Delivering New Cities: The Effect of E-Commerce Warehouses on Traffic and City Structure

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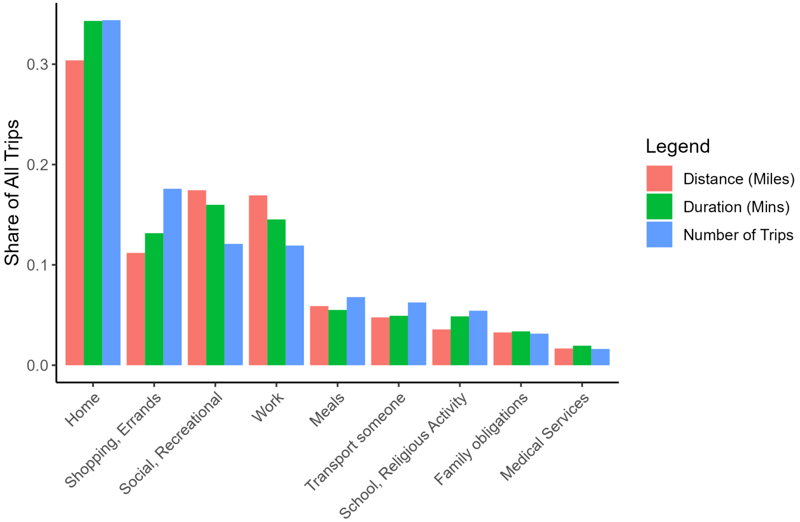
Digital Technology has Influenced the Structure of Cities

- AirBnB *Almagro and Dominguez-Iino (2024)*, Garcia-Lopéz et al. (2020), Xu and Xu (2021)
- Uber *Gorback (2024)*, Anderson and Davis (2021)
- Remote Work *Gaspar and Glaeser (1998), Delventhal et al. (2022), Althhoff et al. (2022), Monte et al. (2023), . . .*
- **E-commerce** Relihan (2024), Chun et al. (2023), Chava et al. (2023), Dolfen et al. (2023)

Shopping Makes up a Large Share of Our Trips



Source: 2009 National Household Travel Survey; author's calculations

However, We Are Doing More and More Shopping Online

2010: e-commerce sales were 4.7% of total retail sales (Census 2010 Annual Retail Trade Surve)

2019: e-commerce sales were 10.7% of total retail sales (Census 2019 E-Stats)

2021: e-commerce sales were 14.7% of total retail sales (Censes 2021 E-Stats)

This has significant implications for how people and goods flow around cities.

This Paper

Research Question: How does the arrival of Amazon Warehouses impact traffic around the city?

(1) Use difference-in-difference methods to evaluate the effect of warehouses on neighborhood-level traffic.
(2) Explore mechanisms for the changes in traffic.
(3) Use a spatial modeling framework to model how shopping affects demand for residential and retail locations within cities and how this changes after the introduction of e-commerce.

How does e-commerce change trips taken around the city?

Short run:

+ Delivery vans and trucks
− Fewer personal shopping trips
? Substitute to other types of trips

More broadly it changes the desireability of neighborhoods:

- Noise and air pollution near warehouses
- Less travel cost of being far from stores
- Change in the retail landscape

⇒ The distribution of traffic may change to reflect the re-sorting of people in cities.

Outline

Setting

Data

Empirical Strategy

Results

Mechanisms

Conclusion

Setting - Amazon Warehouses

Setting - Amazon Warehouses

Before

Growing Concern for Pollution Impacts of Warehouses

CALIFORNIA

Gavin Newsom signs law to limit new warehouses

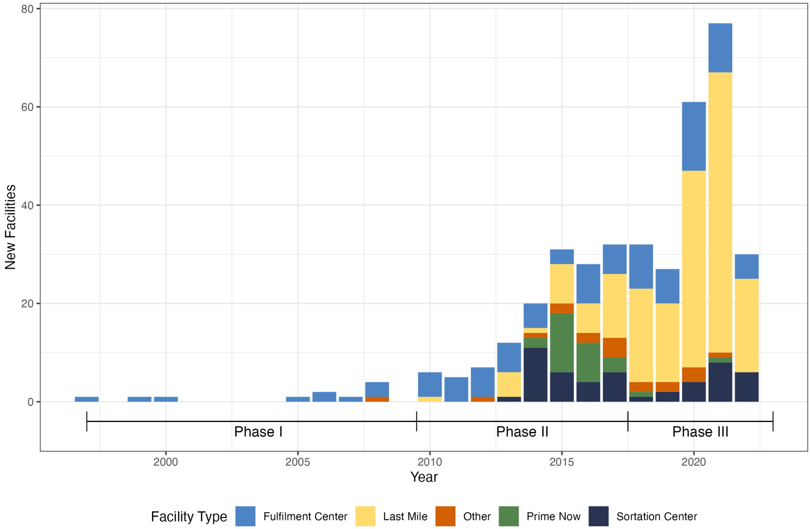
Environmental and business groups alike had lobbied against the bill, which establishes a 300-foot minimum distance between new warehouses and inhabited buildings.

