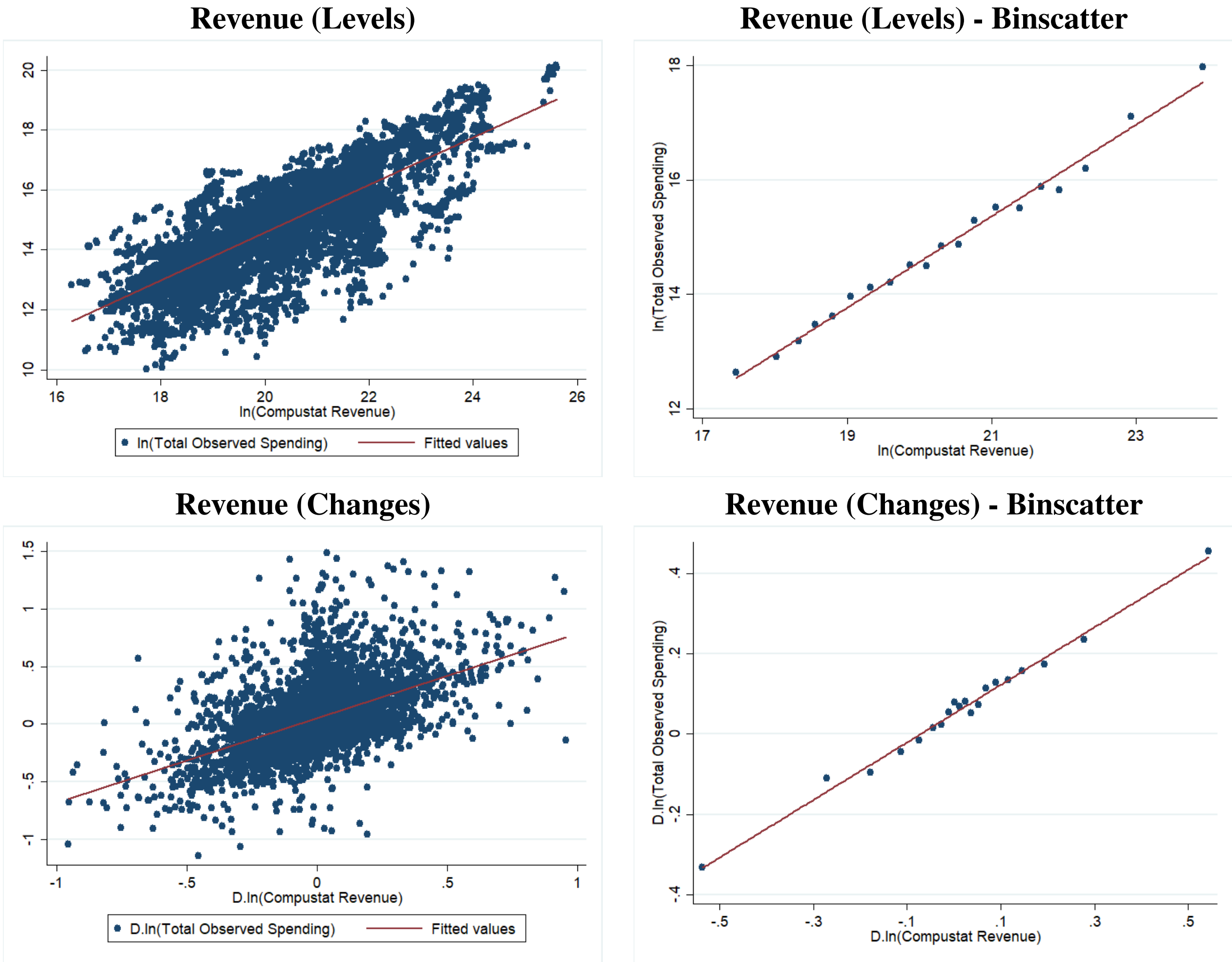
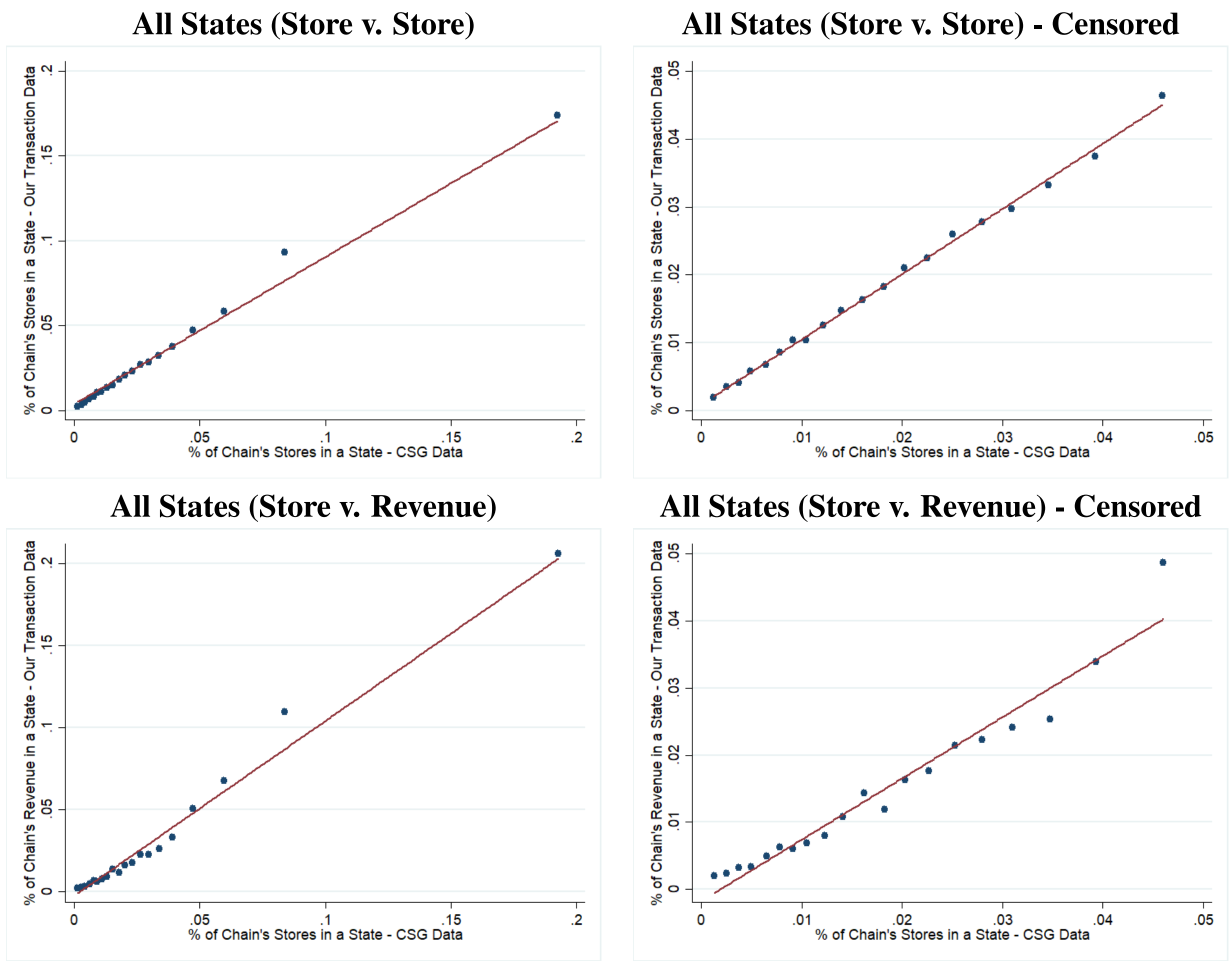
Figure 1: Comparison Between Reported Revenue and Observed Spending



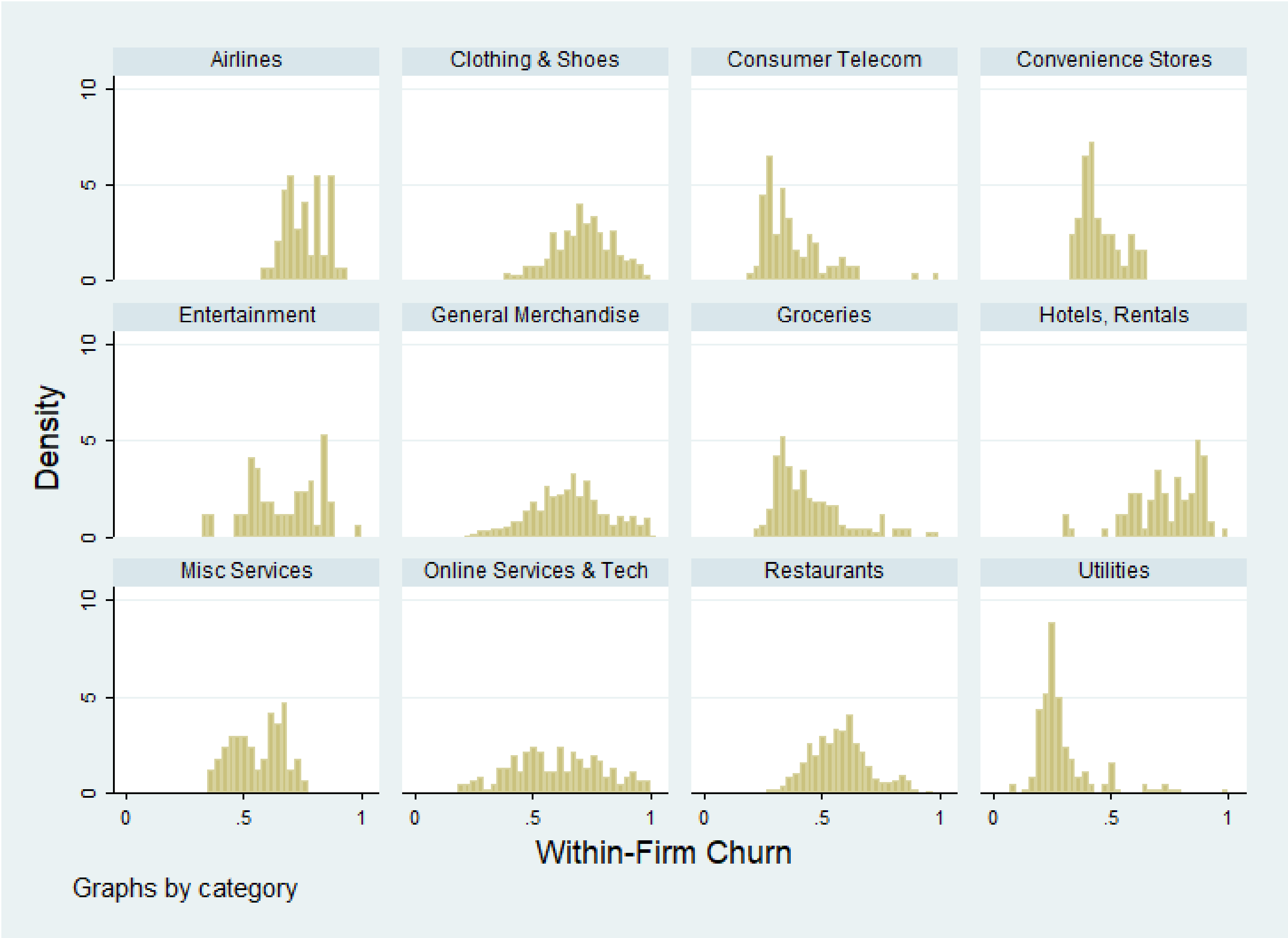
Notes: These graphs show the relationship between firm-level revenue measured in two ways: through Compustat and as observed in our transaction data. Each dot denotes a firm-quarter observation. Along the x-axis, we measure $ln(Revenue_{it})$ obtained from Compustat. Along the y-axis, we measure the total spending observed at a firm in a quarter within our transaction database. The top two panels examine levels of revenue and observed transaction spending. The bottom two panels examine changes in revenue and observed transaction spending.

