Customers and Retail Growth

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Abstract

Using Visa debit and credit card transactions in the U.S. from 2016 to 2019, we document the importance of customers in accounting for sales variation across merchants, across stores within retail chains, and over time for individual merchants and stores. Customers, as opposed to transactions per customer or dollar sales per transaction, consistently account for about 80% of sales variation. The top 5% of growing and shrinking merchants account for the bulk of customer reallocation in a given year. We then write down a simple growth model that incorporates both the extensive and intensive margins by which firms can increase sales, and illustrates why the distinction could matter. In this context, we show that the extensive customer margin amplifies the role of large firms in sales and sales growth, but does not stimulate aggregate growth.

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[*] Einav, Klenow, and Levin: Stanford University and NBER; Murciano-Goroff: Boston University. Conclusions expressed herein are those of the authors and do not necessarily represent the views of Visa, Inc. We are grateful to Sam Kortum and Sara Moreira for helpful discussions, and to Jean-Felix Brouillette and Yue Cao for excellent research assistance.

1. Introduction

Over the last two decades, a stream of research has emphasized the role of customer acquisition in firm dynamics, trade, and growth. Influential models include Fishman and Rob (2003), Luttmer (2006), Arkolakis (2010, 2016), and Perla (2019). Gourio and Rudanko (2014) and Gilchrist, Schoenle, Sim and Zakrajšek (2017) argue that such frictions play a role in business cycle fluctuations, Eslava, Tybout, Jinkins, Krizan and Eaton (2015) present evidence and a customer search model of exporting firm dynamics, and Bernard, Dhyne, Magerman, Manova and Moxnes (2019) document the importance of the number of customers in Belgian inter-firm transactions. Bornstein (2018) argues that consumer aging interacts with customer inertia to explain the decline in both labor's share and firm entry in recent decades. Bagwell (2007) surveys models and evidence on the role of advertising in reaching and attracting customers.

In this paper, we use Visa debit and credit card transactions from 2016–2019 to bring new systematic and direct evidence to bear on the importance of customers in the U.S. retail sector.[1] The Visa data covers a significant part of consumer spending in the U.S. Roughly 93% of households used at least one debit or credit card in 2018 (Foster, Greene and Stavins, 2019). Around 24% of all U.S. consumer spending flowed through Visa in 2019.[2] If Visa's 60% share is representative of all debit and credit card spending, then Visa spending patterns are relevant for around 40% of all consumption.[3]

We start by decomposing Visa sales at a chain and store level into the number of unique credit and debit cards, transactions per card, and sales per transaction. We find that the number of customers dominates the decomposition

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[1] The sample is anonymized. Neither the name, address, nor any personal information about the cardholder is observable, other than what can be inferred given a card's transaction history.

[2] Visa (2019)'s 2019 10-K filing reports $3.242 trillion in nominal payments volume for consumer credit and debit. This is 24.4% of BEA nominal consumption in 2019 of $13.280 trillion.

[3] Consistent with wide spending coverage, in Yelp data for seven mid-sized cities (Pittsburgh, Charlotte, Urbana-Champaign, Phoenix, Las Vegas, Madison, and Cleveland) in 2017, three quarters of the outlets who reported payment information and 93% of tem indicated that they accepted credit cards (https://www.yelp.com/dataset).

across merchants, across stores within merchants, and over time within stores or merchants.

The customer margin is more important for brick-and-mortar transactions than for e-commerce. Focusing on offline retail, we show that about 80% of sales variation can be traced to the number of customers, and that the importance of customers per store plays an even bigger role than the number of stores for sales variation across merchants and over time for a given merchant. For only the largest merchants does the store margin play a big role. Perhaps surprisingly, the importance of customers is remarkably consistent across all retail categories, such as furniture, electronics, restaurants, or gas stations.

Our decomposition does not distinguish between adding low-spending vs. high-spending customers. If expanding stores and merchants tend to add low-spending customers, this will tend to overstate the contribution of new customers and understate the role of spending increases by retained customers. To address this, we show that retained customers do tend to increase their spending more at fast-growing merchants and stores. Even with a generous adjustment for the spending of gained and lost customers versus retained customers, however, we find that the extensive margin accounts for 60% of sales growth variation across merchants and stores.

We then continue by showing that the majority of aggregate sales increases and decreases can be traced to the 5% fastest growing and shrinking merchants in a given year. This is consistent with a stream of results on the role of fast-growing firms in aggregate job creation, such as Decker, Haltiwanger, Jarmin and Miranda (2016). We find that most of this tail behavior in the Visa data reflects adding or losing customers. Though in the retail sector rather than the manufacturing sector, our evidence of a large extensive margin for customers is in the spirit of findings by Foster, Haltiwanger and Syverson (2008, 2016) and Hottman, Redding and Weinstein (2016). These studies estimate that fast-growing manufacturers experience rising demand for their products, as opposed to selling a wider array of products more cheaply. One explanation for this could be that such firms are attracting more customers, perhaps linked to the quality and variety of their products. Baker, Baugh and Sammon (2020) also analyze customers using debit and credit card transactions, specifically from 2010 to 2015. Their focus is on a smaller set of 550 firms, 420 of whom are publicly traded and hence have observable stock returns. Their analysis, like ours, emphasizes the importance of the customer margin.

As a way to illustrate why and how the customer margin could be important, and different from the intensive (quality or price) margin, we write down a simple model of firms dynamics and growth that incorporates both the extensive and intensive margins of growth. In the model, firms invest in improving the quality of their products each period, which generates endogenous growth in the aggregate. Innovation outcomes are stochastic, so firms are heterogeneous in their quality levels and growth rates. There are knowledge spillovers across firms, as firms can invest in imitating the quality of their competitors. There is also business stealing from both innovation and marketing efforts. We assume that firms spend on marketing to access customers each period. Because they sell more to each customer they access, firms with higher quality products spend more to access more customers. Customer acquisition thereby amplifies size differences stemming from quality differences across firms. Customers are a static function of current year marketing efforts; firms do not lower markups early on to build their customer base dynamically. This is consistent with empirical evidence on Irish exporting firms and U.S. consumer goods manufacturers documented by Fitzgerald and Priolo (2018) and Fitzgerald, Haller and Yedid-Levi (2019).

The model illustrates how our evidence on the customer margin can inform quantitative modeling and policy analysis. In the model, the more that customers amplify the effects of quality differences, the more large firms invest in marketing and research, and the bigger the aggregate growth contribution of the largest firms. Yet, calibrating the model based on the empirical facts we document, we find that the customer margin does not boost aggregate growth.

The rest of the paper proceeds as follows. Section 2 describes the Visa dataset. Section 3 presents evidence on the importance of customers for sales variation. Section 4 describes the growth model, its calibration, and the results. Section 5 concludes.

2. Data

Our primary source of data relies on all credit and debit card transactions that were processed through Visa's electronic payments network in the US between January 2016 and December 2019. The Visa network is the largest network in the market, accounting for about 50% of the credit card transaction volume and about 70% of the debit card volume over this period, with Mastercard, American Express, and Discover sharing the rest.[4]

The unit of observation is a transaction, which includes a merchant identifier, an anonymized card identifier, the time and date of the transaction, and the transaction amount. We do not see the specific items purchased, nor their prices or quantities. The merchant details include an exact store location, so each merchant's store can be uniquely identified.

We apply standard filters used by Visa's data analytics team. We exclude PIN-debit transactions (as opposed to signature-debit transactions) because their volume flowing through Visa fluctuates substantially with regulatory changes during our sample period. We also exclude transactions that are not sales drafts (these would include chargebacks, failed transactions, or payment holds, which would not culminate in an actual transaction), those coming from prepaid gift cards, and those conducted by cards that transacted at fewer than five merchants during the lifetime of the card (these are likely specialized merchant-specific rewards cards). We also exclude transactions associated with merchants located outside the US (which would flow through the US Visa network if the card is issued by a US bank). Online Appendix A provides more detail.

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[4] https://WalletHub.com/edu/market-share-by-credit-card-network/25531.

Given the focus of the paper, we further restrict the analysis to merchants who are (self) classified as operating in the retail sector (Census Bureau NAICS 44 and 45) or as restaurants (NAICS 722), and we limit our primary analysis to in-person transactions where the card was used in a brick-and-mortar store. Thus, our main sample drops NAICS code 454 ("Nonstore Retail"), which consists almost exclusively of online transactions. We also exclude Gas Stations (NAICS 447) when we decompose aggregate time series changes, given that gasoline sales are heavily driven by price fluctuations (Levin, Lewis and Wolak, 2017).

Overall, the 2016–2019 Visa data contain an annual average of 428 million cards, 31.5 billion transactions, and $1.07 trillion in sales for the retail sector plus restaurants.[5] Of these sales, 60% (of the dollar volume) were credit transactions and 40% were debit transactions. Visa spending covers a similar share of sales and restaurant spending in 2019 as consumption overall. Thus, if other card transactions are similar in nature to Visa's, then Visa spending would be representative of approximately 40% of all retail and restaurant sales.

We analyze the Visa data at three levels of aggregation. First, we aggregate the transaction data to a store-card-year level to calculate each card's yearly spending in each store. Second, we aggregate the data to a store-year level. We calculate, for every store-year, the following variables: number of distinct customer accounts (that is, unique cards), the number of transactions (swipes), and the dollar volume of transactions. Third, we aggregate the data to a merchant-year level, that is across all merchant locations in a given year. We then calculate, for each merchant, the following variables: number of distinct locations (stores), number of distinct customer accounts (cards), number of transactions, and dollar volume.