AB 98 becomes law despite widespread opposition from businesses, local governments and environmental justice groups. | iStock

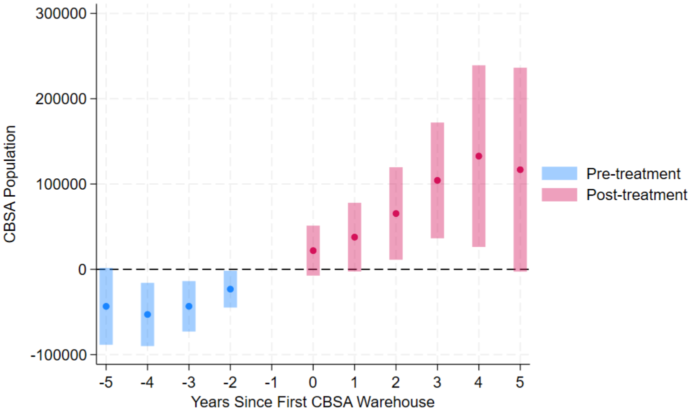
By BLANCA BEGERT

Warehouse Locations

Amazon's Distribution Network Expanded in 3 Phases

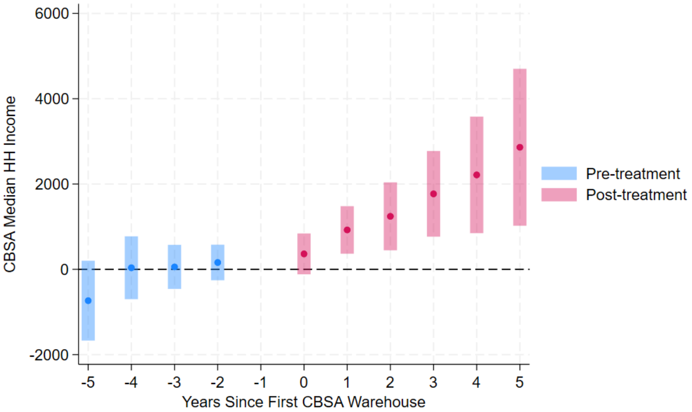


Amazon Targets Growing Cities



$$pop_{it} = \beta_0 + \sum_{\tau \neq -1} \beta_1 \mathbf{1}\{year - event\_year = \tau\} + \alpha_i + \alpha_t + \varepsilon_{it}$$

Amazon Targets Growing Cities



$$inc_{it} = \beta_0 + \sum_{\tau \neq -1} \beta_1 \mathbf{1}\{year - event\_year = \tau\} + \alpha_i + \alpha_t + \varepsilon_{it}$$

Outline

ZCTA Traffic Description

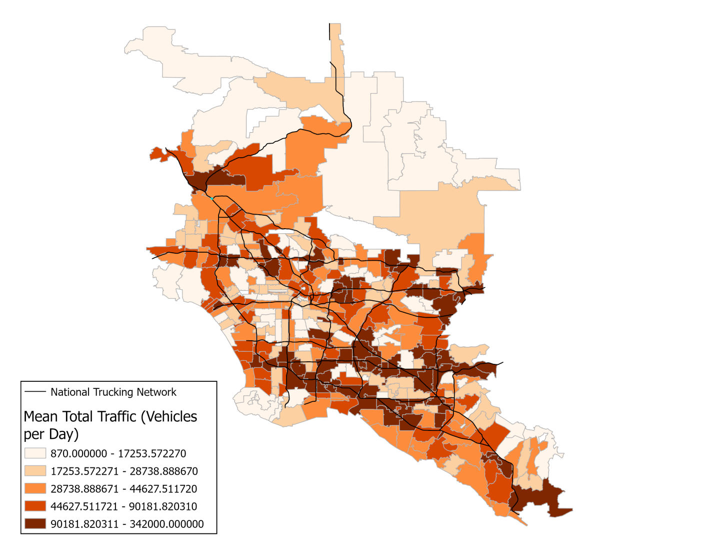
Unit of analysis: ZIP Code Tabulation Area (**ZCTA**)

Traffic measurement:

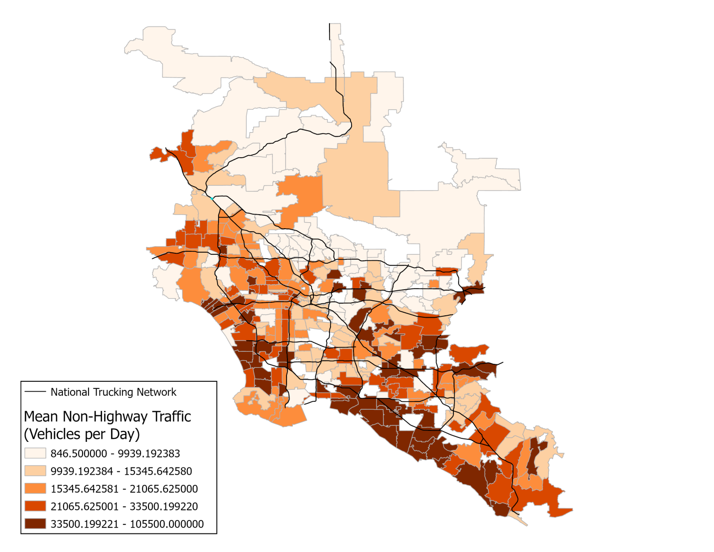
- Average of all daily traffic counts taken in a ZCTA during a year
- Broken into highway and non-highway traffic
- All interstate and other major roads are required to have counts at least once every three years

Source: Pierce County, WA, Traffic Engineering

ZCTA Traffic, Los Angeles-Long Beach-Anaheim (2010)



ZCTA Traffic, Los Angeles-Long Beach-Anaheim (2010)



ZCTA Summary Stats (2010)

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 50	Pctl. 75	Max
Road Type: Highway								
Average Traffic	5,427	38,026	48,632	52	7,233	17,902	49,052	324,000
Number of Traffic Counts	5,427	12	29	0	0	0	12	531
Total Number of Intersections	5,427	958	771	6	420	765	1,262	5,784
Interpolated Data Flag	5,427	0.59	0.49	0	0	1	1	1
Road Type: Non-Highway								
Average Traffic	22,709	6,918	9,485	5	1,340	3,566	9,291	207,405
Number of Traffic Counts	22,709	8.2	21	0	0	0	7	531
Total Number of Intersections	22,709	687	655	0	239	505	924	13,988
Interpolated Data Flag	22,709	0.58	0.49	0	0	1	1	1

