NEXUS TAX LAWS AND ECONOMIES OF DENSITY IN E-COMMERCE:

A STUDY OF AMAZON'S FULFILLMENT CENTER NETWORK

By

Jean-François Houde, Peter Newberry, Katja Seim

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NEXUS TAX LAWS AND ECONOMIES OF DENSITY IN E-COMMERCE: A STUDY OF AMAZON'S FULFILLMENT CENTER NETWORK

JEAN-FRANÇOIS HOUDE
Department of Economics, University of Wisconsin-Madison

PETER NEWBERRY
Department of Economics, Terry College of Business, University of Georgia

KATJA SEIM
Department of Economics and School of Management, Yale University

We quantify the distortionary effects of nexus tax laws on Amazon's distribution network investments between 1999 and 2018. We highlight the role of two features of the expansion of Amazon's network: densification of the network of distribution facilities and vertical integration into package sortation. Densification results in a reduction in the cost of shipping orders, but comes at the expense of higher facility operating costs in more expensive areas and lower scale economies of processing shipments. Nexus laws furthermore generate additional sales tax liabilities as the network grows. Combining data on household spending across online and offline retailers with detailed data on Amazon's distribution network, we quantify these trade-offs through a static model of demand and a dynamic model of investment. Our results suggest that Amazon's expansion led to significant shipping cost savings and facilitated the realization of aggregate economies of scale. We find that abolishing nexus tax laws in favor of a non-discriminatory tax policy would induce the company to decentralize its network, lowering its shipping costs. Non-discriminatory taxation would also entail lower revenue, however, as tax-inclusive prices would rise, resulting in a fall in profit overall. This drop and the decline in consumer welfare from higher taxes together fall short of the increases in tax revenue and rival profit, suggesting that the abolishment of nexus laws would lead to an increase in total welfare.

KEYWORDS: E-commerce, sales tax, nexus laws, Amazon, distribution, logistics, shipping.

1. INTRODUCTION

ONLINE RETAIL has grown substantially over the two last decades, accounting for 12% of all retail spending in Q1 of 2020.[1] The largest online retail platform, Amazon.com, henceforth Amazon, is central to this growth. Between 1999 and 2018, Amazon's share of online spending has grown from 10% to 45%, contributing to the rise in the concentration in retail markets (Autor, Dorn, Katz, Patterson, and Van Reenen (2020)). This increasing dominance suggests that e-commerce is associated with important economies of scale and

Jean-François Houde: houde@wisc.edu
Peter Newberry: pwnewberry@uga.edu
Katja Seim: katja.seim@yale.edu

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[1]See https://www.census.gov/retail/mrts/www/data/pdf/ec_current.pdf.

[Correction added on 6 February 2023, after first online publication: The copyright line was updated.]

scope, leading to a "winner-take-all" trajectory. The importance of demand-side increasing returns to scale on platform competition is well understood (see Greenstein (1993), Chu and Manchanda (2016), Cao, Zhe Jin, Weng, and Zhou (2021)). A less studied source of supply-side economies of scale is investment in distribution networks. Rather than relying on existing hub-and-spoke networks operated by independent logistic companies, Amazon is now the third largest delivery company globally, and industry experts forecast that it will soon operate a fully integrated logistic supply chain.

While this investment strategy mimics that of vertically integrated brick-and-mortar retail chains, such as Walmart, Kmart, and Target (Jia (2008), Holmes (2011), Zheng (2016)), a fundamental difference between e-commerce platforms and traditional retailers is that consumers can make purchases online without being physically close to product inventories. Holding fixed prices, this implies that online retailers can optimize the configuration of their logistic networks to minimize costs, taking as given the spatial distribution of demand.[2] Nexus tax laws change the nature of this optimization problem by tying (tax included) retail prices with the physical presence of facilities in a given state. Such laws favor retailers with small geographic footprints and can distort investments in cost-saving technologies.

The goal of this paper is to measure these distortions by evaluating the effect of discriminatory tax policies such as nexus tax laws on the distribution network of online retailers. To accomplish this objective, we study Amazon's growth between 1999 and 2018 through the lens of a dynamic model of investment in a distribution network.

In the model, Amazon chooses the locations of new logistic facilities anticipating the impact of its network configuration on current and future revenue and on the cost of fulfilling orders. We focus on two types of facilities: (i) fulfillment centers and (ii) sortation centers. Fulfillment centers are facilities where goods are stored, orders are packed, and packages are transferred to downstream facilities for sorting and final delivery. In contrast, sortation centers are facilities where packages are sorted by destination in preparation for final delivery. By locating fulfillment and sortation centers close to each other, Amazon can integrate the order fulfillment process vertically and fulfill an order entirely in-house, up to the last mile.

We model the cost of fulfilling orders as a combination of three components. First, the cost of warehouse space, a fixed cost, depends on the local rental rate and a congestion penalty of operating in urban areas. The other two components, which are variable costs, are the labor costs of processing the orders at a facility and shipping costs. The latter depend on total shipping distance and whether orders are handled by an integrated sortation center or by an independent shipping company.

The model predicts that the optimal network configuration is the outcome of two trade-offs. First, Amazon faces a trade-off between shipping cost savings (density) and order processing and fixed costs (scale), given current and future demand. Second, nexus tax laws induce a trade-off between economies of density and revenue. Upon building a distribution facility in a new state, online retailers have to collect sales taxes on all purchases from that state. The magnitude of this opportunity cost is modulated by the elasticity of demand, as well as tax collection delays negotiated between Amazon and state governments.

[2] In Houde, Newberry, and Seim (2021), we showed that consumer spending at Amazon is independent of distance to distribution centers. We interpret this result as suggesting that, during our sample period, Amazon was able to guarantee a uniform delivery speed (e.g., 2-day shipping), independently of the proximity of consumers to storage facilities.

We measure the relative importance of each of these forces in determining the location of new facilities in three steps. In the first step, we estimate a model of demand for online and offline goods. We combine data on household-level online spending at various websites from the comScore Web Behavior database, data on retail spending in total from the Consumer Expenditure Survey, and data on the propensity to shop online from Forrester Research. We estimate a CES specification that allows us to predict household spending and Amazon's revenue in each county and measure the elasticity of Amazon's revenue to local tax changes, a key ingredient to quantifying the revenue side of the network expansion trade-offs. We identify the demand elasticity using quasi-random variation in Amazon's tax-inclusive price caused by the timing of Amazon's entry into different states. We control for nationwide improvements in quality, convenience, and product variety with year-platform fixed effects. The results confirm that consumers are responsive to price, with a demand elasticity of approximately −1.5, similar to the estimates from Einav, Levin, and Sundaresan (2014) at −1.8 and Baugh, Ben-David, and Park (2018) at −1.5. The estimate implies that a customer in a non-taxed location spends 9.8% more at Amazon than the same customer in a location with the average sales tax rate of 6.5%.

In the second step, we use the volume of orders originating from each county in each year, as predicted by the demand model, to estimate the production technology of processing orders. Since we do not observe how Amazon allocates orders to fulfillment centers, we use a simple probabilistic model of product availability to predict order flows. We rely on data on the distributions of capacity and number of employees across facilities to identify the likelihood of product availability and the order processing technology. We estimate that a given fulfillment center is able to satisfy an order with a probability of approximately 50%. As a result, building a denser network of facilities reduces shipping costs by reducing the probability that orders are fulfilled by more distant fulfillment centers. At the same time, the results imply that there are sizable increasing returns to scale to order processing, which leads to an incentive to build fewer, but larger facilities with higher capacity utilization rates.

In the final step, we estimate shipping and fixed costs using a moment inequality estimator. Following Holmes (2011), we specify a set of moment inequalities that rationalize Amazon's observed network expansion strategy. We compare the firm's discounted profit stream under the observed distribution center locations to its profit under alternative locations Amazon could have chosen, but elected not to. For a given fulfillment center, we define alternative locations as the locations of other facilities opened at later dates. We find values of cost parameters that render the observed network roll-out more profitable than these alternatives.

We exploit variation in taxes and input prices across counterfactual networks to identify the effects of distance and vertical integration into sortation on shipping costs and the effect of local congestion on fixed costs. For example, moving up the opening date of a facility in a low-population, low-tax state and in turn delaying the opening of a facility in a more populous, high-tax state implies both higher revenue streams due to lower exposure to sales tax early on and longer shipping distances and thus higher cost. By independently varying the relative magnitudes of the predicted tax implications and input prices, we estimate bounds on each of the cost parameters.

Our estimates imply that Amazon's average cost of shipping an order decreased from \$2 to \$0.30 over the sample period. Highlighting the potential supply chain efficiencies associated with vertical integration into sortation, we find that a significant contributor to these lower shipping costs is in-house sortation, reducing shipping costs by 40% in 2018. Overall, the results suggest that the economies of density in shipping costs exceed the scale economies to order processing. As a result, Amazon's implied long-run average total cost of order fulfillment exhibits substantial economies of scale. By expanding its network, Amazon reduced its total average fulfillment cost by about 46%, despite facing larger labor and fixed costs.

We next use the estimated demand and fulfillment cost functions to illustrate the effect of nexus tax laws on the configuration of the distribution network, Amazon's cost and profit, and other components of welfare. We simulate counterfactual profit-maximizing network configurations under two tax regimes. We contrast the current nexus tax laws with a non-discriminatory tax policy, where Amazon collects sales tax in all states. Since the computational burden of solving the dynamic investment problem that Amazon faces is prohibitive, we approximate its solution with a series of static profit maximization problems evaluated at different levels of demand. The solutions to these static problems show that the estimated demand and cost functions are able to predict the network expansion observed in our sample period well.

We find that a move to a non-discriminatory tax system would lead to larger and less centralized simulated distribution networks than under the nexus tax policy. Evaluated at 2018 demand, this tax reform would lower the average shipping cost and distance by 22% and 13%, respectively. The lower shipping costs are partially offset by increases in labor and fixed costs, so that total average costs are 5.3% lower under a non-discriminatory tax regime. Overall, Amazon's profit would fall with a move to non-discriminatory taxation, as the decrease in revenue and demand due to more transactions being taxed outweighs the decrease in average costs. Consumer welfare falls, even though Amazon's rivals' profits rise, as the higher tax-inclusive prices on Amazon lead to some demand diversion. Since tax revenue is higher under a non-discriminatory policy, the net welfare effect depends on the magnitude of the fiscal multiplier. Assuming a multiplier of 1.64 (Dupor, Karabarbounis, Kudlyak, and Mehkari (2021)), our estimates suggest that the nexus policy decreases total welfare by about \$5 billion in aggregate. Ignoring the supply-side response of Amazon would overstate the welfare cost of nexus laws by 8%. This highlights the importance of modeling firms' investment decisions when analyzing tax policy.

Our work relates to several strands of literature. First and foremost, we contribute to a growing literature measuring the effect of discriminatory tax policies on the location of economic activities. For instance, Serrato, Carlos, and Zidar (2016) measured the impact of corporate taxes on the mobility of workers and firms, and Fajgelbaum, Morales, Carlos Suárez Serrato, and Zidar (2019) measured the equilibrium effect of state tax dispersion on misallocation of production. Slattery (2020) and Kim (2020) analyzed welfare effect of tax competition and location-based subsidies. While this literature provides general predictions regarding the spatial distribution of firms and workers, our paper is the first to analyze how spatial dispersion in taxes affects investments in an environment with economies of density. Bruce, Fox, and Luna (2015) and McGarry and Anderson (2016) provided early reduced-form evidence that nexus laws impact the location choices of online retailers, while our paper quantifies their effect of fulfilment cost and welfare.

Our analysis is also related to recent operations research and economics literature on the management of online firms' distribution networks (see Agatz, Fleischmann, and Van Nunen (2008), for an overview) and on the relationship between a brick-and-mortar retailer's store locations and its distribution network. Building on Jia (2008), who estimated the aggregate scale economies, irrespective of source, from operating multiple stores in close geographic proximity, Holmes (2011) estimated the savings in distribution costs associated with clustering stores near a distribution center. Zheng (2016) related the proximity of a rival's distribution center to the chain's expected future entry. These studies take the configuration of the distribution network as given and rely on variation in the distances from a distribution center to potential store locations to identify scale economies. Instead, we study the development of the network of fulfillment centers as a strategic choice for the firm. Little work to date has studied such classic industrial organization questions as the role of cost differences in affecting firms' competitive positions in the context of distribution in online markets.

Finally, an increasing body of work focuses on the estimation of demand in online retail markets (e.g., Dolfen et al. (2022)), the most relevant being studies on the responsiveness to sales tax and the gains from variety. Einav, Levin, and Sundaresan (2014) estimated the demand response to sales tax using eBay data, exploiting the fact that a buyer has the option to buy from an out-of-state seller who does not charge sales tax. Baugh, Ben-David, and Park (2018) used a differences-in-differences approach to estimate the effect of the 'Amazon tax', or changes in sales-tax collection on Amazon between 2013 and 2015. In estimating the tax sensitivity, neither set of authors was able to consider substitution to other taxed or non-taxed online outlets. We thus contribute to this literature by expanding the estimation of demand for retail goods beyond a single online firm to a large number of online and offline retailers.

The remainder of the paper is organized as follows. The next section describes the consumer spending data and summarizes expansion of the network. Section 3 specifies Amazon's optimization problem and the components of the profit function, while Section 4 presents the estimates of the model parameters. Section 5 uses these estimates to analyze the impact of the distribution network expansion and the role of sales tax laws therein. Section 6 concludes. The Online Appendix is located in the Supplemental Material (Houde, Newberry, and Siem (2022)) and the Supplemental Appendix may be found in the replication files as well as the authors' websites.

2. DATA AND STYLIZED FACTS

To analyze the expansion of Amazon's distribution network, we rely on several data sources. The available network data cover the years 1999 to 2018, which defines our sample period. The other data do not cover the entire sample period, so we use a combination of our estimated models, interpolation, and extrapolation to construct the missing observations. Section 4 and Online Appendices A and B.1 in the Supplemental Material describe these processes.

We begin by briefly discussing each source and the process by which we construct our primary variables, although we leave many of the details for the appendices. We then present important facts and trends in the data that we rely on to identify the determinants of Amazon's profit function.

2.1. *Retail Spending and Orders: Data*

The main input into our demand model is the spending on retail goods by a county's representative household. We construct a panel of annual spending, differentiating between different types of shopping outlets, or shopping 'modes'. We consider three online shopping modes that vary in their exposure to sales tax and a single offline shopping mode.

We rely on the comScore Web Behavior Database from 2006 to 2016 to construct the spending series for the three online modes. comScore records the price, the domain, and the date of every transaction made by a random sample of online shoppers.[3] For each respondent, comScore also records the five-digit ZIP code and a number of demographics. The sample includes 40 (12) thousand households and covers 85% (54%) of U.S. counties in its largest (smallest) sample year. The counties covered are the most populous, as 99% (92%) of U.S. households live in the represented counties in the largest (smallest) sample year (see Table A.I).

We manually classify each transaction's seller into a retailer type based on the seller's physical footprint across the United states. Amazon, which we denote as shopping mode 1, has sales tax liabilities in select states due to its growing distribution network, but, during most of our sample, not in states where it does not have a physical presence.

Shopping mode 2 consists of the online arms of nationwide retailers with a broad physical store network, such as walmart.com, which we denote as taxed online retailers. Mode 3, which we denote as non-taxed online retailers, covers firms that rely on the online sales channel only but do not operate extensive distribution networks; they thus lack a physical presence across states (e.g., overstock.com). Therefore, the variation in retailer tax collection obligations across shopping modes, combined with within- and across-state variation in sales tax rates, changes the relative price of a given purchase across locations and modes. Using this classification, we calculate the mode-level annual spending for each household in the comScore sample.

We make two important adjustments to the comScore spending variables. First, we account for households who do not shop online by using survey data from Forrester on the prevalence of online shopping as a function of demographics. Second, we correct for the fact that comScore tracks only the subset of user transactions made on a single registered device by scaling up household expenditures to match average spending per household from Amazon's financial statements. We similarly scale other online spending using reports from the U.S. Department of Commerce. We calculate spending on the offline mode, mode 0, by combining data from the annual Consumer Expenditure Survey and Census tables. We then calculate the county-level weighted average annual spending on each mode using population weights from the U.S. Census, giving us annual mode-level spending for the representative household in each county. Online Appendix A of the Supplemental Material provides details.