Finally, we note that we also have access to Visa data before 2016, going back to 2007, but it is less granular with respect to stores and merchants. For the largest merchants (which covers about 70% of the transactions and 60% of the

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[5] Appendix Table A2 provides these statistics for each year separately.

dollar volume during these years), pre-2016 data do not provide exact location for each transaction, but only a 5-digit zip code, which makes it infeasible to distinguish stores of the same merchant within a zip. Smaller merchants in these earlier years are grouped by NAICS, so it is also infeasible to distinguish different stores of different small merchants within a NAICS-zip combination, rendering them mostly unusable for our purpose. Therefore, in our main analysis we use the complete complete set of merchants and stores uing data from 2016–2019, but we also report results that use larger merchants only for this longer panel of 2007–2019 (see Online Appendix B).

3. Customers are important: Descriptive facts

3.1. Sales Decompositions

Measurement. To gauge the importance of customers to a merchant's or store's sales, we decompose sales into three margins we can observe in the Visa data:

$$S = N \cdot \frac{V}{N} \cdot \frac{S}{V}, \tag{1}$$

where S denotes total merchant (or store) sales in dollars over a given period, N is the number of unique customer accounts that transact at the merchant or store over that period, and V is the total number of visits (transactions) at the merchant or store in that period. The decomposition breaks down total sales into a customer extensive margin (the number of cards) and two intensive margins — the frequency at which customers visit the merchant or store, V/N, and the average transaction amount (the "ticket size"), S/V.

At the merchant level, we can further decompose how merchants reach customers into their number of locations (stores), L, and the number of unique customers per store, so that the total decomposition becomes:

$$S = L \cdot \frac{N}{L} \cdot \frac{V}{N} \cdot \frac{S}{V}. \tag{2}$$

To operationalize this decomposition, we take logs of both sides in equation (1) or (2) and regress each right-hand-side component on log sales. These coefficients add up to 1 by construction. The coefficients are equivalent to a variance decomposition in which the covariance terms are split equally.

Overall results. Table 1 presents this decomposition at the merchant level using different subsamples of merchants in 2019. Panel A reports results from all sectors (that is, not only retail), covering over two million different merchants. In this broad sample, the customer margin accounts for 74% of sales variation across merchants, transactions per account around 4%, and the ticket size accounts for the remaining 22%. When we look at only online transactions (Panel B), the customer margin falls to 67% of variation in online sales across merchants. In contrast, the customer margin accounts for 81% of variation in offline sales across about 1.8 million merchants in 2019. Of this 81%, 71% comes from accounts per store and only around 10% from the number of stores.

Our primary focus is on offline retail (plus restaurants), a sector that contains almost a million distinct merchants in 2019. The results (in Panel D) are very similar to those obtained using the broader set of offline merchants. For comparison, the bttom panel (Panel E) shows that for the much smaller set of 2,700 large “named” merchants, which Visa tracks all the way back to 2007, the store margin is much more important, accounting for 56% of the variation in sales vs. only 35% that is accounted for by accounts per store.

In Table 2 we focus on the offline retail (plus restaurants) sector, now showing additional types of variation. The first row (Panel A) reproduces the corresponding cross-sectional analysis we already reported in Panel D of Table 1. The second row (Panel B of Table 2) uses the same set of merchants, over the four years of data (2016–2019), but now focusing on variation in sales over time within each merchant. To do so, we aggregate observation at the merchant-year level (there are 3.9 million observations at this aggregation level) and include in all regressions merchant and year fixed effects so that the variation is coming from merchants that grow faster or slower than the average for that year. The

Table 1: Sales Decomposition for Different Merchant Samples

	Stores	Acct/Store	Trans/Acct	Dollar/Trans
A. All Data		0.743	0.037	0.221
$(N = 2,176,981)$		(<0.001)	(<0.001)	(<.001)
		[0.551]	[0.017]	[0.091]
B. Online		0.673	0.073	0.254
$(N = 606,346)$		(<0.001)	(<0.001)	(<0.001)
		[0.645]	[0.083]	[0.232]
C. Offline	0.095	0.714	0.032	0.159
$(N = 1,794,469)$	(<0.001)	(<0.001)	(<0.001)	(<0.001)
	[0.109]	[0.534]	[0.016]	[0.050]
D. Offline Retail	0.093	0.706	0.035	0.166
$(N = 953,615)$	(<0.001)	(<0.001)	(<0.001)	(<0.001)
	[0.115]	[0.591]	[0.018]	[0.063]
E. Offline Retail, “named”	0.561	0.348	0.056	0.035
$(N = 2,741)$	(0.009)	(0.009)	(0.004)	(0.007)
	[0.601]	[0.366]	[0.079]	[0.009]

Note: N = the number of merchant observations. Acct = the number of unique debit and credit card accounts; Trans = the number of transations. Standard errors are reported in parenthesis, and R-Squared values are in square brackets. Regressions are based on 2019 data. All Data covers all merchants with Visa transactions in consumer NAICS. The “named” merchants are the largest chains. Each regression includes NAICS fixed effects.

customer extensive margin is just as important here, accounting for 85% of the variation of sales within merchants. Much of this (68.5%) is attributed to the changing number of accounts per store, and the rest (16%) to store closings and openings.

Panels C and D of Table 2 report a similar analysis at the single store (rather than the merchant) level, where we control for merchant fixed effect in all regressions so that the object of interest is variation in sales across stores within the same merchant. In Panel C we use a cross section of stores (in 2019), and again find that much (84%) of the variation of sales across stores of the same merchant is accounted for by the customer margin. Finally, in Panel D we look at variation in sales within a store over time by (similar to Panel B) using 2016–2019 data, aggregating variables at the store-year level (we have 8.2 million such observations), and adding store and year fixed effects. The customers margin continues to be the dominant factor (82% in this specification) that explains variation in store sales over time.

Taken together, whether we look across merchants or stores in 2019, or across time for merchants and stores from 2016 to 2019, the number of unique customers explains the vast majority (80% or more) of the variation in sales.

Heterogeneity across retail sectors. In some retail contexts, this general finding seems hardly surprising. For example, in the context of furniture stores, when purchases by a single customer are not frequent, it seems natural that sales are almost entirely driven by how many customers show up. Yet, in other retail contexts this general result is a-priory less obvious. For example, one can imagine that coffee shop sales would be driven not only by how many unique customers show up, but whether they show up once week or every day, or whether they add a pastry to the coffee.

To explore this, we repeat the decomposition exercise using the "within merchant over time", which is our preferred specification (as in Panel B of Table 2), but estimate it separately for different retail categories (defined by 3-digit NAICS). As before, the observation is at merchant-year level (using data from

Table 2: Decomposing Sales in Offline Retail

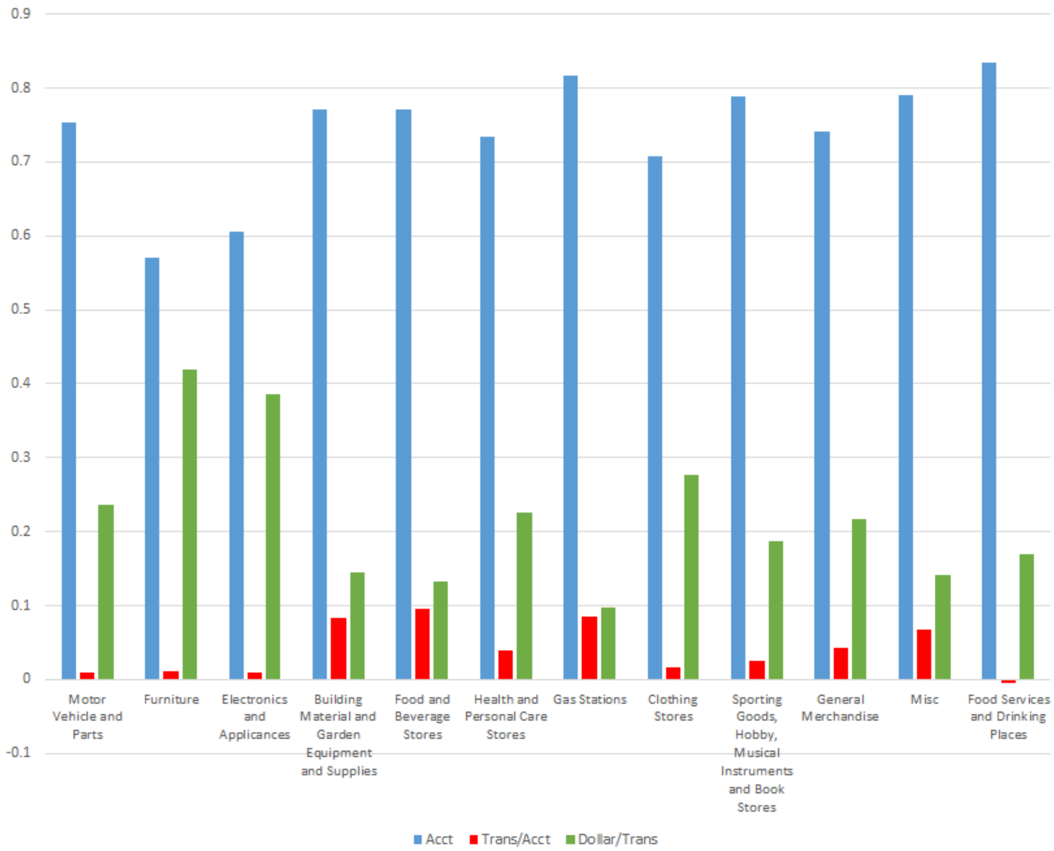
	Stores	Acct/Store	Trans/Acct	Dollar/Trans
A. Across Merchants	0.093	0.706	0.035	0.166
$(N = 953,615)$	[0.115]	[0.591]	[0.018]	[0.063]
B. Within Merchants over Time	0.159	0.685	0.101	0.055
$(N = 3,910,101)$	[0.806]	[0.975]	[0.945]	[0.972]
C. Across Stores within Merchants		0.843	0.079	0.078
$(N = 2,024,687)$		[0.974]	[0.816]	[0.938]
D. Within Stores over Time		0.818	0.137	0.045
$(N = 8,189,195)$		[0.996]	[0.972]	[0.989]

Note: All standard errors are less than 0.001. R-Squared values are reported in square brackets. Across Merchant Decomposition and Across Store within Merchant decompositions are based on 2019 data. Within Merchants over Time and Within Stores over Time are based on 2016–2019 data. Within Merchants over Time regressions include merchant and year fixed effects. Across Stores within Merchants regressions include merchant fixed effects. Within store over Time regressions include store and year fixed effects. See Online Appendix B for robustness with respect to a longer panel of merchant/store data.