Figure 2: Geographic Concentration - Transaction Revenue Data and Chain Store Guide Data



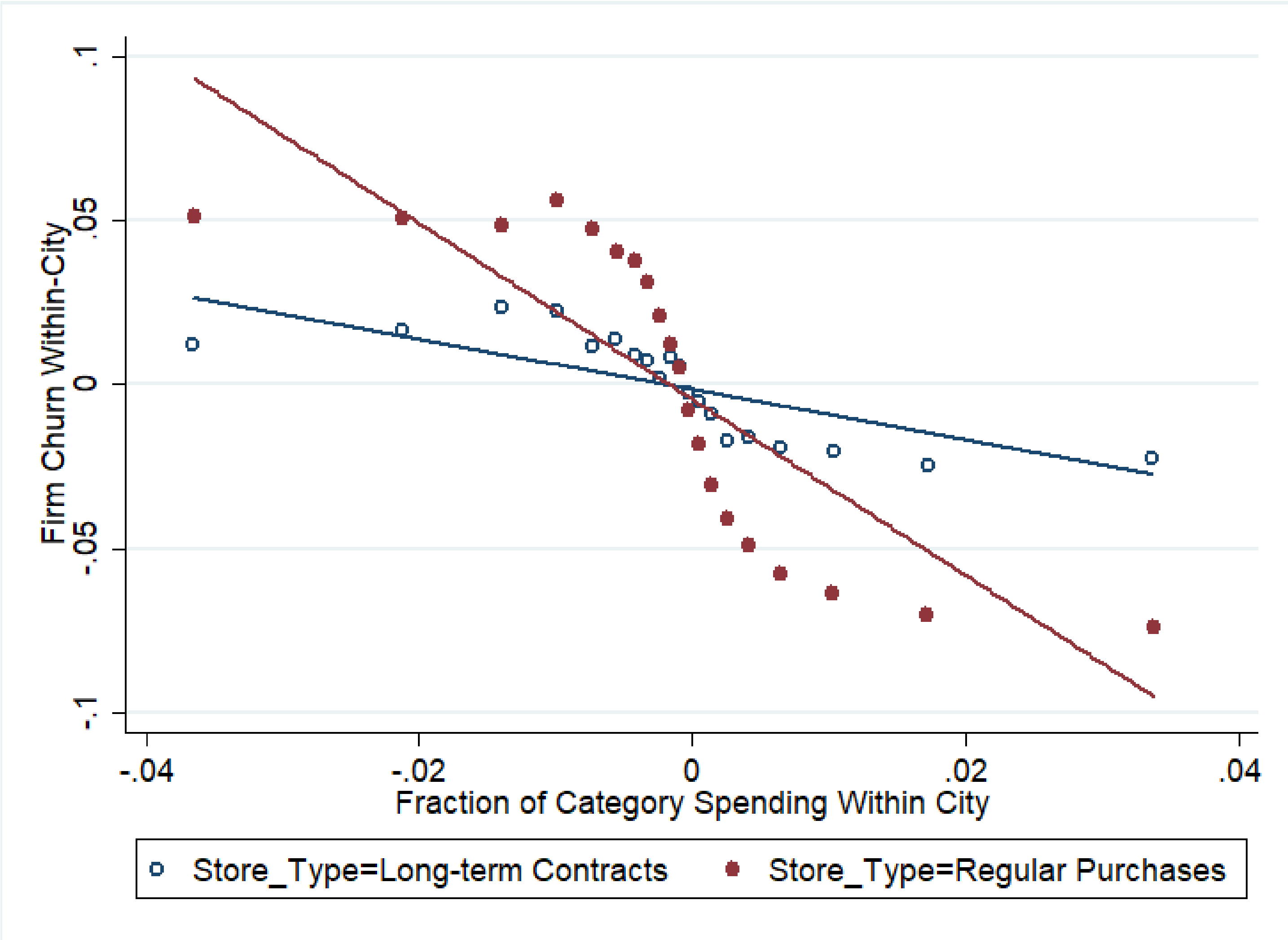
Notes: The graphs demonstrate the relationship between geographic concentration within a firm in two different ways. The first, measured on the x-axis, uses data from Chain Store Guide data and limits our sample primarily to retail firms. The x-axis measures the fraction of a firm's stores that are in a given state in a year (an observation is a firm-state-year). The y-axis measure uses data from our transaction data base and measures the fraction of spending at a retailer that is conducted by users living in a given state. Data covers all retailers able to be matched between samples and spans all 50 states, 2011-2014.

Figure 3: Customer-Base Annual Churn, By Industry



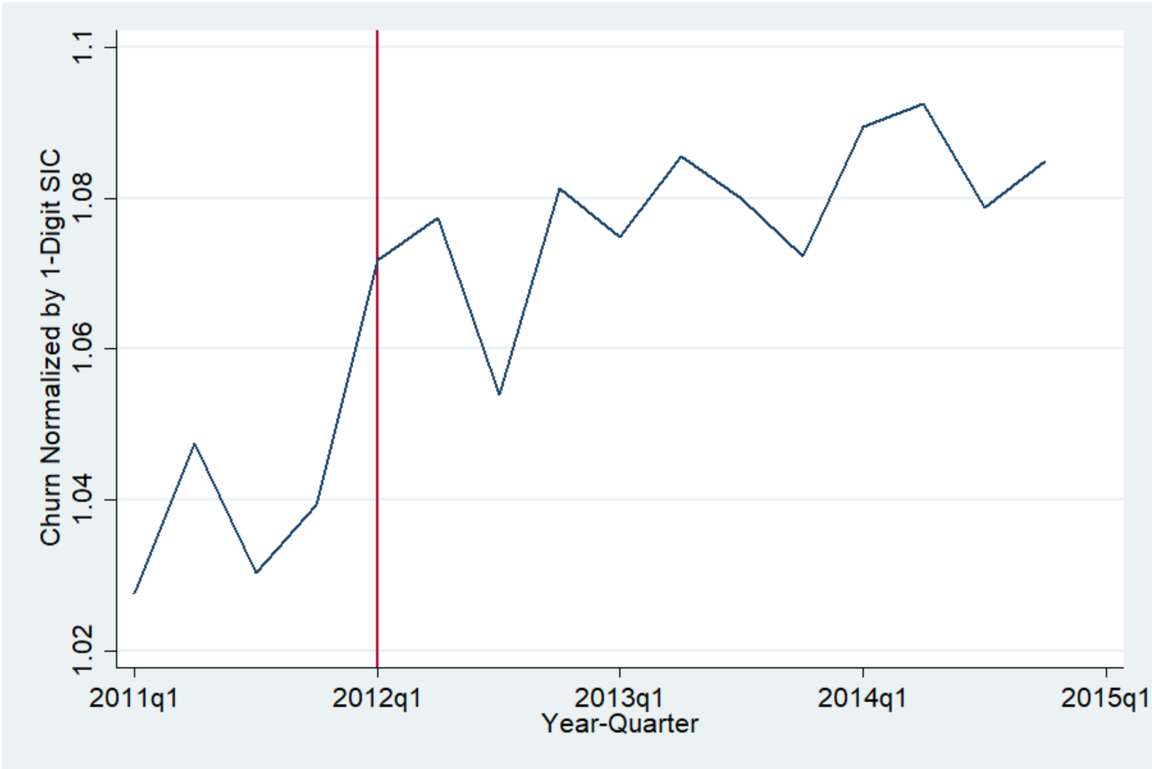
Notes: Each panel denotes the distribution of customer base churn over time across all firms in a given industry grouping in our sample. In this figure, churn is measured as the dollar-weighted overlap between the customer base of a firm f in year t and the customer base of firm f in year $t-1$. Overlap is scaled between 0 and 1 where 1 is an identical customer base and 0 is no overlap between customer bases across years.

Figure 4: Churn and Local Sales Shares Within Category



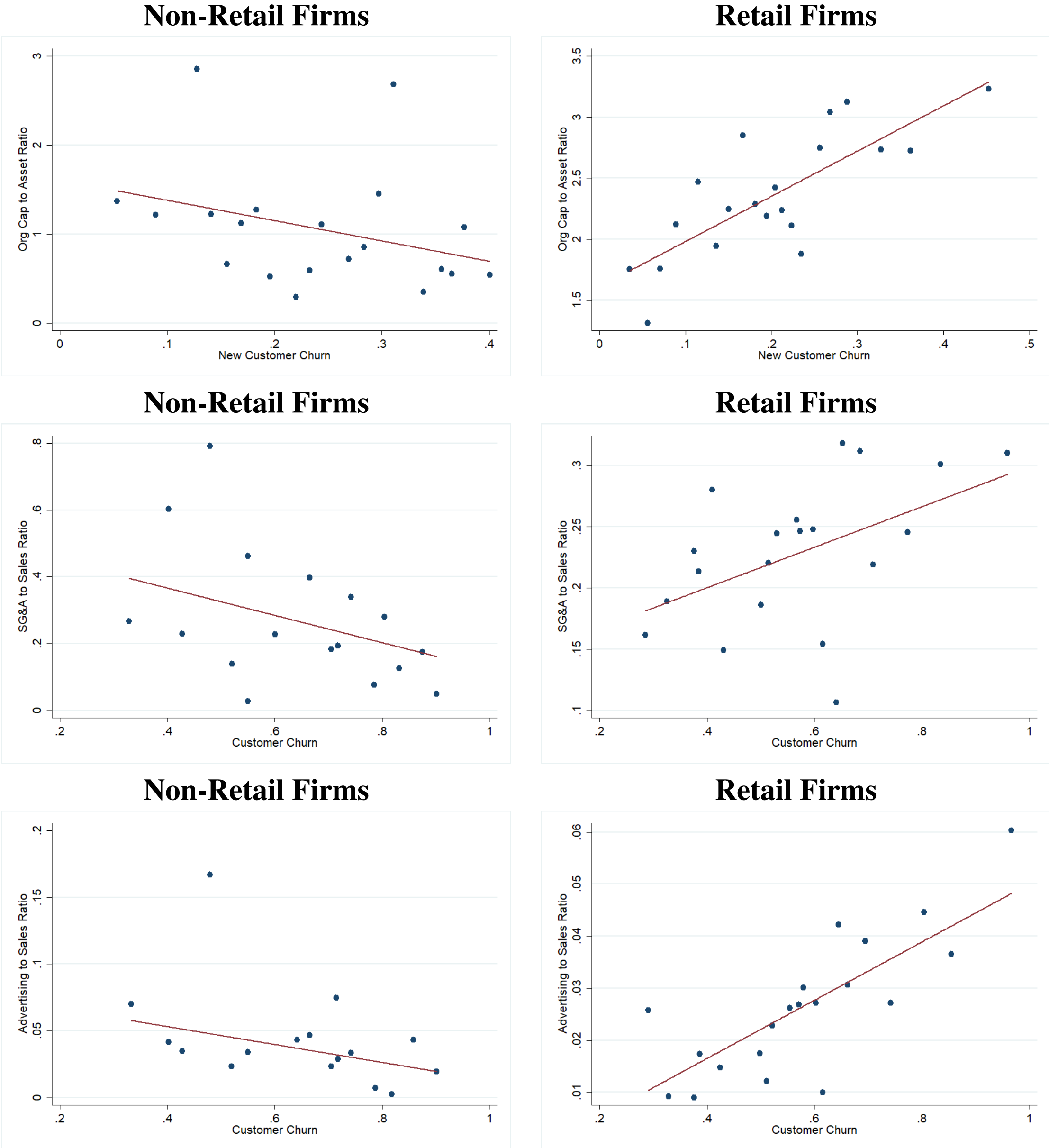
Notes: Pictured are bin-scatter plots of churn against the fraction of spending in a category done at a given retailer. Local spending shares are defined as $\frac{Spending_{icjt}}{\sum Spending_{cjt}}$ where i indexes firms, c indexes categories of spending, j indexes cities, and t indexes years. Churn is also measured at a city-firm-year level. Both variables are residuals of regressions on year and firm dummies. Firms are split into two categories. The first is composed of Utilities and Telecom firms (Long-term Contracts). The second is composed of Restaurants, Convenience Stores, General Merchandise, Groceries, and Entertainment (Regular Purchases).