In addition, the demand model includes a number of consumer demographics, which we collect from the American Community Survey and the Decennial Census, and measures of local concentration of offline retailers, which we collect from the Census's County Business Patterns. See Online Appendix A.

2.2. *Distribution Network: Data*

We obtain information on Amazon's distribution network from the supply-chain consulting company MWPVL, International (http://www.mwpvl.com/). For each distribution facility, MWPVL provides information on the location, size in square feet of floor space, employment, facility type, opening date, and closing date, where applicable.

We rely on the facility type to identify two primary types of distribution centers. First, we group all distribution centers that store non-grocery items into a single category of fulfillment center.[4] We drop specialized distribution centers, including 'PrimeNow Hubs',

[3]comScore also records browsing behavior for households who do not shop online. We do not rely on these data here.

[4]This includes non-sortable centers, handling large items that the firm cannot ship in combination with any other products, and small and large sortable centers, handling items that the firm is able to combine into a single package.

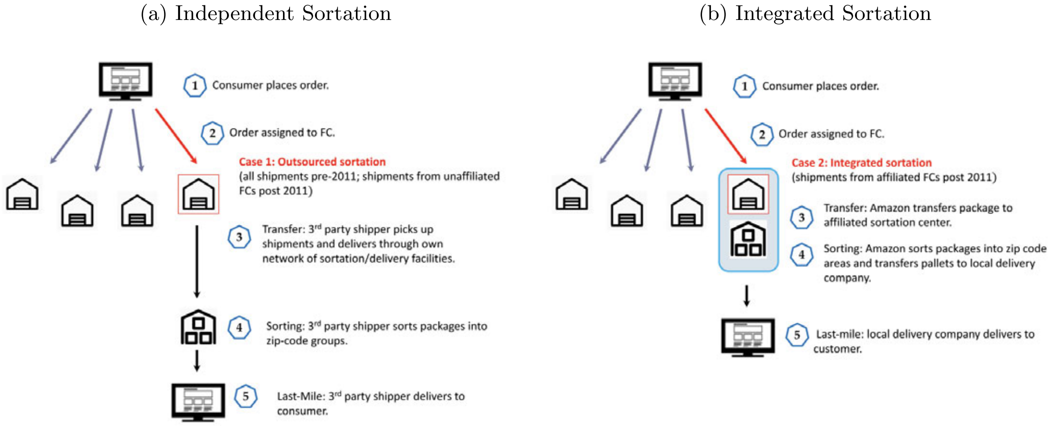


FIGURE 1.—Logistic of online transactions.

Amazon Fresh grocery delivery centers, return centers, and distribution centers for select high-value items such as jewelry.

The second type of facility, the sortation center, is a downstream facility in the delivery process. For most of our sample, independent shippers such as UPS and FedEx handled much of the order fulfillment process, including the shipping process, routing the packages through their own network of sortation and delivery facilities from the fulfillment center to the final destination. However, starting in 2014, Amazon began to build its own sortation network, which brings the majority of the fulfillment process in-house: co-located fulfillment centers continuously send shipments to the sortation centers, where these are grouped into three-digit destination zip code areas and transferred for 'last-mile' delivery by either the postal service or another local courier.[5] Figure 1 summarizes the process for both 'outsourced' and 'integrated' shipments.

According to MWPVL, packages that are routed through Amazon's own sortation network satisfy two conditions. First, the final destination must be within the sortation facility's coverage region. MWPVL suggests that a sortation center's catchment area includes destination zip codes within 150 miles from the facility. Second, the sortation center must be near one or more fulfillment centers, at a distance of at most 25 miles.

2.3. *Cost Components: Data*

We assume that the costs Amazon faces when making network decisions are split into fixed costs and variable costs per order. Fixed costs consist of the cost of warehouse space. We recognize, per square foot of warehouse space, the observed rental rate and a congestion penalty to urban locations. We approximate the rental rate with local commercial rents for warehousing space. The primary source for these data is Moody's Analytics REIS database which covers most MSAs between 2006 and 2018. Online Appendix A describes how we construct county-level rents per square foot using these data. The congestion penalty allows for the possibility that fixed costs are higher in urban counties, where, for example, integrating facilities into the highway network is more difficult. We rely on the population density of the facility's county, obtained from the Census, to be a

[5]Since the end of our sample period, Amazon has also begun to invest in last-mile delivery, in particular in urban areas.

proxy for such costs. We estimate the total fixed cost of a facility as the square footage reported by MWPVL times the sum of rent and congestion payment.

The variable costs of an order include the wholesale cost of the product, the labor cost of processing the order, and the shipping cost. We follow Holmes (2011) to infer wholesale costs, or the cost-of-goods sold, from the gross margins reported in Amazon's financial statements. See Online Appendix A in the Supplemental Material.

We scale the number of employees at a facility by an average annual wage to obtain annual labor costs of processing shipments at that facility. We use the average annual county-level wage of a retail employee from the Bureau of Labor Statistics as our measure of wages for fulfillment and sortation center employees. We obtain employment data for 131 of the 165 facilities in 2017 from a combination of industry reports and Amazon's financial statements (see Online Appendix A). We also observe system-wide employment in 2017 from an Amazon press release.[6]

Finally, we assume that shipping cost increases with shipping distance and calculate the distance a shipment travels from a given fulfillment center to the consumer in a given county. We use the Haversine formula to calculate the straight-line distances from the fulfillment center to each county's population-weighted centroid.

2.4. *Sales Taxes: Data*

The sales tax data come from two primary sources. First, we obtain state, county, and local sales tax rates from Thomson Reuters' Tax Data Systems for the years 2006–2016. For each year and county, we calculate the average tax rate, as tax rates can vary within a county and may change mid year. We assume that this sales tax rate applies to all consumer transactions at taxed online and brick-and-mortar retailers, as well as to taxable transactions on Amazon.[7] The average sales tax rate is 6.5% across counties and years, and there is a significant of amount of time-series and cross-sectional variation in rates (see Table A.V).

Second, we observe the date on which Amazon began to collect sales tax in every U.S. state. We rely on data from Baugh, Ben-David, and Park (2018) for states that realized the change before the end of 2015. For the remaining states, we obtain the date of the change using various news sources. In 2017, Amazon voluntarily began collecting sales tax on all of its transactions, regardless of consumer location. This change was largely inconsequential, however; at the time, the company was already collecting sales tax on orders from over 90% of U.S. households. As our demand model is at the annual level, we assume that the sales tax collection obligation applies to a given year and all subsequent years if it is effective before August of the year; otherwise, we assign it to the following year.

Changes in the sales tax status are triggered by Amazon's expanding distribution network due to nexus tax laws. As we discuss above, these laws require retailers to collect sales tax from consumers if they have a physical presence in the consumer's state of residence. Otherwise, the consumer is responsible for remitting a use tax, but few consumers

[6]Source: https://press.aboutamazon.com/news-releases/news-release-details/amazon-now-hiring-over-120000-jobs-us-holiday-season.

[7]Note that in five states, clothing purchases are generally sales tax exempt. We conduct two robustness checks where we remove either all households from the affected states or all purchases categorized as "Apparel" from the sample. The exemptions do not appear to drive the estimated tax responsiveness. See Houde, Newberry, and Seim (2021).

do so.[8] Not surprisingly, with the rapid growth of e-commerce, brick-and-mortar retailers and policymakers, fearing significant tax revenue losses, began supporting legislation to revise the definition of nexus as early as 2008 (see Bruce, Fox, and Luna (2009)). This culminated in a 2018 Supreme Court decision, where the court ruled that states could put tax collection responsibility on online retailers that exceed a minimum transaction threshold.

The onset of Amazon's tax collection does not always coincide with the opening of the first facility in the state. For example, Amazon opened its first facility in Tennessee in 2011 and did not start collecting sales tax in the state until 2014. Such gaps reflect negotiations about tax collection responsibilities between state governments and Amazon. Amazon's ability to extract tax delay concessions from state governments varies with the growth of its network and its demand, as we discuss in Online Appendix A.3. Hereafter, we call such delays 'tax abatement' agreements, although we are being somewhat loose with this terminology. We account for the delays in our model by assuming a deterministic schedule that maps the year of the first entry into a state into the year when Amazon begins collecting sales tax. See Section 4.3.

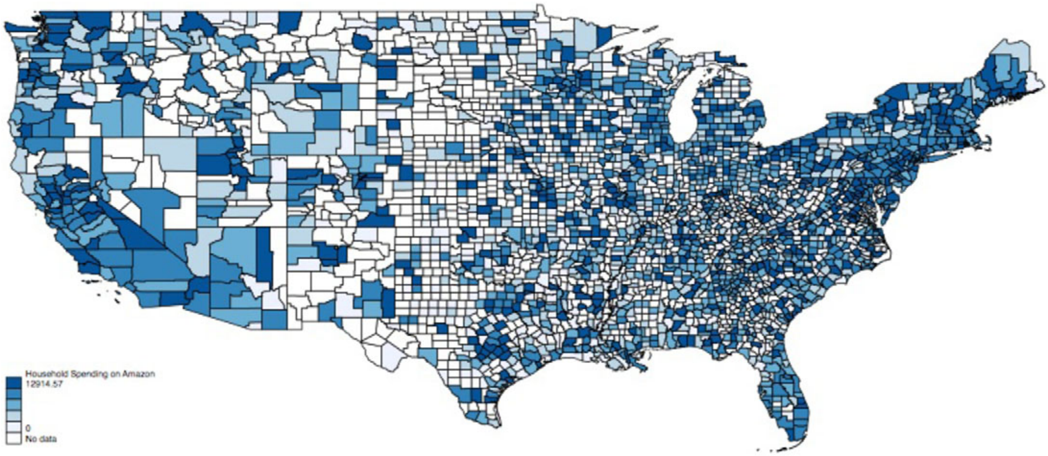
2.5. *Trends: Retail Spending and Orders*

The basic descriptive patterns in spending demonstrate, not surprisingly, significant growth in online shopping during our sample, with an average annual growth rate in household spending of about 12%. At the same time, offline spending experiences an average annual decline of 5%. The online growth reflects, in large part, Amazon's expansion. The company's sales grow on average 33% per year during our sample, while non-taxed and taxed online retail grow 10% and 8%, respectively, per year. Amazon's share of online retail thus increases from about 6% in 2006 to 31% in 2016. Table A.I and Figure A1 in Online Appendix A.1 demonstrate these patterns.

While the growth in online spending in many locations in the United States mirrors the aggregate trends, there is significant cross-sectional variation in the level of spending on Amazon. We explore this geographic variation in Figure 2, where we categorize counties based on the quintiles of the distribution of spending on Amazon by the county's representative household in 2016. The map indicates that counties in larger markets, such as counties around San Francisco, Chicago, and New York, fall into the top or second spending quintiles of all counties. At the same time, a number of counties in less densely populated areas, such as counties east of the Mississippi River, also exhibit high levels of spending, placing them in the same quintiles. This spatial variation in spending provides incentives for Amazon to decentralize its distribution network and to reduce shipping cost to not just major metropolitan areas, but also some of these less urban areas.

Below the map, we break down average household spending on Amazon in 2016 across urban and rural counties, wealthy and non-wealthy counties, and by Census regions. The data suggest that households in urban or high-income counties spend more on Amazon than rural counties and low-income counties. There is also regional variation in spending with the Northeast and the West having higher spending levels. See Table A.IV for these spending averages for each of the sample years.

[8]See, for example, http://www.npr.org/sections/money/2013/04/16/177384487/most-people-are-supposed-to-pay-this-tax, accessed on 1/12/2017.



AVERAGE ANNUAL HOUSEHOLD SPENDING BY DEMOGRAPHIC GROUP ($, 2016).

Density		Income		Region			
Urban	Rural	High	Low	Northeast	Midwest	South	West
1125	1020	1219	989	1159	1019	1007	1181

FIGURE 2.—Geographic distribution of spending on Amazon (2016). Notes: We classify counties with a population density of at least (less than) 500 people per square mile as urban (rural) and counties with median household income of at least (less than) $80,000 as high (low) income.

2.6. *Trends: Distribution Network*

Table I summarizes the roll-out of Amazon's fulfillment and sortation centers over the period 1999 to 2018, in three-year increments. The company expanded its fulfillment center network from five individual facilities in 1999 to 128 by 2018.

Often, this expansion takes the form of locating new facilities within close proximity of existing facilities, which we treat as co-location going forward. We use a clustering algorithm to define groups of co-located fulfillment centers, or 'clusters', as of the end of the sample period. Roughly, this amounts to grouping facilities that are within 20 miles of each other. We assign the centroid of the locations of all clustered facilities at the end of our sample as the cluster's location, recognizing that shipping costs and distances to the various facilities within the cluster are largely the same. Therefore, in the logistic model we describe below, we calculate the shipping cost at the level of the cluster.

As an example, in 2018, Amazon operates six fulfillment centers near Harrisburg, PA, which we group into a cluster located at the centroid of the six facilities. This cluster first came into existence in 2010 when Amazon opened two facilities in Harrisburg. Over the next eight years, it opened four additional nearby facilities, expanding the cluster in both number and size. The number of clusters, which we list in parentheses next to the number of fulfillment center locations in Table I, grew from five in 1999 to 70 in 2018. Hereafter, we use the terms 'cluster' and 'location' interchangeably, as they both serve to indicate a potential site for expansion, either in the form of de-novo entry, if no fulfillment center is active in the cluster at a point in time, or in the form of incremental expansion through the addition of new facilities. We refer to clusters with at least one operating fulfillment center as 'active clusters'.

The growth in fulfillment centers has been accompanied by a densification of the network. One indication of this densification is the increase in the number of states with

TABLE I

EXPANSION OF THE DISTRIBUTION CENTER NETWORK.

	Facilities			Size (100k ft^2)			Households	
Year	FC	SC	States	FC Cluster	SC	Employees	Distance	With SC
1999	5 (5)	0	4	5.9	–	305.8	307.6	–
2002	6 (6)	0	4	6.0	–	329.3	301.2	–
2005	9 (9)	0	6	5.6	–	337.3	268.8	–
2008	15 (12)	0	8	7.8	–	455.3	253.3	–
2011	25 (14)	1	9	13.2	3.2	1009.8	240.1	1.8
2014	57 (33)	12	17	14.0	3.5	965.1	127.2	48.7
2017	98 (52)	30	28	15.2	3.2	1984.1	73.8	81.7
2018	128 (70)	35	30	15.1	3.3	1906.7	67.4	82.8

Note: Under facilities, we depict the numbers of fulfillment centers, with the number of active clusters in parentheses, sortation centers, and states with a facility. Size is the average square footage of fulfillment and sortation centers and employees the number of employees of a cluster. Distance denotes the population-weighted average distance in miles from a county's centroid to the closest fulfillment center location. Households with SC is the percent of U.S. households with a sortation center within 25 miles.

at least one active cluster, which rose from four in 1999 to 30 in 2018. Table I also depicts network density in miles, measuring the population-weighted average great-circle distance between each consumer location, which we take to be a county's population-weighted centroid, and its closest cluster. The average distance to the consumer fell from 308 miles in 1999 to only 67 miles in 2018. Most of this decline is due to the expansion of the distribution network into the most densely populated states along the coasts in the mid-2010s. We illustrate these patterns in Figure 3, which maps locations of clusters (red) in 2006 and 2018, shading states by the number of households and presenting the state average sales tax rate. The size of each bubble indicates the number of fulfillment centers in the active cluster.

Panel (b) of Figure 3 adds the location of the 35 sortation centers (yellow) that Amazon built by 2018. As the map and Table I illustrate, sortation centers primarily serve large urban areas: by 2018, the relatively small number of sortation centers is able to serve a set of counties that together account for 83% of U.S. households.

Table I shows that both the size and the number of employees per cluster have increased substantially over time. In addition, Amazon has expanded into more expensive areas: Table II shows that the average rent per square foot in Amazon's facility locations is below the national average (in parentheses) in 1999, but about 10% higher than the national average in 2018. Similarly, the average population density of counties with a facility, our measure of congestion, has increased substantially over time, and the wages in these counties are about $1000 above the national average by the end of the sample. This suggests that, while the distribution network's expansion has reduced the distance to the average consumer and thus shipping cost, it has also disproportionately increased fixed and labor costs.

