Domestic Trade Shocks and E-Commerce Expansion: Evidence from Amazon's Distribution Facilities*

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Abstract

This paper studies Amazon's distribution facility expansion as a domestically originated trade shock, using data on the near universe of Amazon distribution facilities, product listings, and sellers. I develop a multi-region, multi-sector spatial retail trade model that incorporates endogenous online retail entry and consumer search. Guided by the model, I show that the entry of Amazon distribution facilities leads to an increase in local online seller entry and online retail sales. These effects are consistent with a reduction in shipping frictions that increases interregional trade flows. Quantitative analysis shows that Amazon's expansion between 2007 and 2017 increases average state-level welfare by 6.7 percent, driven largely by price effects. However, Midwestern states experience negative income effects, and regional disparities widen in both real income and employment.

Keywords: e-commerce, trade, inequality
JEL Codes: F11, F16, F17, L81, O18, R11, R13

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1 Introduction

Over the past two decades, e-commerce has reshaped the U.S. retail landscape, transforming how goods are distributed, sold, and consumed. Between 2000 and 2024, the share of U.S. retail sales conducted online increased from less than 1 percent to nearly 16 percent. Amazon is at the forefront of this transformation, accounting for about 38 percent of U.S. e-commerce market share in 2024. This shift raises important questions about how e-commerce platforms like Amazon are influencing the geography of trade and regional welfare.

A core feature of Amazon's expansion has been the growth of its fulfillment network. Between 1999 and 2024, the number of Amazon facilities grew from 8 to 1,392. These include centers that receive goods from sellers, large warehouses that fulfill customer orders, and local hubs that handle last-mile delivery. Over this period, the average distance from a U.S. county to the nearest Amazon facility fell sharply—from 503 kilometers to just 127 kilometers. This spatial expansion lowers domestic barriers to moving goods across regions.

While much of the classic trade literature focuses on international competition and associated job losses—such as the well-known China shock (Autor et al. 2013; Caliendo et al. 2019)—the rapid growth of e-commerce also stands to influence trade patterns and regional welfare. Existing research has examined the effects of e-commerce on demand, retail productivity, and pricing strategies (Goldmanis et al. 2010; Pozzi 2013; Ellison and Ellison 2018), as well as consumer welfare (Fan et al. 2018; Dolfen et al. 2019). However, the role of e-commerce as a domestically originated trade shock driven by innovations in shipping and distribution remains largely underexplored.

In this paper, I examine Amazon's distribution facility expansion and make three contributions to the understanding of the effects of improvements in logistical infrastructure. I begin by constructing a comprehensive micro-level dataset that covers the near universe of Amazon fulfillment centers, product listings, and sellers. First, I develop a spatial retail trade model, where online retailers select entry locations to maximize profitability across markets, and consumers search with match frictions. The model yields predictions on online retail entry decisions and sales, directly mapping to the Amazon data. Second, guided by the model, I estimate the effects of Amazon distribution facility entry on key seller outcomes, including the number of active sellers, sales volumes, and pricing. I then show that the observed effects align with the model mechanism in which Amazon's distribution facility expansion lowers effective iceberg trade costs, thereby increasing interregional trade flows. Third, I quantify the aggregate effects of Amazon's expansion on welfare using the model and explore the distributional consequences across regions.

A central component of this paper is the construction of a new, comprehensive dataset linking Amazon's distribution facilities to product-level and seller-level outcomes. I begin with proprietary data that document nearly the entire universe of Amazon facilities from 1999 to 2024, including precise opening years, locations, square footage, and functional roles.

These data also include planned but unbuilt facilities, enabling us to estimate the effects of both actual and placebo Amazon expansions. I link these data to microdata that track product listings, daily prices, sales ranks, and seller activity on Amazon's U.S. platform. Using a stratified random sample of products, I merge in related seller profiles, which I then use to identify fulfillment methods and business locations. I focus on U.S.-based third-party sellers that do not ship from China. Together, these data allow us to study how the entry of Amazon distribution facilities affects seller outcomes, interregional trade, and employment at the county-by-sector level.

To guide the empirical analysis, I build a multi-sector spatial trade model focused on intra-regional retailing. The model includes two types of retailers in a vertical production structure: local brick-and-mortar retailers, who buy intermediate goods and serve only local consumers, and online retailers, who choose entry locations based on cost advantages in sourcing inputs from and selling to multiple markets.[1] Consumers engage in costly sequential search and matching as in Weitzman (1979), evaluating each retailer based on a random match value that reflects the match efficiency.[2] Workers are heterogeneous in productivity and choose employment sectors optimally á la Roy (1951). The resulting gravity equation extends the standard form by incorporating not only origin-specific production costs but also the probability of online entry and competition between retail channels. This structure allows us to link the model closely to micro data on Amazon seller entry and performance.

I use the model guide the analysis of a central mechanism of Amazon's facility expansion: that the entry of a new distribution facilities lower bilateral iceberg trade costs for online retailers. This reduction raises the profitability of serving distant markets, which in turn leads to three key outcomes: (i) the number of active online sellers increases and existing sellers expand their sales; (ii) these effects are stronger for heavier goods and in larger markets, but not for lighter goods or smaller markets; (iii) seller prices and local GDP should remain unaffected, consistent with a trade-cost channel rather than a local demand shock or firm productivity shock. Lastly, I directly test whether interregional retail trade flows increase with additional facility entry using data from the Commodity Flow Survey, providing further support for the model's mechanism.

To test these predictions, I estimate a difference-in-differences specification to examine how local seller outcomes change after Amazon opens a fulfillment center. Using detailed seller-by-product data, the baseline results support the model's implications. Counties that receive a new facility experience a statistically significant increase of about 2 to 3 percent in the number of active sellers, reflecting greater market entry. The quantity of goods sold also

[1] This setup differs from the multinational production framework in Arkolakis et al. (2018), where firms select optimal production locations to serve specific markets; here, retailers choose locations that maximize profitability across all markets, considering both upstream and downstream production processes and costs.

[2] Despite its rich micro-foundation, this framework aggregates to an extended gravity trade model with Constant Elasticity of Substitution (CES) demand. The CES demand shifter reflects the match efficiency of the online platform, and the measure of variety is related to the presence of online retailers.

rises by a similar margin, and the variety of product categories expands by 2 to 3 percent. These effects hold after accounting for county-by-year and seller-by-county fixed effects, and the parallel trends assumption is satisfied across all outcomes.