2016 to 2019), and each regression includes merchant and year fixed effects.

The results are shown in Figure 1. Customers are the primary driver of merchant sales in all sectors. Customers explain at least 70% of the variation in merchant sales over time in every category except furniture and electronics. In the latter two NAICSs, customers account for about 60% of the variation in sales, and the average transaction amount accounts for much of the rest. The frequency of visits explains very little of sales variation in thee two, a well as all other retail categories.

Figure 1: Decomposing Merchant Sales Growth by Industry



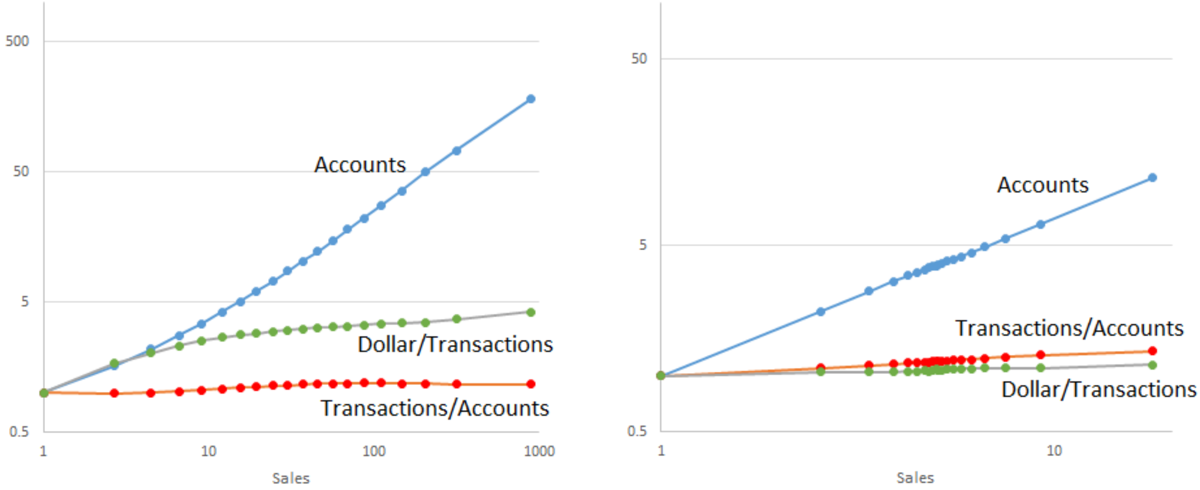
Note: This figure displays the coefficients of the "Within Merchant over time" decomposition by industry. The regressions are run with Visa data from 2016 through 2019, and include merchant and year fixed effects.

Non-linearities. Our linear regressions may hide important non-linearities.

We explore this in Figure 2. We partition merchants into 20 bins in terms of their sales (Figure 2a) or sales growth (Figure 2b), with an equal number of merchants in each bin, and plot their components vs. sales (or sales growth) on a log-log base 10 scale. The first bin is normalized to one for all variables.

In the cross section of merchants in 2019 (Figure 2a), the number of unique customers is even more important across larger merchants, with visits per customer and average transaction amount being less important across the largest merchants. When we look at sales variation over time within a merchant (Figure 2b), after residualizing merchant and year fixed effects, the relationship look approximately linear.

Figure 2: Decomposing Merchant Sales



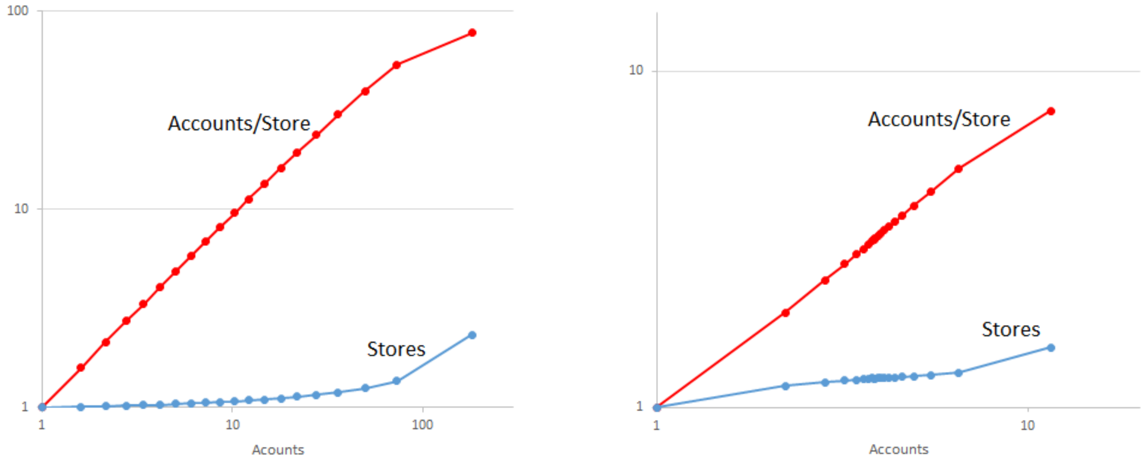
(a) across Merchants

(b) within Merchants over time

Note: Panel (a) is based on a cross section of all merchants in 2019. In panel (a), we group the x-axis into 20 bins, and report averages by bin, normalizing each variable by its average for the first bin. Panel (b) repeats the same exercise, but for the panel of merchant-years over 2016–2019. For (b) we de-mean each variable by its merchant average and its year average, so the plot reflects fast vs. slow-growing merchants over time. Both panels are plotted on a log (base 10) scale.

Figure 3 further decomposes the number of unique customers into the number of stores and the number of unique accounts per store, respectively. It shows that, both in the cross section and over time, the number of stores is not an important source of sales variation for the bottom half (in terms of sales) of merchants, which may be natural as many smaller merchants only have a single store. For larger merchants stores become more important, in particular for the largest set of merchants (top ventile). This is similar to the role of establishments in firm size more generally, as documented by Moscarini and Postel-Vinay (2012) for example. That is, most variation in firm size comes from its employment per establishment, except for the largest firms which have many more establishments.

Figure 3: Stores vs. Accounts Per Store



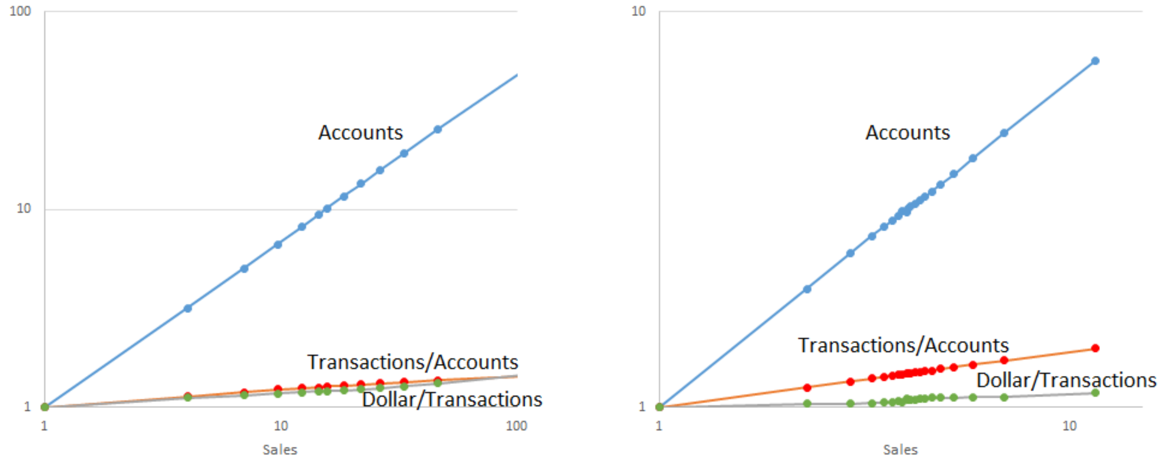
(a) across Merchants

(b) within Merchants over time

Note: Panel (a) is based on a cross section of all merchants in 2019. In panel (a), we group the x-axis into 20 bins, and report averages by bin, normalizing each variable by its average for the first bin. Panel (b) repeats the same exercise, but uses the panel of merchant-years from 2016–2019. For (b), we de-mean each variable by its merchant average and its year average. Both panels are plotted on a log (base 10) scale.

Figure 4 repeats this exercise at the store (rather than merchant) level, both for a cross section of stores in 2019 (Figure 4a) and within tore over time (Figure 4b). The pattern is remarkably similar for stores and for merchants, except that at the store level the relationships are approximately linear throughout.