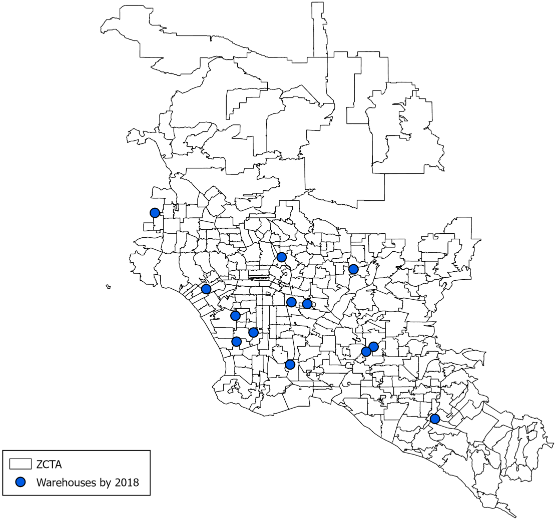
Overall Traffic

Amazon Warehouse Data

Collected by MWPVL International, a supply chain research and consulting firm:

- Address, opening date (always year and occasionally month or quarter), type of facility, size, and description
- More than 1,500 facilities across 47 states and DC

Warehouse Data, Los Angeles-Long Beach-Anaheim (2018)



Outline

Event Study, Callaway and Sant'Anna (2010)

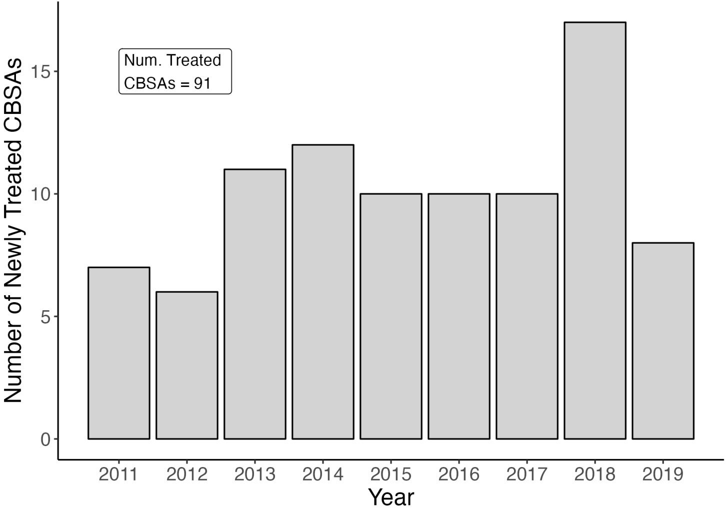
For each group of ZCTAs treated at year g, I compute the ATT at t years after treatment,

$$ATT(g,t) = E[Y_t - Y_{g-1} | G = g] - E[Y_t - Y_{g-1} | D_t = 0, G \neq g],$$

where G is the year that a ZCTA was first treated, and D_t is an indicator equal to 1 if a ZCTA has been treated by time t.

$$\Rightarrow \theta(\tilde{t}) = \sum_{g}^{T} \omega_{\tilde{t}}(g,t) ATT(g, g+\tilde{t})$$