Figure 5: Customer Churn at JC Penny



Notes: Plotted is the level of quarter over quarter customer churn at JC Penney normalized by the average level of quarter over quarter churn within the industry (one digit SIC code). A red line denotes the quarter (Q1 2012) in which JC Penney instituted a radical new pricing strategy.

Figure 6: Organization Capital, S,G&A, Advertising, and Customer Churn



Notes: Retail firms defined as public firms in our sample with a one-digit SIC code of '5'. Organization Capital defined as in Eisfeldt and Papanikolaou (2013). SG&A expenses and Advertising expenses obtained for all firms with non-missing data in Compustat. Customer churn scaled between zero and one and is measured as the similarity of a firm's customer base at time t relative to the customer base at time $t-1$, weighted by customer spending. Observations in the underlying data are firm-year. Plotted data cover 2011-2014 to exclude partial-year observations.

Table 1: Summary Statistics, by Firm-Quarter

Variable	# Obs.	Mean	10%	25%	50%	75%	90%
Observed Spending	10,528	$8,368,492	$51,955	$439,811	$1,616,576	$5,324,263	$16,539,201
$\frac{ObservedSpending}{CompustatRevenue}$	6,751	0.0061	0.0002	0.0013	0.0041	0.0076	0.0127
Number of Transactions	10,528	204,425	734	6,964	39,472	131,970	423,665
Unique Users	10,528	66,317	353	4,082	19,969	64,603	171,473

Notes: Table reports basic summary statistics regarding the 558 matched firms in our sample. Compustat revenue data are only available for the subset of public firms in our sample. An observation is a firm-quarter. Quarters with no observed transactions for a given firm are dropped.

Table 2: Firm Quality Index and Yelp Ratings

VARIABLES	(1) All Stores	(2) Restaurants	(3) General Stores	(4) Clothing	(5) Groceries
Yelp - $$	11,845***	8,176***	11,364***	18,135***	8,240***
	(402.7)	(622.9)	(833.4)	(1,023)	(1,355)
Yelp - $$$-$$$$	32,677***	24,016***	39,666***	32,214***	28,858***
	(685.9)	(2,128)	(1,458)	(1,430)	(1,502)
Year FE	YES	YES	YES	YES	YES
Observations	3,808	918	1,054	796	364
R^2	0.482	0.356	0.567	0.329	0.510

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Observations are individual retailers from our sample able to be matched to Yelp. Independent variables are indicators for a firm's price range in Yelp, where the excluded category is Yelp '$'. Coefficients denote the average difference in firm 'quality' corresponding to different Yelp price categories. Firm 'quality' is determined by the dollar-weighted average income of customers at a given retailer.

Table 3: Customer Churn, Brand Value, and Markups

VARIABLES	(1) B-to-M	(2) B-to-M	(3) ln(Brand Val)	(4) ln(Brand Val)	(5) $\frac{MktValue}{Customer}$	(6) $\frac{MktValue}{Customer}$	(7) Markup	(8) Markup
Annual Customer Churn	0.0823	0.104**	-4.826***	-2.705***	-0.682***	-0.598***	-0.571**	-0.530*
	(0.0626)	(0.0524)	(0.731)	(1.026)	(0.189)	(0.186)	(0.265)	(0.280)
ln(Firm Sales)	-0.00684	0.0675*	1.293***	1.599***	0.171***	0.101***	-0.0550*	0.0266
	(0.00789)	(0.0385)	(0.104)	(0.143)	(0.0236)	(0.0232)	(0.0326)	(0.160)
Observations	1,227	1,208	403	402	1,071	1,071	1,070	1,037
R^2	0.022	0.788	0.445	0.558	0.098	0.398	0.005	0.900
Firm FE	NO	YES	NO	NO	NO	NO	NO	YES
Industry FE	NO	YES	NO	YES	NO	YES	NO	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Customer churn for each firm is calculated at a firm-year level. Brand values calculated by Brand Finance's Brandirectory which looks at components such as emotional connection, financial performance and sustainability and then applies royalty rates to calculate a capitalized brand value. Patent intensity is calculated as the value patents (using the extended replication file for Kogan et al. (2017)) scaled by market capitalization. Markup data are obtained from Loualiche (Forthcoming) who calculates markups using the method in De Loecker et al. (2020). Number of customers for a firm is estimated by first calculating average spending per customer at a firm in our data, then dividing total firm sales (from Compustat) by that average customer spending. Value per customer is then measured as the market value of the firm divided by the estimated number of customers. Brand value and market value per customer are invariant over time within a firm.

Table 4: Customer Churn and Firm Investment Dynamics

VARIABLES	(1) Cash	(2) Leverage	(3) Q	(4) SD(Invest Rate)	(5) All Firms	(6) Retail	(7) All Firms	(8) Retail
Avg Annual Churn	-0.105***	2.560***	-3.743***	0.0233***				
	(0.0232)	(0.508)	(0.405)	(0.00708)				
SG&A to Sales	0.245***	-0.805**	-0.770***	-0.00261				
	(0.0166)	(0.362)	(0.280)	(0.00494)				
Q_{t-1}					0.00487***	0.0109***	0.00776***	0.00907***
					(0.000194)	(0.000671)	(0.00102)	(0.00118)
Q_{t-1} *Low SG&A					0.00371***	-0.00204**	0.000878	0.000614
					(0.000297)	(0.000889)	(0.00112)	(0.00128)
Q_{t-1} *High Churn							0.00317***	0.00379***
							(0.00111)	(0.00128)
Observations	3,764	3,761	3,050	3,511	44,180	5,768	3,279	2,430
R^2	0.290	0.053	0.149	0.202	0.638	0.655	0.614	0.621
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	NO	NO	NO	NO	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	NO	NO	NO	NO
Size Controls	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Dependent variable in columns 5-8 is investment rate: the ratio between capital expenditures and lagged assets. Tobin's Q is measured as the inverse of book-to-market ratio. Customer churn is calculated at a firm-year level and then averaged across all years in the sample (2010-2015). Sample includes investment data from 2000-2019. 'Low SG&A' ('High Churn') is a firm-level indicator for being in the bottom (top) half of the SG&A (customer churn) distribution. Retail firms are those with the one-digit SIC code of 5. Size (revenue) controls are firm sales in columns 1-4 and firm sales interacted with lagged Q in columns 5-8.

Table 5: Customer Churn and Volatility

	CAPM β	CAPM β	CAPM β	CAPM β	Idio. Vol.	Idio. Vol.	Idio. Vol.	Idio. Vol.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Churn	0.651***	0.329***	0.338***	0.304***	1.330***	0.525***	0.982***	0.524**
	(0.088)	(0.102)	(0.089)	(0.101)	(0.224)	(0.202)	(0.251)	(0.219)
ln(Lagged Revenue)	-0.0270**	-0.0255*	-0.0272*	0.0845	-0.198***	-0.261***	-0.206***	-0.398**
	(0.013)	(0.015)	(0.015)	(0.084)	(0.029)	(0.026)	(0.033)	(0.174)
Observations	919	919	919	919	919	919	919	919
R-squared	0.16	0.291	0.29	0.732	0.269	0.436	0.386	0.821
Specification	Univar	SIC2 FE	HP50 FE	Firm FE	Univar	SIC2 FE	HP50 FE	Firm FE

Notes: The level of customer churn is calculated at a firm-year level (2011-2014), and it is the churn from last year's customer base. "CAPM β" is the beta from a regression of a stock's daily excess returns on the excess returns of the market in a given year. "I. Vol." is idiosyncratic volatility, 100 times the standard deviation of daily CAPM residuals in that year. "Ln(Lagged Revenue)" is the natural logarithm of last year's total revenue from Compustat. To be included, a firm must have non-missing, non-negative total lagged revenue. All regressions are equal weighted. Standard errors are clustered at the firm level. All LHS variables Winsorized at the 1% and 99% level.

Table 6: Customer Churn and Revenue Decline During COVID-19 Outbreak

VARIABLES	(1) ln(Spend)	(2) ln(Spend)	(3) ln(Spend)	(4) ln(Spend)	(5) ln(Spend)
March 2020	-0.307***	-0.00933	0.258**		
	(0.00885)	(0.0261)	(0.112)		
Mar 2020*Churn		-0.519***	-0.935***	-0.494***	-0.837***
		(0.0428)	(0.0820)	(0.0514)	(0.0951)
Observations	141,363	141,363	42,306	141,363	42,306
R^2	0.910	0.910	0.920	0.916	0.924
Month/Day/DoW FE	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Month*Beta Control	NO	NO	YES	NO	YES
Month*Size Control	NO	NO	YES	NO	YES
Industry*Month FE	NO	NO	NO	YES	YES

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: The level of customer churn for each firm is calculated at a firm-year level and then averaged across all years in the sample (2010-2015). 'March 2020' is an indicator equal to one in March of 2020. It is interacted with the continuous measure of churn and with churn as binned into four quartiles. Spending data spans January 1, 2019 to March 31, 2020. Continuous measure of churn ranges from roughly 0.33 - 0.9.

Table 7: Double Sort on Churn and Organization Capital

Churn OK/AT	Low Low	Low 2	Low High	2 Low	2 2	2 High	High Low	High 2	High High	HML Low	HML 2	HML High
Mkt. Excess Ret.	0.817***	0.968***	0.733***	1.053***	0.900***	1.211***	1.088***	1.332***	1.406***	0.271**	0.364***	0.672***
	(0.066)	(0.070)	(0.078)	(0.083)	(0.083)	(0.118)	(0.080)	(0.076)	(0.114)	(0.104)	(0.105)	(0.110)
Alpha	0.00794***	0.00274	0.00537*	0.00184	-0.00142	-0.00548	0.00406	-0.00128	-0.0127***	-0.00388	-0.00402	-0.0181***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)
Observations	120	120	120	120	120	120	120	120	120	120	120	120
R-squared	0.547	0.656	0.491	0.571	0.497	0.494	0.585	0.732	0.535	0.052	0.103	0.205
St. Dev.	0.143	0.155	0.136	0.181	0.166	0.224	0.184	0.202	0.249	0.154	0.147	0.193

Notes: Each month, we form 3 value-weighted portfolios based on average churn at the GVKEY level between 2011 and 2015. We then form 3 sub portfolios based on organization capital over assets from the Eisfeldt et al. (2020) replication file. We then regress the excess returns of these portfolios on the excess return of the market factor from Ken French's data library using data from 2010 to 2019. The HML columns represent a long-short portfolios, which go long high churn firms, and short low churn firms, within each OK/AT tercile. Robust standard errors in parenthesis. The last row reports the standard deviation of each portfolio over the whole 2010-2019 sample.