A key concern is that Amazon's facility placement may be endogenous, even after controlling for fixed effects and verifying parallel trends. Amazon might have targeted counties that were already on a path of strong online retail growth. To address this concern, I follow an approach similar to Donaldson (2018) by using planned but unbuilt facilities as a placebo test. These unbuilt sites went through the same internal planning and selection process as the built ones, making them a credible counterfactual for anticipating seller growth. The results show that unbuilt facilities have no meaningful effect on seller entry, sales, or product variety. The estimated coefficients are small and statistically insignificant across all outcomes. This strengthens the interpretation that the observed impacts stem from actual facility construction and not from Amazon's foresight. It also suggests that the expansion responds more to cost and logistical considerations than to unobserved local trends in e-commerce.

I next examine whether Amazon facility entry changes the pattern of interregional trade. Guided by the structure of the model, I estimate how the average number of Amazon facilities between two regions affects both bilateral trade flows and relative trade shares. The results show that facility expansion leads to a clear and sizable increase in trade across regions. Each additional facility raises nominal bilateral trade by about 1.5 log points. This effect becomes even stronger when I control for existing transportation infrastructure, suggesting that Amazon's entry is not simply correlated with better logistics but actively reduces trade frictions. I also find that relative trade shares—defined as sales from the origin region relative to local sales in the destination—rise by 1.4 log points per added facility. Using the model's structure, I translate these estimates into an implied 30 percent reduction in iceberg trade costs per facility, providing direct evidence that Amazon's physical expansion lowers the cost of reaching distant markets.

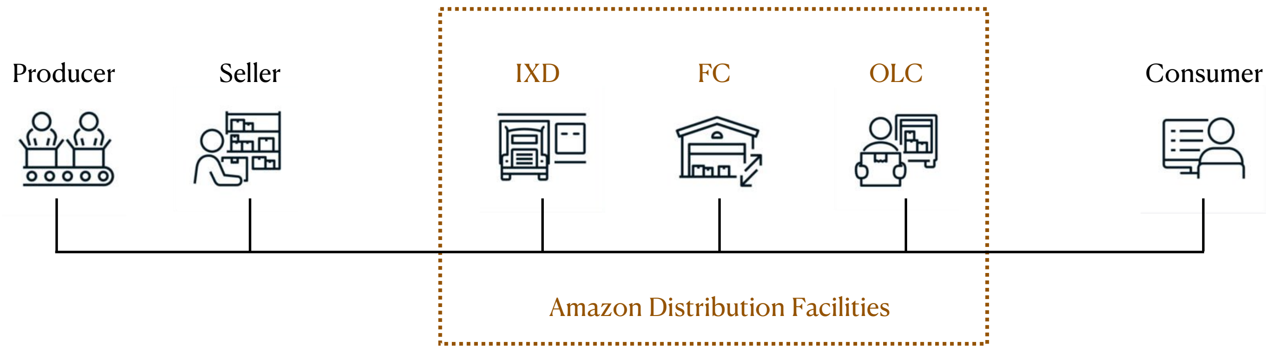
Lastly, quantitative analysis of the model shows that Amazon's expansion significantly reshaped aggregate regional outcomes, raising average state-level welfare by 6.7 percent between 2007 and 2017. Most of this gain comes from lower prices due to improved retail logistics, which would have increased welfare by 13.1 percent on their own. However, uneven income effects, caused by shifts in employment and economic activity, reduce this gain by 5.4 percent. States with a comparative advantage in online retail—such as New York, Massachusetts, and California—benefit from both price and income gains, while several Midwestern states see income losses despite lower prices. Amazon's expansion also drives large labor reallocation away from brick-and-motar retail and manufacturing toward online retail, reducing non-employment by 1.3 percent overall but widening disparities across regions. Areas with low initial online retail presence experience smaller employment gains in e-commerce and larger shifts from manufacturing toward service jobs and non-employment. Notably, even as the empirical analysis documents localized gains in manufacturing employment near new facilities, the aggregate effect across states is negative at 4.3 percent. As a result, regional inequality intensifies, with the Gini index on real income risen by 20 percent.

Literature Review. This paper builds on a growing literature examining the effects of e-commerce on retail market structure, consumption, and local labor markets. Prior studies show that the rise of online retail reduces demand for physical department stores, raising productivity but lowering markups in the consumer goods sector (Stanchi 2019; Goldmanis et al. 2010), and that fulfillment center rollouts by Amazon can reduce income and employment at nearby brick-and-mortar stores (Chava et al. 2024). On the consumption side, Dolfen et al. (2019) find that e-commerce raises consumer welfare through substitution to online merchants, and Fan et al. (2018) show that e-commerce expands domestic trade, especially benefiting consumers in smaller markets. In contrast, this paper focuses on the supply-side implications of logistical expansion. Using rich microdata on Amazon distribution facilities, product-level outcomes, and third-party sellers, I study how reductions in domestic trade frictions reshape seller performance, interregional trade, and upstream manufacturing employment, guided by a general equilibrium spatial retail trade framework.

The framework of this paper extends the spatial trade literature by modeling a multi-sector economy in which online retailers choose entry locations endogeneouly across regions to minimize production and distribution costs. Unlike prior models that study multinational firms serving specific markets (e.g., Arkolakis et al. 2018, 2017), online retailers in this framework serve multiple regions simultaneously. Further, the model features a vertical structure where brick-and-mortar and online retailers source inputs across regions and face iceberg trade costs. Online retailers differ by reaching distant markets and choosing locations strategically, shaping domestic retail trade flows. The model yields a gravity equation that incorporates both endogenous entry probabilities and bilateral trade costs. This structure links directly to rich microdata on Amazon facility openings, seller performance, and trade flows, supporting empirical analysis of the effects of Amazon infrastructure expansion.