Figure 4: Decomposing Store Sales



(a) across stores within merchants

(b) within stores over time

Note: Panel (a) uses a cross section of stores in 2019 and de-means each store by its merchant average. We group the x-axis into 20 bins, and report averages by bin, normalizing each variable by its average for the first group. Panel (b) repeats the same exercise, but uses a panel of stores from 2016–2019, de-meaning each variable by its store average and its year average. All panels are plotted on (base 10) log scale.

Results by store age. In Online Appendix B we repeat this analysis for the much smaller set of large merchants who linked back to 2007 in the Visa data. The results look qualitatively similar, with the exception that the number of stores is much more important across large merchants and, to a lesser extent, over time within large merchants.

An advantage of a longer panel is that we can look at whether store dynamics differ by firm age. In Online Appendix B, we decompose the sources of store growth separately for stores in their first two years since entry, years 3-5, and stores that have been open for 6+ years. Customers remain the primary driver of revenue growth for all three age groups (77%, 81%, and 85%, respectively), but new stores rely more than established stores on the average transaction amount to grow their sales (15% vs. 6%, respectively).

Returning vs. newly acquired customers. One possible concern about the above analysis is that it confounds compositional effects. For example, we might be overstating the extensive margin if returning customers increase their spending a lot at growing stores, but average spending does not grow much because new customers spend less than returning customers.[6]

To address this concern, we regress the log change of spending per returning customer on the log change of total sales for merchant-years from 2016 to 2019 (adding year fixed effects).[7] We report the coefficient for all retail (first bar) and separately by 3-digit NAICS in Figure 5. By this metric, returning customers account for 38% of the variance of sales growth in all NAICS. Their contribution ranges from 26% among clothing stores to almost 47% among food and beverage stores. This 38% is notably higher than the approximately 20% variation in sales that we attributed to the intensive margin earlier, when we did not adjust for composition. Still, we continue to find that the extensive margin accounts for most of sales growth variation (62%) by this metric. In Online Appendix D we report similar results at the store level.

3.2. Customers and aggregate growth

Skewed individual contributions to aggregate retail growth. Having established the importance of the customer margin for growth at the merchant and store levels, we now explore how this translates to retail-wide aggregates.[8]

Let S_{it} denote merchant i's total sales in year t, and $\Delta S_{it} = S_{i,t} - S_{i,t-1}$ be the

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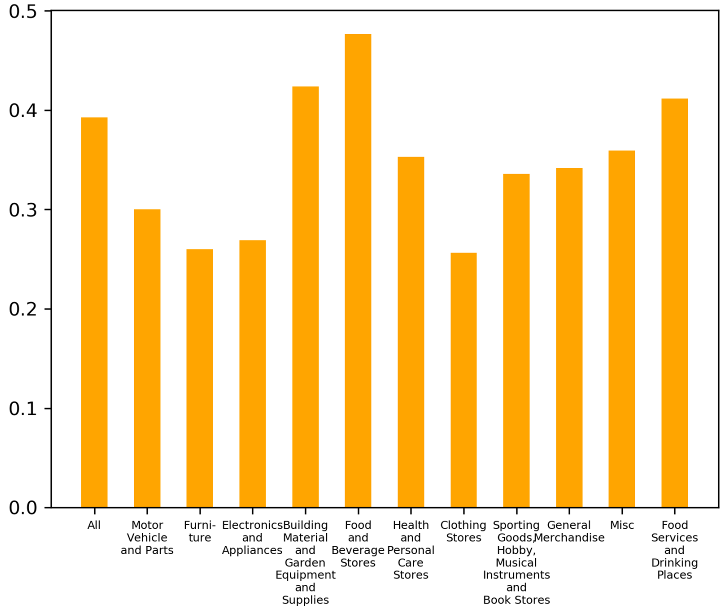
[6] In the case of Pareto distribution of spending across customers, one might see the entry of new customers exactly offset the growing spending of returning customers.

[7] Unlike the earlier decomposition analysis, this is not a precise decomposition because – due to turnover of cards – tracking returning vs. new customers requires us to limit attention to the subset of cards that are active over two consecutive years.

[8] Since the volume of transactions on the Visa network has been steadily increasing over time, throughout this section we measure both aggregate and merchant sales in 2012 CPI dollars and re-scale each of them by Visa's share of the debit and credit card market by dollar volume in the corresponding year (obtained from https://wallethub.com/edu/cc/market-share-by-credit-card-network/25531). As mentioned in Section 2, in this part of the analysis we also excluded gasoline sales.

Figure 5: Spending per returning customer on firm sales growth



The figure reports the coefficient in the regression of annual log change of spending per returning customer on annual log change of total sales. An observation is a merchant-year level. The regression uses 2016-2019 data and includes a year fixed effect.

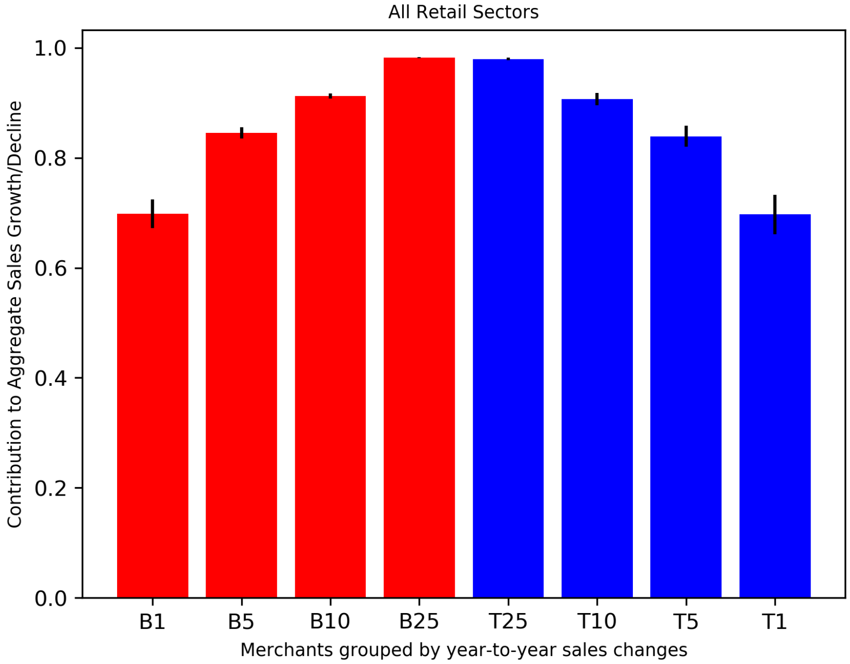
change in merchant i's sales from year $t-1$ to year t. In each year t, we order merchants by ΔS_{it}, and place them into groups, year by year, which account for the top or bottom 1%, 5%, 10%, or 25% of merchants in terms of their sales change in that year. The top 1% saw the biggest increases in their sales, and the bottom 1% saw the biggest decreases in sales.

We next divide the total increases (or decreases) in each group by the sum of all increases (or decreases) across all merchants in the same year. This is analagous to breaking down the gross job creation and destruction rate as in Davis, Haltiwanger and Schuh (1998), only for the gross sales creation and destruction rates. That is, we trace how much of all sales creation and destruction, respectively, comes from the biggest increases and decreases.

Figure 6 plots the contribution of each group to aggregate sales increases or decreases, averaged across the three observations 2016-2017, 2017-2018, and 2018-2019. In a similar spirit to Decker et al. (2016), the figure illustrates that a small fraction of growing merchants is responsible for a large fraction of aggregate growth, and similarly a small number of shrinking merchants are responsible for a large fraction of the aggregate decline. The top 1% growers and shrinkers each contribute more than 60% of aggregate sales increases and decreases, respectively. The top and bottom 5% contribute more than 80%, the top and bottom 10% contribute about 90%, and the top and bottom 25% contribute more than 99%. The patterns appear to be fairly symmetric for growing and shrinking merchants.

As we noted, in Figure 6 the grouping of firms is done year by year. This implies that the identity of tail firms is changing from year to year. How important are *cumulative* sales increases and decreases to the aggregate increases and decreases from 2016 to 2019? To find out we rank merchants based on their cumulative sales changes from 2016 to 2019. This includes entrants among the growers and exiting merchants among the shrinkers.

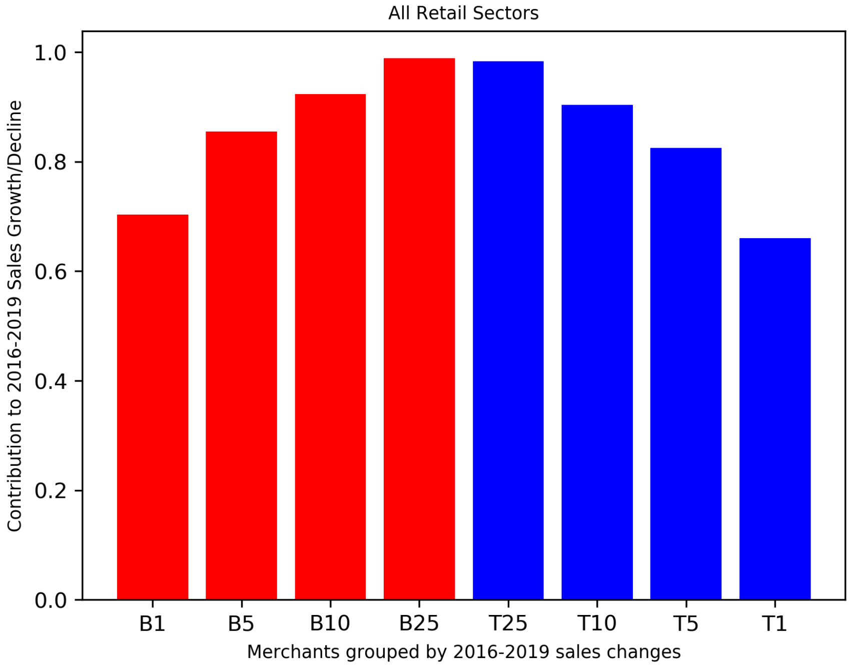
Figure 6: Contribution to Aggregate Sales Changes



The figure reports the average contribution of each merchant group as defined in the text to aggregate sales change over year with the error bar extending one standard deviation up and down. An observation is a merchant-year and the figure uses a panel of merchants from 2016 to 2019. Each bar corresponds to a merchant group. TX refers to top X% merchants and BX refers to the bottom X% of merchants according to their absolute sales changes.