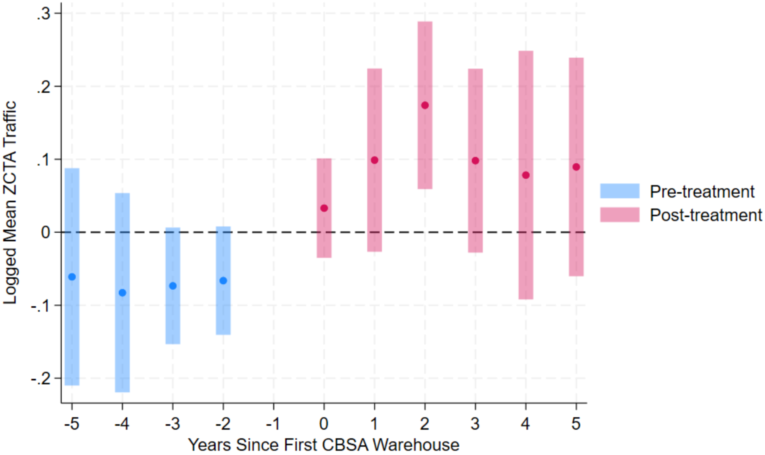
Treatment Timing is Staggered



ZCTAs

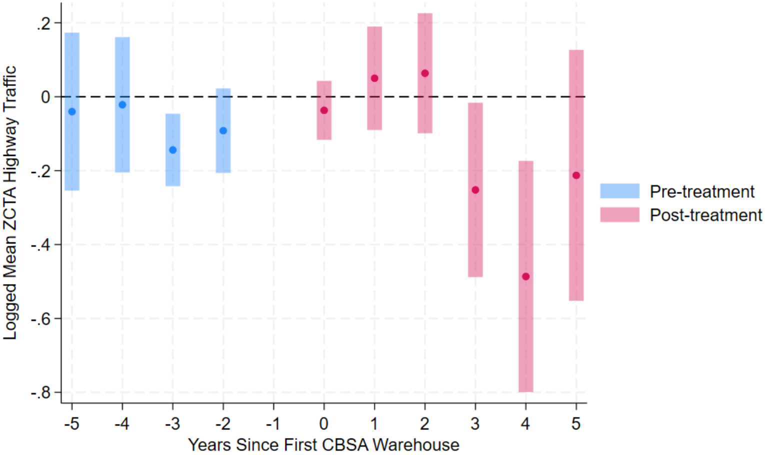
Outline

Effect of a CBSA Warehouse on All ZCTA Traffic



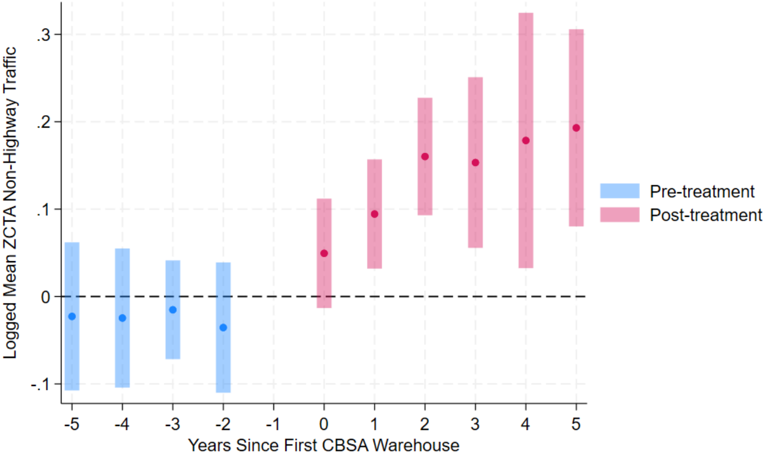
Only Not-Yet Treated

Effect of a CBSA Warehouse on Highway ZCTA Traffic



Only Not-Yet Treated

Effect of a CBSA Warehouse on Non-Highway ZCTA Traffic



Only Not-Yet Treated

Further Heterogeneity Ideas

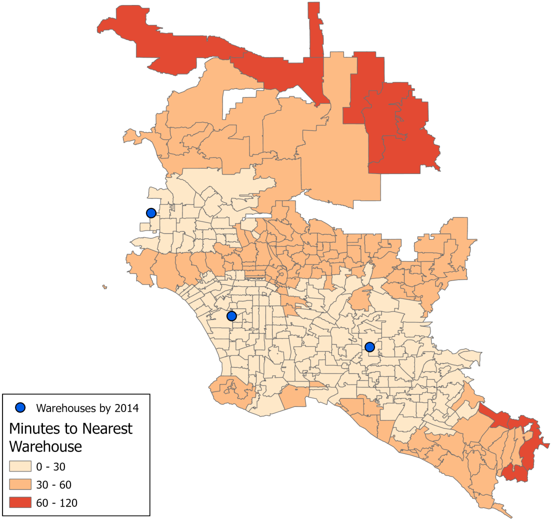
- ZCTAs that match the characteristics of e-commerce users
- Density of retail establishments
- Population density of the ZCTA
- Share of low SES households or other ZCTA demographics

Outline

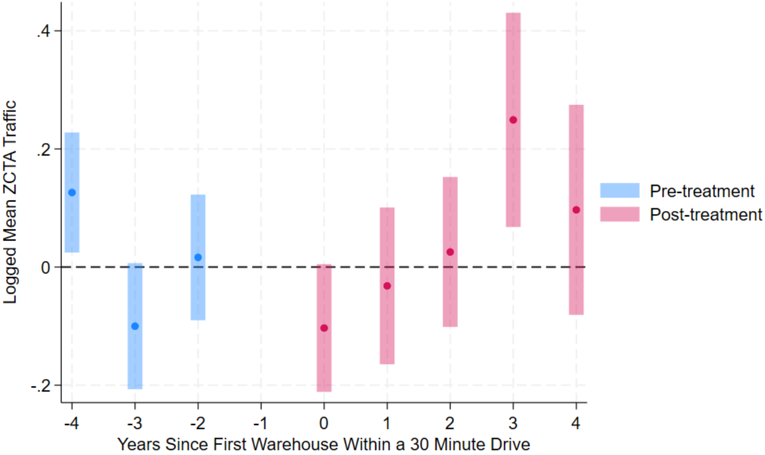
What can explain these effects?

1. Delivery vans and trucks
2. Substitution away from personal shopping trips
3. Re-sorting of people across the city due to changes in neighborhood desireability:
   - Noise and air pollution near warehouses
   - Less travel cost of being far from stores
   - Change in the retail landscape

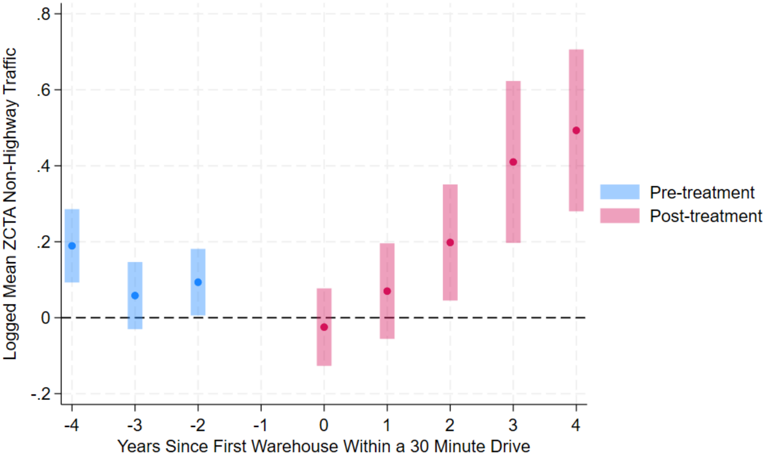
Proximity Treatment Exploits Variation Within a City



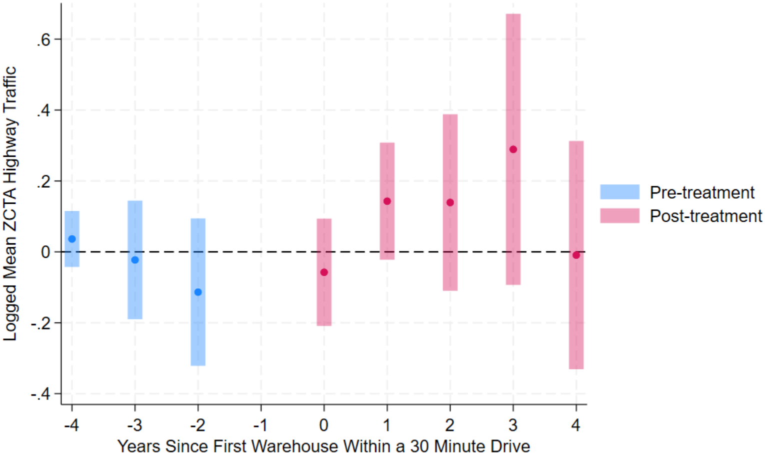
Effect of a Very Close Warehouse on ZCTA Traffic



Effect of a Very Close Warehouse on Non-Highway ZCTA Traffic



Effect of a Very Close Warehouse on Highway ZCTA Traffic



National Household Travel Survey

"Daily non-commercial travel by all modes [and purposes], including characteristics of the people traveling, their household, and their vehicles."