A large body of research has studied how international trade shocks, particularly China's accession to the WTO, have affected regional labor markets in the United States. On the empirical side, Autor et al. (2013) and related studies document the persistent negative effects of rising Chinese import competition on U.S. manufacturing employment across regions. Structural models such as Caliendo et al. (2018), Caliendo et al. (2019), and Lee (2020) interpret these effects through general equilibrium frameworks with regional specialization and labor mobility. In contrast, this paper studies a domestically-originated trade shock—Amazon's fulfillment center expansion—which reduces internal shipping costs and increases downstream market access. While both shocks generate spatially uneven effects, Amazon's expansion raises local manufacturing employment in affected regions, even as aggregate manufacturing continues to decline. The analysis highlights a distinct channel through which domestic logistical infrastructure shapes trade flows and regional labor markets, separate from the

Figure 1: Amazon's Distribution Facility Network



Notes: This figure illustrates Amazon's integrated distribution facility network, which connects sellers and producers to customers across the United States. The system includes three main facility types: fulfillment centers (FCs) that store, pack, and ship inventory; inbound cross-dock centers (IXDs) that receive goods and redistribute them to FCs; and outbound logistics centers (OLCs), including sortation centers, delivery stations, and air hubs, that manage last-mile and long-distance delivery.

external trade shocks driven by globalization.

The rest of the paper is organized as follows. The next section provides background on the rise of Amazon and describes the microdata on Amazon facilities, products, and sellers, along with other data sources used in the analysis. Section 3 presents the spatial retail trade model and outlines the main empirical predictions. Section 4 tests these predictions by estimating the effects of Amazon facility entry. Section 5 discusses the quantitative results on the aggregate impacts of Amazon's expansion. The last section concludes.

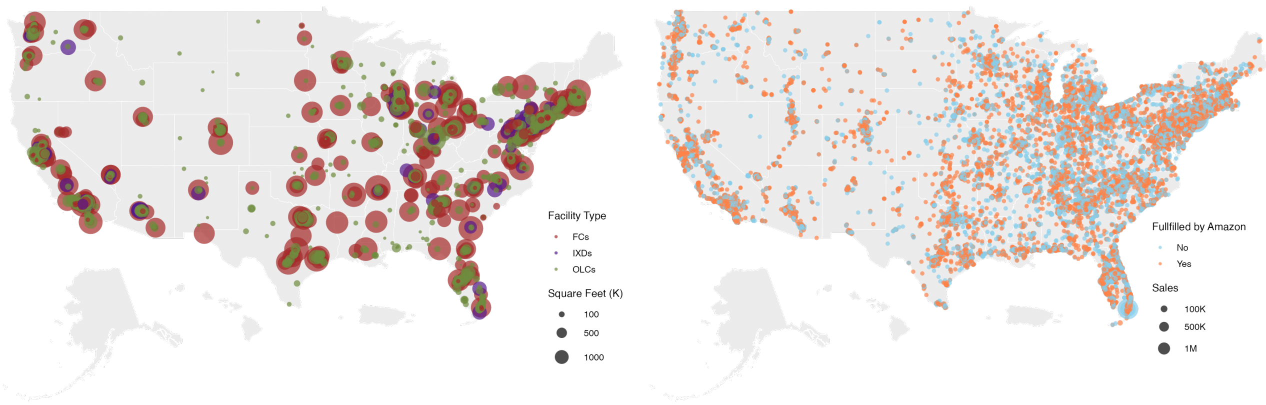
2 Background and Data

2.1 Amazon Distribution Facilities

We obtain detailed information on Amazon's fulfillment and distribution facilities from the supply-chain consulting firm MWPVL (`www.mwpvl.com`). The dataset provides the specific year each facility is opened, the exact geographic location, the square footage of the facility, and the primary function role of each facility. In addition, the data tracks both active and closed facilities, as well as facilities that were publicly announced or planned but ultimately not built or opened.

Amazon's distribution network forms an integrated system that connects sellers and suppliers to customers across the country. It consists of three main types of facilities, as illustrated in Figure 1. First, fulfillment centers (FCs) are the core of Amazon's operations. These are warehouses that store inventory, pick and pack items, and ship orders to customers. They vary by size and the type of goods handled, from small items like books and electronics, large items such as furniture, to groceries and apparel. Second, inbound cross-dock centers

Figure 2: Spatial Distribution of Amazon Facilities and Third-Party Sellers



Panel A. Amazon Facilities

Panel B. Amazon Third-Party Sellers

Notes: This figure presents Amazon's facility growth, differentiated by facility sizes and distribution across regions. The data comes from MWPV, a supply chain consulting company (www.mwpvl.com). The focus is on large fulfillment centers that handle non-perishable goods, which are more likely to influence retail patterns and regional economies.

(IXDs) receive shipments from sellers and suppliers and redistribute them to fulfillment centers, reducing storage needs and improving inventory flow. Third, outbound logistics centers (OLCs) handle the final stages: sortation centers organize packages by destination region, delivery stations prepare them for final delivery routes, and air hubs manage long-distance shipments.

Figure 2 Panel A shows the spatial distribution of Amazon's distribution facility network, which reflects the trade-off between reaching customers quickly and logistical and cost concerns. On the one hand, many facilities are strategically located near major population centers like New York and Chicago so packages can be delivered within just a few hours. On the other hand, Amazon frequently builds FCs and delivery stations on the outskirts of cities or in smaller towns—such as Pasco, Washington, and Staunton, Virginia—both with populations under 80,000 and where land is cheaper and more available. Some delivery stations require over 30 acres just for parking delivery vans, which is hard to find in city centers. Additionally, proximity to highways and major ports also plays a role, with many national IXDs located near inland ports and main transport roads such as Stockton, California, and Middletown, Pennsylvania.

The spatial distribution of distribution Amazon's facility network positions it as a domestic trade system that systematically reduces the frictions of moving goods, similar to the reduction of iceberg costs in traditional trade theory. The network follows a clear hierarchy: IXDs work like domestic ports, regional FCs serve as inland hubs, and OLCs function as final distribution points. Table 1 documents the rapid growth of Amazon's domestic distribution network from 1999 to 2024 and the resulting decline in shipping distance. FCs expanded from 8 to 518 facilities, covering 224 counties by 2024, with total capacity increasing from 46 to 4,826 million

Table 1: Amazon Facility Expansion Over Time

Year	Facilities	Counties	Size (1m ft^2)	Distance (km)
Fulfillment Center (FC)				
1999	8	8	4.6	503.4
2004	8	8	4.5	558.6
2009	18	15	11.3	505.8
2014	71	47	58.3	363.5
2019	261	121	192.3	253.6
2024	452	185	470.7	186.4
Inbound Cross-dock Centers (IXD)				
1999	-	-	-	-
2004	-	-	-	-
2009	2	2	1.4	1073.9
2014	3	3	2.2	880.5
2019	13	12	9.8	522.8
2024	67	48	53.9	374.2
Outbound Logistics Centers (OLC)				
1999	-	-	-	-
2004	1	1	0.1	1422.8
2009	1	1	0.1	1422.8
2014	28	24	7.4	390.7
2019	234	146	36.7	208.0
2024	873	327	171.6	127.0

