Assessing the Gains from E-Commerce

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What we do

- Document the rise of e-commerce using Visa data
- Estimate resulting consumer surplus $> 1\%$ of consumption
- Find gains are increasing in county population density
- Find gains are half as big for incomes below $50k

Related literature

Gains from e-commerce and the internet

- Brynjolffson and collaborators (2003, 2012, 2017)
- Goolsbee and Klenow (2006, 2018)
- Varian (2013)
- Syverson (2016)
- Couture, Faber, Gu and Liu (2018)

Consumer surplus from new products more generally

- Feenstra (1994)
- Hausman (1997, 1999)
- Weinstein and collaborators (2006, 2010, 2018)

Visa data

Raw data is similar to line items in monthly statements:

- Transaction amount and day
- Unique card identifiers (credit and debit)
- Store name, NAICS, ZIP (longitude-latitude in recent years)
- January 2007 through December 2017

Merged with *Experian* data the last few years:

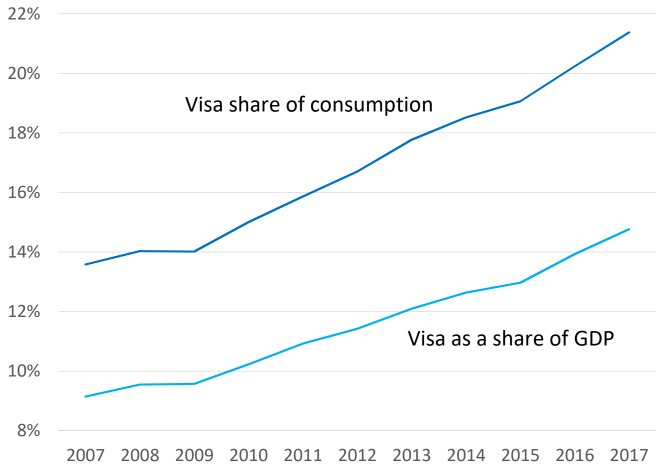
- Card income
- Card location

Visa summary statistics

U.S. annual averages from 2007 through 2017

- 380 million cards
- 35.9 billion transactions
- \$1.93 trillion in sales
  - 55% credit, 45% debit

Flowing through Visa



Sources: Visa and BEA

E-commerce in the Visa data

Visa transaction flags:

- CP $\equiv$ Card Present (brick-and-mortar)
- CNP $\equiv$ Card Not Present
  - phone or mail order
  - recurring bill payments
  - ECI $\equiv$ e-commerce indicator
  - missing values

For missing values we allocate within 3-digit NAICS years:

$$\text{e-commerce} = \frac{\text{ECI}}{\text{ECI + phone/mail/recurring}} \times \text{CNP}$$

E-Commerce industries

Retail	Example
Nonstore Retail	Amazon
Clothing	Nordstrom
Misc Retail	Staples
General Merchandise	Walmart
Electronics	Best Buy
Building Material, Garden Supplies	Home Depot
Furniture	Bed Bath & Beyond
Sporting Goods, Hobby	Nike
Health, Personal Care	CVS
Food	Safeway
Ground Transportation	Uber

Non-Retail	Example
Admin, Support Services	Expedia Travel
Air Transportation	American Airlines
Accommodation	Marriott
Car Parts	AutoZone
Rental Services	Hertz Rent-A-Car