A Other Transaction-based Measures of Customer Base Characteristics

A.1 Customer Income Distributions and Concentration

Figure A.6 shows a selection of customer income distributions for pairs of firms in the same industry. For instance, the bottom right panel displays the distribution of customer income (weighted by spending at the firm) within two grocery stores: Save-a-Lot and Whole Foods. We sort income into $1,000 bins and censor the histogram at $300,000 for visibility. We can see that Whole Foods customers tend to be substantially richer than those of Save-a-Lot, indicating a higher quality firm.

Another illustration of the benefit of linking users to firms using this class of transaction data is the ability to get information not only about levels of spending at a particular firm, but the distribution of spending (i.e. revenue) within a firm across its customers. In Table A.8, we display statistics that illustrate how concentrated firm revenue is within its customer base. Looking across broad industry categories, we show that there is a substantial amount of variation in revenue concentration. For instance, the top 5% of customers for a given Utility firm provides approximately 15% of a firm's revenue.[20] In contrast, revenue for hotels and airlines is much more concentrated within their customers, with the highest spending 5% of customers making up almost 30% of their revenue in our sample. This variation in concentration is maintained down the distribution of customers, with the top 20% of customers making up around 40% of revenue in low customer concentration industries and over 75% in high customer concentration industries.

A.2 Market Value Per Customer

Although our dataset only covers about 0.8% of the US population, it is still useful for estimating the total number of customers at a given firm. To do this, we start by calculating spending per customer at the firm-year level: total spending divided by the number of unique households that shopped at the firm that year.[21] Then, to get an estimate of the number of customers, we divide

[20]Here, we mean the percent of revenue in our matched dataset. In this example, the top 5% of customers make up 15% of the revenue *we can see in our matched dataset*, not 15% of the revenue in Compustat.

[21]From both the numerator and the denominator we exclude household-firm-quarter observations with less than $1 of total spending.

total sales (SALE) in Compustat by spending per customer.

An alternative method would be to scale the number of customers at the firm-year level in our sample by our coverage of the US population. With an average coverage of 0.8%, the total number of customers at each firm should be about 1/0.008=125 times as large as the number in our sample. This gives similar estimates to the 'spending per customer' method for many large retail firms e.g., Saks and Nordstrom. It also gives similar estimates for national restaurant brands e.g., Bloomin' Brands (owner of Outback Steakhouse) and Red Lobster.

This method, however, leads to substantially different estimates for firms with a significant amount of sales outside the US e.g., Tim Hortons. While most Tim Hortons locations are in Canada, they do have several hundred US locations. This means that while their customers appear in our sample, scaling up the number of customers by a factor of 125 will likely understate the true total number of customers. If the average customer, however, is similar in the US and Canada, then our 'spending per customer' method will yield accurate estimates despite our lack of Canadian coverage.

The next step is to calculate the market value per customer: the total market capitalization at the end of the year divided by the estimated number of customers in that year. Common-sense intuition suggests that market value per customer should be higher for low-churn firms. From a present value perspective, a customer should be more valuable to a firm if they are likely to continue spending there for a long period of time. Figure A.7 plots logged average market value per customer vs. average churn. There is a statistically significant and economically large negative relationship between market value per customer and churn. The standard deviation of churn is $\approx$0.16, so a 1 SD increase in churn would decrease market value by about 30-40% per customer.

This result is driven mostly by differences across industries: Some of the firms with the highest market value per customer are utility companies like Dominion Energy and Duke Energy as well as Telecom companies like AT&T and Verizon. Some of the firms with the lowest market value per customer firms are struggling brick-and-mortar retailers like Barnes & Noble and Sears. While the relationship is still negative and significant when including industry fixed-effects, the magnitude of the slope is only about 1/2th as large.

A.3 Measuring Components and Variants of Customer Churn

One advantage of the utilization of this class of disaggregated transaction data is that many variants of customer base characteristics can be constructed. We construct a number of alternate measures of customer churn to complement our headline index. Below we note the calculation underpinning our baseline index as well as several of these variants. Overall, these measures are highly correlated with one another, featuring correlation coefficients between 0.81 and 0.97. The one exception is $Churn_{walletshare}$ which is negatively correlated with other churn metrics. That is, while overall customer base churn tends to be driven by extensive margin movements of customers (gaining new customers and attrition of existing customers), intensive margin fluctuations are actually negatively correlated with extensive margin changes.

1. $Churn_{baseline,f,t-k} = \left(\sum_i |s_{f,i,t} - s_{f,i,t-k}|\right)/(2)$ where the sum $\sum_i |s_{f,i,t} - s_{f,i,t-k}|$ is taken over all customers that shop at firm f in *either* year t or year $t-k$.

2. $Churn_{old,f,t-k} = \left(\sum_i |s_{f,i,t} - s_{f,i,t-k}|\right)/(2)$ where the sum $\sum_i |s_{f,i,t} - s_{f,i,t-k}|$ is taken over all customers that shop at firm f *only* in year $t-k$ *and not* year t.

3. $Churn_{new,f,t-k} = \left(\sum_i |s_{f,i,t} - s_{f,i,t-k}|\right)/(2)$ where the sum $\sum_i |s_{f,i,t} - s_{f,i,t-k}|$ is taken over all customers that shop at firm f *only* in year t *and not* year $t-k$.

4. $Churn_{walletshare,f,t-k} = \left(\sum_i |s_{f,i,t} - s_{f,i,t-k}|\right)/(2)$ where the sum $\sum_i |s_{f,i,t} - s_{f,i,t-k}|$ is taken over all customers that shop at firm f *both* in year $t-k$ *and* year t.

5. $Churn_{existingcustomers,f,t-k} = \left(\sum_i |s_{f,i,t} - s_{f,i,t-k}|\right)/(2)$ where the sum $\sum_i |s_{f,i,t} - s_{f,i,t-k}|$ is taken over all customers that shop at firm f *only* in year $t-k$.

6. $Churn_{growthadjusted,f,t-k} = \left(\sum_i |s_{f,i,t,t-k} - s_{f,i,t-k,t-k}|\right)/(2)$ where the sum $\sum_i |s_{f,i,t} - s_{f,i,t-k}|$ is taken over all customers that shop at firm f *only* in year $t-k$. Note that here the denominators are modified such that the spending shares are always taken as a share of total firm spending at $t-k$ rather than t and $t-k$.

Decomposing churn into its constituent components (eg. $Churn_{old,f,t-k}$, $Churn_{new,f,t-k}$, and $Churn_{walletshare,f,t-k}$) also allows us to examine the path that these variables take over time within a firm. On average, we see that $Churn_{old,f,t-k}$, and $Churn_{walletshare,f,t-k}$ are fairly stable over time within a firm, while $Churn_{new,f,t-k}$ gradually decreases. Total baseline customer churn, $Churn_{baseline,f,t-k}$, is also fairly stable over time during out sample period. Splitting firms into quintiles according to their drift in churn, we find that the top four quintiles all shift churn by less than 0.1 (about 25% of a standard deviation) over three years. Only the bottom quintile shifts by more, with a drop in churn of approximately 0.3.

B Customer Base Overlap and Stock Predictability

B.1 Customer Base Similarity

Another aspect of firms' customer bases that we can capture with our data is the similarity of firm i's customer base to that of firm j. Again, we define $s_{f,i,t}$ as the share of firm f's revenue in our matched sample that comes from customer i in year t. We define similarity between firms f and j in year t as:

$$Similarity_{(f,j),t} = -\left(\sum_i |s_{f,i,t} - s_{j,i,t}| \right) /(2) + 1 \tag{A.1}$$

where the sum $\sum_i |s_{f,i,t} - s_{j,i,t}|$ is taken over all customers that shop at *either* firm f or j in year t. As with our churn measure, this sum can vary between zero and two. We multiply by $-1/2$ and add 1 so that a similarity score of one would imply that the firms have the exact same revenue share from each customer, and a value of zero would imply no overlap in customer bases. We calculate this measure for all firm-firm pairs in our sample at an annual frequency.

Figure A.8 displays the average level of customer base similarity within a broad industry group for all firm-firm pairs in that industry. As with the customer base churn metric discussed above, there exists substantial variation in cross-firm similarity across industries. Firms within the Utility industry are the most dissimilar to other Utility firms – which is to be expected as most customers have only a single utility provider and do not vary in their provider much over time. In contrast, restaurants have the highest amount of within-industry cross-firm similarity – over 5 times higher than that of Utility firms. This reflects the fact that many users tend to spend large amounts of money eating out but spread their spending across multiple restaurants rather than focusing on a single restaurant.

We note that, on average, within-industry customer base similarity is higher than that across industries. That is, many users tend to disproportionately weight their spending towards a particular industry, not simply a particular firm within an industry. However, for both within- and cross-industry firm-firm pairs we see some that are highly dissimilar and some that are highly similar. Moreover, the set of most similar firms for a given firm tends to span industries.[22]

B.2 Portfolio Analysis

The connection between firms is still an under-explored area in asset pricing. An exception to this is Cohen and Frazzini (2008), which shows that firms connected via the supply chain have predictable returns. Our measure of customer overlap seems like a natural way to identify economically linked firms. If a set of customers are hit by an economic shock, the collection of firms where these customers shop should be similarly affected. Unlike the supply chain linkages in Cohen and Frazzini (2008), which are reported in firms' SEC filings, our measure of customer base overlap is not easily observable. If this information is not fully incorporated into stock prices, it may be possible to form portfolios which generate significant alpha relative to known risk-factors.

To test this, we start with all securities in the CRSP/Compustat merged database, and then restrict to ordinary common shares (share codes 10 and 11) traded on major exchanges (exchange codes 1, 2 and 3). We also remove financial firms (SIC codes 6000-6999) and utilities (SIC codes 4900-4999). After matching this subset to our customer-base overlap data, we have about 250 firms per month between 2010 and 2018. We form five portfolios each month using the following procedure. First, we compute the average overlap between firms' customer bases for each pair of firms in our sample. We compute this average using the average of annual overlap between 2011-2014, as these are the only years in our sample with four quarters of data. We use a single average, even though this introduces a look-ahead bias in our portfolio formation, as the overlap does not change much over time.

Each month, we identify the 10 firms with the highest overlap for each firm in the matched dataset. We then form a value-weighted portfolio of these 10 firms, and calculate the return of

[22]For instance, the ten firms with the most similar customer bases to Walmart are: Yum Brands, Dine Brands, Darden Restaurants, Sonic Corp, Netflix, Amazon, Kohl's, Dollar Tree, Domino's, and Papa Johns. Among retailers, the ten firms with the most similar customer bases to Walmart are: Amazon, Kohl's, Dollar Tree, Bed Bath and Beyond, Autozone, Sally Beauty, Gamestop, Office Depot, Big Lots, and Dicks Sporting Goods.

this portfolio over the past quarter. We then sort firms into 5 portfolios: Portfolio 1 (low) has firms whose 10 most overlapping firms had the lowest stock returns over the past quarter. Portfolio 5 (high) has firms whose 10 most overlapping firms had the highest stock returns over the past quarter. We then form a hedge portfolio which is long portfolio 5 and short portfolio 1. We want to test whether the return of firms with high customer-base overlap has predictive power for future returns, adjusting for known risk-factors. We regress the returns of our portfolios on the 5 Fama-French factors (Fama and French (2015)) and a momentum factor (see e.g., Jegadeesh and Titman (1993)) obtained from Ken French's website.

We display the results in Table A.9. Alpha is monotonically increasing from the Low to High portfolios. Further, our hedged portfolio has a large and statistically significant alpha of almost 1% per month. This suggests that when firms with similar customer bases to a given firm j have high (low) returns, firm j will likely have high (low) returns in the future[23]. At this point, it is not clear whether this is alpha a risk-premium or an anomaly. To our knowledge, there is no theoretical model of asset prices with heterogeneous/overlapping customer bases, but we conjecture the effect we find is an *anomaly*. Given that our data is not publicly available, it would not be surprising if this information was not fully incorporated into stock prices.