Notes: This table reports the expansion of Amazon's domestic distribution network from 1999 to 2024 for three types of facilities. Fulfillment Centers (FC) are the hubs for storing and shipping customer orders. Inbound Cross-Dock Centers (IXD) transfer inbound shipments to downstream FCs with minimal storage time. Outbound Logistics Centers (OLC), including sortation centers and delivery stations, handle last-mile delivery operations. The table reports the number of facilities, unique counties served, total facility size (in millions of square feet), and the average distance to all U.S. county centroids.

square feet. As the network expanded, the average shipping distance from a fulfillment center to a county centroid fell from 503 to 186 kilometers. IXDs expanded in parallel, though they remain fewer in number and smaller in capacity than fulfillment centers. OLCs that handle final-mile delivery grew more rapidly. This network expansion and distance reduction significantly lowered domestic shipping frictions, mirroring the reduction of iceberg costs.[3]

2.2 Amazon Products and Sellers

We obtain detailed information on Amazon products and sellers from Keepa (`www.Keepa.com`), an online marketing intelligence company. Keepa has collected Amazon product data since 2011, tracking any item viewed by consumers and updating its database daily or weekly depending on the type of information. As of January 2023, Keepa's database covers more than 674 million products across 36 root categories sold on Amazon in the United States. The

[3] Appendix Figure A1 illustrates the spatial evolution of Amazon's distribution facilities from 2000 to 2020. Between 2000 and 2010, most centers were concentrated in three states: New York, Kentucky, and Arizona. Starting in 2010, the network expanded rapidly, with facilities spreading across most U.S. states and showing dense concentrations along the east and west coasts.

product data we use from Keepa include each product's root category and brand, along with longitudinal information such as prices, sales ranks, and ratings.[4] For our analysis, we draw a 0.1 percent random sample from each category and focus on the period from 2016 to 2024, after Amazon's major expansion in e-commerce. Appendix Table **??** reports the number of products from each category included in our analysis.

Moreover, Keepa tracks Amazon sellers starting in 2016 and assigns each seller a unique identifier. This identifier links to the seller's Amazon profile, which includes business name, address, fulfillment methods, and whether the seller ships from China. There are two main ways to sell on Amazon. First-party seller sales involve vendors providing inventory to Amazon, which then controls pricing and lists these products as "ships from and sold by Amazon.com." Amazon also facilitates third-party sellers through fulfillment, storage, and advertising services, with third-party sellers accounting for a growing share of both units sold and sales revenue.[5] For our seller analysis, we focus on third-party sellers by excluding any seller or business name containing "Amazon." We further restrict the sample to sellers based in the United States who do not ship directly from China. Since each product may be offered by multiple sellers at any given time, we assign the product to the seller holding the "BuyBox," which accounts for over 80 percent of sales.[6]

Figure 2 Panel B shows the spatial distribution of sellers in our selected sample, weighted by their in-sample sales. The data indicate that both small and large businesses offer products on Amazon's platform, and their geographic distribution closely aligns with the distribution of Amazon's facility network. This alignment is particularly strong for sellers that use Amazon's fulfillment services, where Amazon handles warehousing and shipping, but sellers retain product ownership and maintain direct relationships with manufacturers (Amazon 2024).[7]

Trade Flow. For the data patterns regarding intra-regional trade flows, I rely on Commodity Flow Survey (CFS) that provides representative shipment level trade flows in value and quantity for all the 30 manufacturing and retail sectors across 50 U.S. states.

[4] Several marketing studies show that sales quantities and rankings on e-commerce platforms follow a Pareto distribution. Using book sales data and experiments, Chevalier and Goolsbee (2003) estimated the slope coefficient to range from -0.76 to -1.11, while Brynjolfsson et al. (2011) found a coefficient of -0.88 using online sales data from 734 products. Following this approach, we convert sales ranks to quantities using a coefficient of -0.9. Since sales levels can vary across product categories, the intercept is also important. We adopt Brynjolfsson et al. (2011)'s estimation of 8.13, which reflects broader product coverage. Combined with price data, this allows us to estimate total product sales over time.

[5] From the first quarter of 2016 to the last quarter of 2024, the share of paid units sold by third-party sellers on Amazon's platform increased from 48 percent to 62 percent (Amazon 2025). Over the same period, Amazon's revenue from third-party seller services grew substantially, rising from 22,993 million dollars in 2016 to 156,146 million dollars in 2024, representing nearly a six-fold increase (Amazon 2017).

[6] BuyBox is the "Add to Cart" and "Buy Now" section of the product detail page. Winners of the BuyBox are determined by Amazon algorithm that takes into account the price, product rating, delivery method of the sellers.

[7] While Amazon sets manufacturing standards that sellers' upstream partners must meet, it does not control where or from whom sellers source their products, leaving sourcing decisions to the sellers.

3 A Spatial Retail Trade Model

In this section, we develop a multi-sector spatial retail trade model to study how Amazon's expansion of its fulfillment network affects seller outcomes, domestic trade flows, and local employment. The model captures two key forces. First, Amazon's distribution network reduces delivery frictions and improves logistical efficiency, effectively lowering the cost of interregional retail trade. To represent this, the model introduces two types of retailers within a vertical production structure: Online retailers buy intermediate goods and sell across all regions, choosing entry locations to maximize revenue based on spatial variation in production costs and trade frictions, which shape intra-regional trade flows of retail goods. In contrast, brick-and-mortar retailers serve only local consumers. Second, the model incorporates consumer search across regions under imperfect information, leading to a CES demand structure where the match efficiency of online platforms acts as a demand shifter.

The model environment consists of N regions indexed by n and m, and three sectors ($J = 3$): one non-tradable service sector and two tradable goods sectors (durables and non-durables). Each tradable sector includes three subsectors: intermediate manufacturing (M), online retail (R), and brick-and-mortar retail (B). Workers are heterogeneous in their productivities and make optimal decisions about which sector to work in.