Some additional aspects of the distribution network expansion are noteworthy. Until 2010, Amazon placed fulfillment centers in relatively low-population and low-tax states near highly populated or high-tax areas. For example, Amazon opened two facilities in Nevada on the California border, close to that state's major cities. The company also opened one fulfillment center each in New Hampshire and Delaware, both of which are close to major East Coast cities and have zero sales tax. Indeed, the second to last column of Table II highlights that prior to 2011, the average sales tax rate in states with a fulfillment center is lower than the nationwide average. At the same time, the percentage

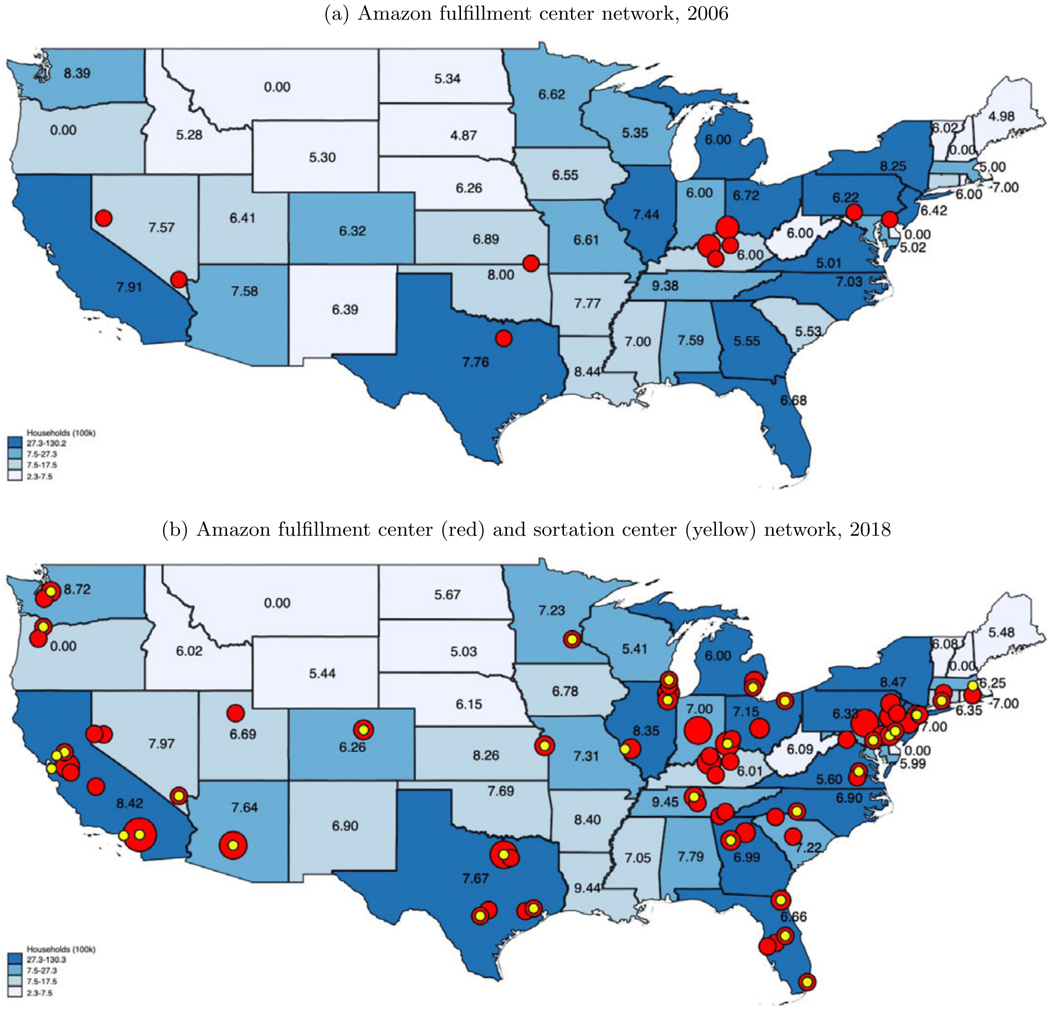


FIGURE 3.—Distribution center network, 2006 and 2018. Notes: Counties categorized into and shaded by quintiles of the distribution of number of households. Size of each bubble scales with number of fulfillment centers.

of taxed consumers only increased by about 11% (last column of Table II) between 1999 and 2011, even though, as Table I indicates, the average distance between consumers and their closest fulfillment center fell by 22% over that period. These patterns suggest that the company actively chose locations that mitigate consumer exposure to sales taxes, in terms of either the tax level or the size of the customer base exposed to taxes.[9]

[9]Work documenting consumers' sensitivity to sales taxes, in terms of the extensive margin of shopping online, includes Goolsbee (2000a), Goolsbee (2000b), Alm and Melnik (2005), Ballard and Lee (2007), and Scanlan (2007). Ellison and Fisher Ellison (2009), Smith and Brynjolfsson (2001), Anderson, Fong, Simester, and Tucker (2010), and Goolsbee, Lovenheim, and Slemrod (2010) studied the intensive margin response to sales tax. Numerous papers, including Asplund, Friberg, and Wilander (2007), Agarwal, Marwell, and McGranahan (2017), and Chetty, Looney, and Kroft (2009), study the response to sales taxes in offline markets.

TABLE II

LOCAL DETERMINANTS OF PROFITABILITY.

Year	Rent ($/sq ft)	Population Density (pop/sq mile)	Wage ($k)	Sales Tax (%)	Taxed Households (%)
1999	3.5 (3.6)	302.7 (245.8)	14.4 (13.8)	5.1 (6.0)	0
2002	3.7 (3.8)	414.7 (248.9)	15.7 (15.3)	5.1 (6.0)	0
2005	4.1 (4.0)	562.2 (252.1)	17.2 (16.7)	5.7 (6.0)	2.7
2008	4.2 (4.2)	512.1 (257.0)	18.8 (18.5)	6.0 (6.1)	11.3
2011	4.0 (4.0)	595.6 (259.2)	20.0 (19.3)	6.6 (6.2)	11.3
2014	4.2 (4.2)	685.0 (266.0)	21.1 (20.4)	6.8 (6.3)	69.2
2017	4.7 (4.4)	1059.5 (270.8)	22.8 (22.0)	6.6 (6.4)	97.6
2018	5.0 (4.6)	1156.7 (272.0)	23.6 (22.7)	6.6 (6.4)	97.6

Note: We display average commercial rents, population per square mile, and annual wages at the county level and average state-level sales tax rates for counties with an active fulfillment center cluster, compared to the average across all counties or states in parentheses. Taxed households represent the share of U.S. households who live in states with positive sales tax and for whom Amazon remits sales taxes.

As Amazon grew in scale, however, the network of fulfillment centers expanded beyond such locations, presumably to be closer to population hubs despite sales tax implications and higher fixed costs of warehousing in densely populated areas. For example, by 2014, we see entry into highly populated states, such as California and Virginia, and high-tax states, such as Tennessee (9.5% tax rate in 2013). By 2018, Amazon added fulfillment centers in Georgia, Illinois, North Carolina, and Ohio. The average sales tax rate in states with a fulfillment center surpassed the overall average in 2011. Further, the growth in the share of households subject to sales tax rises to over 90% by 2017, when Amazon began to collect tax from all consumers.

3. MODEL

We are interested in modeling the investment decisions leading to the expansion of Amazon's distribution network. Here, we detail components of the online retailer's underlying per-period payoff function, paying particular attention to the firm's logistic problem, which drives the trade-offs it faces in choosing the network of distribution facilities dynamically, as demand and order flows evolve. We conclude this section with a description of this dynamic optimization problem.

3.1. *Distribution Network*

We use the following notation to describe the distribution network. Facilities are indexed by $j = 1, \dots, n$, and are fully described by their entry year (a_j), capacity (k_j), location (l_j), and type ($m_j = \{FC, SC\}$).[10] The index j represents a unique label attached to each facility. We assume that locations are chosen from a finite set of possible locations, $l = 1, \dots, L$. In line with the co-location of facilities we observe in the data, each location l can accommodate multiple fulfillment centers and up to one sortation center. We thus use l to describe both the cluster and its location. We use $n_t = \sum_{j=1}^{n} 1(a_j \leq t)$ to denote the number of active facilities in period t. Similarly, $K_{lt} = \sum_{j=1}^{n} 1(a_j \leq t) \times 1(l_j = l \text{ and } m_j = FC) \cdot k_j$ measures the fulfillment capacity of cluster l in period t.

[10] We abstract from facility exits as only one fulfillment center closes during the sample.

We assume that the square-footage and type of each facility are fixed, so that the distribution network evolves over time based on the opening of new facilities. We summarize the network in period t, given the chosen sequence of opening decisions $\mathbf{a} = \{a_1, \dots, a_n\}$, by an $n_t \times 3$ matrix:

$$N_t(\mathbf{a}) = \{(k_j, l_j, m_j) | \forall j \text{ s.t. } a_j \leq t\}.$$

We use $\mathbf{a}^0$, n_t^0, and N_t^0 to denote the observed sequence of entry decisions and observed number of active facilities and characteristics of these facilities in period t.

3.2. *Demand and Revenue Function*

We use a representative agent framework to predict orders and revenues as a function of the network configuration and sales tax laws. Consumers are located at the population-weighted center of their county, indexed by $i = 1, \dots, I$. They allocate their retail budget B_i between brick-and-mortar retailers ($k = 0$) and the three online modes ($k = 1, 2, 3$).

Preferences for each mode reflect differences in tax exposure. For Amazon, or mode 1, nexus tax laws imply that the distribution of sales tax across counties at a point in time reflects its distribution network. For the remaining modes, exposure to sales tax does not vary across counties within a year.

Beyond differences in tax exposure, we allow for two dimensions of differentiation between online modes: quality and variety. We assume that consumers have CES preferences over modes where each mode offers a mass of varieties ω with distribution $F_{kt}(\omega)$. We treat ω as a quality index by assuming that the marginal utility of consumption of variety ω depends on a separable function of ω and consumer i's mode-specific taste for variety at time t, α_{ikt}. We assume that the offline mode offers a single variety.

We show in Supplemental Appendix A.1 that consumers' expenditure function is given by

$$e_{ikt} = \int \alpha_{ikt} \omega \tilde{p}_{ikt}(\omega)^{1-\sigma} P_{it}^{\sigma-1} B_{it} \, dF_{kt}(\omega). \tag{1}$$

$\tilde{p}_{ikt}(\omega)$, the tax-inclusive price of variety ω on mode k, equals $p_{ikt}(\omega)(1+\tau_{ikt})$, where p_{ikt} is the pre-tax price and τ_{ikt} is the sales tax a resident in county i pays on purchases from mode k (see below). P_{it} is the tax-inclusive Dixit–Stiglitz price index (Dixit and Stiglitz (1977)).

Equation (1) allows us to construct a log-linear function describing the spending in county i on mode k relative to the offline option, mode 0:

$$\begin{aligned}
\tilde{e}_{ikt} &= \ln e_{ikt} - \ln e_{i0t} \\
&= \ln(\alpha_{ikt}) - \ln(\alpha_{i0t}) + (1-\sigma)\big(\ln(\rho_{kt}) - \ln(p_{i0t})\big) \\
&\quad + (1-\sigma) \underbrace{\big(\ln(1+\tau_{ikt}) - \ln(1+\tau_{i0t})\big)}_{\Delta\tau_{ikt}} + \ln\left(\int \omega^{2-\sigma} \, dF_{kt}(\omega)\right) \\
&= \xi_{kt} + \lambda_k Z_{it} + \gamma_k C_{it} + \bar{\xi}_i + \Delta\xi_{ct} + (1-\sigma)\Delta\tau_{ikt} + \epsilon_{ikt},
\end{aligned} \tag{2}$$

where ξ_{kt}, as a mode-year fixed effect, captures mode-level determinants of expenditure, including aggregate quality and variety—the last term in the second line of Equation (2). The vector Z_{it} contains demographics of the representative household, and C_{it} contains variables that measure the level of local offline competition. The next two terms represent unobserved relative preferences for online shopping. We assume that these preferences consist of a county-level, time-invariant component, $\bar{\xi}_i$, and a time trend that captures changes in preferences at the level of the county's Census Division, $\Delta\xi_{ct}$.

Since we do not observe prices for the offline option, the time-varying controls and fixed effects account for county-level and time-series variation in prices at brick-and-mortar retailers in county i. $\Delta\tau_{ikt}$ is the difference in log sales tax rates between mode k and the offline option. Last, the model residual ϵ_{ikt} includes time-varying shocks to the willingness to pay of consumers for the three retail modes relative to the outside option, as well as measurement error in spending shares. See Supplemental Appendix A.1 for a step-by-step derivation of Equation (2).

We use consumer expenditure to derive aggregate revenue for Amazon, or mode 1, net of tax remitted to state and local taxing authorities, by summing across locations:

$$R_t(N_t) = \sum_i M_{it} \frac{e_{i1t}}{1+\tau_{i1t}(N_t)}, \tag{3}$$

where M_{it} is the number of households. Similarly, the number of orders originating from county i is given by

$$Q_{it}(N_t) = M_{it} \frac{e_{i1t}}{\big(1+\tau_{i1t}(N_t)\big)\bar{p}_t}, \tag{4}$$

where $\bar{p}_t$ is the average pre-tax price of Amazon's varieties.

We impose the following assumptions on pricing and the distribution of orders across third-party and Amazon's direct sales.

PRICING ASSUMPTIONS:

a. *Each variety ω is available in each county i and its price does not vary across counties*.

b. *The pre-tax price of variety ω is set competitively by Amazon and a continuum of third-party sellers according to a log-linear hedonic function*:

$$\ln p_{kt}(\omega) = \rho_{kt} + \ln \omega.$$

c. *Amazon earns variable profit according to common revenue-sharing agreements with manufacturers and third-party sellers*.

d. *Third-party sales are non-taxable and have a constant market share across consumer locations*.

Assumption a reflects that Amazon does not employ spatial price discrimination on its platform and that such discrimination is not widespread on other platforms; thus, the tax-inclusive price varies across locations solely due to differences in sales taxes and variation in price over time is captured by the mode-year fixed effect ξ_{kt}.[11]

Assumption b allows us to treat prices as independent of the network configuration. It captures the fact that a large number of sellers are active on the platform, selling products that are available from a variety of other online and offline retailers.

[11] Evidence in Cavallo (2017) showed that over the period 2014–2016, online prices in the United States do not change with the location of the consumer. The retailers covered in the analysis include Amazon's biggest competitors, such as target.com and walmart.com, who reportedly priced nationally during the full sample. Cavallo's work suggests furthermore that reported efforts at spatial price discrimination by specialized online retailers in the early 2010s, most notably Staples.com, were short-lived and temporary, presumably due to consumer backlash.

We make Assumption *c* mostly for convenience since we observe limited information about the characteristics of products and contractual terms between Amazon and its suppliers. Assuming a common revenue-sharing formulation, together with Assumption *d*, allows us to write the revenue net of cost of goods sold as a linear function of gross revenue:

$$\text{Revenue Net Cost}_t = R_t(N_t) \times \bar{\mu}_t.$$

Here, $\bar{\mu}_t$ denotes the average markup Amazon earns on direct sales, μ_t^{own}, and on third-party sales, μ_t^{3PS}, weighted by the contribution of each channel to orders:

$$\bar{\mu}_t = s_t^{\text{3PS}} \mu_t^{\text{3PS}} + \left(1 - s_t^{\text{3PS}}\right) \mu_t^{\text{own}},$$

where s_t^{3PS} denotes the share of third-party orders in year t.

Assumption *d* implies that consumers can always find an untaxed third-party seller, which allows us to recognize the effect of third-party sellers on local sales tax liabilities.[12] As a result, the sales tax rate on each mode is given by

$$\tau_{ikt} = \begin{cases} \left(1 - s_t^{\text{3PS}}\right) 1_{i1t}^{\text{taxable}} \tilde{\tau}_{it} & \text{if } k = 1 \text{ (Amazon)}, \\ \tilde{\tau}_{it} & \text{if } k = 0, 2 \text{ (taxed offline and online retailers)}, \\ 0 & \text{if } k = 3 \text{ (non-taxed online retailers)}, \end{cases}$$

where $\tilde{\tau}_{it}$ is the sales tax rate in county i and year t and 1_{i1t}^{taxable} is an indicator variable equal to 1 if Amazon collects sales tax in county i in year t. In estimating the demand model, we use Amazon's observed physical presence and each state's observed sales tax abatement schedule to determine the tax rate residents of each county pay.