As mentioned above, our portfolio formation process involves some look-ahead bias. We compute the overlap in customer bases one time using all the data between 2011 and 2014, and apply that to portfolio formation between 2010-2018. Table A.10 forms portfolios, but without a look ahead bias. We use the overlap in year t to form portfolios in year $t + 1$. For example, we use overlap data from 2011 to form portfolios in 2012. This shrinks our sample, as we do not extend portfolio formation back to 2010, or extend forward to 2016-2018. Even in this smaller sample, and without the look-ahead bias, the alphas are monotonically increasing from the low to high portfolios. Further, the alpha on the hedge portfolio is almost unchanged in magnitude, and is still statistically significant. This suggests that this look-ahead bias is not driving our results.

Another concern is that our measure of customer overlap is picking up a firm characteristic already known to predict returns or risk premia. An obvious one is momentum, as it's possible that the returns of similar firms are highly correlated with a firm's own past returns. This is unlikely to

[23] In unreported results, we find that this is mostly coming from across-industry customer-base similarity, rather than within-industry customer-base similarity. One explanation for this may be that within-industry links are more visible to investors who do not have access to data like ours.

drive our results, however, as we are already controlling for the momentum factor in all the asset pricing regressions.[24]

We perform several tests of the robustness and utility of this customer base overlap measure. For instance, another potential proxy for customer base overlap is correlation of stock returns. To test where we could obtain similar results simply utilizing these correlations, we compute the correlation of each pair of firms' daily stock returns from 2011-2014. In each month, we identify the 10 most correlated firms. We repeat the procedure for forming 5 portfolios as described above, except we use the 10 most correlated firms instead of the 10 firms with the highest overlap on customer base. Portfolio 1 (low) has firms whose 10 most correlated firms had the lowest returns over the past quarter. Portfolio 5 (high) has firms whose 10 most correlated firms had the highest returns over the past quarter. We display these results in Table A.11. There is no pattern in the alphas from low to high, suggesting that our measure of customer base overlap contains important independent information.

Despite the results in Table A.11, it's possible that our results are still related to past correlation in stock returns. To further rule out this channel, we perform a double sort in Table A.12. The first sort is on performance of high customer base similarity firms with above/below median past returns. The second sort is on performance of high past stock market correlation with above/below median past returns. We then form two hedge portfolios on the overlap dimension. Both hedge portfolios have statistically significant alphas, again suggesting that our results are not driven only by correlation in stock returns among firms with high customer base overlap.

B.3 Earnings Announcements

To understand the mechanism behind the results in Table A.9, we examine days where we know fundamental information about firms is released: earnings announcements.

For simplicity, we explain everything from the perspective of a single example firm, Wal-Mart (WMT). All the regressions, however, use data from all the firms in our dataset that we can

[24]In unreported results, we perform a 2-by-2 double-sort on own firm returns from $t-12$ to $t-2$ as in Jegadeesh and Titman (1993), and returns of firms with high customer base overlap over the past quarter. We find that the returns on portfolios that go long firms with overlapping firms which have high returns, and short firms with overlapping firms which have low returns has a positive alpha regardless of whether we restrict to only low past-return/momentum firms, or high past-return/momentum firms. This is not surprising, given the poor performance of momentum strategies between 2010 and 2018.

match to IBES. We require matching to IBES because this provides the *time* of each earnings announcement. This is important, because it lets us determine the first day that investors could trade on that information during normal hours – we call this the effective earnings announcement date. For example, if earnings were released at 8AM on a Monday, we would identify that as the effective earnings date. If earnings were released at 5PM on a Monday, the next trading day would be the effective earnings date. In all the tests that follow, we restrict to firms which have the same fiscal period end as WMT (although not necessarily the same fiscal year end), and that release earnings in the same quarter as WMT.[25]

In Table A.13, we use a definition of standardized unexpected earnings (SUE) as the year-over-year (YOY) earnings growth divided by the standard deviation of YOY earnings growth over the previous 8 quarters (see e.g., Novy-Marx (2012)). We are interested in whether earnings growth in firms with high customer base overlap with WMT has predictive power for earnings growth at WMT.

Column 1 is a regression of WMT's SUE on the SUE of the 20 firms with the highest overlap to WMT, which released earnings before WMT in a given calendar quarter. Column 2 is a regression of the SUE of the 20 firms with the highest overlap to WMT on WMT's SUE, but which released earnings after WMT in a given calendar quarter. Column 1 implies that when firms with similar customers to WMT have high earnings growth, and report earnings before WMT, WMT also has high earnings growth. Column 2 says that when WMT has high earnings growth, high overlap firms which report later in the quarter also have high earnings growth.

Having shown predictability in fundamentals, we want to show predictability in stock returns around earnings announcements. Define earnings-day returns as the cumulative market-adjusted log returns from $t-5$ to $t+1$ where t is an earnings announcement date. We define market-adjusted returns as in Campbell et al. (2001): The difference between the excess return on the stock, and the return on the market factor from Ken French's data library. We are interested in whether high earnings day returns for firms with high customer base overlap with WMT has predictive power for earnings day returns for WMT.

Column 3 is a regression of WMT's earnings day returns the earnings day returns of the 20 firms with the highest overlap to WMT, which released earnings before WMT in a given calendar

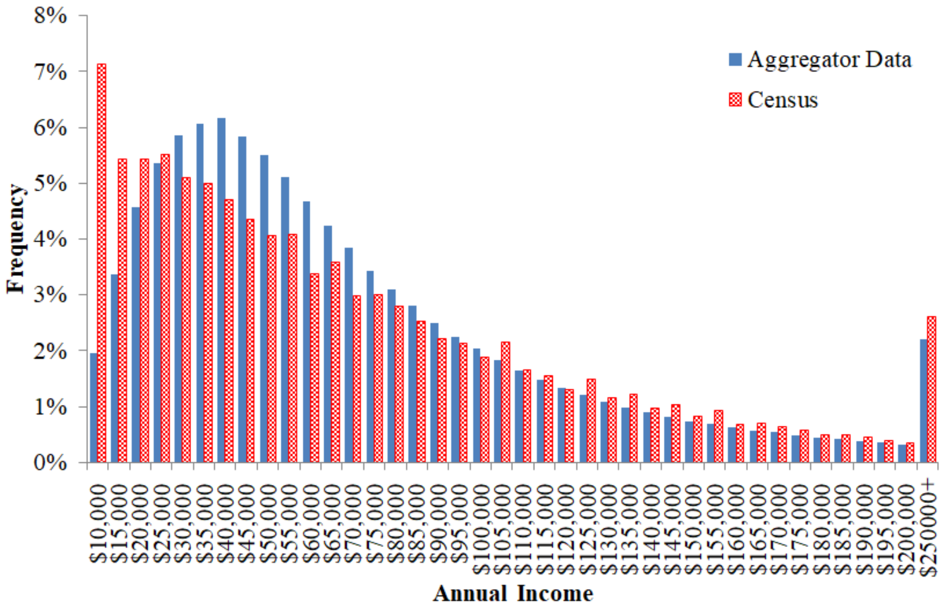
[25]This excludes firms which release earnings late which represents news in and of itself, Begley and Fischer (1998).

quarter. Column 4 is a regression of the earnings day returns of the 20 firms with the highest overlap to WMT on WMT's earnings day returns, but which released earnings after WMT in a given calendar quarter. Column 3 implies that when firms with similar customers to WMT have high earnings day returns, and report earnings before WMT, WMT also has high earnings day returns. Column 4 says that when WMT has high earnings day returns, high overlap firms which report later in the quarter also have high earnings day returns.

Finally, we are interested in how analysts covering WMT, and firms with overlapping customer bases, react to the release of new information. Define forecast (in)accuracy as the absolute difference between actual earnings per share and the average analyst forecast of earnings per share, normalized by the share price at the time of the earnings announcement. We are interested in whether analyst accuracy for firms with high customer base overlap with WMT has predictive power for analyst accuracy for WMT. The logic is that analysts could use large surprises at firms with large overlap to correct their forecasts for WMT. If this were true, when those other firms had a large surprise, relative to analyst estimates, we would expect WMT to have a smaller surprise.

Column 5 is a regression of WMT's analyst accuracy on the analyst accuracy of the 20 firms with the highest overlap to WMT, which released earnings before WMT in a given calendar quarter. Column 6 is a regression of the analyst accuracy of the 20 firms with the highest overlap to WMT on WMT's analyst accuracy, but which released earnings after WMT in a given calendar quarter. Both columns are insignificant, which suggests that analysts do not use this overlap information to update their forecasts.

Figure A.1: Income Distribution - Aggregator Data vs. U.S. Census

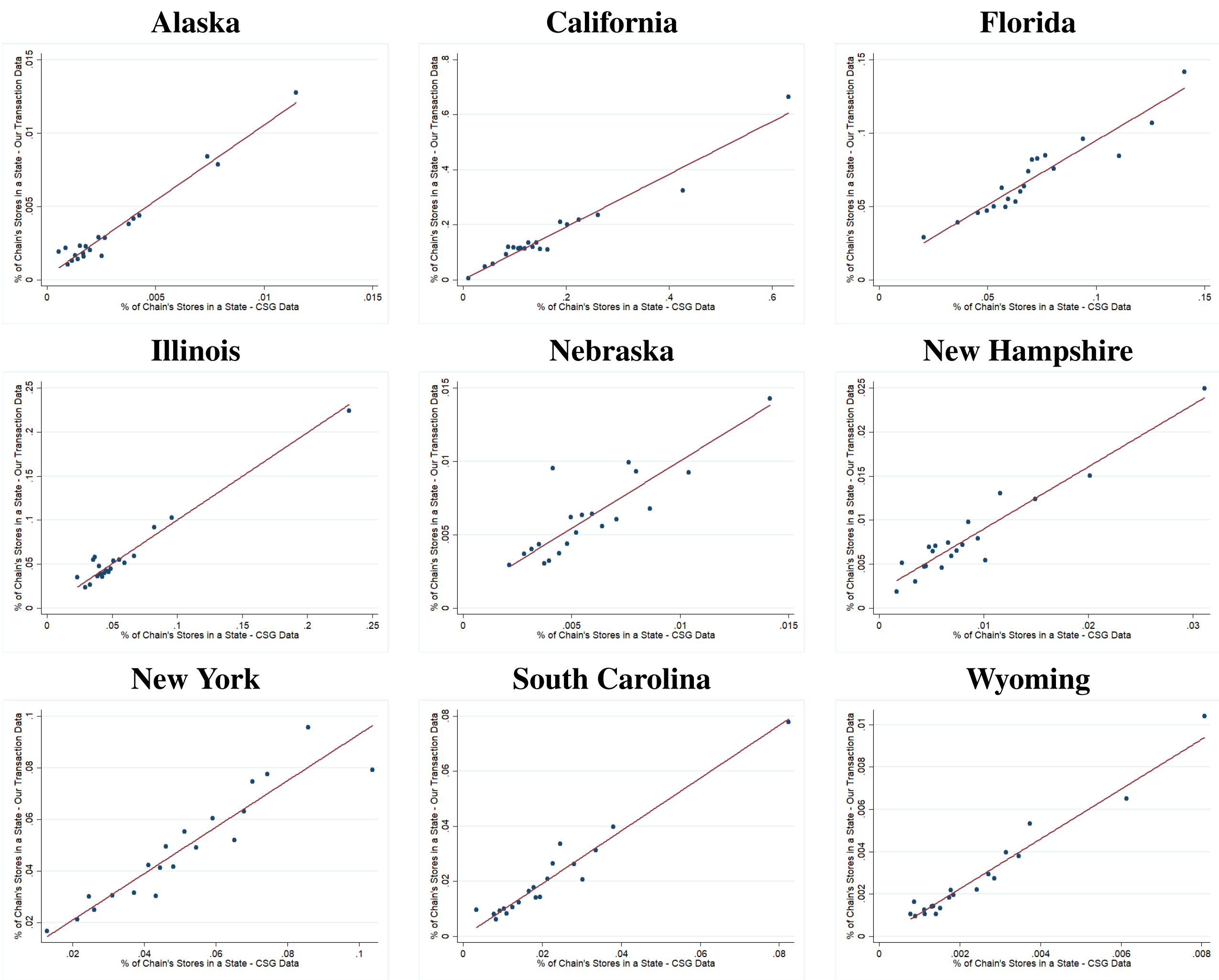


Notes: This figure compares the distribution of 2014 income of the account aggregator and the U.S. Census. The Census data uses the variable *HINC-06* and is available for download at census.gov. The difference in distributions at the bottom end of the income distribution is due to censoring of zero income users in our dataset. See Section 2 for more details.