3.1 Search-Based Demand Derivation

Consumer Search Micro-Foundation: There is a continuum of consumers in region n, each consuming goods from the durable and non-durable retail sectors, as well as services, with sectoral weights η^j. The retail sector operates under monopolistic competition, where each retailer sells a unique variety. Consumers have access to a total measure of $1 + O^j$ retailers for sector j goods, consisting of a measure 1 of local brick-and-mortar stores and O^j, the normalized measure of online retailers. Among these, O^j_m represents the online retailers originating from region m ($O^j = \sum_m O^j_m$). Under Cobb-Douglas utility and given income y_n, a consumer's optimal consumption from a chosen retailer is $c^{j,K}_{nm} = \eta^j y_n / p^{j,K}_{nm}$, where $p^{j,K}_{nm}$ is the price of goods from retailers in origin m, and $K = \{B, R\}$ distinguishes between brick-and-mortar and online retailers.

Consumers face unknown match value with retailers and resolve this uncertainty by engaging in sequential ordered searches. Specifically, the indirect utility a consumer from region n derives from purchasing from a retailer in m is expressed as $v^j_{nm} = \ln \eta^j y_n - \ln p^{j,K}_{nm} + \epsilon^{j,K}_{nm}$. Here, $\epsilon^{j,K}_{nm}$ represents the unknown, idiosyncratic match value between the consumer and the retailer, which is independently distributed according to the function $F(\epsilon)$. For local brick-and-mortar stores, the match value is normalized to zero ($E(\epsilon^{j,B}_{nn}) = 0$), while the average relative match value for online retailers is given by $\ln(\mu)$ ($E(\epsilon_{nm}^{j,R}) = \ln(\mu)$).[8] Consumers incur a utility cost s for each sequential search to reveal the match value $\epsilon_{nm}^{j,K}$ of a retailer, deciding after each revelation whether to stop or continue searching.

In line with Weitzman (1979), the optimal consumer strategy is to direct their search by the sequence $\bar{\epsilon}_{nm}^{j,K} - p_{nm}^{j,K}$, where $\bar{\epsilon}_{nm}^{j,K}$ represents the minimum match value that makes the consumer indifferent between continuing to search or stopping ($s = \int_{\epsilon_{nm}^{j,K}}^{\bar{\epsilon}_{nm}^{j,K}} (1 - F(\epsilon))d\epsilon$).[9] This sequential search process leads to an eventual purchase choice (Choi et al. 2018; Armstrong 2017; Armstrong and Vickers 2015). Defining $\omega_{nm}^{j,K} \equiv min\{\epsilon_{nm}^{j,K}, \bar{\epsilon}_{nm}^{j,K}\}$, which represents the "effective match value" of a retailer, the consumer will buy from the retailer from m if it maximizes $\omega_{nm}^{j,K} - p_{nm}^{j,K}$.[10]

$$\begin{aligned} D_{nm}^{j,K} &= P(\omega_{nm}^{j,K} - \ln p_{nm}^{j,K} > max_g \; \omega_{ng}^{j,K} - \ln p_{ng}^{j,K}) \\ &= \int \Pi_{g \neq i} F_{\omega_{ng}^{j,K}}(\epsilon - \ln p_{ng}^{j,K}) f_{\omega_{nm}^{j,K}}(\epsilon - \ln p_{nm}^{j,K}) d\epsilon \end{aligned} \tag{1}$$

Optimal Demand Derivation: Sequential ordered search by consumers results in a CES demand framework in two steps. First, consumers' purchase decisions based on $\omega_{nm}^{j,K}$ align with a discrete choice formulation, as outlined in Anderson et al. (2022). The demand from a representative consumer in region n for a retailer in region m, denoted as $D_{nm}^{j,K}$, follows a discrete choice model when $F_{\omega_{nm}^{j,K}} = F_{\varepsilon_{nm}^{j,K}}$, where $\varepsilon_{nm}^{j,K}$ captures the random utility component of $\omega_{nm}^{j,K}$. Second, CES demand emerges as a special case of this discrete choice framework. Assuming $E(\epsilon_n^{j,B}) = 0$ and $E(\epsilon_n^{j,R}) = \ln(\mu)$, we can express $\varepsilon_{nm}^{j,K}$ as $\ln(\mu) + \chi^j \tilde{\varepsilon}_{nm}^{j,K}$, where $\tilde{\varepsilon}_{nm}^{j,K}$ has a mean of 0 and unit variance, and χ^j represents the sector-specific variance of the effective match value $\omega_{nm}^{j,K}$.[11] Under the assumption of an extreme type we distribution for $\tilde{\varepsilon}_{nm}^{j,K}$, the demand function simplifies to $D_{nm}^{j,K} = \frac{(p_{nm}^{j,K}/\mu)^{-1/\chi^j}}{\sum_{g=1}^{N} (p_{ng}^{j,R}/\mu)^{-1/\chi^j} + (p_{nn}^{j,B})^{-1/\chi^j}}$, representing a standard CES expenditure share.

Theorem 1 presents the final CES demand function for consumers and highlights the role of search and matching in shaping consumer behavior. The parameter μ plays a central

[8] This relative match value $\ln(\mu)$ distinguishes the shopping experiences between physical and online stores. Taking the logarithm simplifies the representation and is without loss of generality. A value of $\mu > 1$ suggests consumers derive higher utility from online shopping, whereas $\mu < 1$ indicates the opposite.

[9] The consumer will stop and make a purchase from either a local brick-and-mortar store or an online retailer in m if $max\{v_{nm}^{j,K}, -max_{g \in \bar{O}} \ln p_{nm}^{j,K} + \epsilon_{nm}^{j,K}\} > max_{g \in \bar{O}} - \ln p_{ng}^{j,K} + \epsilon_{ng}^{j,K}$, where $\bar{O}$ denotes the retailers the consumer has searched so far.

[10] As Choi et al. (2018) shows, to guarantee the existence and uniqueness of the equilibrium, one needs the density and loss functions of $\omega_{nm}^{j,K}$ to be log-concave, and the density function to be unbounded above. These are taken as assumptions for this paper.

[11] This implies that $\omega_{nm}^{j,K}$ has a mean of $\ln(\mu)$, reflecting the abundance of online retailers relative to local stores. Given the lower cost of searching additional retailers online, $\omega_{nm}^{j,K}$ closely approximates $\epsilon_{nm}^{j,K}$, with a mean of $\ln(\mu)$.

role: as online shopping becomes more efficient and matching improves, μ increases, shifting consumers' demand towards online retailers. The measure of non-local online retailers, O_m^j, determines the variety of goods available for consumption, while the variance of consumers' effective match value, χ^j, shapes the elasticity of substitution among retailers, given by $\sigma^j = \frac{1+\chi^j}{\chi^j}$. Lower uncertainty about the value of goods from online retailers reduces χ^j, making retailers more substitutable. Under monopolistic competition, this elasticity determines the markup charged by retailers, $\tilde{\sigma}^j = \frac{\sigma^j}{\sigma^j-1}$.