In Figure 7, we then show that tail firm contributions remain remarkably similar when looking at cumulative changes from 2016 to 2019. Evidently, many firms are growing and shrinking by large amounts over the three year period. This could reflect the short time horizon, but in Online Appendix B we document that the patterns are very similar when we use the longer (2007–2019) panel, which include a much smaller set of merchants.

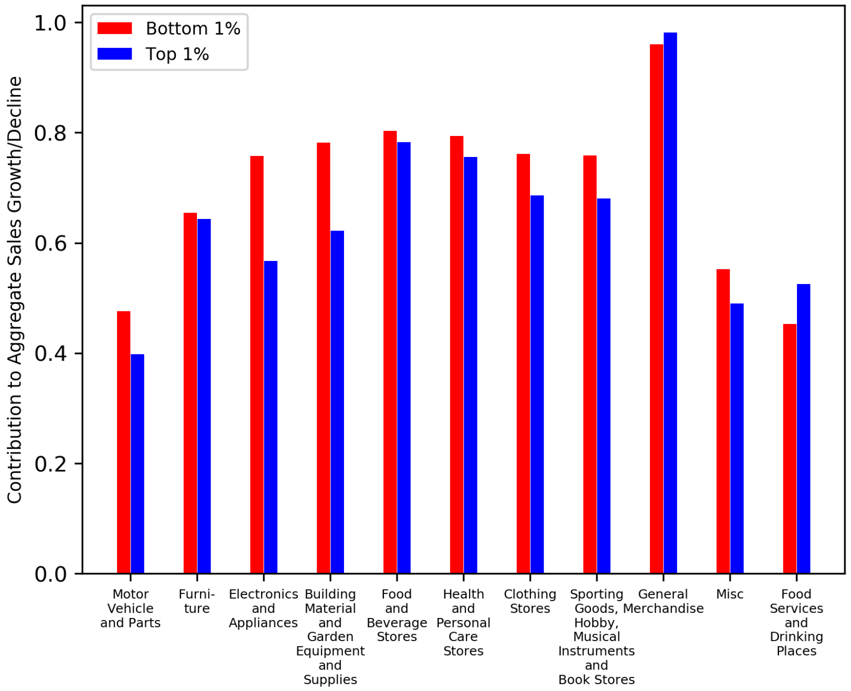
Figure 7: Persistence of Merchant Contributions



The figure reports the contribution of each firm group as defined in the text to aggregate sales change between 2016 and 2019. Each bar corresponds to a firm group. TX refers to top X% firms and BX refers to bottom X% firms by the absolute sales changes between 2016 and 2019.

Figure 8 reports the contributions of the top and bottom 1% of merchants for each 3-digit NAICS from 2016 to 2019. The importance of these tail merchants varies from around 40% in motor vehicles and parts to over 90% for general merchandise, but is mostly in the range of 50% to 80%. Thus, this is a robust feature across retail NAICSs that extreme growers and shrinkers account for a large fraction of aggregate sales changes.

Figure 8: Contribution to Aggregate Sales Changes By NAICS



The figure reports the average contribution of top and bottom 1% merchants to within-NAICs aggregate sales change over year for each retail NAICs. An observation is a merchant-year and the figure uses a panel of merchants from 2016 to 2019. The calculation of each merchant group's contribution is described in the text.

The importance of customers for the tails. We now try to assess the extent to which the extensive margin of customers account for these tail patterns. To do so, we decompose merchant sales changes into two components: changes in the number of customers and changes in sales per customer. Let N_{it} denote the number of unique customers visiting merchant i in year t and S_{it}/N_{it} denote the sales per customer for merchant i in year t. Each merchant's sales changes can be written as

$$\Delta S_{it} \equiv \Delta N_{it} \cdot \overline{S/N}_{it} + \Delta(S/N)_{it} \cdot \overline{N}_{it}$$

where

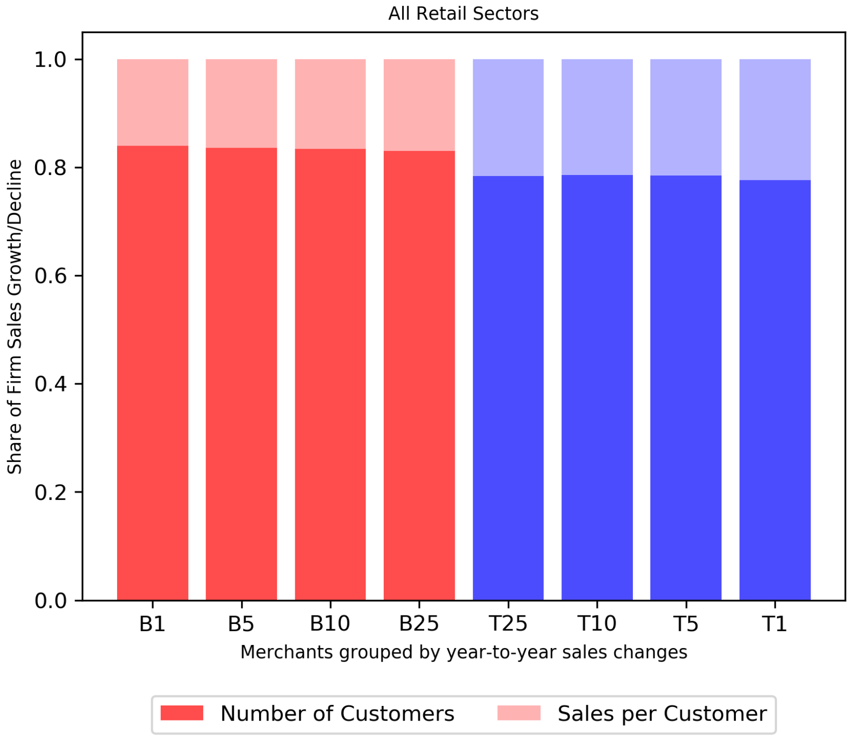
$$\overline{N}_{it} \equiv \frac{N_{it} + N_{i,t-1}}{2}$$

and

$$\overline{S/N}_{it} \equiv \frac{S_{it}/N_{it} + S_{i,t-1}/N_{i,t-1}}{2}.$$

Using this decomposition, we can tell how much of the aggregate sales changes in each group are attributed to changes in the number of unique customers versus changes in sales per customers. Figure 9 shows that the change in customers accounts for around 80% of sales changes in the tails (modestly under 80% for increases, and modestly above 80% for decreases). Thus, the (now familiar) pattern prevails even we focus on the tails of the growth/decline distribution: customer growth accounts for most of the extremes we see in overall sales growth across merchants from year to year.

Figure 9: Customers vs. sales/customer and firm sales changes



The figure reports the average share of sales changes in each firm group that can be attributed to changes in number of customers and changes in sales per customer respectively from 2016 to 2019. By construction, the two shares sum to 1. Each bar corresponds to a firm group. TX refers to top X% firms and BX refers to bottom X% firms by firms' absolute sales changes.

4. A model of growth with customers

Having shown that the customer margin is quantitatively important, we present a model of growth that incorporates this margin to see how it may matter.

4.1. Customers

Consider a unit mass of customers with identical preferences:

$$U = \sum_{t=0}^{\infty} \beta^t \frac{C_t^{1-1/\sigma}}{1-1/\sigma}.$$

Their composite consumption C is a CES aggregate of varieties:

$$C_t = \left(\int_0^1 n_{it} \left(q_{it} c_{it} \right)^{\frac{\theta-1}{\theta}} \mathrm{d}i \right)^{\frac{\theta}{\theta-1}}$$

where $n_{it} \in [0,1]$ is the probability that a customer purchases variety i and q_{it} is the quality of variety i. $\theta > 1$ is the elasticity of substitution between varieties and $0 < \beta < 1$ is the discount factor. Note there is a fixed unit measure of varieties. Finally, we assume that n_{it} is identical across consumers, so it is also the fraction of consumers who buy variety i in period t.

Demand (per customer) conditional on access to variety i is given by:

$$c_{it} = \left(\frac{p_{it}}{P_t} \right)^{-\theta} q_{it}^{\theta-1} C_t, \quad \forall i \in [0,1],$$

where the ideal consumer price index is:

$$P_t \equiv \left(\int_0^1 n_{it} \left(\frac{p_{it}}{q_{it}} \right)^{1-\theta} \mathrm{d}i \right)^{\frac{1}{1-\theta}}.$$

Total quantity demanded for variety i, summed across customers, is:

$$y_{it} = n_{it} c_{it}.$$

4.2. Firms

Each firm uses production labor l_{it} to produce its single variety:

$$y_{it} = l_{it}.$$

It uses marketing labor m_{it} to reach a random fraction n_{it} of customers:

$$n_{it} = \left(\frac{\gamma m_{it}}{\phi M_t}\right)^{\frac{1}{\gamma}} \quad \text{where} \quad M_t \equiv \int_0^1 m_{it} \mathrm{d}i. \tag{3}$$

Here $\gamma > 1$ and $\phi > 0$, and M is aggregate marketing labor across all firms. We note the built-in negative externality with respect to other firms' marketing efforts.