Figure A.2: Consumption - Aggregator Data vs. U.S. Census Monthly Retail Trade Report

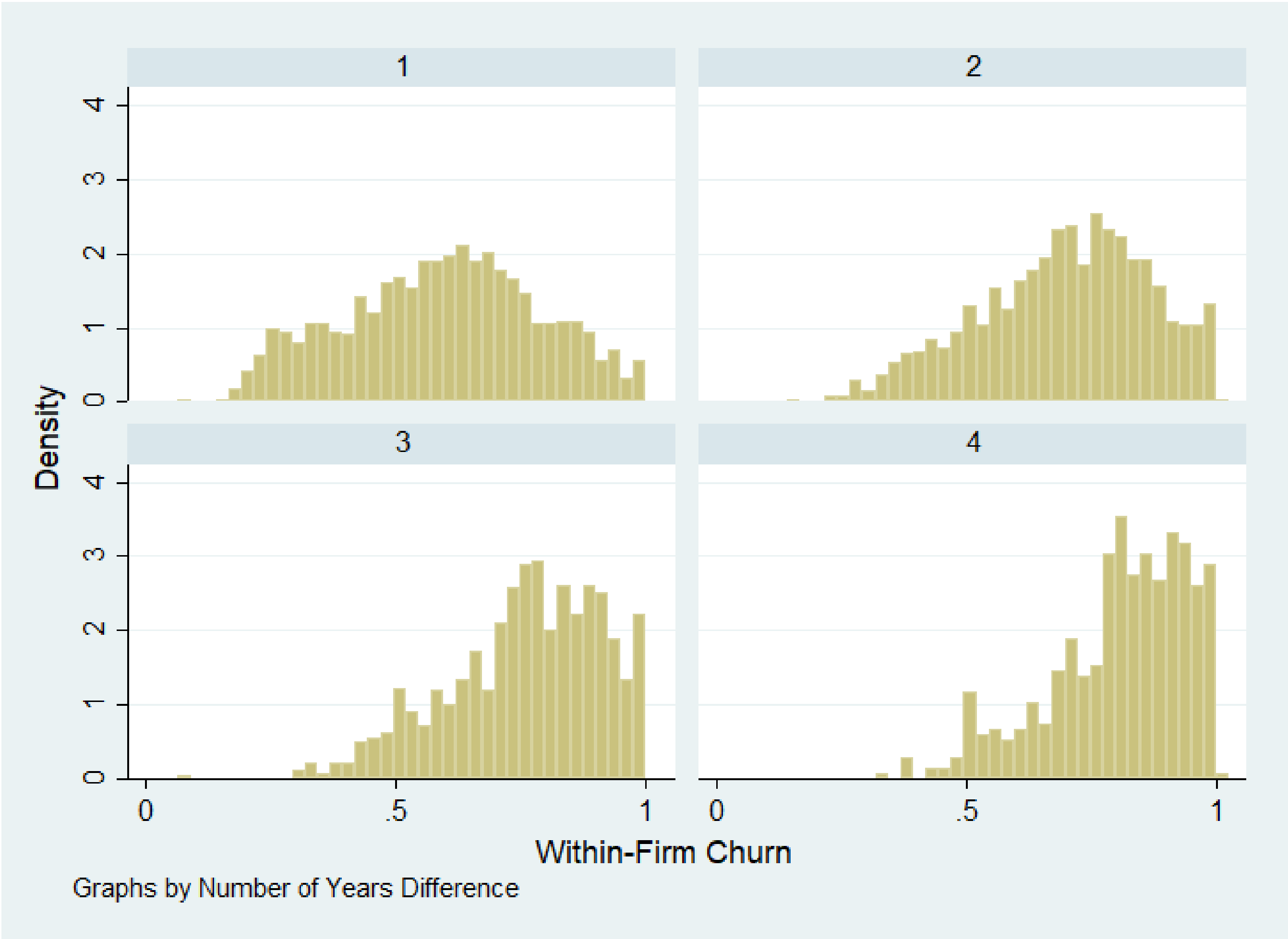
Notes: This figure compares the level of spending observed in the aggregator data to the U.S. Census monthly retail trade report (https://www.census.gov/retail/index.html). We plot spending from January 2011 to April 2015 and scale consumption by the Jan 2011 values to the value of 1 for both data sources.

Figure A.3: Geographic Concentration - Transaction Store Data and Chain Store Guide Data, Selected States



Notes: The graphs demonstrate the relationship between geographic concentration within a firm in two different ways. The first, measured on the x-axis, uses data from Chain Store Guide data and limits our sample primarily to retail firms. The x-axis measures the fraction of a firm's stores that are in a given state in a year (an observation is a firm-state-year). The y-axis measure uses data from our transaction data base and measure the fraction of spending at a retailer that is conducted by users living in a given state. For each graph, the data spans all retailers operating in the listed state in our matched sample, 2011-2014.

Figure A.4: Customer-Base Similarity Within Firm Over Time

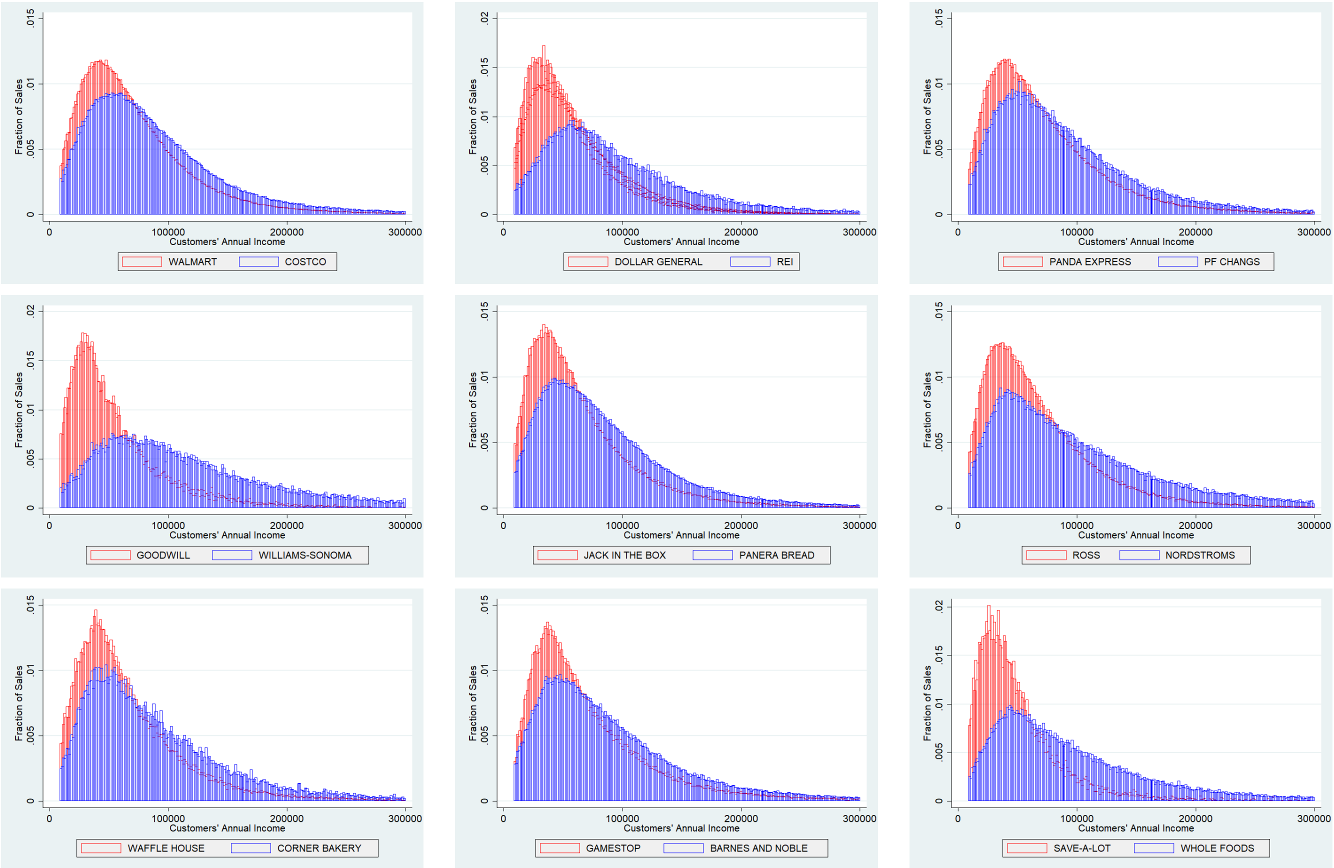


Notes: Each panel denotes the distribution of customer base churn over time across all firms in our sample. Churn is measured as the dollar-weighted overlap between the customer base of a firm f in year t and the customer base of firm f in year $t-x$ where x is between 1 and 4 and is labeled above each panel. Overlap is scaled between 0 and 1 where 1 is an identical customer base and 0 is no overlap between customer bases across years.

Figure A.5: Brand Value and Churn, by Industry

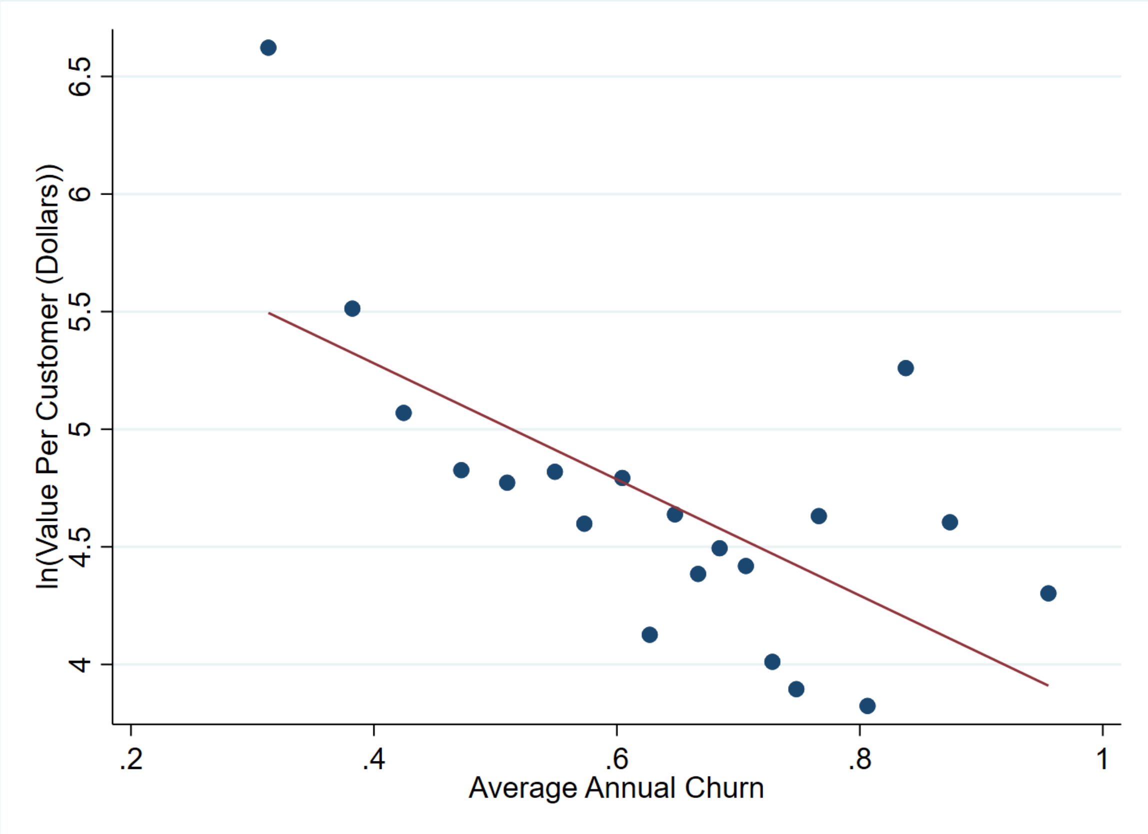
Notes: Churn denotes average annual customer churn within a firm across our sample period. Brand value rankings calculated by Brand Finance's Brandirectory which looks at components such as emotional connection, financial performance and sustainability and then applies royalty rates to calculate a capitalized brand value.