Theorem 1. *A representative consumer in region n with sectoral consumption weights η^j has nest Cobb-Douglas and CES demand as below under sequential ordered search if only if the effective match value $\omega_{nm}^{j,K} = min\{\epsilon_{nm}^{j,K}, \bar{\epsilon}_{nm}^{j,K}\}$ is distributed extreme type I.*

$$C_n = \Pi_{j=1}^J (C_n^j)^{\eta^j}, \quad C_n^j = [(c_{nn}^B)^{\frac{\sigma^j-1}{\sigma^j}} + \mu \sum_{m=1}^N \int_0^{O_m^j} (c_{nm}^R(i))^{\frac{\sigma^j-1}{\sigma^j}} di]^{\frac{\sigma^j}{\sigma^j-1}} \tag{2}$$

Proof: See Appendix B.2.

3.2 Production

Production is organized as a multi-stage vertical process to capture the role of retailers. Retailers first gather intermediate manufacturing goods from various regions, convert them into final products, and sell these to consumers in different regions, applying a markup in the process. This model thus features two layers of intra-regional trade: one for intermediate goods and another for final retial goods.

Intermediate Varieties. The intermediate goods market is perfectly competitive, with a representative firm in each sector j of region n producing a continuum of varieties $e^j \in [0,1]$. The production function is given by:

$$q_n^{j,M}(e^j) = a_n(e^j) \left[h_n(e^j)^{\beta_n} l_n(e^j)^{1-\beta_n} \right],$$

where $a_n(e^j)$ is the factor-neutral productivity for variety e^j, and $l_n(e^j)$ represents labor. The production function also includes regional structures, $h_n(e^j)$ that complemens labor, bundled in a Cobb-Douglas form with shares controlled by β_n. All firms across regions use this constant returns to scale technology and possess no market power. Prices are set to unit costs, as in equation (3), with r_n^h as structure costs and w_n^j as wages. Intermediate goods trade involves an iceberg cost, so κ_{ni}^M units are required to ship one unit from i to n.[12] The price of variety e^j in region n ($p_{ni}^{j,M}(a(e^j))$) is the lowest effective unit cost, adjusted by the iceberg cost,

[12]The iceberg cost satisfies standard requirement $\kappa_{ni}^M > 1$ for $i \neq n$ and $\kappa_{ni}^M = \kappa_{in}^M$.

also specified in equation (3).

$$c_n^{j,M} = \left[(\frac{r_n^h}{\beta_n})^{\beta_n} (\frac{w_n^j}{1-\beta_n})^{1-\beta_n} \right], \quad p_{ni}^{j,M}(a(e^j)) = \min_i \{ \kappa_{ni}^M \frac{c_n^{j,M}}{a_i(e^j)} \}. \tag{3}$$

Further parameterizing the productivity distribution as in Eaton and Kortum (2002) gives a gravity representation of trade. Specifically, let the productivity vector across regions be $a(e^j) = \{a_1(e^j), \ldots, a_N(e^j)\}$, where each $a_n(e^j)$ is a random draw from a Fréchet distribution with shape and scale parameters θ^j and $T_n^{j,M}$, respectively: $\phi_n^j(a_n(e^j)) = \exp(-T_n^{j,M} z^{-\theta^j})$.[13] Using the properties of the Fréchet distribution, the expenditure share of region n on region i for sector j intermediate goods, $x_{ni}^{M,j} = X_{ni}^{M,j} / X_n^{M,j}$, can then be expressed in a gravity formula:

$$x_{ni}^{j,M} = \frac{(\kappa_{ni}^M c_i^{j,M})^{-\theta^j} T_i^{j,M}}{\sum_{m=1}^N (\kappa_{nm}^M c_m^{j,M})^{-\theta^j} T_m^{j,M}}. \tag{4}$$

Retail Sector. The retail sector connects upstream intermediate producers with downstream consumers. In a given region and sector, both online retailers and brick-and-mortar retailers first gather various intermediate varieties $e^j \in [0,1]$ from the lowest-cost producers. These varieties are then combined into a retail bundle $q_n^{j,R/B}$ for the production of retail goods, as described in equation (5), where α^j regulates the elasticity of substitution among the varieties in sector j.[14]

$$q_n^{j,R/B} = [\int_0^1 q_n^{j,M}(e^j)^{\frac{\alpha^j - 1}{\alpha^j}} d\phi^j(a^n(e^j))]^{\frac{\alpha^j}{\alpha^j - 1}} \tag{5}$$

$$Q_n^{j,R/B} = z_n^{j,R/B} \left[(h_n^{j,R/B})^{\beta_n} (l_n^{j,R/B})^{1-\beta_n} \right]^{\gamma_n^j} \left[q_n^{j,R/B} \right]^{1-\gamma_n^j} \tag{6}$$

The retailers then combine the retail good aggregate with other inputs in a nested Cobb–Douglas production function to produce the final retail good, with share of value-added given by γ_n^j as in equation (6). Both type of retailers uses labor and structure bundle with shares controlled by β_n, similar to that of intermediate producers. Given retail sector's

[13] The Fréchet shape parameter θ^j determines the dispersion of productivities across regions and thus the within-sector specialization, while $T_n^{j,M}$ regulates regions' absolute production advantages and cross-sector specialization.

[14] This model structure differs from the input-output linkages in Costinot and Rodríguez-Clare (2014) and those in recent quantitative trade models, where intermediate goods production also requires these aggregates as inputs. In contrast, this structure more accurately reflects the retail industry, where intermediate production relies solely on primary factors, and and retail goods are intended for final consumers only. Further, not only the intermediate varieties are tradable, the final retail goods are also tradable to capture e-commerce.

production function, the unit cost of retail good is given by:

$$c_n^{j,R/B} = (\varrho_n^{j,R/B})^{\gamma_n^j}(p_n^{j,M})^{1-\gamma_n^j}, \tag{7}$$

where $p_n^{j,M} \equiv (\Gamma(\frac{\theta^j+1-\alpha^j}{\theta^j}))^{\frac{1}{1-\alpha^j}}(\sum_{m=1}^{N}(\kappa_{nm}^M c_m^{j,M})^{-\theta^j}T_m^{j,M})^{\frac{1}{-\theta^j}}, \varrho_n^{j,R/B} \equiv (\frac{r_n^{j,R/B}}{\beta_n})^{\beta_n}(\frac{w_n^{j,R/B}}{1-\beta_n})^{1-\beta_n}$.