Online Visa spending shares (in %), selected NAICS

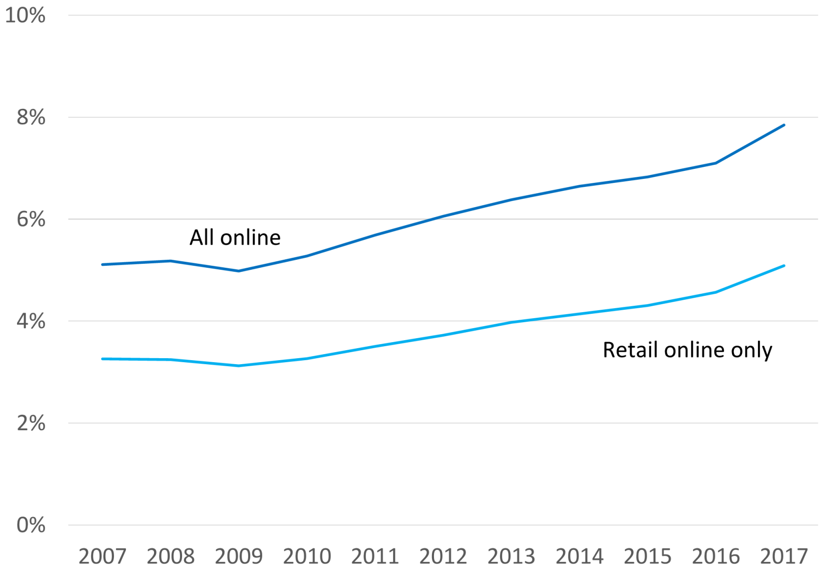
	2007	2017
Nonstore Retailers	90	96
Air Transport	87	97
Electronics	42	51
Furniture	35	43
Clothing	22	37
General Merchandise	8	15
Food	5	6

Estimating e-commerce in the U.S. overall

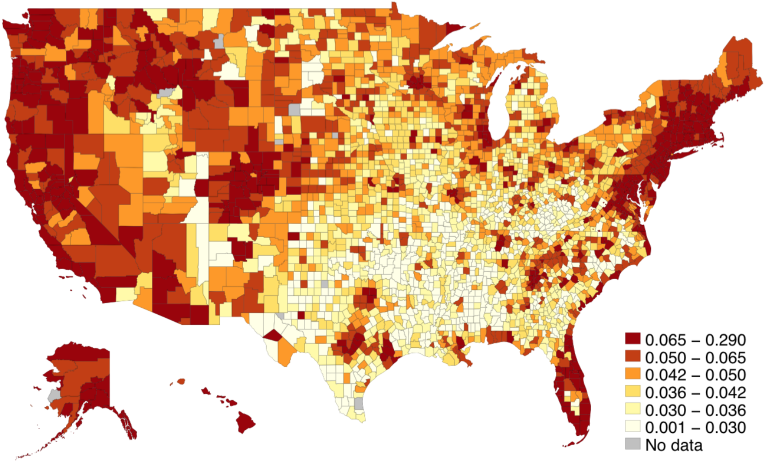
$$\text{U.S. Online Share} = \frac{\text{Total Card Spending}}{\text{Consumption}} \cdot \text{Visa Online Share}$$

- Calculate e-commerce share in Visa as described above
- Assume Visa representative of all card transactions
- Assume non-card transactions are all offline

Share of U.S. consumption online



Online share by county in 2016



Consumer problem

$$\max \ U = \left[\sum_{m=1}^{M} (q_m \cdot x_m)^{1-\frac{1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$$

subject to

$$M_b^{\phi} F_b + M_o^{\phi} F_o + \sum_{m=1}^{M} p_m \cdot x_m \leq w$$

- q_m = “quality” of merchant m
- x_m = quantity purchased from merchant m
- p_m = price per unit at merchant m
- $M = M_b + M_o =$ total merchants bought from
- M_b (M_o) = # of merchants shopped at in-store (online)
- F_b (F_o) = scale of fixed costs for shopping in-store (online)

Welfare

Consumption-equivalent welfare is proportional to

$$\left(\frac{1}{1 - s_o}\right)^{\frac{\phi-1}{\phi(\sigma-1)}}$$

where s_o denotes the share of card spending online:

$$s_o \equiv \frac{oM_o}{oM_o + bM_b}$$

Consumers gain from rising s_o due to online options becoming better (rising q_o) and easier access to online merchants (falling F_o)

Estimating ϕ (convexity of fixed shopping costs)

According to the model, we can estimate ϕ using one of two regressions that yield the same answer by construction:

$$\ln M = \alpha + \frac{1}{\phi} \cdot \ln\left(oM_o + bM_b\right)$$

$$\ln\left(\frac{oM_o + bM_b}{M}\right) = \eta + \frac{\phi - 1}{\phi} \cdot \ln\left(oM_o + bM_b\right)$$