3.3. *Order Flow*

The demand model allows us to predict the number of orders originating from county i. We use a simple logistic model to assign a given order to a fulfillment cluster, depending on the availability of goods across clusters and the distance between the clusters and the order's county of origin. The logistic model returns the flow of orders in the network, which we use to determine the variable shipping and order processing costs.

First, we assume that a particular variety is held in every fulfillment center, but is out-of-stock with some probability. We model product availability at a cluster as an i.i.d. binary random variable with probability that a product is available given by

$$\phi_t(K_{lt}) = 1 - \exp\left(-\psi \frac{K_{lt}}{\text{Variety}_t}\right). \tag{5}$$

The availability probability increases in the total fulfillment capacity of cluster l, K_{lt}, but decreases in the variety of goods available on Amazon in period t. Equation (5) thus implies that an increase in variety leads to a higher stock-out probability, giving Amazon an incentive to add fulfillment centers and thus capacity to a given location as variety increases.

[12]This assumption entails an upper bound on the sales tax sensitivity. We have also conducted our analysis assuming that all third-party transactions are taxed, resulting in a lower-bound, but significant, sensitivity to sales-tax induced price variation. The true price sensitivity likely lies in-between these extreme cases, but Assumption *d*'s is closer to the literature.

We rule out the possibility of a network-wide stock-out and assume that orders are processed by the closest active cluster with available inventory. This leads to an $L \times I$ origin-destination fulfillment matrix $\Omega(N_t)$, where, in light of the large number of orders, element (l, i), $\Omega_{l,i}$, measures the fraction of orders from county i that are fulfilled by location l. As $\psi \to \infty$, the probability that the nearest active cluster fulfills a given order approaches 1.

Conditional on orders being assigned to cluster l, we assume that they are distributed across the individual fulfillment centers that make up cluster l in proportion to facility size k_j.

Last, we rely on the industry evidence on sortation center catchment areas discussed in Section 2.2, together with the assignment of orders to clusters, to determine orders that are fulfilled fully by Amazon. We summarize the share of orders from county i that is routed through a sortation center at cluster l by an $L \times I$ matrix $\Omega^{sc}(N_t)$. Element (l, i) of Ω^{sc} equals to the sum of orders from a household in county i, in percent, that are fulfilled by any cluster l', $\Omega_{l',i}$, that is within 25 miles of a sortation center l, provided the county falls in the 150 mile delivery catchment area of the sortation center at l.

We use these assumptions to predict the quantity of orders handled by facility j in period t as a function of the availability parameter ψ, the aggregate variety carried by Amazon, and the network:

$$q_{jt}(\psi) = \begin{cases} \sum_i Q_{it}(N_t)\Omega_{l,i}(N_t)\frac{k_j}{K_{lt}}1(a_j \leq t) & \text{if } m_j = FC \text{ and } l_j = l, \\ \sum_i Q_{it}(N_t)\Omega^{sc}_{l,i}(N_t)1(a_j \leq t) & \text{if } m_j = SC \text{ and } l_j = l. \end{cases} \tag{6}$$

Supplemental Appendix A.3 provides detail on the derivation of this function.

3.4. *Cost Function*

The cost of fulfilling orders has three components: (i) shipping costs, (ii) labor costs in processing orders, and (iii) fixed costs of facilities consisting of rents and congestion costs.

We begin with the shipping cost, which has two components. First, is a ‘distance cost’ that is assumed to be a linear function of the delivery distance. Second, orders that Amazon routes through its own sortation centers, which we refer to as ‘vertically integrated’, entail a constant, per-order reduction in shipping cost relative to non-integrated orders.

This leads to the following system-wide shipping cost function:

$$\begin{aligned} C_t^{\text{Shipping}}(N_t) &= \theta_d \cdot \Big(\sum_l \sum_i \Omega_{l,i}(N_t)Q_{it}(N_t)d_{il}\Big) + \theta_{vi} \cdot \Big(\sum_j q_{jt}1(m_j = SC)\Big) \\ &= \theta_d \cdot D_t(N_t) + \theta_{vi} \cdot Q_t^{vi}(N_t), \end{aligned} \tag{7}$$

where d_{il} and $D_t(N_t)$ are the shipping distance in miles from county i to cluster l and in total, respectively, and $Q_t^{vi}(N_t)$ is the volume of vertically integrated orders. If $\theta_d > 0$, Amazon can reduce the cost of shipping to a particular county i either by opening up fulfillment centers in new locations, reducing the distance to the nearest cluster, or by expanding the capacity of the nearest cluster, thereby increasing the likelihood of product availability at the nearest cluster. If $\theta_{vi} < 0$, shipping costs can be further reduced by locating a sortation center near existing fulfillment capacity. This creates a complementarity in the choices of sortation center and fulfillment facility locations. Network density and vertical integration capture the idea that Amazon can lower shipping cost by reducing its reliance on independent shipping companies either through a lower distance that the shippers must cover, which in turn allows Amazon to put downward pressure on negotiated rates, or through in-house sorting of packages.

We model the labor cost of processing using a Cobb–Douglas function, resulting in the following labor demand functions for each facility type:

$$L_{jt}(N_t) = A_{m_j} q_{jt}(\psi)^{\gamma}, \tag{8}$$

where $q_{jt}(\psi)$ is given by Equation (6) and A_{m_j} is the productivity of a facility of type m_j. The total labor cost is obtained by aggregating across facilities:

$$C_t^{\text{Labor}}(N_t) = \sum_j \sum_l w_{lt} L_{jt}(N_t) 1(l_j = l),$$

where w_{lt} is the annual wage in cluster l. Importantly, if $\gamma < 1$, the production technology exhibits economies of scale. Therefore, in addition to locating facilities in low-wage areas, Amazon can lower labor cost by concentrating fulfillment capacity in a small number of fulfillment centers.

Last, the fixed cost of operating network N_t is given by

$$\begin{aligned} F_t(N_t) &= \sum_j \sum_l k_j \cdot (r_{lt} + \kappa \text{Pop Density}_{lt}) 1(l_j = l) \\ &= C_t^{\text{Rent}}(N_t) + \sum_j \sum_l k_j \cdot (\kappa \text{Pop Density}_{lt}) 1(l_j = l). \end{aligned} \tag{9}$$

C_t^{Rent} is the fixed cost of space, which scales with a rental rate of r_{lt}. The parameter κ measures how the fixed cost per square foot increases as the population density of location l increases. Such additional penalties reflect either congestion or measurement error in rental rates, both of which are likely more pronounced for large facilities.

3.5. *Optimization Problem*

Putting together revenue and the various cost components yields the firm's flow profits associated with network N_t:

$$\pi_t(N_t) = \bar{\mu}_t R_t(N_t) - C_t^{\text{Shipping}}(N_t) - C_t^{\text{Labor}}(N_t) - F_t(N_t). \tag{10}$$

We are interested in understanding the trade-offs associated with the location choice of each new active facility, conditional on the number and characteristics of facilities built every year. Like Holmes (2011), we characterize the expansion of the network as the outcome of a constrained dynamic optimization problem with perfect foresight:

$$\begin{aligned} \Pi(\mathbf{a}^0) = \max_{\mathbf{a}} & \sum_{t=0}^{\infty} \beta^t \pi_t(N_t) \\ \text{s.t.} \quad & N_t = N_t^0(\mathbf{a}) \\ & \sum_j 1(a_j = t) = n_t^0 - n_{t-1}^0, \end{aligned} \tag{11}$$

where $\beta = 0.95$ is Amazon's discount factor and $n_t^0 - n_{t-1}^0$ is the observed number of facilities opened in period t. The solution to this problem, which describes the optimal roll-out of the distribution network, is, under revealed preference, given by $\mathbf{a}^0$.

3.6. *Discussion*

We close this section with a discussion of several of our assumptions.

Willingness-to-Pay and Network Investments. We begin first with the potential interaction between Amazon's demand and proximity to fulfilment centers. The demand model from Equation (2) does not allow preferences to depend on the distribution network, in terms of either configuration or size. One might imagine that the network configuration, such as the consumers' distance to the closest fulfillment cluster, shapes their willingness-to-pay to the extent that proximity to facilities results in shorter shipping times. In this case, ignoring the network configuration's contribution to spending might furthermore bias the estimated elasticity of substitution if, for a given county location, changes in distance to the closest fulfillment center are correlated with changes in relative taxes.

Note, however, that tax liability is tied to each customer's state of residence, while the closest fulfillment center to a given customer may be in a nearby state. Tax abatements also drive a wedge between the timing of tax and shipping distance changes. In the short run, the entry of new facilities thus varies taxes independently of shipping distance. In Houde, Newberry, and Seim (2021), we exploited this fact to test whether Amazon spending responds to various proxies for shipping speed from the closest fulfillment, controlling for tax exposure, and cannot reject the hypothesis that consumer spending is independent of proximity to an Amazon facility, our maintained assumption here. This is consistent with the limited variation in shipping times on Amazon in practice: since 2005, Amazon has offered the same shipping terms, free two-day shipping on eligible purchases, to all Prime members irrespective of location.[13]

Instead, Equation (2) allows for uniform improvements in shipping speed across locations through the mode-level fixed effect ξ_{kt}. The relatively short time-series dimension of our data precludes us from identifying independently how spending varies with the aggregate size of the network, N_t, as a proxy for network density. In estimating the cost function and our counterfactual analyses, we hold mean preferences for Amazon and the remaining modes fixed. The perturbations we rely on in estimation only change the location of a single facility in a given year, but not change the total size of the network. Similarly, the alternative networks we consider in our counterfactuals are small deviations of the current network, suggesting that it might be unlikely that Amazon or its competitors would adjust quality, prices, or aggregate variety, all of which are subsumed in ξ_{kt}, in response.

Perfect Foresight. Second, we assume that Amazon has perfect foresight about future demand and supply conditions, an assumption that is common to the literature. It also reflects that Amazon is a large, forward-looking company that has spent significant resources to improve the sophistication of its predictions about future market conditions. It is difficult, of course, for us to represent accurately the company's expectations regarding demand and supply conditions post-sample. In estimating the shipping and fixed cost

[13]See https://money.cnn.com/2018/04/28/technology/amazon-prime-timeline/index.html, accessed in Oct 2019.

contributions to the company's network roll-out decisions, which we describe in detail below, we circumvent the need to do so by exploiting only the optimality of the timing of the opening of each facility within the sample period, holding fixed the facilities' chosen locations and their total number at the end of the sample. Post-sample market conditions, such as the entry or expansion of e-commerce rivals, which might give rise to entry deterrence motives behind the chosen size and configuration of the distribution network, thus do not affect our estimation. In the counterfactuals, we abstract from such considerations.

A second advantage to exploiting the optimality of the timing of facility openings, rather than the optimality of the number of facilities, is that we can disregard unobserved sunk costs or benefits to opening facilities, provided these are the same across facilities. We thus abstract from location-specific unobserved sunk costs to opening a facility, such as the local government subsidies studied in Slattery (2020).

Cost Savings From Vertical Integration. Third, we recognize the gains to vertical integration into package sortation in a reduced-form way, by making shipping cost dependent on whether the delivery goes through an in-house sortation center. While not specifically modeled, the benefits from in-house sorting, rather than contracting with UPS or FedEx, stem from two sources. There are the cost efficiencies of bypassing the downstream shippers, who hold significant market power. Amazon and the downstream shippers also face a hold-up problem. UPS or FedEx would have to invest a significant amount in their network in order to handle Amazon's volume at guaranteed shipping times. The reputational concerns that shipping delays raise for Amazon provide the company with incentives to invest in its own network. Modeling these incentives underlying Amazon's increasing expansion into delivery services is an interesting avenue for future research.[14]

Additional Modeling Assumptions. Finally, and more broadly, our data are mute on some details of Amazon's and its competitors' operations. On Amazon's side, we observe only the aggregate share of sales by third-party sellers on Amazon's Marketplace and assume it is constant across locations, even though Amazon's tax obligations differ between direct and third-party sales.[15] Our demand and network data are also not sufficiently detailed to distinguish between types of goods. As a result, we assume that the capacity of a fulfillment cluster affects only the probability of product availability, but not the range of varieties available at the location or an individual facility in the cluster. Conditional on fulfillment capacity, all clusters thus carry every product variety with the same probability. Last, we observe only a cross-section of employment at each fulfillment center, together with aggregate trends in fulfillment employment. This forces us to hold the fulfillment technology fixed over time. To the extent that there are productivity improvements in fulfillment through, for example, automation, we may overstate the importance of economies of scale in fulfillment.

On the competitors' side, we do not observe detailed information on the locations of their distribution facilities and thus do not model their network choices. On the demand side, as we control for time-varying mode-level preferences, we capture the growth in demand for competing modes, however, which may be the result of system-wide improvements in delivery reliability and/or speed due to network investments in response to Amazon's total network size.

[14]The logistics company MWPVL provides a summary of the primary benefits of Amazon's vertical integration. See the article at http://www.mwpvl.com/html/amazon_building_new_sortation_network.html, accessed on 11/10/2018, for details.

[15]See Amazon's Annual Letter to Shareholders, 2018, available at https://www.sec.gov/Archives/edgar/data/1018724/000119312519103013/d727605dex991.htm, accessed 6/30/2020.

4. EMPIRICAL ANALYSIS

In this section, we discuss our econometric approach to estimating the above demand and cost functions and the empirical results. In Section 4.1, we discuss the estimation of the demand model, which we use to derive Amazon's total revenue, $R_t(N_t)$, and the geographic distribution of orders, $Q_{it}(N_t)$, as a function of the network. Section 4.2 focuses on the estimation of the order flow matrices, $\Omega(N_t)$ and $\Omega^{sc}(N_t)$, and the labor demand function, $L_{jt}(N_t)$. Finally, in Section 4.3, we lay out the estimation of the fixed costs and the shipping costs associated with fulfilling an order.

4.1. *Demand*

We estimate the determinants of log spending on each mode, relative to log spending at brick-and-mortar retailers, in Equation (2) using weighted least-squares, based on the number of observations in the comScore sample for county i that we use to calculate $\tilde{e}_{ikt}$. We include as demographic shifter Z_{it} the income, age, and race of the representative household. We measure race as the share of people in county i who are of a given race. To allow for non-linearities in the effects of age and income, we also include the share of people in the county with incomes above \$100,000 and the share of people in the county who are under the age of 35. The competition variables in C_{it} include the log of county i's population density as a proxy for travel costs and the number of all and of small (under 50 employees) retail establishments per 1000 people in county i. We interact the demand shifters in Z_{it} and C_{it} with an Amazon mode indicator to capture varying preferences for Amazon by demographic group and by the level of offline competition. These preferences could represent mode-specific targeting, heterogeneity in preferences for quality, variety, and convenience, or variation in price sensitivity.

The identification of the elasticity of substitution, σ, comes from variation in relative taxes across counties and time ($\Delta\tau_{ikt}$). The within-county variation exploits the timing of tax changes triggered by Amazon's expansion decisions and tax abatements, similar to a difference-in-difference regression. The intensity of the "treatment" via tax rates varies across counties within the same state, contributing to the identification of σ. Our main identifying assumption is that the timing and magnitude of tax changes are independent of changes in the demand residual, conditional on aggregate regional and mode-level trends.

We present the estimated parameters and standard errors of two specifications in Table III. Specification I restricts σ to be the same for all consumers, while Specification II allows σ to vary with the income of the representative consumer. We interact the relative tax rate with the share of households in county i who have an income above \$100,000.

As noted above, for each specification, we estimate a base effect of demographics and offline competition on the demand for all online modes relative to the offline option and allow for an incremental effect of the covariates on the demand for Amazon. The estimated coefficients are consistent across specification, so we focus our discussion on the heterogeneous-σ model.

The estimates suggest that the propensity to shop online falls with age and that households with a head under the age of 35, in particular, prefer to shop on Amazon. Log-income does not have any significant linear impacts on spending, but high-income households have lower preferences for online shopping. Asian households prefer online shopping, and in particular shopping on Amazon, while black households shop disproportionately offline. Online shopping does not vary with population density, but the total number of offline competitors decreases spending across all three modes. However, if those retailers are small, then the effects of competition disappear.