Normalizing the nominal wage for labor to one as the numeraire, the firm's static profit maximization problem is:

$$\max_{p_{it}, m_{it}} \left(p_{it} - 1\right) y_{it} - m_{it}. \tag{4}$$

Assuming that firms engage in monopolistic competition, they set their price to a constant markup above unit marginal cost:

$$p_{it} = \mu \quad \text{where} \quad \mu \equiv \frac{\theta}{\theta - 1}. \tag{5}$$

Substituting the firm's price in its demand function yields:

$$c_{it} = \left(\frac{q_{it} P_t}{\mu}\right)^{\theta - 1} \cdot \frac{P_t C_t}{\mu}. \tag{6}$$

From equations (4), (5), and (6) the firm's static marketing problem becomes:

$$\max_{n_{it}} n_{it} \left(\frac{q_{it} P_t}{\mu}\right)^{\theta - 1} \cdot \frac{P_t C_t}{\theta} - \frac{\phi M_t n_{it}^{\gamma}}{\gamma}.$$

This marketing problem yields the following first order condition:

$$n_{it} = \min\left\{\left(\frac{q_{it}P_t}{\mu}\right)^{\theta-1} \cdot \frac{P_tC_t}{\theta\phi M_t}, 1\right\}^{\frac{1}{\gamma-1}}. \tag{7}$$

Denoting $\Gamma \equiv \frac{\gamma}{\gamma-1}$, it follows that a firm's flow profits are:

$$\Pi_{it} = \left[\left(\frac{q_{it}P_t}{\mu}\right)^{\theta-1} \cdot \frac{P_tC_t}{\theta\phi M_t}\right]^{\Gamma} \cdot \frac{\phi M_t}{\Gamma}. \tag{8}$$

It is useful to define an aggregate quality index as:

$$Q_t \equiv \left(\int_0^1 q_{it}^{\Gamma(\theta-1)} \mathbf{d}i\right)^{\frac{1}{\Gamma(\theta-1)}}.$$

Aggregate spending on all goods is:

$$P_tC_t = \int_0^1 p_{it}n_{it}c_{it}\mathbf{d}i. \tag{9}$$

Substituting (5), (6), and (7) in equation (9), and rearranging, we arrive at:

$$P_tC_t = \theta\phi M_t \left(\frac{\mu}{Q_tP_t}\right)^{\gamma(\theta-1)}. \tag{10}$$

Substituting (10) into (8), we have:

$$\Pi_{it} = \frac{\phi M_t q_{it}^{\Gamma(\theta-1)}}{\Gamma Q_t^{\gamma(\theta-1)\Gamma}} \cdot \left(\frac{\mu}{P_t}\right)^{\gamma(\theta-1)}. \tag{11}$$

Now, the consumer's budget constraint is given by:

$$P_tC_t = L_t + M_t + \int_0^1 \Pi_{it}\mathbf{d}i \tag{12}$$

where L_t and M_t are aggregate production labor and aggregate marketing labor, respectively.

Substituting (10) and (11) into (12), aggregate consumption becomes:

$$P_t C_t = \frac{\theta\Gamma\left(L_t + M_t\right)}{\theta\Gamma - 1}. \tag{13}$$

Substituting (13) into (10), we have:

$$\frac{\theta\Gamma\left(L_t + M_t\right)}{\theta\Gamma - 1} = \theta\phi M_t \left(\frac{\mu}{Q_t P_t}\right)^{\gamma(\theta-1)}.$$

Substituting this into (11), flow profits can be expressed as:

$$\Pi_{it} = \frac{\left(L_t + M_t\right) q_{it}^{\Gamma(\theta-1)}}{\left(\theta\Gamma - 1\right) Q_t^{\Gamma(\theta-1)}}. \tag{14}$$

Now defining a firm's relative quality as $z_{it} = q_{it}/Q_t$, we can rewrite equation (14) as:

$$\Pi_{it} = \frac{\left(L_t + M_t\right) z_{it}^{\Gamma(\theta-1)}}{\theta\Gamma - 1}. \tag{15}$$

4.3. Innovation

A firm with absolute quality q_{it} and relative quality z_{it} that hires research labor s_{it} sees its quality follow a controlled binomial process with probability $x_{it} \in [0, 1]$:

$$q_{it+1} = \begin{cases} q_{it} e^{\Delta} & \text{w/ prob. } x_{it} \\ q_{it} & \text{w/ prob. } 1 - x_{it} \end{cases} \quad \text{and} \quad s_{it} = b_0 \cdot e^{b_1 x_{it}} \cdot z_{it}^{b_2}.$$

Here Δ, b_0, b_1 and b_2 are all strictly positive. Δ is the step size of successful quality innovations, and x is the probability that a firm succeeds in innovating. b_0 is a scalar for the level of research labor, b_1 governs the exponential rate at which research labor must rise to attain a higher innovation rate, and b_2 quantifies how much more research labor is necessary to innovate from a higher level of relative quality. Note the knowledge spillover in this formulation: the higher the quality of other firms, the lower the cost of successfully innovating ($b_2 > 0$).

A continuing firm's value function is given by:

$$v_t(z) = \Pi_t(z) + \max_{x \in [0,1]} \left\{ R_t^{-1} \left[x V_{t+1}\left(z e^{\Delta - g_t}\right) + (1-x) V_{t+1}\left(z e^{-g_t}\right) \right] - s_t(z,x) \right\}$$

where R is the gross interest rate. The Euler equation produces the usual relationship between the growth rate g (here of the aggregate quality index) and the consumer's discount factor in the absence of aggregate uncertainty:

$$(1+g_t)^{1/\sigma} = \beta R_t.$$

The first-order condition of the firm's dynamic problem implies:

$$x_t(z) = b_1^{-1} \log\left(\frac{V_{t+1}\left(z e^{\Delta - g}\right) - V_{t+1}\left(z e^{-g}\right)}{R_t b_0 b_1 z^{b_2}} \right).$$

After innovation outcomes are realized, firms can decide to imitate a random draw from the quality distribution of non-imitating firms at a fixed cost ϵ denominated in units of labor. With this option, the value function is:

$$V_{t+1}(z) = \max\left\{ v_{t+1}(z), \int_{\underline{z}}^{\infty} v_{t+1}(z) \mathrm{d}F_t(z) - \epsilon \right\}. \tag{16}$$

The lower bound of the support for relative quality distribution $\underline{z}$ is therefore determined by a "free re-entry condition":

$$v_{t+1}(\underline{z}) = \int_{\underline{z}}^{\infty} v_{t+1}(z) \mathrm{d}F_t(z) - \epsilon.$$

Our imitation option is in the spirit of Lucas and Moll (2014) and Perla and Tonetti (2014). Unlike these papers, however, growth would cease in our model without innovation. Our combination of endogenous growth through innovation with imitation is closer to Benhabib, Perla and Tonetti (2019).

The endogenous growth rate of the aggregate quality index is given by:

$$1+g_t = \left(\int_{\underline{z}}^{\infty} \left[\left(x_t(z)e^{\Delta} + (1-x_t(z))\cdot\left(1-\delta_t(z)+\delta_t(z)\frac{\bar{z}}{z}\right)\right)\cdot z\right]^{\Gamma(\theta-1)} \mathrm{d}F_t\left(z\right)\right)^{\frac{1}{\Gamma(\theta-1)}}.$$

$F_t\left(z\right)$ denotes the cumulative distribution function of relative quality. $x_t(z)$ is the fraction of z firms who successfully innovate, and e^{Δ} is their gross quality growth. Fraction $1-x_t(z)$ of z firms fail to successfully innovate. Of these, fraction $1-\delta_t(z)$ do not imitate their competitors, and fraction $\delta_t(z)$ do. For firms with high enough z, the imitation indicator $\delta_t(z) = 0$ and they choose not to imitate their competitors. Firms with low enough z have $\delta_t(z) = 1$, pay to imitate their competitors, and achieve average gross quality growth of $\bar{z}/z$, where $\bar{z}$ is the average z for surviving firms (those not re-entering).

4.4. Labor market clearing

To recap, labor is used for production, marketing, re-entry, and research:

$$\begin{aligned} L_t &= \int_{\underline{z}}^{\infty} l\left(z\right)\mathrm{d}F_t\left(z\right) \\ M_t &= \int_{\underline{z}}^{\infty} m\left(z\right)\mathrm{d}F_t\left(z\right) \\ E_t &= \int_{\underline{z}}^{\infty} \delta\left(z\right)\mathrm{d}F_t\left(z\right) = \delta_t\epsilon \\ S_t &= \int_{\underline{z}}^{\infty} s\left(z\right)\mathrm{d}F_t\left(z\right), \end{aligned}$$

where δ_t is the aggregate fraction of firms who choose to imitate a surviving firm's quality, and $\delta_t(z)$ is an indicator of whether the firm chooses to imitate.