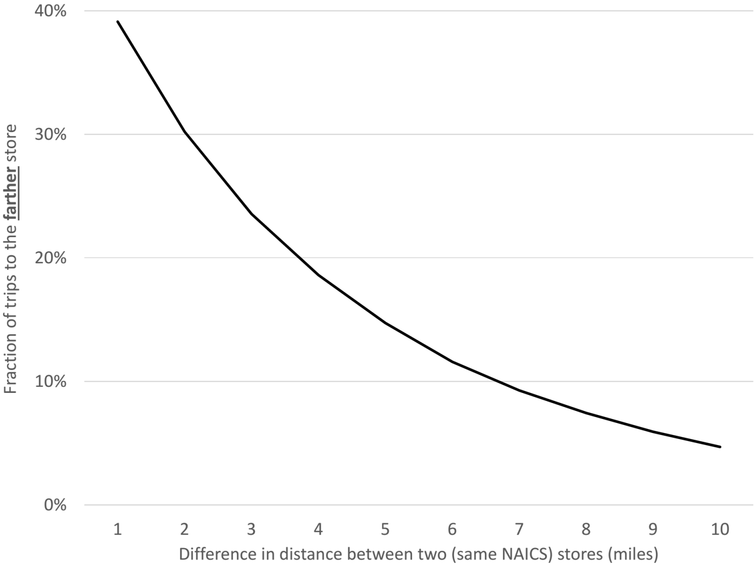
Extensive and intensive margin Engel Curve slopes should reflect ϕ

Estimates of ϕ (convexity of fixed shopping costs)

	2007	2017
$\widehat{\phi}$	1.73	1.75
# of cards	283M	462M
R^2	0.67	0.67

Standard errors are tiny ...

Relative trips vs. distance



Converting distance into WTP (willingness to pay)

- A straight-line mile requires 1.5 miles of driving on average (Einav et al, 2016)
- 1.4 minutes per mile of driving on average (Einav at al, 2016)
- 2017–2017 average hourly wage = \$23 per hour (BLS)
- 2007–2017 average fuel + depreciation per mile = \$0.535 (IRS)
- Each mile counts as two miles of round trip travel
- Each mile costs \$0.80 in direct costs and \$0.79 in time costs, for a total of \$3.18 per roundtrip mile

Estimating σ

- Assuming distance is uncorrelated with preferences (controlling for merchant fixed effects), we can use how visits change with distance to estimate σ

- Aggregating to the merchant j, merchant k, $dist_{ij}$, $dist_{ik}$ level:

$$\ln\left(\frac{Trips_j}{Trips_k}\right) = \ln\left(\frac{q_j}{q_k}\right) - \sigma \cdot \ln\left(\frac{p_{jk} + \tau_{ij}}{p_{jk} + \tau_{ik}}\right)$$

- p_{jk} = average ticket size at merchants j, k
- τ = transportation costs for i to j or k
- We capture relative quality with cross fixed effects

- Regress on both online-offline and offline-offline samples

Estimates of σ

	online-offline	offline-offline
$\widehat{\sigma}$	4.3	6.1
# of obs	3.6M	14.0M
R^2	0.97	0.94

Standard errors are tiny (on the order of 0.001)

Substitutability by NAICS

	$\widehat{\sigma}$
Building Material, Garden Supplies	7.7
Motor Vehicle and Parts Dealers	7.5
Furniture and Home Furnishings Stores	7.4
General Merchandise Stores	5.8
Health and Personal Care Stores	5.5
Clothing and Clothing Accessories Stores	5.2
Miscellaneous Store Retailers	5.2
Sporting Goods, Hobby, Music, Book Stores	4.2
Food and Beverage Stores	3.6
Electronics and Appliance Stores	3.4

Note: The 10 offline/online 3-digit NAICS

Consumption-equivalent gains by 2017

1 big CES nest (baseline)	1.06%
16 CES nests (allocating nonstore retail)	1.62%

Welfare gains by card income in 2017

Income ($)	Gains
0-50k	0.46%
50k-100k	1.28%
100k-200k	1.46%
200k+	1.13%

Welfare gains by county density in 2017

	Gains
Quartile 1 (sparse)	0.77%
Quartile 2	0.99%
Quartile 3	1.17%
Quartile 4 (dense)	1.29%

Quartiles based on population (25% in each quartile).

Retail Apocalypse

Due to rising q_o and falling F_o:

	2007–2017 Change
b	–1.6%
M_b	–3.7%
Profits	0%