⇒ 66,038 households in 2001; 150,149 households in 2009; 129,696 households in 2017; 27,290 households in 2022

(1) Who uses e-commerce?
(2) Does travel behavior differ for e-commerce users?
(3) Does travel behavior differ in places with an e-commerce warehouse regardless of e-commerce usage?

Comparing ZCTAs by Growth in Overall Traffic

	Bottom Half			Top Half			Difference
	n	mean	sd	n	mean	sd	(Top - Bottom)
Ever Gets Warehouse	3504	0.07	0.26	3531	0.08	0.27	0.011
Population per Sq. Mi.	3504	4043.78	9767.08	3531	3431.59	7266.90	-612.187
Highway Present	3504	0.25	0.43	3531	0.16	0.36	-0.097***
Median HH Income	1824	62454.84	26811.46	1842	63825.34	27128.38	1,370.499
Bachelor's Degree	911	0.18	0.10	925	0.19	0.10	0.011**
White	1830	0.78	0.23	1852	0.78	0.21	0.004
Under 18	1830	0.23	0.06	1852	0.23	0.07	0.001
Renter	1825	0.30	0.18	1844	0.30	0.19	0.005
Median Rent	1784	969.01	315.56	1785	1001.53	321.88	32.525**
Has a Vehicle	1825	0.92	0.09	1844	0.93	0.08	0.004
Commute (Mins)	1826	30.02	6.14	1850	29.94	6.47	-0.077
Retail Estabs. per Sq. Mi.	3504	26.83	153.58	3531	19.79	73.59	-7.048
Restaurants per Sq. Mi.	3504	15.96	68.16	3531	11.55	44.04	-4.413

ZCTAs are sorted based on within CBSA percentile of traffic growth from 3 years before the CBSA's first warehouse to 3 years after. Standard errors for the significance test of the difference are clustered at the CBSA level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Comparing ZCTAs by Growth in Highway Traffic

	Bottom Half HW			Top Half HW			Difference
	n	mean	sd	n	mean	sd	(Top - Bottom)
Ever Gets Warehouse	454	0.12	0.32	479	0.14	0.35	0.025
Population per Sq. Mi.	454	3325.14	4863.87	479	2554.95	4120.32	-770.190***
Highway Present	454	1.00	0.00	479	1.00	0.00	0.000
Median HH Income	264	60087.09	25892.56	275	61522.51	28462.96	1,435.422
Bachelor's Degree	97	0.18	0.09	104	0.16	0.08	-0.014
White	264	0.71	0.27	275	0.73	0.25	0.018
Under 18	264	0.23	0.06	275	0.24	0.05	0.015***
Renter	264	0.35	0.18	275	0.32	0.18	-0.028
Median Rent	260	1003.46	319.57	272	988.11	315.68	-15.344
Has a Vehicle	264	0.90	0.10	275	0.92	0.08	0.016
Commute (Mins)	264	28.66	5.35	275	30.03	6.00	1.375***
Retail Estabs. per Sq. Mi.	454	18.36	39.48	479	12.75	22.13	-5.615**
Restaurants per Sq. Mi.	454	11.90	35.55	479	7.31	16.55	-4.599**

ZCTAs are sorted based on within CBSA percentile of highway traffic growth from 3 years before the CBSA's first warehouse to 3 years after. Standard errors for the significance test of the difference are clustered at the CBSA level.
* p $<$ 0.10, ** p $<$ 0.05, *** p $<$ 0.01

Comparing ZCTAs by Growth in Non-Highway Traffic

	n	mean	sd	n	mean	sd	Difference (Top - Bottom)
Ever Gets Warehouse	3273	0.07	0.25	3302	0.08	0.27	0.015**
Population per Sq. Mi.	3273	3988.36	9820.70	3302	3498.77	7691.84	-489.592
Highway Present	3273	0.17	0.38	3302	0.19	0.39	0.020
Median HH Income	1733	62685.15	26248.91	1764	62656.28	27249.28	-28.868
Bachelor's Degree	886	0.18	0.09	900	0.19	0.10	0.013*
White	1744	0.79	0.22	1769	0.77	0.23	-0.021
Under 18	1744	0.23	0.06	1769	0.23	0.06	0.005
Renter	1734	0.29	0.18	1766	0.31	0.18	0.021**
Median Rent	1690	968.23	313.83	1716	989.65	316.62	21.422
Has a Vehicle	1734	0.93	0.09	1766	0.92	0.08	-0.003
Commute (Mins)	1740	30.08	6.33	1767	29.89	6.35	-0.191
Retail Estabs. per Sq. Mi.	3273	27.32	157.04	3302	19.20	73.51	-8.122
Restaurants per Sq. Mi.	3273	15.89	68.77	3302	11.62	45.40	-4.274

ZCTAs are sorted based on within CBSA percentile of non-highway traffic growth from 3 years before the CBSA's first warehouse to 3 years after. Standard errors for the significance test of the difference are clustered at the CBSA level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Estimating Location Demand Shocks