As each of the unit mass of consumers is endowed with one unit of labor that they supply inelastically, the labor market clearing condition is simply:

$$L_t + M_t + E_t + S_t = 1.$$

From equations (3), (7), (8), and (15), we can solve for aggregate marketing labor as a function of aggregate production labor:

$$M_t = L_t / \left[\gamma\left(\theta - 1\right)\right].$$

Summing production labor over all firms, we also have:

$$L_t = \int_{\underline{z}}^{\infty} l_t\left(z\right) \mathrm{d}F_t\left(z\right) = \int_{\underline{z}}^{\infty} n_t\left(z\right) c_t\left(z\right) \mathrm{d}F_t\left(z\right).$$

Substituting in (6), (7), and (10), aggregate production labor is also:

$$L_t = P_t C_t \left(\theta - 1\right) / \theta.$$

Finally, from labor market clearing and equation (13), we have an expression relating aggregates for production, marketing, and innovation labor.

4.5. Numerical solution

To solve for the steady state growth path of this model, we proceed by value function iteration. It is convenient to scale the continuing firm value function by the complement of the share of labor devoted to re-entry and research $E+S$, which is constant in steady state:

$$\overline{v}\left(z\right) = v\left(z\right) / \left(1 - E - S\right).$$

The scaled value function can be written as:

$$\overline{v}\left(z\right) = \overline{\Pi}\left(z\right) + \max_{x\in[0,1]} \left\{R^{-1}\left[x\overline{V}\left(ze^{\Delta - g}\right) + \left(1 - x\right)\overline{V}\left(ze^{-g}\right)\right] - \overline{s}\left(z, x\right)\right\}.$$

The other scaled variables are:

$$\overline{\Pi}\left(z\right) = \frac{z^{\Gamma(\theta-1)}}{\theta\Gamma - 1}, \quad \overline{s}\left(z, x\right) = \frac{b_0 \exp\left(b_1 x\right) z^{b_2}}{1 - E - S} \quad \text{and} \quad \overline{\epsilon} = \frac{\epsilon}{1 - E - S}.$$

Integrating over scaled research labor yields:

$$\overline{E}+\overline{S}\equiv\frac{E+S}{1-E-S}=\delta\overline{\epsilon}+\int_{\underline{z}}^{\infty}\overline{s}\left(z,x\right)\mathrm{d}F\left(z\right). \tag{17}$$

To solve for the steady state, we first propose a guess for the value function:

$$V_{\text{guess}}\left(z\right)=\overline{\Pi}\left(z\right)/\left(R-1\right).$$

Next, we find the optimal innovation and re-entry policies with the firm's first-order condition, which are independent of the scaling of the problem. Firms with relative quality z choose the innovation rate

$$x\left(z\right)=b_1^{-1}\log\left(\frac{V\left(ze^{\Delta-g}\right)-V\left(ze^{-g}\right)}{Rb_0b_1z^{b_2}}\right).$$

We substitute these decision rules into the firm's value function to update our guess. When these value function iterations converge we arrive at the innovation and re-entry policy functions in steady state. We use these functions to find the stationary relative quality distribution function $F\left(z\right)$. With it, we can use (17) to compute aggregate re-entry and research labor:

$$E+S=\frac{\overline{E}+\overline{S}}{1+\overline{E}+\overline{S}}. \tag{18}$$

4.6. Calibration

In Table 3 we set our baseline parameter values. A period in the model is one year. We set the intertemporal elasticity of substitution $\sigma=0.5$. We choose an elasticity of substitution between varieties of 3. This is at the lower end of estimates such as in Hottman et al. (2016), but this and other papers typically do not control for the customer margin. We set the discount factor to 0.991 so that, when the baseline growth rate is set to 2% per year, the steady state real interest rate is 5% per year.

We set the level of marketing costs ϕ so that the firm with maximum relative quality reaches all customers: $n(z_{max}) = 1$. We set the elasticity of marketing labor with respect to customers to $\gamma = 1.25$. The elasticity of sales with respect to quality in the model is the sum of the elasticity of customers and elasticity of spending per customer with respect to quality:

$$\xi_{y,q} = \xi_{n,q} + \xi_{c,q} = \frac{\theta - 1}{\gamma - 1} + \theta - 1.$$

With $\gamma = 1.25$ and $\theta = 3$, the customer share of the sales elasticity is 80%, which matches our finding in Section 3.

We choose a step size of 4%, conveniently one half of the target steady state growth rate of 2%. With $\theta = 3$, $\gamma = 1.25$, and $\Delta = 0.04$, sales grow by 20% for expanding firms and shrink by 20% for contracting firms:

$$\text{Sales growth} = g \cdot \xi_{y,q}.$$

We choose the research cost parameters to achieve a 3% R&D share and a 2% growth rate. We choose the research spillover parameter to match the convexity of variable profits with respect to relative quality. As in Atkeson and Burstein (2010), this makes the innovation rate flat with respect to firm size, consistent with the empirical regularity of *Gibrat's Law*. This requires $b_2 = 10$. We choose the entry cost parameter to obtain a 1% re-entry rate.

4.7. Results

We are now ready to characterize equilibrium outcomes. For contrast, we also show what happens in an economy with no customer margin. We achieve this by setting $\gamma = \infty$ and $\Gamma = 1$, so that labor is not needed to access customers. We keep all other parameter values the same when we make this comparison.[9]

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[9] With no customer margin, the elasticity of sales with respect to quality would be only $\xi_{y,q} = \xi_{c,q} = \theta - 1$. To achieve relative sales growth of 40% in a model without customers, relative quality would need to grow by 20% rather than by 4% as in the customer economy.

Table 3: Parameter Values

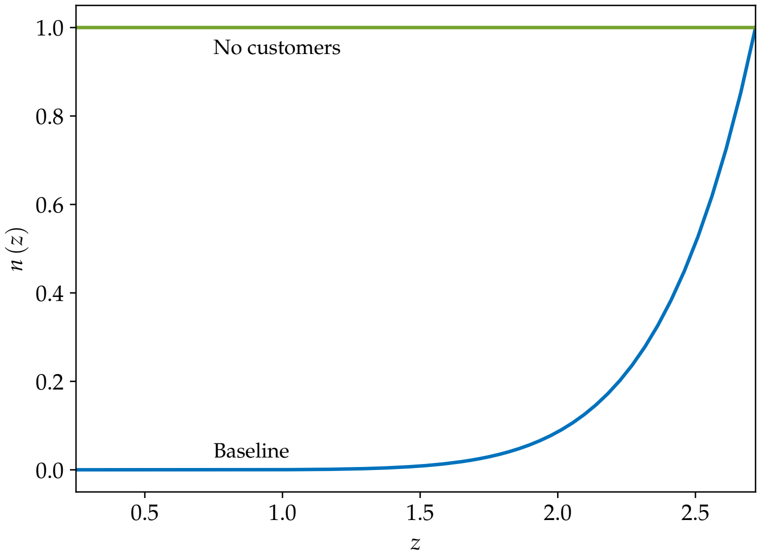
Symbol	Parameter	Value
σ	Intertemporal elasticity of substitution	0.5
θ	Elasticity of substitution between varieties	3
β	Discount factor	0.991
ϕ	Scale of marketing costs	$2.75 \cdot 10^4$
γ	Elasticity of marketing costs wrt customers	1.25
Δ	Quality step size	0.04
b_0	Linear research cost	$3.44 \cdot 10^{-6}$
b_1	Convex research cost	14
b_2	Research spillover parameter	10
ϵ	Re-entry cost	1.18

Figure 10 shows how n, the fraction of consumers the firm sells to, varies with the firm's relative quality z. It is log-linear with elasticity $\gamma/(\gamma-1)$ in the Baseline. This in turn makes the value of the firm much more convex with respect to z in the Baseline than in the No Customers case — see the log-log scale in Figure 11.

Because the customer margin makes variable profits increase much faster in relative quality, it induces higher quality firms to do more innovation than they would otherwise do. This can be seen in Figure 12. A corollary is that R&D intensity (research spending as a share of sales) is flat with respect to z in the baseline case, whereas it falls with z in the model without a customer margin. As a result, the stationary distribution of relative qualities is much more dispersed with customer variation than without it (Figure 13).

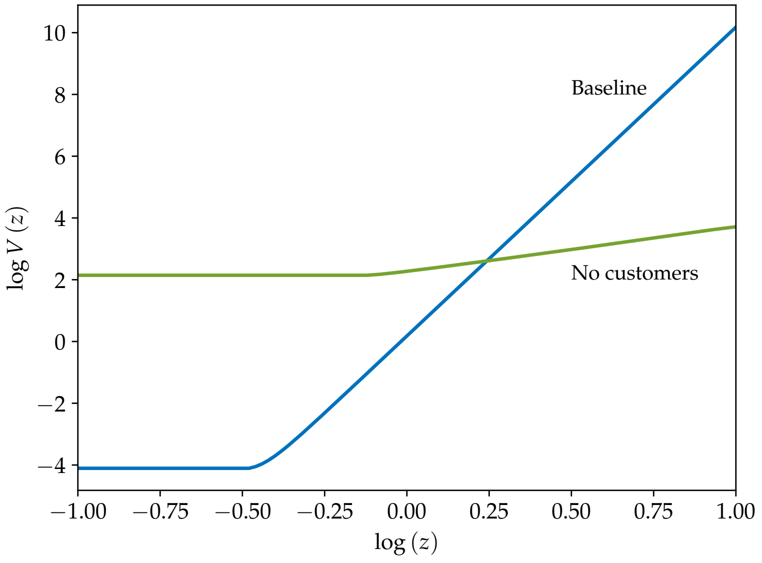
The distribution of sales ends up being much more dispersed with an extensive margin for customers in Figure 14. Higher quality firms have more customers, and this endogenously induces more quality dispersion.