TABLE III

DEMAND ESTIMATES.

	Specification I: Homogeneous σ		Specification II: Heterogeneous σ	
	Est	SE	Est	SE
Elasticity (σ):				
Constant	−1.516	0.399	−2.488	0.507
% income 100k+		4.179	1.343	

	Specification I: Incremental Amazon		Specification I: Base		Specification II: Incremental Amazon		Specification II: Base	
	Est	SE	Est	SE	Est	SE	Est	SE
Demographics (λ_k):								
Age	0.013	0.008	−0.020	0.010	0.013	0.008	−0.020	0.010
% under 35	1.701	0.397	−0.043	0.402	1.677	0.397	−0.037	0.402
log(Income)	0.222	0.22	0.013	0.008	0.226	0.22	0.013	0.008
% income 100k+	0.257	0.395	−1.857	0.533	0.311	0.396	−1.741	0.534
% black	−0.361	0.077	−0.647	0.637	−0.365	0.077	−0.648	0.637
% asian	0.873	0.209	2.252	1.215	0.881	0.209	2.162	1.216
Offline Competition (γ_k):								
log(Pop density)	0.014	0.008	0.626	0.228	0.014	0.008	0.617	0.228
Retailers/pop	−0.380	0.307	−0.828	0.415	−0.376	0.307	−0.821	0.415
Small retailers/pop	0.387	0.317	0.894	0.426	0.382	0.317	0.89	0.425

The estimated elasticity of substitution in the homogeneous model, which is approximately the own price elasticity in a CES model for choices with small shares, is a precisely estimated −1.52.[16] This result is in line with the findings of Einav, Levin, and Sundaresan (2014) and Baugh, Ben-David, and Park (2018). The magnitude of σ suggests that a move from no taxes to the average tax rate of 6.5% results in a decrease in demand of about 10% (6.5 times 1.52). The results of the heterogeneous specification indicate that the price sensitivity is lower for high-income households. Specifically, a county at the 25th percentile, with 8% of households having incomes above \$100,000, has an elasticity of −2.21, while a county with 15% of high-income households, the 75th percentile, has an elasticity of −1.89. We investigate the robustness of our estimated elasticity to alternative spending measures and demand specifications in Supplemental Appendix C.

To illustrate the importance of the estimated elasticity, we use the estimated Equation (3) to calculate Amazon's counterfactual revenue assuming a zero tax rate on Amazon transactions throughout the sample and compare it to the firm's predicted revenue under its actual tax obligations. Few states collected taxes before 2006, and so the effect of taxes is growing over time, especially after 2012. The loss in revenue under the actual tax path, relative to a world with zero taxes, amounts to approximately \$9 billion by the end of the sample in 2018, or 4% of sales, suggesting that changes in Amazon's sales tax liability significantly impact revenue.

With the estimates of the heterogeneous demand model in Table III, we calculate Amazon's total revenue (Equation (3)) for each year from 1999 to 2018 as a function of the network configuration, which we utilize to estimate the cost parameters. To do so, we first generate the expenditure function for each county and year outside of the comScore sample using a combination of extrapolation, imputation, and data from Amazon's financial statements. Online Appendix B.1 describes this process.

[16]The maximum spending share of any of the online modes is under 5%.

4.2. *Order Flow and Labor Demand*

In this section, we discuss the estimation of the first set of cost parameters that enter (i) the availability probability (ψ), which determines the number of orders handled by location j, and (ii) the labor demand function (A_{fc}, A_{sc}, γ), given the level of orders. We estimate the flow of orders across the network by combining the predicted distribution of orders from the demand model with data on platform-level variety and facility-level fulfillment capacity and employment.

Using the expenditure function derived from the demand model, we predict the number of orders originating from each county and year by dividing the predicted expenditure by a yearly price index for goods sold on Amazon, following Equation (4). To validate this approach, we compare the predicted orders for the representative household in each county to orders calculated directly from the comScore data for the subset of periods and counties with data overlap; the correlation is 0.65.

To obtain the predicted number of orders handled by each facility j in year t from the distribution of orders originating from each county, $\hat{q}_{jt}$, we require estimates of the origin-destination probability matrices in Equation (6). These depend on product availability at cluster l. Equation (5) summarizes our assumption that product availability is proportional to fulfillment capacity at location j, which we observe, divided by aggregate variety available on Amazon, which we calculate using the comScore data. The comScore data contain limited product characteristics to use in deriving a measure of aggregate variety, however. We therefore rely on features of the observed item-level price distribution to derive a proxy. We use the interquartile range of item-level price, relative to the median price, as a measure of the dispersion in available varieties over time. This proxy for aggregate variety is highly correlated with alternatives, such as the number of unique prices we observe in the data for a given year, but is less dependent on the sample size. We normalize the variety index to one in 2018 to facilitate the interpretation of the model parameters. Online Appendix A.6 describes how we construct the price and variety indices in detail. Note that since neither price nor variety vary across county locations, the indices do not enter our estimated demand model directly; they are subsumed in mode-year fixed effects.

For a given parameter value for ψ, the proportionality factor that maps variety-adjusted fulfillment capacity into product availability, we can now calculate the number of orders that flow through facility j, $\hat{q}_{jt}$, following Equation (6). Plugging these into Equation (8) in turn yields the predicted employment of facility j in year t, conditional on its size k_j and location l:

$$L_{jt}(N_t|\theta^1) = A_{m_j}\hat{q}_{jt}(\psi)^{\gamma}.$$

As noted in Section 2, we observe the number of employees for most fulfillment and sortation facilities in 2017 (denoted by $\hat{L}_{j,2017}$ for facility j) and system-wide employment in 2017 (denoted by $\hat{L}_{\cdot,2017}$). We use both sources of information to construct a minimum-distance estimator:

$$\min_{\theta^1}\sum_j \big(L_{j,2017}(N_{2017}|\theta) - \hat{L}_j\big)^2 + \big(L_{\cdot,2017}(N_{2017}|\theta) - \hat{L}_{\cdot,2017}\big)^2,$$

where $\theta^1 = (A_{\text{fc}}, A_{\text{sc}}, \gamma, \psi)$ denotes the vector of parameters determining labor demand. Heuristically, the parameters are identified as follows. The two productivity parameters (A_{fc}, A_{sc}) enter linearly in the labor demand function and are therefore identified from

TABLE IV

ORDER FLOW MODEL ESTIMATES.

(a) Estimates summary

	Specification I: Stockout		Specification II: Nearest		Goodness of Fit			
						Data	Specification	
	Est	SE	Est	SE		Est	I	II
Availability (ψ)	0.49	0.21	–		OLS: $Y =$	$\ln L$	$\ln \hat{L}$	$\ln \hat{L}$
Orders (γ)	0.47	0.10	0.31	0.08	Intercept	5.39*	6.22*	6.40*
A_{fc}	1.81	0.75	3.52	1.00	$FC \times$ Dens.	0.25*	0.11*	0.08*
A_{sc}	0.41	0.17	0.68	0.25	$FC \times k_j$	0.64*	0.71*	0.38*
					SC	0.21	−0.62*	−0.80*
SSR	37.62		40.08		2017 $\ln L$	4.83	4.92	4.93

(b) Summary statistics of the flow of orders

Years	Ave Shipping Distance (miles per order)	VI Orders (%)	Fullfillment prob. Closest	2nd Closest	3rd Closest
2006	450.43	0.00	0.48	0.26	0.17
2012	303.82	0.02	0.65	0.21	0.08
2018	141.80	0.37	0.51	0.23	0.12

Note: The goodness-of-fit regression results are from OLS regressions of log employment at a facility on local shifters of demand and facility characteristics. The last row of Table IV(a) shows the distribution of log employment in the data and that predicted by the model. The summary statistics in the bottom panel are calculated using parameters from Specification I.

the covariation in observed employment across facilities, by type, and the predicted number of orders. The returns to scale parameter (γ) is identified from covariation across facilities in capacity and predicted orders, which translates into differences in predicted orders per employee. Finally, the order flow parameter (ψ) is identified from the covariation in the spatial distribution of employees and orders predicted by the model.

We report the estimates of θ^1 for two specifications in Table IV(a) and summary statistics for three years of our sample calculated using our main model in Table IV(b). Our main model is the ‘Stockout’ specification, which assumes that orders originate from the closest fulfillment center with availability. We also report estimates for a specification where the order originates from the closest facility, abstracting from availability. The estimate of γ is significantly less than 1 in both specifications, implying that the production function exhibits increasing returns to scale. Increasing returns to scale in fulfillment is expected since the process of packaging orders is largely automatized and relies on robotic technologies.

The availability parameter, which drives the allocation of orders to facilities, is equal to 0.49. Rows 3–5 of Table IV(b) show that across years, this value implies that almost 90% of orders come from one of the three closest facilities, with roughly 50% coming from the closest in 2018. Due to expansion in variety and a resulting higher probability of stockouts, delivery from the closest facility is slightly declining over time, despite expansion in capacity. Comparing Table IV(b) and Table I shows that this manifests itself in an average shipping distance per order of 142 miles in 2018, while the average distance to the closest fulfillment center is only about 70 miles in 2018. Nevertheless, the expansion of the network of fulfillment centers led to a substantial decrease in the average shipping distance over the period 2006 to 2018, from 450 to 142 miles. The expansion of the sortation center network also led to an increase in the share of orders that Amazon handles fully in-house; the model predicts that in-house sortation applies to 37% of orders in 2018. This matches estimates from outside sources, which suggest that in 2014, at most 40% of Amazon's orders were sorted in-house.[17]

The last three columns of Table IV(a) evaluate the goodness-of-fit of the models. We report results of three OLS projections of observed (labeled 'Data') and predicted 2017 facility employment on the type of the facility and, for fulfillment centers, the capacity of the facility and the population density of the surrounding area. The last row displays actual and predicted average log employment calculated using the regression coefficients.

Overall, both models fit the data well, in particular in relating fulfillment center capacity to labor. Standard errors are omitted due to space, but all the coefficients across the three projections are significant at the 5% level except for the one on the *SC* indicator. This coefficient is negative and significant when using the predicted employment but positive and insignificant in the data. The difference is likely due to the fact that the data are limited in both the number of sortation centers for which we observe employment and the variation in observed employment across sortation centers. In contrast, the model predicts rich variation in employment across the entire set of sortation centers. Comparing the two models suggests that the 'Stockout' model is a better fit. As an additional validity check, we compare the year-over-year growth of system-wide employment predicted from the model to a measure of growth calculated from Amazon's financial statements, and we are able to match the observed growth well. See Online Appendix A.2 for how we construct the measures of system-wide employment.

4.3. *Shipping and Fixed Costs*

The parameters of the cost function that remain to be estimated are the ones that enter the shipping cost and fixed cost functions: $\theta^2 = \{\theta_d, \theta_{vi}, \kappa\}$, following the functional forms in Equations (7) and (9). We take a revealed preference approach by finding parameter values that render the observed network more profitable than alternative, perturbed networks. This leads to a moment inequality estimator.

Approach. We focus on alternative network roll-outs where we swap the opening dates of two facilities to construct revealed-preference inequalities. Under our perfect foresight assumption, changing the opening date of facility j to that of facility j', and vice versa, holding the facility's other characteristics of location and size fixed, must result in a lower discounted net-present value of profits than under the observed network $\mathbf{a}^0$:

$$\Pi(\mathbf{a}^0; \theta^2) - \Pi(\mathbf{a}^{j,j'}; \theta^2) \geq 0,$$

where $\Pi(\mathbf{a})$ is defined in Equation (11). We use three criteria to select potential entry date swaps: (i) facility j opened more than one year before facility j', (ii) facilities j and j' are of the same type (*FC* or *SC*), and (iii) the difference between the sizes of j and j' is less than 550,000 sq ft, the inter-quartile range of capacity differences. This leads to $M = 5577$ potential permutations.

[17]See https://nypost.com/2017/12/29/trump-says-amazon-is-making-us-postal-service-dumber-and-poorer/, which states that USPS handled 40% of Amazon's shipments in 2014. Because USPS's agreement with Amazon covers primarily last-mile delivery, this estimate should be the maximum share of shipments that go through Amazon's sortation centers.

Importantly, the condition that strategy $\mathbf{a}^0$ yields higher profit than $\mathbf{a}^{j,j'}$ only depends on the profit flow differences between the entry dates of facilities j and j', which we can calculate without having to solve the infinite-horizon dynamic programming problem. In contrast, counterfactual network roll-outs that involve locations that Amazon does not choose in our sample lead to a network configuration that differs from Amazon's chosen one by the end of the sample. In this case, we would need to make additional assumptions about Amazon's expectation regarding future market conditions post-sample including, for instance, strategic deterrence considerations regarding the entry of potential e-commerce rivals. By focusing only on deviations involving observed facility locations, our estimation results are robust to the presence of these dynamic considerations, while exploiting the significant cross-sectional variation in the attributes of chosen locations.

We decompose the value function differences, $\Pi(\mathbf{a}^0;\theta^2)-\Pi(\mathbf{a}^{j,j'};\theta^2)$, into a return function $\Delta\Pi(\mathbf{a}^0,\mathbf{a}^{j,j'};\theta^2)$ of predicted differences and an unobserved error associated with swap (j,j'), $\epsilon^{j,j'}$, capturing deviations of the true value function difference from our prediction. This leads to the following inequality condition:

$$\Pi(\mathbf{a}^0;\theta^2)-\Pi(\mathbf{a}^{j,j'};\theta^2)=\Delta\Pi(\mathbf{a}^0,\mathbf{a}^{j,j'};\theta^2)+\epsilon^{j,j'}\geq 0.$$

Separating the contribution of changes in fulfillment cost from the remaining components of the return function $\Delta\Pi$ highlights that the return function is linear in θ^2, reflecting the linearity of the fulfillment cost function:

$$\Delta\Pi(\mathbf{a}^0,\mathbf{a}^{j,j'};\theta^2)=Y^{j,j'}-\left(\theta_d X_d^{j,j'}+\theta_{vi}X_v^{j,j'}+\kappa X_p^{j,j'}\right).$$

Here, $Y^{j,j'}$ is the difference in discounted gross profit net of wages and rents between the chosen and counterfactual networks:

$$\begin{aligned}Y^{j,j'}=&\sum_{t=t(j)}^{t(j')}\beta^t\left(\hat{R}_t(N_t|\mathbf{a}^0)-\hat{C}_t^{\text{Labor}}(N_t|\mathbf{a}^0)-C_t^{\text{Rent}}(N_t|\mathbf{a}^0)\right).\\&-\sum_{t=t(j)}^{t(j')}\beta^t\left(\hat{R}_t(N_t|\mathbf{a}^{j,j'})-\hat{C}_t^{\text{Labor}}(N_t|\mathbf{a}^{j,j'})-C_t^{\text{Rent}}(N_t|\mathbf{a}^{j,j'})\right),\end{aligned}$$

where a hat indicates that the function was estimated in a previous step. $Y^{j,j'}$ thus measures the net effect of the network configuration on gross revenue through tax changes and on wages and rents through adjustments in the timing of location choices.

Similarly, the term $X_d^{j,j'}$ is the discounted difference in total shipping distance, calculated as

$$X_d^{j,j'}=\sum_{t=t(j)}^{t(j')}\beta^t\left(\hat{D}_t(N_t|\mathbf{a}^0)-\hat{D}_t(N_t|\mathbf{a}^{j,j'})\right).$$

We define the differences in the discounted sum of vertically integrated orders, $X_{vi}^{j,j'}$, and in the discounted sum of our congestion proxy—population density scaled by facility square-footage—$X_p^{j,j'}$, analogously (see Online Appendix B.2).[18]

[18]In considering counterfactual networks, we abstract from changes in the cost of tying manufacturers into the network as manufacturers already serve the many locations of retailers like Wal-Mart and Target.

In calculating the components of the return function, we rely on the previously estimated demand and order flow models to predict revenue, wages, and rents under the two networks in the years between the swapped facilities' opening dates. This entails predicting Amazon's revenue and total number of orders in each county and the assignment of these orders to fulfillment centers for the observed and counterfactual networks during the relevant time period.