Figure A.6: Income Distribution of Customer Base, Firm-level Comparisons



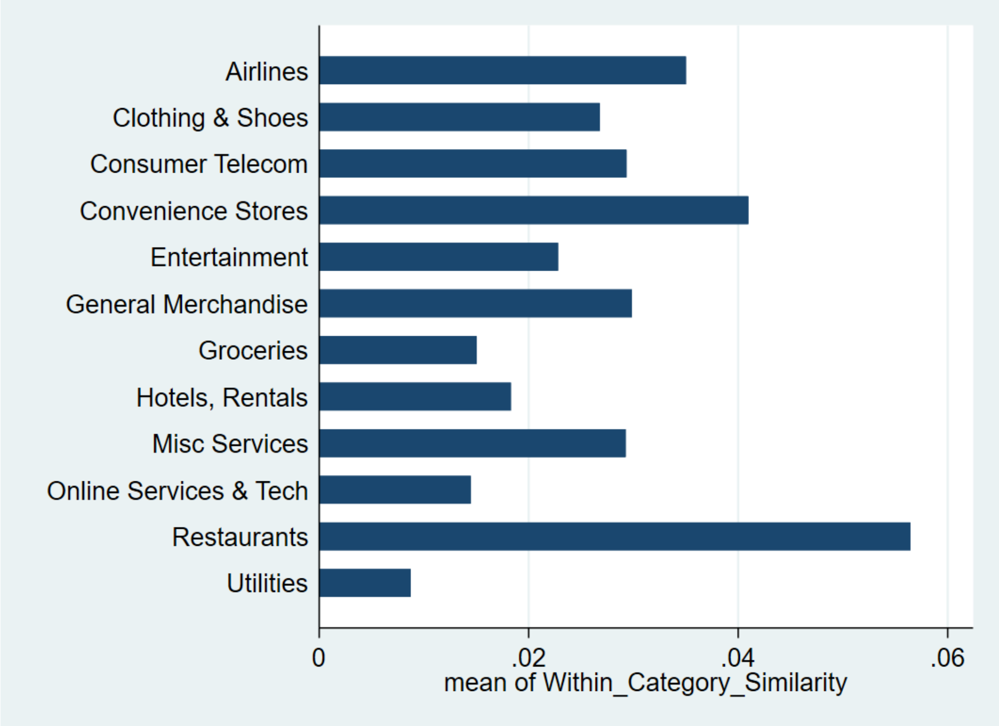
Notes: Figures demonstrate the distribution of income among customers for a selected sample of firms. Customer's are dollar-weighted by sales at a firm, so a user spending \$500 at a firm will have double the weight in the histogram as a user spending \$250. Annual income is binned in \$1,000 increments and is censored at \$300,000 for illustrative purposes. In each panel, two firms of similar types are compared. Data spans 2010-2015.

Figure A.7: Market Value per Customer vs. Churn



Notes: Y-axis is logged average market value per customer between 2011 and 2015. X-axis is average churn between 2012 and 2015 i.e., using data from 2011-2015. Estimates of market value per customer are Winsorized at the 1% and 99% level.

Figure A.8: Similarity of Firm Customer Bases Within Category, by Category



Notes: Bars denote the average cross-firm similarity within the listed industries. That is, the similarity between firm i and firm j who are both operating in broad industry classification x.

Table A.1: Examples of Transaction String Data

Description	Count of Txns	Average Txn Amount	Frac Debit	Avg Loose Recurring
home depot	11,002,662	74.31	0.911	0.001
starbucks corpx	8,676,113	7.14	0.999	0.007
jack in the box	3,035,066	8.91	1.000	0.005
aeropostale	327,696	41.53	0.948	0.001
duane reade th ave new	160,318	18.72	1.000	0.004
bos taxi med long island cny	46,648	17.68	1.000	0.002
sbc phone bill ca bill payment	22,248	83.07	1.000	0.132
golden pond brewing	2,385	38.98	1.000	0.001
cross bay bagel	1,542	15.46	1.000	0.000
lebanese taverna bethe	1,542	68.44	0.999	0.005
racetrac purchase racetrac port charlot	1,357	31.32	1.000	0.007
trader joes rch palos vr	1,273	41.91	1.000	0.000
chevys fresh mex aronde	956	36.83	1.000	0.000
graceys liquor	113	15.99	1.000	0.018

Notes: Table denotes sample transaction descriptions from our database of financial transactions. Each panel displays the cleaned description string (e.g., removing numerics), the number of observations of that string in our data, the average transaction amount for that description string, the fraction of transactions that are debited from an account (instead of credited), and the fraction of transactions that are similar to a previous transaction to that description within a user.

Table A.2: Matching to Largest Firms by Industry

Industry	Avg. Rank Matched	Avg. Rank Unmatched	Avg. Percentile Rank Matched	Avg. Percentile Rank Unmatched	% of Top 5 Matched	% of Top 5 Unmatched
Airlines	6	15	73%	32%	100%	0%
Clothing & Shoes	19	21	52%	48%	100%	0%
Consumer Telecom	20	66	84%	45%	80%	20%
Entertainment	11	24	77%	45%	40%	60%
General Merchandise	69	103	59%	39%	100%	0%
Groceries	6	10	58%	18%	100%	0%
Hotels, Rentals	16	32	73%	43%	60%	40%
Others Services & Tech	95	195	74%	47%	20%	80%
Resturants	30	82	76%	34%	100%	0%
Utilities	23	77	83%	43%	60%	40%

Notes: We rank Compustat firms based on their total revenue in 2014. We then compare the numerical ranks (with one being the highest), and percentile ranks (with 100% being the highest) of the firms in our matched sample, with Compustat at large by industry. We then keep the 5 largest firms in each industry by revenue, and count how many of those firms are in our matched dataset. When matching to Compustat, and calculating the ranks, we restrict the sample to U.S. firms, with a traded common stock, non-missing revenue and non-missing NAICS industry.

Table A.3: Customer Churn and Local Categorical Sales Shares

VARIABLES	(1) Churn	(2) Churn	(3) Churn	(4) Churn	(5) Churn	(6) Churn
Fraction of Category Spending in City		-0.742***		-0.566***		-0.553***
		(0.00288)		(0.00285)		(0.00285)
Observations	311,264	311,264	311,264	311,264	311,256	311,256
R^2	0.076	0.241	0.350	0.422	0.701	0.762
Year FE	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Category FE	NO	NO	YES	YES	YES	YES
Firm FE	NO	NO	NO	NO	YES	YES

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: The level of customer churn is calculated at a firm-city-year level (2011-2014), and it is the churn from last year's customer base. Fraction of local categorical spending is computed as $\frac{Spending_{icjt}}{\sum Spending_{cjt}}$. City-firm-years are excluded if they feature fewer than 50 customers.

Table A.4: Single Sort on Customer Churn

	Low	2	3	4	High	5 - 1
Mkt. Excess Ret.	0.627***	0.958***	0.983***	1.028***	1.198***	0.571***
	(0.051)	(0.069)	(0.073)	(0.057)	(0.083)	(0.099)
Alpha	0.00526***	0.00729**	0.000721	-0.00177	0.00388	-0.00138
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)
Observations	120	120	120	120	120	120
R-squared	0.595	0.568	0.609	0.715	0.621	0.215
St. Dev.	0.105	0.165	0.163	0.158	0.197	0.16

Notes: Each month, we form 5 value-weighted portfolios based on average churn at the GVKEY level between 2011 and 2015. We then regress the excess returns of these portfolios on the excess return of the market factor from Ken French's data library using data from 2010 to 2019. The column "5-1" represents a long-short portfolio, which goes long high churn firms, and short low churn firms. Robust standard errors in parenthesis. The last row reports the standard deviation of each portfolio over the whole 2010-2019 sample.

Table A.5: Customer Churn and Margin Volatility

	Net Profit Margin		Cashflow Margin		Gross Profit Margin		Gross Profit to Assets	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Churn	-2.808*	-0.261	-4.407***	-1.726	-2.358***	-2.290**	1.746	-6.397**
	(1.639)	(1.896)	(1.652)	(1.869)	(0.784)	(1.061)	(1.805)	(2.645)
ln(Revenue)	-0.759***	-0.459***	-0.794***	-0.582***	-0.0561	0.0476	-0.734***	-0.748***
	(0.156)	(0.152)	(0.171)	(0.183)	(0.093)	(0.105)	(0.224)	(0.193)
Observations	302	302	302	302	302	302	302	302
R-squared	0.069	0.263	0.077	0.262	0.02	0.157	0.06	0.241
Specification	Bivariate	Category FE	Bivariate	Category FE	Bivariate	Category FE	Bivariate	Category FE

Notes: In each column, the left-hand-side is 100 times the standard deviation of average annual margins between 2010 and 2019, Winsorized at the 1% and 99% levels. Net profit margin is (income before extraordinary items)/sales, cashflow margin is (income before extraordinary items + depreciation and amortization)/sales, gross profit margin is (sales-cost of goods sold)/sales and gross profit to assets is (sales-cost of goods sold)/total assets. The right hand side variables are average churn and average ln(Revenue) between 2011 and 2014. The columns labeled "Category FE" have fixed effects for the categories in our database e.g., Airlines, Clothing & Shoes, etc. Robust standard errors in parenthesis.

Table A.6: Double Sort on Firm Size and Customer Churn

Revenue		Low			2	
Churn	Low	2	High	Low	2	High
Mkt. Excess Ret.	0.990***	1.144***	1.185***	0.732***	1.003***	1.339***
	(0.089)	(0.082)	(0.113)	(0.074)	(0.073)	(0.075)
Alpha	0.00143	-0.0028	-0.00680*	0.00683***	-0.00364	-0.00143
	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Observations	120	120	120	120	120	120
R-Squared	0.507	0.532	0.512	0.525	0.567	0.762

Revenue		High		Low	2	High
Churn	Low	2	High	HML	HML	HML
Mkt. Excess Ret.	0.470***	0.977***	1.013***	0.195*	0.607***	0.543***
	(0.059)	(0.068)	(0.057)	(0.104)	(0.086)	(0.084)
Alpha	0.00527**	0.00654***	0.002	-0.00823*	-0.00826**	-0.00327
	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)	(0.003)
Observations	120	120	120	120	120	120
R-Squared	0.38	0.655	0.724	0.024	0.32	0.276

Notes: Each month, we form 3 portfolios based on the previous year's total revenue in Compustat. Then, within each of these 3 portfolios, we form 3 sub-portfolios based on average churn at the GVKEY level between 2011 and 2015. We then regress the excess returns of these value-weighted portfolios on the excess return of the market factor from Ken French's data library using data from 2010 to 2019. The columns labeled "HML" represent a long-short portfolio, which goes long high churn firms, and short low churn firms. Robust standard errors in parenthesis.