Here, $p_n^{j,M}$ represents the price index of the aggregate intermediate varieties, derived from the properties of the Fréchet distribution applied to the productivity vector $\phi^j(a^j(e^j))$, with $\Gamma(.)$ being the gamma function evaluated at $\frac{\theta^j+1-\alpha^j}{\theta^j}$.[15] The term $\varrho_n^{j,R}$ denotes the unit cost of labor and structure in the retail sector. Given the monopolistic market structure of the retail sector, the price of retail goods shipped from market i to n is calculated as $p_{nm}^{j,R} = \tilde{\sigma}\frac{\kappa_{nm}^R c_m^{j,R}}{z_m^{j,R}}$, where $\tilde{\sigma}$ is the markup, $c_m^{j,R}$ is the unit retail cost, and κ_{nm}^R represents the iceberg cost that subsumes shipping cost and other bilateral frictions.

Online Retailer Entry. Given a measure O^j of potential entrants of online retailing in sector j, each retailer enters the location that maximizes revenue across regions. Online retailers draw a vector of productivities across locations $(z_1^{j,R}, ..., z_N^{j,R})$ and enter region m by paying a fixed entry cost in labor units f_m.[16] After entry, they import intermediate inputs from multiple regions and distribute the final retail goods to consumers across all destinations.[17] An online retailer will enter region m only if the total expected revenue from sales to all destinations exceeds the entry cost $\sum_n \left(\tilde{\sigma}^j \frac{c_m^{j,R}}{\mu z_m^{j,R}} \frac{\kappa_{nm}^R}{P_n^{j,R}}\right)^{1-\sigma^j} \eta^j X_n \geq \sigma^j w_m^{j,R} f_m$. This condition determines the threshold unit cost below which it is profitable for an online retailer to enter a given market.

$$\bar{c}_m^{j,R} = \frac{\mu z_m^{j,R}}{\tilde{\sigma}^j}\left[\frac{\sigma^j}{\eta^j}\frac{w_m^{j,R} f_m}{\sum_n (\kappa_{nm}^R / P_n^{j,R})^{\sigma^j-1} X_n^{-1}}\right]^{\frac{1}{1-\sigma^j}}. \tag{8}$$

This setup highlights the key forces that shape online retailer outcomes. Online retailers choose to enter the region m that maximizes revenue, which is affected by the cost of buying upstream manufacturing goods and the weighted sum of iceberg trade costs to all destination markets. These weights depend on total expenditure in each destination X_n and

[15] Since the vector of productivity draws for variety e^j across regions is $a(e^j) = \{a_1(e^j), \ldots, a_N(e^j)\}$, their joint distribution becomes $\phi^j(a^j(e^j)) = \exp\left\{-\sum_{n=1}^N T_n^{j,M}(z)^{-\theta^j}\right\}$. The parameter condition $\theta^j + 1 - \alpha^j > 0$ is assumed to ensure that the price index is well-defined.

[16] Each brick-and-mortar store's productivity is tied to its specific location $z_n^{j,B}$.

[17] This setup departs from the framework typically seen in the multinational production literature, such as in Arkolakis et al. (2018), where a firm selects the optimal production location specifically to serve a targeted destination. Instead, in this model, retailers select a location that maximizes profitability across all markets, considering upstream and downstream production processes and cost structures.

the corresponding retail price index $P_n^{j,R}$. Retailers prefer to enter regions where trade costs to large markets are low or where manufacturing goods are cheap.

To gain tractability and derive closed form solution for online retailers' entry, we follow the multinational production literature (Arkolakis et al. 2017, 2018) to assume that the productivity vectors of online retailers are randomly drawn from a multi-variate Pareto distribution $P(Z_1^{j,R} < z_1, ..., Z_N^{j,R} < z_N) = 1 - (\sum_{m=1}^{N}[T_m^{j,R} z_m^{-\tau}]^{\frac{1}{1-\rho}})^{1-\rho}$.[18] Define $\xi_m^j \equiv \sum_n (\frac{c_m^{j,R}\kappa_{nm}^R}{P_n^{j,R}})^{\sigma^j - 1}\frac{1}{X_n}$, so the probability of a sector j retailer to enter in region m can then be expressed as

$$\Psi_m^j = P(m = \arg\min_m\{\xi_m^j / z_m^{j,R}\} \cap c_m^{j,R} < \bar{c}_m^{j,R}) = \psi_m^j(\bar{c}_m^{j,R})^{\tau}, \tag{9}$$

where $\psi_m^j = T_m^{j,R}(\xi_m^j)^{\frac{-\tau}{1-\rho}} / \sum_{m=1}^{N}[T_m^{j,R}(\xi_m^j)^{-\tau}]^{\frac{-\rho}{1-\rho}}$.[19] This equation presents a probabilistic formulation of online retailers' entry decision, accounting for the elasticity of substitution across regional productivities in retail production, parameterized by τ and ρ.

The location of online retailers plays an important role in determining the intra-regional aggregate trade flows. With a total of measure O^j of online retailers in sector j, the measure of online retailers entering location m is $O_m^j = O^j \Psi_m^j$. Therefore, the total sales from region m to n is the product of sales per firm and the measure of firms: $(\frac{p_{nm}^{j,R}/\mu}{P_n^{j,R}})^{1-\sigma^j}\eta^j X_n O_m^j$. We can then obtain the bilateral online retail expenditure share $x_{nm}^{j,R}$ as in equation (10), which represents an extended gravity equation of Chaney (2008)'s version of the Melitz model.

$$x_{nm}^{j,R} = \frac{\Psi_m^j(\kappa_{nm}^R c_m^{j,R}/\mu)^{1-\sigma^j}}{\sum_h \Psi_h^j(\kappa_{nh}^R c_h^{j,R}/\mu)^{1-\sigma^j} + \frac{1}{O}(c_n^{j,B})^{1-\sigma^j}} \tag{10}$$

$$x_n^{j,B} = \frac{\frac{1}{O}(c_n^{j,B})^{1-\sigma^j}}{\sum_h \Psi_h^j(\kappa_{nh}^R c_h^{j,R}/\mu)^{1-\sigma^j} + \frac{1}{O}(c_n^{j,B})^{1-\sigma^j}} \tag{11}$$