To predict the consumer's tax exposure under the two alternative networks, we assume that the first entry into a state triggers the nexus laws' physical presence rule, but that the tax status of consumers in all counties adjusts only after a period of tax abatement. We assume a deterministic schedule for the abatement period depending on the year of first entry of (i) five years if $t < 2008$, (ii) two years if $2008 \leq t \leq 2010$, and (iii) immediate if $t > 2010$.[19]

Estimator Set-up. The residual value function difference, ϵ, arises from various potential sources: measurement error in the demand model, unobserved fixed cost components, including unobserved subsidy payments by state and local governments, or misspecification of the firm's beliefs regarding sales tax changes. We focus on the interpretation of ϵ as measurement error. One challenge is that ϵ is potentially correlated with both gross profit differences $Y^{j,j'}$ and, through variable cost channels, differences in distance $X_d^{j,j'}$ and vertically integrated orders $X_{vi}^{j,j'}$.

We address this simultaneity problem by constructing a vector of H nonnegative instrumental variables $Z^{j,j'}$ that are correlated with changes in the profit components, but uncorrelated with $\epsilon^{j,j'}$. This allows us to consistently estimate θ^2 using the following moment inequalities conditions:

$$E\big[Z_{j,j'} \cdot \big(Y^{j,j'} - \big(\theta_d X_d^{j,j'} + \theta_{vi} X_{vi}^{j,j'} + \kappa X_p^{j,j'}\big)\big)\big] + \underbrace{E\big[Z^{j,j'} \cdot \epsilon^{j,j'}\big]}_{=0} \geq 0.$$

Following Pakes, Porter, Ho, and Ishii (2015), we use this condition to construct sample moment inequalities:

$$\frac{1}{M} \sum_{j,j'} Z_h^{j,j'} \cdot \underbrace{\big(Y^{j,j'} - \big(\theta_d X_d^{j,j'} + \theta_{vi} X_{vi}^{j,j'} + \kappa X_p^{j,j'}\big)\big)}_{\Delta\Pi(\mathbf{a}^0, \mathbf{a}^{j,j'}; \theta^2)} = \tilde{m}_h\big(\theta^2\big) \geq 0, \quad \forall h = 1, \dots, H.$$

To construct valid moment conditions, we assume that the econometric error $\epsilon^{j,j'}$ is mean zero and independent of the sequence of predetermined demand and cost shifters that enter profits, including county demographic characteristics on the demand side and county wages, rents, and sales tax rates on the cost side.

We use this assumption to construct proxies for the gross profit and cost components entering the return function $\Delta\Pi(\mathbf{a}^0, \mathbf{a}^{j,j'}; \theta^2)$ that are orthogonal to $\epsilon^{j,j'}$. We calculate population-weighted (rather than demand- or revenue-weighted) changes in distance and vertical integration associated with each swap (j, j'). Let $\hat{X}_d^{j,j'}$ and $\hat{X}_{vi}^{j,j'}$ denote these predetermined proxies for the order-weighted distance and vertical integration variables.

[19]We recognize that in New York, Amazon remitted sales tax prior to opening any fulfillment center, and that in North Dakota and Washington State, Amazon operates non-logistic facilities that triggered sales tax liabilities.

Similarly, we use measures of population-weighted average tax and cost differences as shifters for gross profit differences $Y^{j,j'}$. We measure cost differences using changes in average input prices and population density across active locations induced by swap (j, j'), $\Delta\text{Input prices}^{j,j'}$ and $\Delta\text{Density}^{j,j'}$, respectively. We calculate tax differences, $\Delta\text{Tax}^{j,j'}$, using population-weighted average tax rates under the observed and counterfactual roll-out strategies. See Online Appendix B.2 for details on these variables.

Identification Based on Swap Groupings. We use these proxies to construct H categorical instruments that indicate whether a particular swap (j, j') informs the different economic trade-offs Amazon faces.

To understand how such groupings of swaps facilitate parameter identification, consider first a case where fulfillment cost depends only on shipping distance and $\theta_{vi} = \kappa = 0$. We observe two types of decisions that affect distance to the customer: enter early in a densely populated location or enter late in the same type of location. To construct moments that explain these decisions, the instruments must capture the trade-off between changes in the proximity to final consumers $(\hat{X}_d^{j,j'})$ and changes in gross profit $(Y^{j,j'})$. We consider three gross profit shifters: taxes, wages, and rents. To gain some intuition, we discuss the cases in which a swap triggers a tax change below, but the intuition is similar for the other shifters.

Consider first instances where the firm chose to open a fulfillment center in a densely populated area early and open a comparable fulfillment center in a less densely populated area late. The firm's profit under this chosen network roll-out must exceed its profit under the alternative roll-out where we swap the opening dates of these two facilities. We pair fulfillment center j with all fulfillment centers j' such that swapping each resulting pair's opening dates yields the following changes in taxes and distance. First, the difference in population-weighted distance $(\hat{X}_d^{j,j'})$ is negative; the perturbed network delays the expansion into a densely populated area, and therefore, increases the aggregate shipping distance. Second, the difference in population-weighted tax rates $(\Delta\text{Tax}^{j,j'})$ is positive; the firm delays moving into areas with higher tax rates and with a larger population that has to pay sales tax. We categorize swaps that satisfy both conditions using an indicator variable $Z_h^{j,j'} = \mathbf{1}(\hat{X}_d^{j,j'} < 0 \text{ and } \Delta\text{Tax}^{j,j'} > 0)$. The subscript h indicates a particular moment condition (or instrument).

To the extent that the tax changes associated with these swaps lead to negative gross profit differences on average, the following moment restriction identifies a lower bound for θ_d:

$$E\big[Y^{j,j'} - \theta_d X_d^{j,j'} | Z_h^{j,j'}\big] + E\big[\epsilon^{j,j'} | Z_h^{j,j'}\big] \geq 0 \longrightarrow \theta_d \geq \frac{E\big[Y^{j,j'} | Z_h^{j,j'}\big]}{E\big[X_d^{j,j'} | Z_h^{j,j'}\big]},$$

where $E[X_d^{j,j'} | Z_h^{j,j'}] = E[X_d^{j,j'} | Z_h^{j,j'} = 1]$ is the average total difference in shipping distance conditional on belonging to the group $Z_h^{j,j'} = 1$. The numerator $E[Y^{j,j'} | Z_h^{j,j'}]$ is defined analogously. Intuitively, these types of swaps determine the lowest level of θ_d such that the shipping cost savings from opening in a populated area outweigh the lost revenue due to taxes. An upper bound can be constructed using the opposite trade-off, where we select network swaps such that the firm's actual entry decision into a densely populated, high-tax area occurs late and we compare this network to counterfactual networks where the firm enters in densely populated, high-tax areas early.

Since the gross profit differences $Y^{j,j'}$ net out wages and rents, we can construct similar moment conditions by exploiting the trade-off between distance and input prices across locations. For instance, if we observe the firm entering early in areas with higher wages or rents, the change in shipping cost savings from opening in these areas must outweigh the net profit declines due to higher wage or rental bills.

Table B.I in Online Appendix B.2 defines the set of moment conditions we use in estimation. Our swap groupings $Z^{j,j'}$ capture seven 'trade-offs', leading to fourteen lower- and upper-bound moments. We use six instruments to capture the trade-offs in the timing of the network roll-out induced by nexus tax laws. The first two instruments group swaps that trade off tax and distance. We similarly construct lower- and upper-bound instruments by grouping swaps that capture (a) the tax and vertical integration trade-off (e.g., moving up the opening of a sortation center reduces shipping cost, but increases tax exposure), and (b) the tax trade-off alone, unconditional of changes in shipping cost associated with changes in the timing of a facility opening. Similarly, we construct six instruments to capture the above trade-offs between higher input cost bills, distance, and vertical integration. Finally, we use two instruments that capture the trade-off in the network roll-out between fixed cost savings from lower congestion, proxied by population density, and the distance to populated areas.

Interim Estimates. Above, we motivate the value of grouping swaps in identifying the parameters of interest based on the example of the tax and shipping distance trade-off associated with adjusting the opening date of a facility. Before discussing the estimates of the full model, we use this example to derive initial estimates of the lower and upper bound for the distance coefficient, θ_d, using swaps that isolate the tax and distance trade-off. We also provide estimates of these bounds using swaps that isolate the trade-off between higher input costs and shorter shipping distances. The results of this exercise are displayed Table V. In the first row of the table, we report the change in discounted gross profit (Y) and discounted aggregate shipping distance (X), averaged across swaps that capture the economic trade-off between distance and taxes. To isolate this trade-off, we only include swaps in this subset where the other profit components (e.g., population, input prices, etc.) are 'fixed'. In practice, we condition on swaps that exhibit small differences in these other components relative to the focal fulfillment center j.[20]

TABLE V

MOMENT CONDITIONS AND DISTANCE TRADE-OFFS.

	Lower bound: θ_d $Z^{j,j'} = 1(\Delta\text{Shifter}^{j,j'} > 0 \;\&\; \hat{X}_d^{j,j'} < 0)$		Upper bound: θ_d $Z^{j,j'} = 1(\Delta\text{Shifter}^{j,j'} < 0 \;\&\; \hat{X}_d^{j,j'} > 0)$	
	$E(Y\|Z)$	$E(X_d\|Z)$	$E(Y\|Z)$	$E(X_d\|Z)$
ΔShifter (Gross Profit)				
(a) Tax	−13.30	−93.60	37.10	140.19
(b) Input prices	−5.94	−82.68	7.60	128.21
Bounds: $\frac{E(Y\|Z)}{E(X_d\|Z)}$				
(a) Tax	0.14		0.26	
(b) Input prices	0.07		0.06	

Note: In selecting swaps for inclusion in each instrument category, we condition on population-weighted tax, input price, and distance changes. The statistics in the body of the table, however, represent order-weighted aggregates. The variable ΔShifter refers to the change in one of two population-weighted profit shifters: taxes and average input prices.

[20]We select swaps such that the value of each of the other variables falls within the variable's interquartile range from the focal fulfillment center's realization.

The first entry in the first row of the table shows that the change in discounted gross profits, averaged over swaps that entail a decrease in the population-weighted average tax rate and an increase in population-weighted distance relative to the observed network, is −\$13.30 million. The average change in the discounted aggregated shipping distance for the same subset of swaps is −93.60 hundred million miles. Per the discussion above, these swaps identify the lower bound of the cost parameter. Using the intuition of Equation (4.3), we calculate this bound as the ratio of the average change in gross profits to the average change in distance, holding all remaining exogenous cost contributions approximately fixed. The resulting estimate, presented in the lower portion of the table, suggests that the lower bound of θ_d is \$0.14 per 100 miles. Moving to the right in the first row, we perform the same exercise, but this time we condition on swaps that increase the population-weighted average tax rate and decrease the population-weighted distance relative to the observed network. These swaps identify the upper bound of the distance parameter, which we calculate to be \$0.26 per 100 miles.

Similarly, the second row of Table V presents the average statistics for swaps that feature changes in population-weighted input prices, rather than taxes, and distance. The bottom of the table displays the bounds of θ_d calculated based on these swaps, with \$0.07 being the lower bound and \$0.06 being the upper bound. Therefore, at the midpoint of the smallest lower bound and highest upper bound, a 100-mile increase in distance raises the average shipping cost by \$0.17.[21]

Besides providing initial estimates of the bounds, this exercise also demonstrates that the instruments are inducing the expected trade-off between distance and gross profits. For example, swaps that feature a decrease in taxes and an increase in population-weighted distance relative to the observed network (first row, left side) result in a decrease in gross profit and an increase in aggregate order-weighted shipping distance. The population-weighted proxy variables that define the instruments (i.e., $\Delta\text{Tax}^{j,j'}$ and $\hat{X}_d^{j,j'}$) thus correctly predict a positive correlation between changes in gross profit and shipping distance. This is true for the other instruments in Table V as well.

We note that the distance and gross profit trade-offs in Table V generate only four of the fourteen moment conditions discussed above. We exploit five additional trade-offs in constructing the remaining moments that identify θ_{vi} and κ and aid in identifying θ_d. We repeat the exercise behind Table V for the remaining trade-offs and present preliminary estimates of θ_{vi} and κ in Supplemental Appendix B.2. In the following section, we present the results of the full model, which differs from this exercise in that we jointly estimate the cost function parameters using information contained in all the groupings of swaps that define the fourteen moments.

Full Model Results. We present the estimates of the full model in Table VI. The column labeled 'Est.' corresponds to the parameter vector that minimizes the objective function. In all cases, this is a single point because we use more moment inequalities than parameters (i.e., multiple profit shifters as instruments), and the moment conditions are not jointly satisfied in our sample. To conduct inference, we need to account for the fact that the model parameters are partially identified, and the literature suggests several approaches for doing so. Since our main specification includes multiple parameters, we construct confidence intervals based on the 'profiled test statistic' approach proposed

[21]Note that the estimated lower bound is not necessarily below the estimated upper bound due to sampling error in the moments and our inability to perfectly hold fixed the remaining exogenous cost components, which are correlated with distance.

TABLE VI

COST FUNCTION ESTIMATES.

	Specification 1			Specification 2			Specification 3		
	Est.	CI		Est.	CI		Est.	CI	
θ_d: Dist. ($\times$100 miles)	0.16	0.15	0.17	0.59	0.41	0.88	0.34	0.26	0.49
θ_{vi}: VI orders							−0.52	−0.91	0.01
κ: Density ($\times$100)				2.06	1.48	3.17	0.98	0.69	1.56
Moments	4			8			14		

Note: 'Est.' denotes the parameter value at which the objective function is minimized and CI is the 95% confidence interval calculated as described in the text. All specifications utilize 5577 total swaps.

by Bugni, Canay, and Shi (2017).[22] We construct the confidence interval of each individual parameter by testing repeated null hypotheses that the parameter is equal to a range of candidate values. We define the confidence interval of each parameter as the set of values such that the null hypothesis cannot be rejected at the 5% confidence level. The resulting confidence interval is therefore constructed using the marginal distribution of each parameter, effectively 'profiling-out' the other two parameters.

We present results for three specifications of the cost function here and relegate estimates under alternative assumptions on the demand and order-flow models to Supplemental Appendix C. The first specification corresponds to a model where shipping cost depends only on distance and where the logistic network's fixed costs consist only of observed rents. This leads to an estimated shipping cost per 100 miles of \$0.16, which is similar to the midpoint of the preliminary bounds presented above. Controlling for the effect of density on fixed costs in Specification (2) and then also the cost savings to vertical integration in Specification (3) substantially increases the estimated shipping cost, however, suggesting omitted variables biases in Specifications (1) and (2). The change in θ_d in going from Specification (1) to (2) reflects that opening a facility in high-density areas not only reduces distance to the consumers, but also increases fixed fulfillment costs. The change in θ_d from Specification (2) to (3) reflects that opening a fulfillment center in an urban area also serves the purpose of vertical integration. Our preferred Specification (3) suggests average estimated shipping cost of \$0.34 per 100 miles.

Under Specification (3), we also find significant cost to density; our estimate of κ implies that rents account for only approximately one half or less of the fixed costs to locating in an urban area with a density of 1000 people per square mile. We interpret this as evidence that traffic congestion in urban areas increases the fixed cost of managing large fulfillment centers.

Finally, we estimate cost savings of \$0.52 per order from vertical integration into sortation. To put this estimate into perspective, consider that the order-flow model predicts an average shipping distance of 303 miles in 2012. The variable component of the shipping cost for this average order without an integrated sortation facility is \$1.02, compared to \$0.50 with vertical integration.

[22]To account for correlation between swaps, we estimate the empirical correlation between moments sharing the same facility choice, evaluated at first-stage parameter estimates that assume zero correlation. We use this correlation (0.3) when sampling shocks in the parametric bootstrap procedure described by Bugni, Canay, and Shi (2017). See also (Kaido, Molinari, and Stoye (2019)) for a related approach to constructing profiled test statistics.

TABLE VII

AVERAGE COST DECOMPOSITION.