Table A.7: Triple Sort on Firm Size, Churn and Organization Capital

Size	Small					
Churn	Low		High		HML	
OK/AT	Low	High	Low	High	Low	High
Mkt. Excess Ret.	0.888***	0.945***	1.156***	1.407***	0.268***	0.462***
	(0.072)	(0.119)	(0.099)	(0.125)	(0.081)	(0.133)
Alpha	0.00252	0.00328	-0.0011	-0.0139***	-0.00363	-0.0172***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.005)
Observations	120	120	120	120	120	120
R-Squared	0.553	0.381	0.581	0.567	0.077	0.081
Size	Big					
Churn	Low		High		HML	
OK/AT	Low	High	Low	High	Low	High
Mkt. Excess Ret.	0.871***	0.718***	1.085***	1.176***	0.214**	0.458***
	(0.061)	(0.061)	(0.064)	(0.093)	(0.087)	(0.082)
Alpha	0.00652***	0.00437*	0.00214	-0.00522	-0.00438	-0.00959***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	120	120	120	120	120	120
R-Squared	0.651	0.541	0.688	0.624	0.056	0.216

Notes: Each month, we first split firms into two groups based on whether they had above or below median total revenue in Compustat the previous year. Then, within each of these two groups, we form 3 sub-portfolios based on average churn at the GVKEY level between 2011 and 2015. Finally we form 3 further sub-portfolios based on organization capital over assets from the Eisfeldt et al. (2020) replication file. We then regress the excess returns of these value-weighted portfolios on the excess return of the market factor from Ken French's data library using data from 2010 to 2019. The HML columns represent a long-short portfolios, which go long high churn firms, and short low churn firms, within each total revenue bucket and OK/AT tercile. Robust standard errors in parenthesis.

Table A.8: Customer Base Concentration, by Industry

Category	# Obs.	HHI	Top 5% Share	Top 10% Share	Top 20% Share
Clothing & Shoes	207	0.57	24.8%	37.7%	55.1%
Consumer Telecom	59	0.62	17.9%	30.3%	49.3%
Convenience Stores	44	0.70	40.6%	56.5%	73.2%
Entertainment	56	1.50	25.2%	37.7%	55.1%
General Merchandise	462	0.81	29.1%	43.1%	61.2%
Groceries	166	1.51	42.8%	59.9%	77.3%
Hotels, Rentals, Airlines	96	1.16	29.2%	42.5%	60.7%
Misc Services	59	0.57	24.8%	37.7%	55.8%
Online Services & Tech	126	1.12	24.7%	36.9%	53.9%
Restaurants	369	0.38	27.9%	41.1%	57.9%
Utilities	116	0.83	15.5%	26.7%	44.6%

Notes: Table reports summary statistics across firms in a range of industry groupings. An observation is a firm-year. HHI is within-firm concentration in customer dollars. HHI is measured as the sum of squared fractions of revenue obtained from each customer, multiplied by 10,000. In this table, we equally weight firm-years but remove firms with fewer than 7,500 observed customers in a year.

Table A.9: Customer-Base Similarity and Returns

	Low	2	3	4	High	Long/Short
MKT	1.064***	1.065***	1.071***	0.959***	0.978***	-0.086
	(0.082)	(0.082)	(0.067)	(0.069)	(0.065)	(0.085)
SMB	-0.042	0.021	-0.042	-0.065	-0.198**	-0.155
	(0.150)	(0.130)	(0.139)	(0.110)	(0.092)	(0.174)
HML	-0.207	-0.32	-0.185	-0.027	-0.184	0.023
	(0.158)	(0.197)	(0.126)	(0.166)	(0.143)	(0.178)
RMW	0.438**	0.576***	0.512***	0.273	0.256*	-0.182
	(0.187)	(0.206)	(0.175)	(0.176)	(0.131)	(0.215)
CMA	0.171	0.048	-0.307	-0.077	-0.084	-0.255
	(0.189)	(0.315)	(0.213)	(0.216)	(0.196)	(0.213)
MOM	0.154	0.019	0.236**	0.071	0.081	-0.074
	(0.100)	(0.089)	(0.108)	(0.087)	(0.092)	(0.118)
Alpha	-0.003	-0.002	0.003	0.003	0.005**	0.009***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
Obs	108	108	108	108	108	108
R-sq	0.706	0.674	0.728	0.683	0.715	0.046
Sharpe Ratio	0.664	0.739	1.133	1.074	1.353	0.832
Mkt. Sharpe Ratio	0.91	0.91	0.91	0.91	0.91	0.91

Notes: Specification uses the 10 closest firms (similarity-basis) across years 2010-2018 and excluding finance/utilities. We drop 2010 and 2015 from our customer similarity data and use a value-weighted portfolio of nearest firms. Returns are calculated over the past quarter.

Table A.10: Asset Pricing Application (timing)

	Low	2	3	4	High	HML
MKT	0.806***	0.881***	0.939***	0.883***	0.848***	0.042
	(0.110)	(0.062)	(0.157)	(0.112)	(0.112)	(0.143)
SMB	-0.023	-0.284*	-0.492**	-0.036	-0.13	-0.107
	(0.141)	(0.154)	(0.190)	(0.172)	(0.146)	(0.198)
HML	-0.306	-0.216	-0.411	-0.024	-0.295	0.011
	(0.236)	(0.198)	(0.408)	(0.270)	(0.223)	(0.347)
RMW	0.063	0.055	-0.15	-0.25	0.259	0.195
	(0.315)	(0.237)	(0.449)	(0.235)	(0.239)	(0.373)
CMA	0.703**	0.203	0.047	0.116	0.076	-0.627
	(0.271)	(0.299)	(0.420)	(0.367)	(0.322)	(0.438)
MOM	-0.220*	0.067	0.281*	0.083	-0.014	0.206
	(0.117)	(0.087)	(0.165)	(0.115)	(0.121)	(0.143)
Alpha	-0.002	0	0.004	0.005	0.006	0.008*
	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.005)
Obs	48	48	48	48	48	48
R-sq	0.673	0.728	0.621	0.687	0.636	0.162
Sharpe Ratio	0.492	1.117	1.466	1.512	1.557	1.32
Mkt. Sharpe Ratio	1.079	1.079	1.079	1.079	1.079	1.079

Notes: Specification uses the 10 closest firms (similarity-basis) across years 2012-2016 and excluding finance/utilities. We drop 2010 and 2015 from our customer similarity data and use a value-weighted portfolio of nearest firms. Returns are calculated over the past quarter.

Table A.11: Asset Pricing Application (correlation)

	Low	2	3	4	High	HML
MKT	0.842***	1.042***	0.926***	0.893***	0.946***	0.104
	(0.075)	(0.056)	(0.059)	(0.086)	(0.103)	(0.150)
SMB	0.051	-0.095	-0.053	-0.185	-0.117	-0.169
	(0.121)	(0.108)	(0.101)	(0.121)	(0.148)	(0.228)
HML	-0.209	-0.096	-0.158	-0.1	-0.568***	-0.36
	(0.136)	(0.113)	(0.141)	(0.177)	(0.210)	(0.281)
RMW	0.145	0.563***	0.771***	0.268	0.213	0.069
	(0.157)	(0.163)	(0.169)	(0.189)	(0.227)	(0.278)
CMA	0.068	-0.397**	0.154	0.137	0.591**	0.523
	(0.216)	(0.189)	(0.240)	(0.225)	(0.271)	(0.375)
MOM	0.14	0.074	0.109	0.253*	0.169	0.029
	(0.086)	(0.089)	(0.088)	(0.133)	(0.116)	(0.172)
Alpha	0.004	0	0	0.002	0.003	-0.001
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
Obs	108	108	108	108	108	108
R-sq	0.642	0.761	0.693	0.608	0.569	0.036
Sharpe	1.148	0.941	0.987	1.038	1.098	0.116
Mkt. Sharpe	0.91	0.91	0.91	0.91	0.91	0.91

Notes: Specification uses the 10 closest firms (similarity-basis) across years 2010-2018 and excluding finance/utilities. We drop 2010 and 2015 from our customer similarity data and use a value-weighted portfolio of nearest firms. Returns are calculated over the past quarter. 'Sharpe' denotes the Sharpe Ratio.

Table A.12: Asset Pricing Application (double sort)

	Low Overlap		High Overlap		High-Low	
	Low Corr.	High Corr.	Low Corr.	High Corr.	Low Corr.	High Corr.
MKT	0.959***	0.928***	1.000***	0.833***	0.041	-0.094
	(0.067)	(0.078)	(0.064)	(0.068)	(0.093)	(0.095)
SMB	-0.035	-0.117	-0.068	-0.14	-0.033	-0.023
	(0.112)	(0.140)	(0.112)	(0.094)	(0.176)	(0.186)
HML	-0.218	-0.342*	-0.07	-0.233	0.148	0.108
	(0.135)	(0.204)	(0.131)	(0.142)	(0.208)	(0.263)
RMW	0.377**	0.397*	0.491***	0.169	0.114	-0.228
	(0.177)	(0.203)	(0.144)	(0.173)	(0.245)	(0.270)
CMA	0.038	0.283	-0.299	0.249	-0.337	-0.035
	(0.214)	(0.305)	(0.196)	(0.162)	(0.312)	(0.368)
MOM	0.135**	0.154	0.09	0.214***	-0.044	0.061
	(0.064)	(0.120)	(0.090)	(0.074)	(0.110)	(0.141)
Alpha	-0.002	-0.002	0.004*	0.005**	0.006*	0.007**
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
Obs	108	108	108	108	108	108
R-sq	0.734	0.566	0.732	0.693	0.021	0.018
Sharpe	0.748	0.666	1.19	1.429	0.65	0.627
Mkt. Sharpe	0.91	0.91	0.91	0.91	0.91	0.91

Notes: Specification uses the 10 closest firms (similarity-basis) across years 2010-2018 and excluding finance/utilities. We drop 2010 and 2015 from our customer similarity data and use a value-weighted portfolio of nearest firms. Returns are calculated over the past quarter. 'Sharpe' denotes the Sharpe Ratio.

Table A.13: Customer-Base Similarity and Earnings Reports

	SUE		Earnings Returns		Forecast Accuracy	
	(1)	(2)	(3)	(4)	(5)	(6)
Overlapping SUE	0.00728*					
	(0.004)					
Your SUE		0.0112**				
		(0.005)				
Overlapping return			0.0153***			
			(0.005)			
Your return				0.0336***		
				(0.006)		
Overlapping forecast error					-0.00427	
					(0.003)	
Your forecast error						-0.0067
						(0.006)
Observations	59,660	74,178	59,660	74,178	59,580	73,983
R-Squared	0.208	0.041	0.125	0.057	0.358	0.034

Notes: 20 closest firms, 2010-2018, drop 2010 and 2015 from our data, require firms to have same fiscal period end, and release earnings in the same calendar quarter. All specifications include calendar quarter fixed effects and firm fixed effects. Standard errors clustered at the security level.