Housing Supply: perfectly competitive housing developers choose how much housing to build in neighborhood i at time t to maximize profits

$$\max_{Hit} \; H_{it}R_{it} - LC_{it}Z_i^c - q^x X_{it}^c$$

Housing Demand: workers choose how much housing and final good to consume in neighborhood i at time t to maximize utility

$$U_{iw} = A_i z_{iw} \left(\frac{c_{iw}}{\alpha_i}\right)^{\alpha_i} \left(\frac{h_{iw}}{1-\alpha_i}\right)^{1-\alpha_i}$$

Gupta et al. (2022)

More detail

Estimating Location Demand Shocks

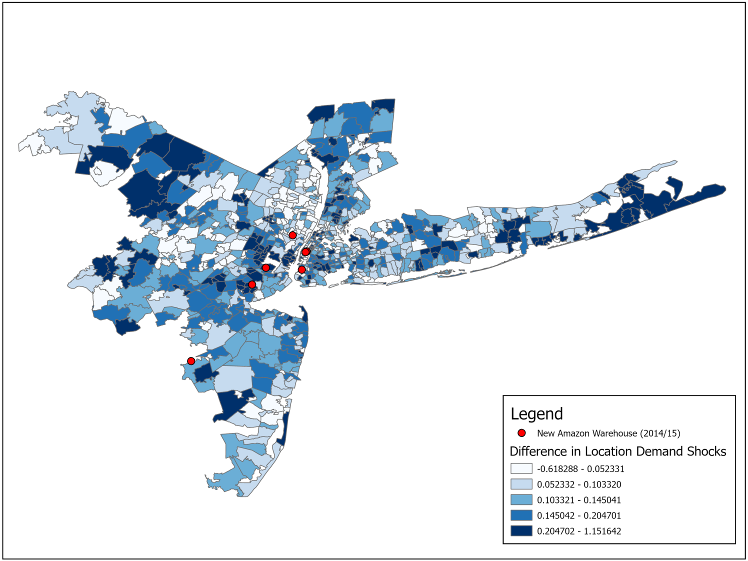
From equilibrium conditions, we can back out location demand shocks:

$$\eta_i = d \ln L_i + \theta \alpha d \ln R_i$$

which I estimate using data on neighborhood populations and house prices, as well as parameters from the literature.

2011 - 2013 2013 - 2015

Location Demand Shock (Post - Pre)



Outline

Conclusion so far. . .

- City-wide traffic appears to increase immediately after the first warehouse opens.
- This is primarily driven by non-highway traffic and the effects are particularly strong near the warehouse.
- There is some suggestive evidence that e-commerce could be contributing to suburbanization.

Next Steps

1. Iterate on the Event Study specification, including new heterogeneity
2. Explore mechanisms using the NHTS data
3. Incorporate results into a spatial model with costly shopping trips

Appendix

Before the Warehouse, 2012

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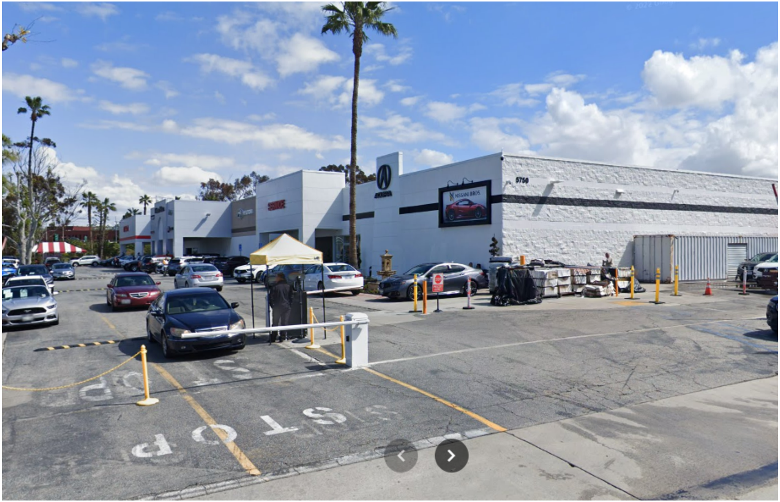
Before the Warehouse, 2019



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Selection Bias Across Cities

Treated CBSA	No			Yes			
Variable	N	Mean	SD	N	Mean	SD	Test
Population	826	126,643	150,808	91	2,056,922	2,742,125	F= 401.808***
Land Area (Sq. Mile)	826	1,525	2,053	91	3,956	3,788	F= 93.023***
Population per Sq. Mile	826	121	118	91	574	496	F= 458.149***
Num. Retail Establishments	826	529	648	91	9,541	13,920	F= 342.543***
Establishments per Thousand People	826	4.1	1.2	91	4.4	0.92	F= 7.083***

Statistical significance markers: * p¡0.1; ** p¡0.05; *** p¡0.01

ZCTA-Level

Selection Bias Within Cities

Treated ZCTA		No			Yes		
Variable	N	Mean	SD	N	Mean	SD	Test
Population	23,151	11,545	14,454	824	29,731	18,201	F= 1234.641***
Land Area (Sq. Mile)	23,151	82	181	824	34	53	F= 58.123***
Highway Presence	23,151	0.22	0.41	824	0.38	0.49	F= 119.042***
Num. Intersections	23,151	670	649	824	996	631	F= 199.884***
Num. Retail Establishments	23,151	51	80	824	140	111	F= 951.343***

Statistical significance markers: * p¡0.1; ** p¡0.05; *** p¡0.01

Balance Table for CBSA Treatment (ZCTA)