	FC	SC	Average cost components				Total
			Shipping	Labor	Rent	Density	
2000	5	0	1.99	0.55	0.12	0.05	2.71
2003	7	0	1.61	0.60	0.11	0.08	2.41
2006	12	0	1.55	0.62	0.11	0.13	2.40
2009	16	0	1.39	0.53	0.08	0.10	2.11
2012	31	1	1.03	0.43	0.07	0.07	1.60
2015	67	21	0.50	0.51	0.09	0.19	1.28
2018	128	35	0.29	0.51	0.08	0.22	1.11
2018*	128	0	0.49	0.48	0.07	0.20	1.23

Note: 2018* corresponds to a counterfactual network with no sortation centers. Average cost components are calculated as the total network cost divided by the total orders predicted by the model.

Predicted Order Fulfillment Costs. To illustrate our model results, we analyze trends in the implied average order fulfillment costs. Table VII summarizes the evolution of average cost over time separately by each cost component. We measure average cost by dividing each cost component by the predicted quantity of orders. In this exercise and all of the following analyses, we utilize the point estimates from Specification (3) in Table VI.

Investments in the logistic network led to a large decrease in shipping cost from nearly \$2 per unit in 2000 to \$0.29 in 2018. The drop was most pronounced between 2009 and 2015, a period during which Amazon quadrupled the number of fulfillment centers. By 2015, shipping no longer represents the largest component of average order fulfillment costs.

Much of the drop in shipping cost from 2015 to 2018 is due to the build-up of the sortation network. In the last row, we calculate the average cost the firm would have incurred in 2018 in the absence of sortation facilities. Eliminating sortation centers, which are located primarily in relatively urban locations, would have increased average shipping cost by 69% (from 0.29 to 0.49), but decreased rents plus wages by 7% (from 0.81 to 0.75), resulting in an overall average cost increase of 11% (or \$0.12).

The labor cost per order remains largely constant over the period, reflecting that the expansion in the volume of transactions increases economies of scale in order processing even as facilities are added. These scale economies offset the increase in employment and higher wages to workers, as fulfillment center openings during this period took place in higher wage counties. Turning to fixed costs, the combined rent and density costs per order increased from 2009 to 2018 due to expansion into more urban areas.

Overall, Amazon was able to decrease total average cost by 55%, as seen in the final column. We note that our order fulfillment cost estimates are lower than ballpark figures collected from outside sources.[23] While such measures are not directly comparable to ours for a number of reasons, they point to the fact that our estimates are likely a lower bound on the fulfillment cost. One reason for this is that our moment inequalities estimator is only able to capture costs that vary across the locations in the network. We are therefore not able to, for example, identify a constant base cost of shipping a package (i.e., a

[23]For example, as shown on https://services.amazon.com/fulfillment-by-amazon/pricing.htm?ld=NSGoogleAS, the fee Amazon charges third-party sellers for order fulfillment ranges from \$2.50 to \$3.50 in Q4 of 2020. However, these fees include costs of ‘picking and packing [the] orders’, ‘customer service’, inventory management, and a mark-up, none of which are included in our estimate.

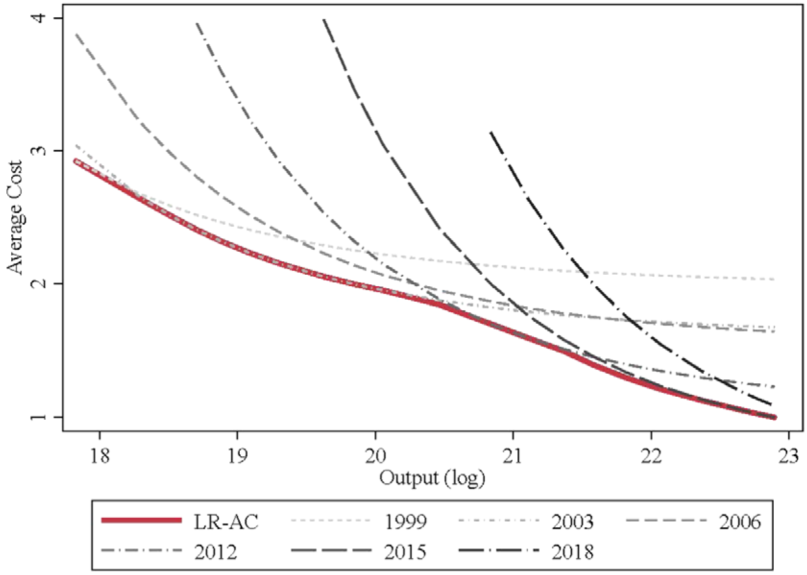


FIGURE 4.—Long-run average cost. Notes: Each curve represents a different network configuration. The average cost is the total average cost of fulfilling an order.

cost function intercept) or the cost contribution of system-wide investments in robotics. Another reason is that our model underestimates the total revenue Amazon earns from third-party sellers as we assume a constant mark-up; our cost estimate is proportional to revenue.

We note, however, that it is not the level of costs that is key to our analysis; it is the trends therein and the relative magnitude of fulfillment costs to the other profit components that ultimately drive Amazon's expansion. The fact that, as we illustrate in Section 5, our model predicts the evolution of the distribution network suggests that we are able to capture these two features of the firm's cost.

Figure 4 illustrates the importance of economies of scale by plotting the implied long-run average cost function across observed network configurations from 1999 to 2018. Each gray curve represents the short-run average cost function calculated with a given network configuration; more recent networks are represented with darker colors. The x-axis represents a grid of (log) aggregate output covering the range of orders that we observe during our sample, extended by 25% beyond the 2018 level. The lower envelope (red) represents the long-run average cost function, or the most efficient technology associated with each output level. The elasticity of the long-run total cost function with respect to output is approximately equal to -0.8.

Amazon's long-run cost minimization problem is characterized by a standard trade-off between fixed and variable costs. As Figure 4 illustrates, denser networks (recent vintages) are associated with lower variable costs (limit of AC as $Q \to \infty$) and higher fixed costs. As the volume of orders expands beyond 500 million units ($\ln Q = 20$), it becomes more efficient to operate a decentralized network with 30+ facilities, instead of the 2006 network with 12 facilities. A volume of orders beyond 3000 million units ($\ln Q = 22$) justifies investing in a network of over 90 facilities, composed of fulfillment and sortation centers (i.e., the 2015 network configuration).

4.4. *Illustration: California Entry*

Beyond quantifying the role of economies of density in network expansion, we aim to assess the role of tax laws in Amazon's investment decisions during our sample period. To motivate how sales tax liabilities through the revenue channel affect firm profitability and thus the return to investing in fulfillment facilities near population centers, we conclude this section with an illustration of the tax-distance trade-off that our estimated model implies.

As an example, we consider a cluster of fulfillment centers in San Bernardino, CA. Amazon opened the first facility at this location in 2012, which also marks Amazon's first entry into California. The firm added two facilities to the cluster in subsequent years. In 2011, the year prior to the opening of the cluster, our model predicts that a majority of southern California orders were fulfilled by the then-closest cluster in Arizona, with the remaining orders coming from clusters in Nevada, Washington State, and Texas.

We compare outcomes under this actual opening sequence to outcomes under a network where Amazon moved up the opening of all three San Bernardino facilities to 2011. The left panel of Table VIII displays the results of this experiment under nexus tax laws. We first focus on the bottom row, which summarizes the overall percentage change in orders, profit, shipping costs, and labor and fixed costs, relative to the actual opening sequence. Under the counterfactual opening dates, the total number of orders decreases by 1% due to the earlier onset of tax liabilities in California. However, Amazon is able to realize savings in shipping costs of about 8%, as orders from southern California are now mostly fulfilled by San Bernadino, instead of further-away facilities. Labor and fixed costs increase by about 5% due to higher wages, rents, and congestion costs, as well as reduced economies of scale across facilities, as each facility handles fewer shipments with the California entry.

We further break down the aggregate effects in the first four rows of the table, where we present outcomes for the most affected clusters. The entry in California results in a redistribution of orders across facilities, as we show in the 'Orders' column. The Arizona facility experiences the biggest drop in fulfilled orders of 88%, suggesting that, once there is entry in southern California, the facility is largely redundant. However, because the remaining shipments are now mostly local, the average cost of shipping orders from this facility decreases by 20%. The large drop in orders also results in a near doubling of labor and fixed costs due to loss of economies of scale. Taken together, the profit contribution of the Arizona facility drops by 68%.

TABLE VIII

EFFECT OF ENTERING CALIFORNIA (2011).

		Nexus (%Change)				Uniform Tax (%Change)		
Distance (m)	State	Orders	Profit	Shipping	L + FC	Orders	Shipping	L + FC
302	AZ	−0.88	−0.68	−0.20	0.99	−0.83	−0.21	0.95
399	NV	−0.17	−0.18	−0.03	0.12	−0.13	−0.04	0.10
965	WA	−0.03	−0.08	−0.24	0.08	−0.03	−0.23	0.07
1169	TX	−0.01	−0.01	−0.04	0.01	−0.01	−0.04	0.01
Total		−0.01	−0.00	−0.08	0.05	0	−0.08	0.05

Note: Distance denotes the distance in miles from each facility to the San Bernardino cluster. 'Orders', 'Profit', 'Shipping', and 'L + FC' denote the percentage change in facility-level output, profit, shipping cost, and labor and fixed costs due to the hypothetical earlier opening of three fulfillment centers in San Bernardino, CA. The last row labeled 'Total' measures the system-wide change in the outcomes of interest.

The remaining, further-away, facilities experience smaller declines in volume. These small changes in volume can, nevertheless, translate into sizable changes in shipping costs, as the Washington State facility illustrates. It sees a drop in volume of only 3%, which, due to its initially low order volume relative to fixed costs, results in an increase in combined labor and fixed costs of 8%. At the same time, the reduction in shipping costs amounts to a sizable 24%, larger than at the Arizona facility. Due to distance, shipments from Washington State to southern California are very costly, so even though only a small number of the Washington State shipments are reallocated to the San Bernardino cluster, these shipments have a large impact on shipping costs for the Washington State cluster. The distance between a new facility and existing facilities thus does not have a monotonically declining impact on the shipping costs at the existing facilities. While the profit impact at existing facilities declines monotonically with distance to the new facility in this particular example, the non-monotonicity in shipping costs could, in principle, translate into similar patterns in facility-level profit. This is similar to Holmes' (2011) approach which allows for a trade-off between cannibalization and density. At the same time, the non-monotone impact of distance between facilities on profit precludes us from using Jia's (2008) methods in solving counterfactual network optimization problems under alternative tax structures in the following section.

In order to illustrate the impact of nexus laws on the firm's profitability, the right panel of Table VIII summarizes profits and costs under an alternative tax treatment where Amazon is responsible for remitting sales tax on all transactions, irrespective of presence in the state, which we term a 'non-discriminatory tax' law. Here, entering a new state no longer triggers a new tax collection and, thus, total demand remains unchanged (see last row) when we move up the San Bernardino opening date. Since demand in California is unaffected, we observe a less significant redistribution of orders than under the nexus laws, when the San Bernardino cluster is able to largely handle all of the southern California orders.

On net, the aggregate reduction in shipping costs from entering San Bernardino earlier would be slightly larger and the increase in other costs slightly lower under non-discriminatory taxes (even though the magnitudes appear to be the same in the table due to rounding). Not shown in Table VIII is the fact that overall profit for Amazon increases by 1% due to the earlier entry in California under non-discriminatory tax laws. Comparing this to the small but negative impact of entry on profit under the nexus laws demonstrates how Amazon's entry incentives change under different tax regimes.

5. TAXES AND INVESTMENT

We now use the estimated model to quantify the combined effect of demand expansion and tax policy on investment in the distribution network. We first use the model to illustrate the optimal growth of the network as online demand expands. We then quantify the effect of nexus tax laws on the growth and configuration of the network to illustrate how the laws distort Amazon's investments and impact Amazon's profit and total welfare.

Finding Counterfactual Networks. Solving the dynamic optimization problem is beyond the scope of this paper. We instead approximate the solution to this problem with a series of static profit maximization problems at different stages of e-commerce demand. We thus find the optimal network that maximizes the static flow profit in Equation (10), which we replicate here:

$$N_t^*(\Theta) = \arg\max_{N_t} \bar{\mu}_t \hat{R}_t(N_t) - \hat{C}_t^{\text{Shipping}}(N_t) - \hat{C}_t^{\text{Labor}}(N_t) - \hat{F}_t(N_t).$$

We consider four years during our sample period—1999, 2006, 2012, and 2018—that are exemplary of the demand expansion that Amazon has experienced and use Θ to denote the dependence of the optimal network on tax policy. In the constrained dynamic problem we relied on in estimation, we hold the locations of facilities fixed and exploit the optimality of the opening sequence only. Here, we now allow the platform to choose both the location and number of facilities of each type, which are summarized by $N_t^*(\Theta)$, thereby studying the effect of tax policy and demand on aggregate levels of investment.

To implement this procedure, we first define a set of potential locations. We start with the locations of the roughly 150 Amazon facilities in 2018, including facilities that we excluded from our prior analysis (e.g., Amazon Fresh grocery delivery centers). We further consider the approximately 770 locations of distribution centers operated by Target and Walmart, from MWPVL, and UPS from Reference USA, in 2018. We keep only the subset of non-Amazon locations that have similar levels of income and population to those chosen by Amazon. Taken together, this results in about 330 unique potential facility locations. Using a distance radius of 20 miles, we use a hierarchical clustering algorithm to group nearby facilities, resulting in $N = 253$ unique potential locations spanning 39 of the 48 contiguous states. See Supplemental Appendix B.3 for a map of the final set of potential locations.

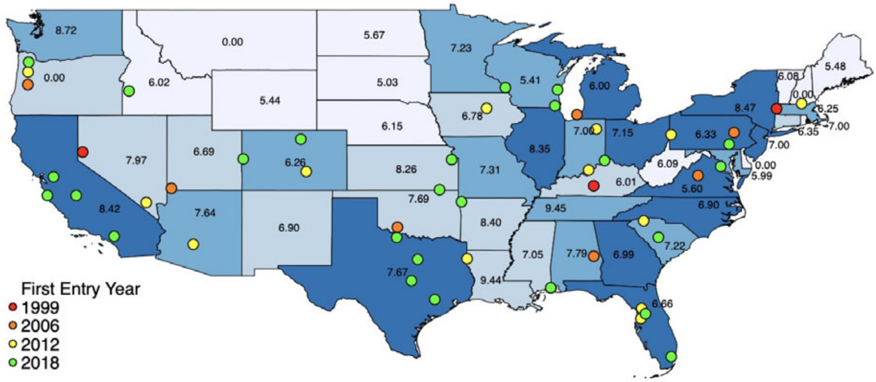
We make the following simplifications to facilitate the comparison of networks across years. First, we assume that all input prices are fixed at their average levels for all time periods. Therefore, the only time varying component is the growth in Amazon's demand relative to other retail modes (i.e., α_{ikt} in our demand model). Second, we abstract away from differential tax treatment of sales by third-party sellers and assume that all Amazon transactions are subject to the sales tax policy. Third, we abstract from capacity choice by setting the size of each fulfillment and sortation center equal to 1,000,000 and 300,000 sq. ft., respectively, the approximate averages in the data.

Despite these simplifications, with approximately 250 locations and two facility types, the sheer number of potential networks renders it infeasible to solve the optimal network problem exactly (except in $t = 1999$). We therefore approximate the optimal network using simulation techniques borrowed from the operations literature. We use the simulation-based Population-Based Incremental Learning algorithm developed by Baluja (1994) that combines ingredients of genetic and standard hill-climbing optimization algorithms. In theory, as the number of simulations grows large, the algorithm converges to a global maximum. In practice, given the scale of our problem, the procedure may not identify the global maximum, in particular in the later years when the optimal number of facilities is large. Therefore, we refer to the solution as an approximation to the optimal network. We find through full enumeration, however, that the procedure predicts the globally optimal network in 1999. Supplemental Appendix B.3 describes the algorithm in detail.

Predicted Optimal Networks Under Nexus Tax Laws. Figure 5a maps the predicted network evolution across four demand states, 1999, 2006, 2012, and 2018, under the nexus tax laws. The color of each dot indicates the first year in which we predict a facility to operate in a given location. This location may or may not have a facility operating again in later years.