Figure 10: Customers and Firm Quality



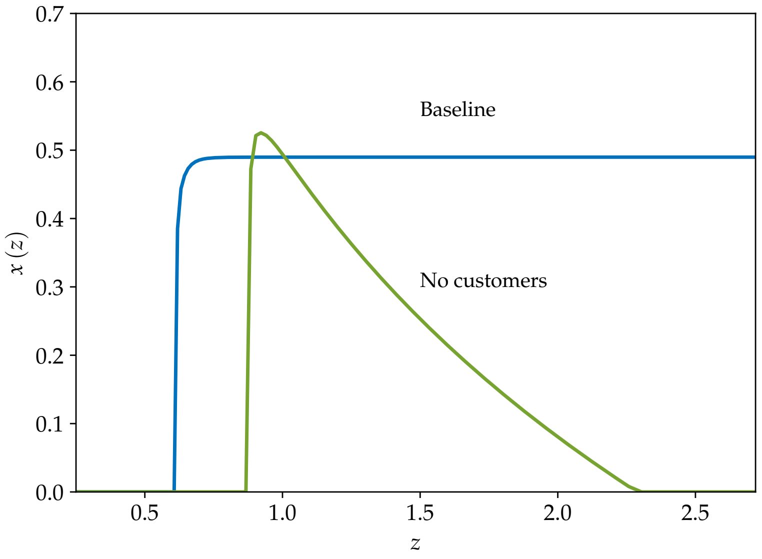
Note: This figure shows how n, the fraction of consumers the firm sells to, varies with the firm's relative quality z. The baseline features $\gamma = 1.25$ and the "no customers" version uses $\gamma = \infty$. γ is the elasticity of marketing costs with respect to customers.

Figure 11: Customers and Firm Value



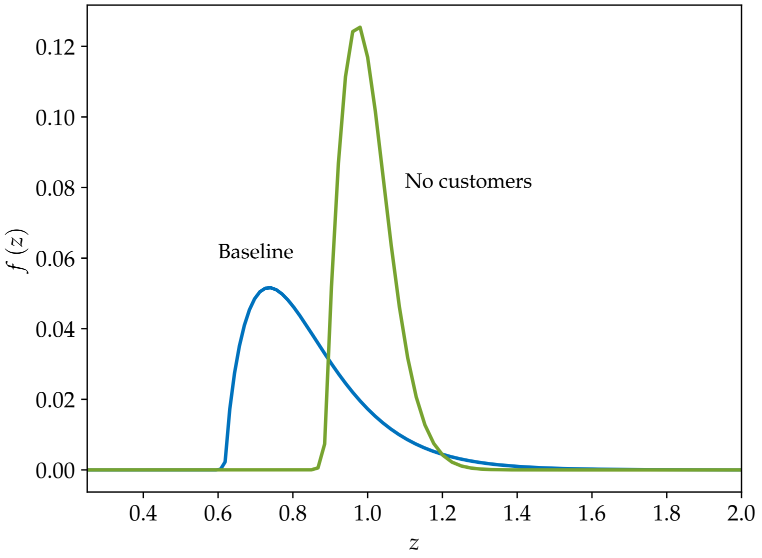
Note: This figure shows how the value of the firm v varies with the firm's relative quality z. The Baseline features $\gamma = 1.25$ and the "No customers" version uses $\gamma = \infty$, where γ is the elasticity of marketing costs with respect to customers.

Figure 12: Customers and Firm Innovation



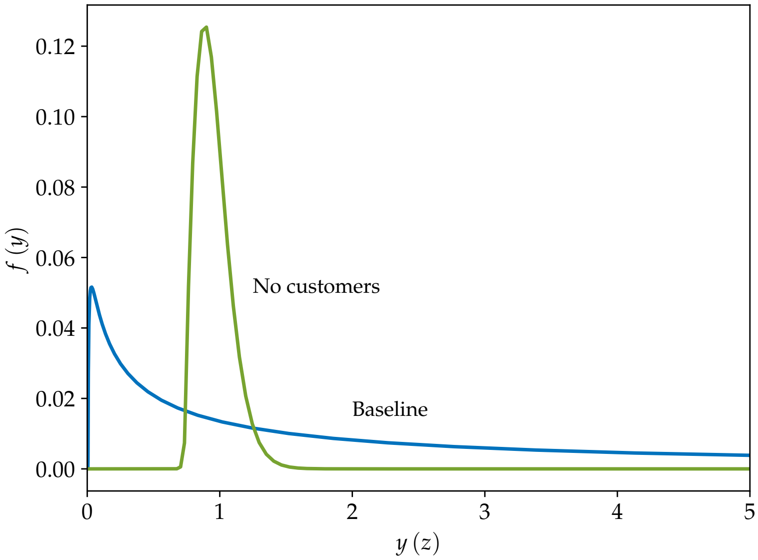
Note: This figure shows how the arrival rate of innovations x varies with the firm's relative quality z. The Baseline features $\gamma = 1.25$ and the "No customers" version uses $\gamma = \infty$, where γ is the elasticity of marketing costs with respect to customers.

Figure 13: The Distribution of Quality



Note: This figure shows the density of firm relative quality z. The Baseline features $\gamma = 1.25$ and the "No customers" version uses $\gamma = \infty$, where γ is the elasticity of marketing costs with respect to customers.

Figure 14: The Distribution of Firm Sales



Note: This figure shows the density of firm sales. The Baseline features $\gamma = 1.25$ and the "No customers" version uses $\gamma = \infty$, where γ is the elasticity of marketing costs with respect to customers.

In Table 4 we compare some variables in steady state across the Baseline and No Customer cases. The endogenous growth rate of aggregate quality rises modestly from 2% in the baseline to 2.04% in the model without a customer margin. This is despite 27% of all labor being freed up from doing marketing when going from the Baseline to the model with no extensive margin for customers. Production labor does soar from 68% of all labor in the Baseline to 94% with no customer margin.

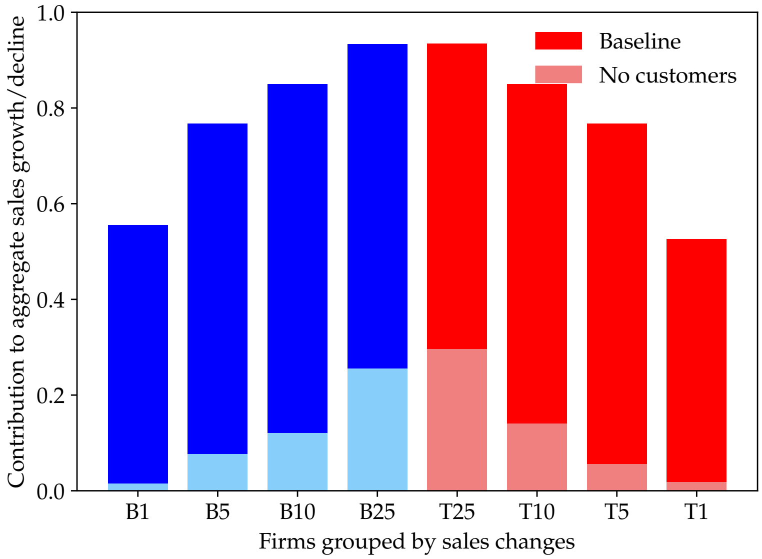
Research labor falls slightly from 3.13% in the baseline to 3.10% of all labor in the model with no extensive margin for customers. The rise in the growth rate instead comes from a higher imitation rate (3.24% without a customer margin, up from 1.25% in the baseline). In the baseline model, re-entrants account for only 0.2 basis points of growth, with the remaining 1.998 percentage points attributed to innovating firms. In the model with no customer margin, re-entrants account for 6.6 basis points, while innovating firms are responsible for 1.97 percentage points. Firms differ much less in their quality and value when all firms access all customers, so imitation gives less of a kick to growth here. This would seem to give left tail firms less reason to pay the imitation cost of mimicking better firms, but the narrower dispersion of firms quality puts more firms in the left tail.

Just like in the data, we can calculate the contribution of the top 1% of firms (based on their sales increases) to aggregate sales increases. Recall from Figure 6 that this is over 60% in the data. As depicted in Figure 15, our baseline model falls short of this, with a contribution of about 53% from the top 1%. Without a customer margin, however, the top 1% of firms would account for less than 2% of all sales increases. Again, this comes from both the direct effect of acquiring customers in response to rising z, and the indirect effect of a much narrower z distribution in the absence of a customer margin.

Table 4: Steady-state endogenous variables

Symbol	Parameter	Baseline	No customers
g	Growth rate	2.00%	2.04%
r	Interest rate	5.00%	5.07%
L	Production labor	68.3%	93.7%
M	Marketing labor	27.3%	0.0%
S	Research labor	3.13%	3.10%
E	Adoption labor	1.25%	3.24%
δ	Re-entry rate	1.11%	2.93%

Figure 15: Firm Contributions to Aggregate Sales Changes



5. Conclusion

Using Visa data on credit and debit card transactions at U.S. retail merchants from 2016 to 2019, we document the paramount importance of the extensive, customer relationship margin in driving variation in retail sales. Customers account for approximately 80% of the sales variation whether we look across merchants, across stores within merchants, or over time within merchants and stores.

We write down a simple growth model that incorporates this extensive margin and illustrates how and why it may matter. In the model, firms pay marketing and research costs to acquire customers and improve their quality. The customer margin has little effect on research and growth, but diverts labor from production to marketing and gives larger firms a much bigger share of sales and sales growth.

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