Treated CBSA		No			Yes		
Variable	N	Mean	SD	N	Mean	SD	Test
Population	14,024	7,459	10,661	9,951	18,810	17,447	F= 3889.487***
Land Area (Sq. Mile)	14,024	113	218	9,951	35	81	F= 1172.673***
Num. Traffic Counts	14,024	4.4	17	9,951	13	24	F= 1061.583***
Num. Intersections	14,024	680	716	9,951	683	547	F= 0.117
Interpolated Data Flag	14,024	0.77	0.42	9,951	0.32	0.47	F= 6190.575***
Num. Retail Establishments	14,024	31	54	9,951	87	102	F= 3032.593***

Statistical significance markers: * p¡0.1; ** p¡0.05; *** p¡0.01

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ZCTA Summary Stats by Road Type (2010)

Road Type	All			
Variable	N	Mean	SD	Median
Average Traffic	23,975	9,955	17,932	4,478
Number of Traffic Counts	23,975	7.9	21	0
Total Number of Intersections	23,975	682	651	500
Interpolated Data Flag	23,975	0.58	0.49	1

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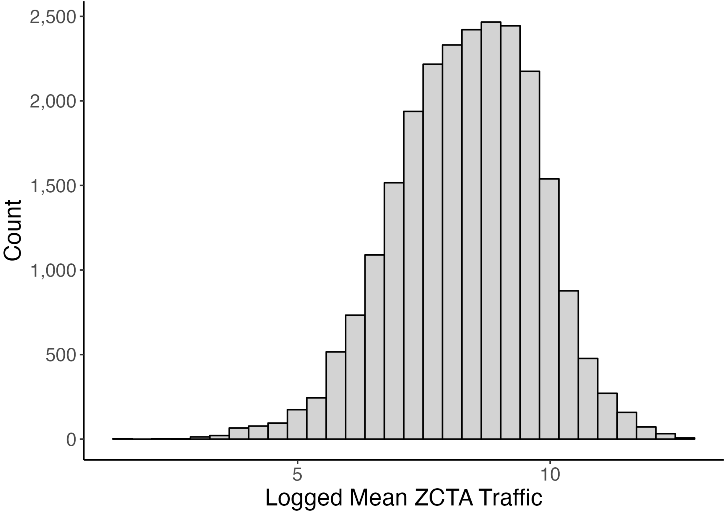
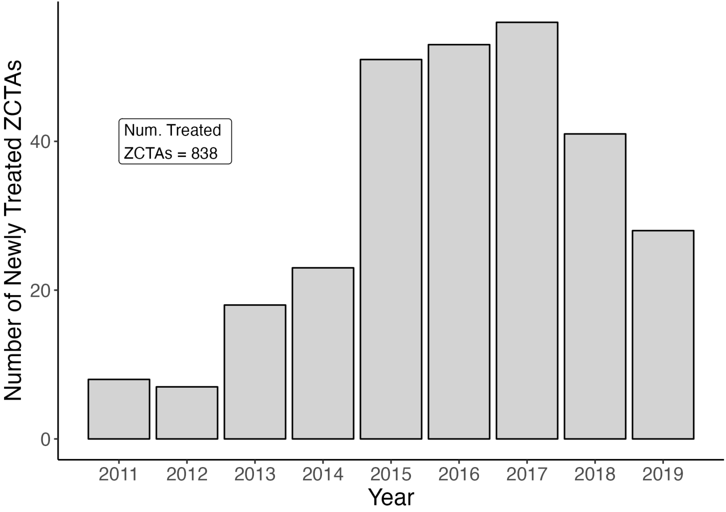
Distribution of ZCTA Traffic (2010)



Newly Treated ZCTAs by Year



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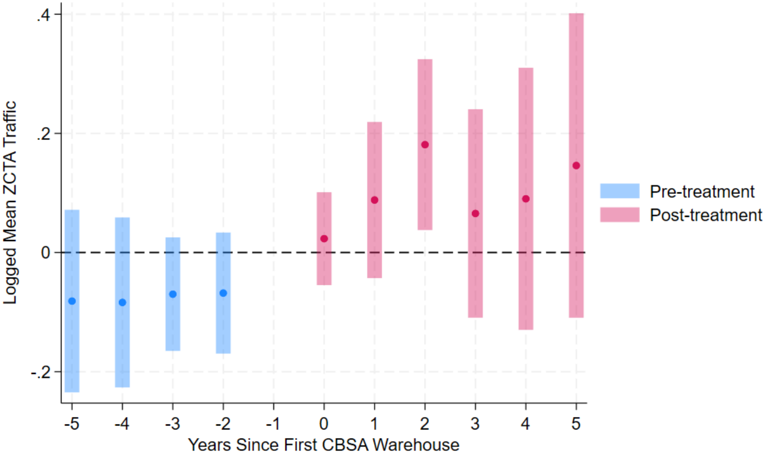
Effect of a CBSA Warehouse on All ZCTA Traffic



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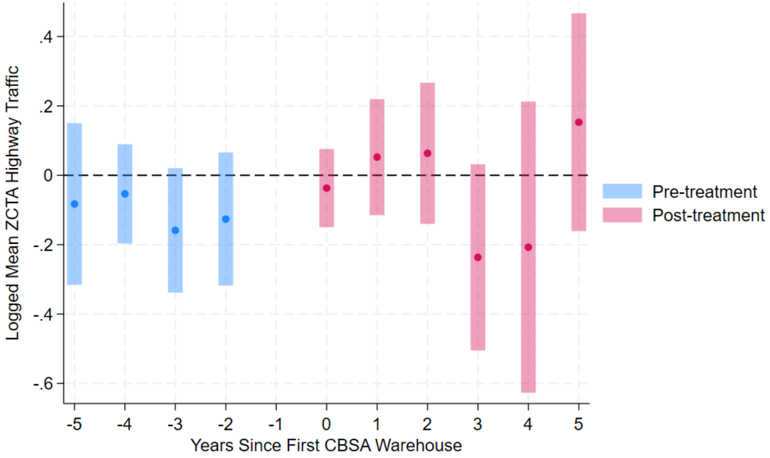
Effect of a CBSA Warehouse on Highway ZCTA Traffic