To analyze model fit, we present a map-based comparison of the observed and predicted network roll-out in Online Appendix B.3. Overall, across years, the static model matches the regional distribution of actual fulfillment centers well, even though it is not always able to predict the exact set of states with physical presence. In 2018, when the network is larger, we predict the set of states with fulfillment capacity well, though the model

(a) Nexus Tax



(b) Non-discriminatory Tax

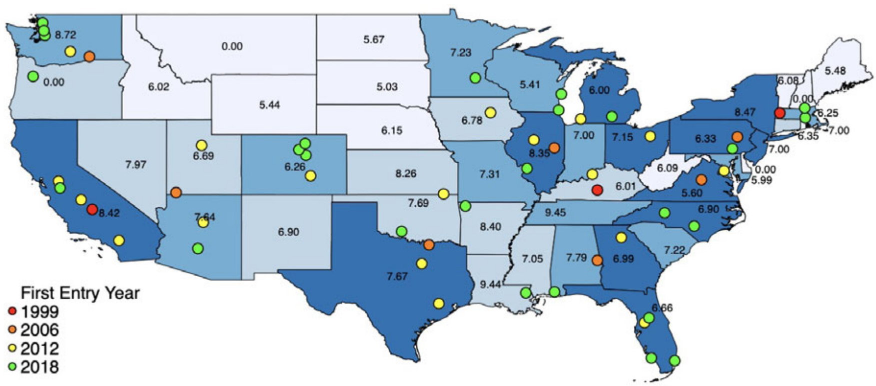


FIGURE 5.—Fulfillment center network and nexus tax laws. Notes: Colors of dots denote the first year in which we predict entry into that location. We shade states by quintiles of the number of households, with the top quintile taking on the darkest color, and display the average sales tax rate in each state.

slightly under-predicts the total number of locations.[24] Our estimates are thus largely able to capture the relative levels of revenue and cost that drive Amazon's network decisions.

We also use Figure 5a to highlight the three primary trade-offs that Amazon faces. First, there is a trade-off between economies of scale (fewer facilities) and density (more facilities): we observe large networks only in 2012 and 2018, once demand has grown sufficiently. Second, sales tax liabilities favor placement of facilities in low-population states, but such placement does not allow the company to benefit from economies of density. This trade-off drives the predicted (and actual) opening of facilities in high-population states like California, Texas, and Florida only in 2012 and in 2018. In these years, local demand is sufficiently high for the benefits of lower shipping costs to outweigh the tax implications. Finally, there is a trade-off between high labor, rent, and congestion costs that favor placement of facilities in low-cost areas, which also typically are low demand and thus do not generate significant economies of density. The patterns of fulfillment center placement in Oregon illustrate this trade-off. In 2006, we predict the optimal fulfillment

[24]The fact that the actual network includes more facilities is due to the fact that Amazon's investment decision is influenced by dynamic considerations such as entry deterrence and anticipated future growth.

center location to be remote and thus, low-cost. In later years, when demand is higher, we predict that locations closer to Portland are optimal.

Predicted Optimal Networks Under Non-Discriminatory Tax Policy. Figure 5b presents the roll-out under a non-discriminatory tax law. A comparison of the two maps suggests that nexus tax laws, not surprisingly, impact the network configuration primarily in high-population or high-tax areas where the revenue implications of raising tax-inclusive prices is largest. Texas provides a good example as our simulations show that Amazon would have entered in 2006 under non-discriminatory tax laws. Under nexus tax laws, however, the model predicts early entries in nearby Oklahoma and Louisiana instead, and entry occurs in Texas itself only in 2018, when cost savings from density finally outweigh the effects of sales tax.

California provides another clear example of the effect of the nexus laws. The model predicts that under non-discriminatory taxes, Amazon would have entered in relatively remote areas of the state in 1999 and expanded closer to high-density areas (San Francisco, Los Angeles, and San Diego) as demand grows, consistent with the presence of large fixed costs in those areas. In contrast, with nexus laws, the model predicts that Amazon would enter California only in 2018, with California orders being fulfilled from Nevada, Oregon, and Arizona beforehand.

Table IX summarizes how demand growth and tax distortions affect Amazon's average cost in aggregate, with each row corresponding to a different state of demand. We present Amazon's average fulfillment cost in total and broken down into its components (columns 1–4), the sales-weighted average shipping distance (column 5), the average sales tax rate paid across orders (column 6), and the fraction of orders subject to positive sales tax (column 7). Finally, we report the number of facilities of each type in the optimal network.

The number of facilities under nexus laws is smaller than with non-discriminatory taxes due to the fact that Amazon has a lower incentive to invest. This difference is especially

TABLE IX

SUMMARY STATISTICS ACROSS TAX REGIMES.

Tax Nexus

	Average Cost ($/Q)				Dist.	Amazon Tax		Facilities	
Year	Shipping	Labor	FC	Total	(miles)	Avg.	% > 0	FC	SC
1999	1.29	0.86	0.32	2.47	376.68	0.26	0.05	3	0
2006	1.14	0.66	0.22	2.02	347.04	0.95	0.15	8	1
2012	0.71	0.48	0.14	1.32	233.02	1.71	0.24	25	4
2018	0.50	0.35	0.08	0.93	173.49	3.08	0.42	65	9

Non-Discriminatory Taxes

	Average Cost ($/Q)				Dist.	Amazon Tax		Facilities	
Year	Shipping	Labor	FC	Total	(miles)	Avg.	% > 0	FC	SC
1999	1.26	0.88	0.37	2.51	366.71	6.74	0.98	3	0
2006	1.10	0.69	0.24	2.03	335.99	6.75	0.98	8	1
2012	0.59	0.52	0.15	1.27	200.65	6.96	0.98	27	5
2018	0.39	0.39	0.10	0.88	150.29	7.13	0.98	74	11

Note: We measure profit in $ million and distance in miles. The columns labeled 'Amazon Tax' are the population-weighted average tax rate paid and the share of the population that pays a positive tax rate on Amazon transactions.

pronounced when demand is high (2018): the model predicts both a smaller sortation network (9 versus 11 facilities) and fewer fulfillment centers (65 versus 74) under nexus laws, in part due to the complementarity between the two types of facilities. The elimination of the nexus tax policy has a large effect on the configuration of the sortation network because the cost savings from vertical integration can only be realized by locating sortation centers close to high-population areas; this makes tax arbitrage strategies based on state boundaries more difficult.

The elimination of the distortions induced by nexus laws lead to a small decrease in the average total fulfillment cost (from \$0.93 to \$0.88) in 2018. The effects are more pronounced for shipping costs: across years, the distorted network exhibits larger shipping costs, amounting to 28% in 2018, due to higher average shipping distances (of 15% in 2018), suggesting that eliminating nexus laws increases the incentive to realize economies of density. These increased economies of density are balanced by larger labor and fixed costs under the non-discriminatory tax regime. With economies of scale in labor and large fixed costs of investment, a less concentrated network leads to cost increases from a lower capacity utilization rate.

Welfare Implications of Non-Discriminatory Tax Policy. We now consider the welfare effect of eliminating nexus tax laws. We assume that the change in total welfare from the reform in year t is given by

$$\begin{aligned}\Delta\text{Welfare}_t = {} & \Delta\text{Amazon Profit}_t + \iota \times \Delta\text{Tax Revenue}_t \\ & - \text{Compensating variation}_t + \mu_t^{\text{rival}} \times \Delta\text{Rival Revenue}_t,\end{aligned} \tag{12}$$

where ι is the fiscal multiplier, μ^{rival} is the profit margin on each dollar of revenue for Amazon's rivals, and Δ measures the change in each outcome variable that results from going from a nexus regime to a non-discriminatory tax regime (i.e., outcome under non-discriminatory − outcome under nexus laws). Table X summarizes the welfare effects.

The top panel of Table X shows reductions in revenue from the increase in sales tax (column 1) and increases in fixed costs from operating more and higher cost centers (column 2). These outweigh the variable costs savings (column 3 and Table IX) that translate into higher margins. The fifth column of Table X(a) indicates that a non-discriminatory tax policy thus results in lower profit for Amazon compared to profit under a nexus policy. The reduction in Amazon's profit in 1999 is relatively small (\$9 million) as demand for Amazon was low and, therefore, a relatively small number of transactions change tax status, but it reaches over \$1 billion by 2018.

In Table X(b), we focus on the other components of welfare. We calculate consumer welfare as the compensating variation (CV), or the amount of income (i.e., budget B) that the consumer would need to receive to make them equally well off under the non-discriminatory tax regime as they are under the nexus regime. That is, we determine

$$CV_t = \sum_i B_{it}^* - B_{it},$$

where B_{it} is the original budget of consumers in county i in year t and B_{it}^* is the budget of consumers in county i and year t under non-discriminatory taxes that makes their utility

TABLE X

WELFARE CHANGES FROM MOVING TO NON-DISCRIMINATORY SALES TAXES.

(a) Amazon Profit Components

	Long Run					Short Run	
Year	Δ Net Rev	Δ Fixed Cost	Δ Var Cost	Variable Margin (nexus/uniform)	Δ Prof	Δ Var Cost	Δ Prof
1999	−18	1	−10	0.071/0.072	−9	−9	−10
2006	−93	0	−44	0.086/0.087	−49	−34	−59
2012	−504	4	−223	0.111/0.114	−285	−109	−396
2018	−1921	66	−768	0.124/0.126	−1220	−300	−1620

(b) Other Components

	Long Run				Short Run
Year	Compensating Variation	Δ Profit Rival	Δ Tax Rev	Fiscal Multiplier s.t. Δ Welfare = 0	Fiscal Multiplier s.t. Δ Welfare = 0
1999	78	3	77	1.091	1.1
2006	394	16	387	1.104	1.129
2012	2419	70	2369	1.112	1.158
2018	9293	250	9266	1.108	1.151

Note: All numbers are measured in $ million, except for margins and multipliers.

equal to that under the nexus policy. In the CES demand model, the latter is given by

$$B^*_{it} = \bar{B}_{it} \frac{\left(\sum_{k=0}^{3} \hat{\alpha}_{ikt} \tilde{p}_{ikt}^{1-\sigma}\right)^{\frac{1}{\sigma-1}}}{\left(\sum_{k=0}^{3} \hat{\alpha}_{ikt} \bar{p}_{ikt}^{1-\sigma}\right)^{\frac{1}{\sigma-1}}},$$

where $\tilde{p}_{ikt}$ and $\bar{p}_{ikt}$ denote the tax-inclusive prices under nexus laws and the non-discriminatory regime, respectively.[25] We use the estimates of the demand model and measures of offline prices from the Bureau of Labor Statistics to calculate the values of $\hat{\alpha}_{ikt}$. See Supplemental Appendix A.2 for the derivation. The first column of Table X(b) shows that consumers are hurt by the non-discriminatory tax policy, which comes from the fact that they are paying higher prices on Amazon. As a result of the growth in consumer demand, consumer welfare losses grow from $78 million in 1999 to over $9 billion in 2018.

In the second column, we present changes in rival profit. We calculate rival revenue using the estimated demand model and assume that the margin μ_t^{rival} is $0.57 * \mu_t^{\text{Amazon}}$, where μ_t^{Amazon} is Amazon's variable profit margin in year t from column 1 of Table X(a)). We use data collected and compiled from the balance sheets of publicly traded retailers to estimate the ratio of the rival margin to Amazon's margin.[26] To give a specific example,

[25]This derivation assumes that each mode has one variety, meaning that our estimate is an approximation of compensating variation under the multi-product case.

[26]The compiled data are found at https://pages.stern.nyu.edu/~adamodar/New_Home_Page/datafile/margin.html, accessed in November of 2021. The ratio is calculated as the ratio of the "Retail (General)"

the rivals' profit margin in 2018 is given by $0.57 * 0.124 = 0.07$. The table shows that Amazon's rivals benefit from a non-discriminatory policy as demand shifts from Amazon to the other modes. Rivals' profit increases by $3 million in 1999 and $250 million in 2018.

Finally, we display the change in tax revenue in the third column of Table X(b). To calculate tax revenue, we multiply the sales tax rate in each county by the taxable sales from offline competitors, mode 2 competitors, and Amazon, if their sales are taxed. Under the nexus policy, Amazon's sales are only taxed in states in which the firm has a facility, while under the non-discriminatory tax policy, all sales are taxed. Our estimated demand model suggests that, as result of the increase in Amazon's tax-inclusive price under the non-discriminatory policy, a portion of the firm's demand shifts to untaxed retailers represented by mode 3. Thus, a non-discriminatory tax policy results in an increase in tax revenue collected.

To assess the aggregate value of the increased tax revenue, we require an estimate of the fiscal multiplier, ι. In the fourth column of Table X(b), we present the 'break-even' value of the fiscal multiplier that equalizes aggregate welfare under the two tax regimes. It ranges from $\bar{\iota} = 1.091$ in 1999 to $\bar{\iota} = 1.108$ in 2018. Dupor et al. (2021) estimated an aggregate fiscal multiplier of 1.64, and Haltom (2018) cited estimates as high as 2.0 and as low as 0.5. The estimate from Dupor et al. (2021) suggests that removing nexus laws increases welfare in 2018 by $\Delta \text{Welfare}_{2018} = -1220 + 1.64 \times 9266 - 9293 + 250 = 4924$ million. To put this in perspective, this change amounts to 0.8% of total online spending in 2018.

The last two columns of Table X(a), labeled 'Short Run', display the changes in Amazon's variable cost and profit that would result from the elimination of the nexus tax laws if Amazon were not able to adjust its network. This allows us to isolate the welfare contribution of Amazon's investment response to the change in tax policy separately from the consumers' demand response. For example, Amazon's variable costs decrease by $300 million when moving to a non-discriminatory policy at its nexus-policy distribution network. Comparing this to the change in costs with a network adjustment suggests that 61% of the reduction in variable costs stems from adjustments in Amazon's investment. As a result, Amazon's profit falls by about 33% more and the break-even multiplier is 4% higher under the fixed distribution network. Again relying on Dupor et al.'s (2021) multiplier of 1.64, the welfare increase from changing the tax policy is about 8% lower when Amazon cannot adjust its network in response. This demonstrates that the investments in Amazon's network play a significant role in determining the effects of tax policy, highlighting the importance of recognizing the supply-side distribution network choices in tax policy analysis.

6. CONCLUSION

We make two primary contributions. First, we quantify the distortions associated with nexus tax laws, a topic of intense political debate. We find that the laws reduced Amazon's incentive to invest in a dense and vertically integrated distribution network, increasing shipping costs by 30%. We estimate that implementing a non-discriminatory tax regime results in a total welfare gain of about $5 billion, where 8% of the gain comes

net margin to the "Retail (Online)" net margin. The assumptions are that the rival modes' net margin can be approximated by the 'General' category, Amazon's can be approximated by the 'Online' category, and the ratio (0.57) remains constant over time. With that, we can use Amazon's margin from out model in year t order to calculate the margin of rivals.

from Amazon's network adjustments in reaction to the policy. Our second contribution is measuring the economies of density in the distribution sector. Most firms in online retail markets outsource large portions of the fulfillment and delivery of orders to third-party shipping companies. Our case study of Amazon highlights that, for large online retailers, the variable cost savings associated with building an integrated distribution network can far outweigh the additional fixed costs and unrealized economies of scale in fulfillment. To capture these trade-offs, we build and estimate a model of Amazon's network formation and show that the benefits of building a dense network are substantial. We estimate a threefold decrease in average shipping cost between 1999 and 2018.

Our work suggests several important avenues for future research. First, we conjecture that a primary driver of Amazon's decision to expand into downstream sortation and, beyond our sample period, last-mile delivery is a hold-up problem that would lead to underinvestment in fulfillment capacity by shippers such as UPS and Fed Ex under incomplete contracts. One could study such inefficiencies with information on the contracts between Amazon and third-party shippers. Second, while our analysis focuses on the direct costs and benefits of Amazon's expansion, the impact on traffic congestion and pollution are likely significant. Quantifying the relationship between the network and these external costs is a topic we hope to explore. Third, we do not allow for a systematic relationship between tax incentives offered by local governments and investment by Amazon in our model. With data on subsidies similar to those used in Slattery (2020), a model of bargaining between firms and governments could be added to our dynamic model of investment. Finally, we take the growth of third-party sellers and their reliance on Amazon as given in our model, but this growth could potentially lead to anti-competitive rent-seeking behavior arising from monopsony power. This concern is commonly raised by proponents of antitrust enforcement efforts against the firm.[27] Data that separate third-party sales from Amazon's direct sales applied to our framework would allow for a quantification of the market power Amazon commands from its status as a key logistics supplier.

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