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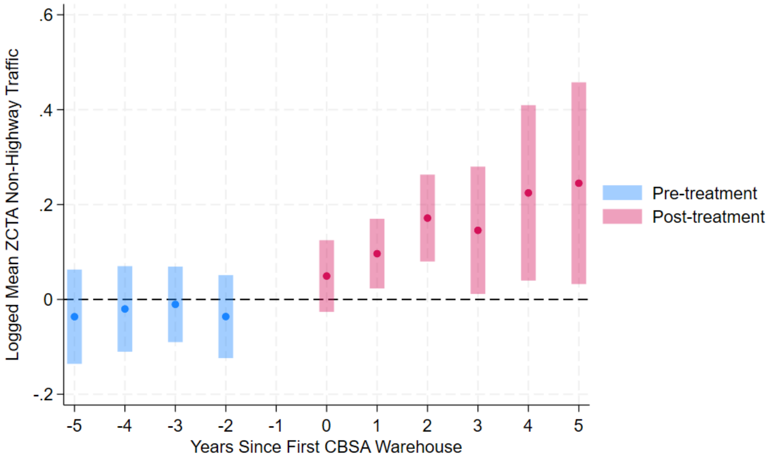
Effect of a CBSA Warehouse on Non-Highway ZCTA Traffic



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Housing Supply

Perfectly competitive developers with Cobb-Douglas production technology solve the following problem, subject to a zero profit condition:

$$\max_{Hit} \; H_{it}R_{it} - LC_{it}Z_i^c - q^x X_{it}^c$$

- H_{it} is the amount of housing supplied in neighborhood i at time t
- R_{it} is the rental price of housing
- LC_{it} is the local land cost
- Z_i^c is a time-invariant amount of local land
- q^x is a national rental rate for capital
- X_{it}^c is the local construction capital required

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Worker Location Choice

Workers w living in neighborhood i maximizes the following utility function by choosing how much housing and final goods to consume in i, h_{iw} and c_{iw} respectively.

$$U_{iw} = A_i z_{iw} \left(\frac{c_{iw}}{\alpha_i} \right)^{\alpha_i} \left(\frac{h_{iw}}{1 - \alpha_i} \right)^{1-\alpha_i}$$

where A_i is the residential amenity level in neighborhood i and z_{iw} is a worker-specific preference shock over locations drawn from a Fréchet (Type I E.V.) distribution with $T_i > 0$ and $\theta > 1$.

$$G_i(Z) = e^{-T_i Z^{-\theta}}$$

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Log-Linearized Equilibrium

$$d \ln H_i = \sigma_i d \ln R_i + d\xi_i \tag{1}$$

$$d \ln h_i = -d \ln R_i + d \ln \alpha_i + d \ln w_i \tag{2}$$

$$d \ln L_i = -\theta\alpha d \ln R_i + \eta_i - d\tilde{u} \tag{3}$$

$$d \ln H_i = d \ln L_i + d \ln h_i \tag{4}$$

$$d \ln L = \sum_i L_i d \ln L_i \tag{5}$$

where $\eta_i = \theta d \ln w_i - \theta\tilde{\alpha}_i d \ln R_i + \theta d \ln A_i$ represents shocks to location demand, $d\xi_i$ are housing supply shocks, and $d\tilde{u}$ is the change in the city-wide set of neighborhood options.

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Estimating Location Demand Shocks

By assuming there is no change in the set of neighborhoods ($d\tilde{u}$) we can back out the following equations for the location demand shock:

$$\eta_i = d \ln L_i + \theta \alpha d \ln R_i$$

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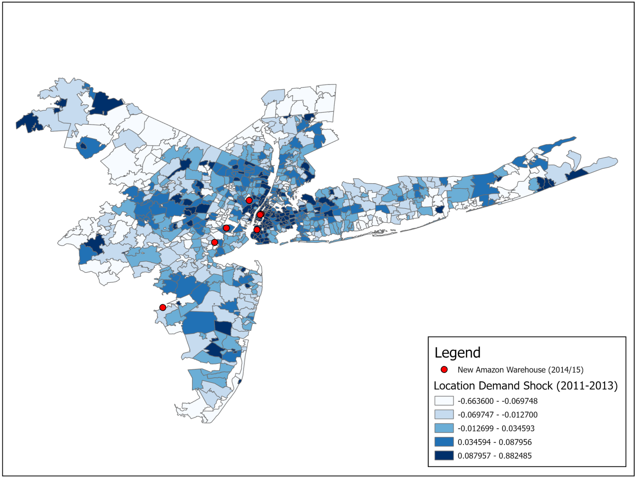
Location Demand Shock (2011-2013)



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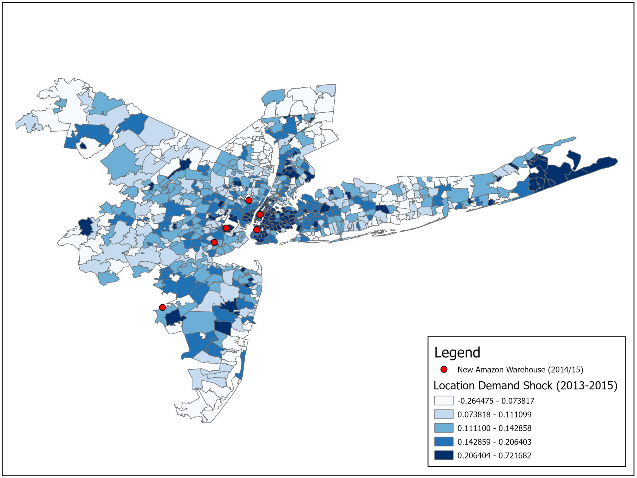
Location Demand Shock (2013-2015)



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