Unlike standard gravity equation of trade, the numerator ("bilateral resistance") depends not only on the retail production cost of the origin, but on the probability of online retailers entering that region, as well as the online matching efficiency; the denominator ("multi-lateral resistance") includes both the sum of bilateral resistance as well as the cost of local brick-and-mortar store divided the measure of available online retailers. Further, this model allows substantial quantitative tractability because the location probability of online retailers (Ψ_m^j) can be directly observed from the data. The model also characterizes the regional expenditure

[18] The support of this distribution requires $z_m \geq (\sum_{m=1}^{N}(A_m^j)^{\frac{1}{1-\rho}})^{1-\rho}$ and $\rho \in [0, 1)$. The scale parameter $T_m^{j,R}$ measures the absolute advantage of region m in producing sector j goods, whereas τ controls the degree of heterogeneity across different vectors, and ρ controls the degree of heterogeneity within a single vector of different realizations.

[19] Note that $\tilde{\sigma}$ and η^j do not appear in the definition of ξ_m^j and Ψ_m^j since they are constant within a sector.

share on local brick-and-mortar stores, $x_n^{j,B}$, in addition to the inter-regional expenditure share on online retailers.

3.3 Labor Supply

To study worker sorting and heterogeneous labor supply across sectors, I adopt a Roy (1951)-style framework with probabilistic productivities (Lagakos and Waugh 2013; Hsieh et al. 2019; Galle et al. 2022; Lee 2020). In each region n, workers draw sector-specific productivities $z_n^{j,K}$, where j denotes sector and $K = M, R, B, \emptyset$ indexes tradable subsectors.[20] Non-employment is treated as sector 0, with wage w_n^0 as the return to home production (see Dvorkin 2014; Caliendo et al. 2019). Worker productivities are drawn independently from Fréchet distributions $v_n^{j,K}(z)$, with shape ν_n and scale $A_n^{j,K}$.[21] The joint distribution is another Fréchet: $v_n(z_n) = \sum_{j=0}^{J} \sum_{K=M,R} A_n^{j,K} z^{-\nu_n}$. Workers choose the sector (j, K) that maximizes their wages per unit of labor supplied $w_n^{j,K} z_n^{j,K}$.[22] We can derive the probability of employment in sector (j, K) as:

$$\pi_n^{j,K} = \frac{A_n^{j,K} (w_n^{j,K})^{\nu_n}}{\Phi_n}, \text{ where } \Phi_n = \sum_{j=1}^{J} \sum_{K=\{M,R,B,\emptyset\}} A_n^{j,K} (w_n^{j,K})^{\nu_n} + A_n^0 (w_n^0)^{\nu_n}. \tag{12}$$

The employment probability in sector (j, K) depends on its wage return relative to all alternatives, shaped by ν_n, which captures labor supply elasticity.[23] Hence, e-commerce-induced wage shifts reallocate labor across sectors. The Fréchet structure also yields tractable expressions for labor supply in efficiency units. For sector (j, K), this supply is:

$$l_n^{j,K} \equiv \Gamma(\frac{\nu_n - 1}{\nu_n}) \frac{\Phi_n^{1/\nu_n}}{w_n^{j,K}} \pi_n^{j,K} L_n, \tag{13}$$

which affects workers' income as well as firms' output. The wage return for workers in sector (j, K) simplifies to $w_n^{j,K} l_n^{j,K} = \Gamma(\frac{\nu_n - 1}{\nu_n}) \Phi_n^{1/\nu_n} \pi_n^{j,K} L_n$.

[20] Specifically, $z_n^{j,K}$ has six dimensions: $z_n = \{z_n^0, z_n^1, z_n^{2,M}, z_n^{2,R}, z_n^{2,B}, z_n^{3,M}, z_n^{3,R}, z_n^{3,B}\}$, where sectors 0 and 1 represent non-employment and services, and sectors 2 and 3 represent durable and non-durable goods. Subsections M, R, B correspond to intermediate producers, online retailers, and brick-and-mortar retailers.

[21] The scale parameter $A_n^{j,K}$ regulates the absolute advantage, while ν_n regulates comparative advantage.

[22] The optimal choice set for a sector (j, K) is defined as $\Lambda_n^{j,K} \equiv \{z_n^{j,K} \mid z_n^{j,K} > z_n^{H,k} \, \forall \, (H, k)\}$, indicating a worker will choose to work in (j, K) if the drawn productivity vector falls within this set.

[23] As discussed in Galle et al. (2022), if $\nu_n \to \infty$, the households become homogeneous in employment choices and $\nu_n \to 1$ delivers the same comparative statics as sectoral specific labor supply.

3.4 Market Clearing

In the goods market, expenditure clears in two ways: consumers buy retail goods from various retailers, while retailers obtain intermediate varieties from different producers:

$$X_n^{j,R} = \sum_{i=1}^{N} X_{in}^{j,R} = \sum_{i=1}^{N} x_{in}^{j,R}(I_i L_i), \text{ where } I_i L_i = \sum_{k=0}^{J} \sum_{K=\{M,R,B,\emptyset\}} (r_i^{h,k} h_i^{K,k} + w_i^k l_i^{K,k}) - \Omega_i, \quad (14)$$

$$X_n^{j,M} = \sum_{i=1}^{N} X_{in}^{j,M} = \sum_{i=1}^{N} (1-\gamma_i^j) x_{in}^{j,M} X_i^{j,R}. \quad (15)$$

The total revenue from selling sector j retail goods produced in region n, $X_n^{j,R}$, equals the sum of sales across all regions, $\sum_{i=1}^{N} X_{in}^{j,R}$, where each region's sales equal the retail expenditure share $x_{in}^{j,R}$ multiplied by total income $I_i L_i$. In the benchmark model, households' total income is derived from earnings, minus the region's trade deficit Ω_i that is assumed to be exogenous. Similarly, the total revenue for sector j intermediate goods from region n, $X_n^{j,M}$, equals the sum of sales across regions, $\sum_{i=1}^{N} X_{in}^{j,M}$, where each region's sales equal the intermediate expenditure share $x_{in}^{j,M}$ multiplied by $(1-\gamma_i^j)X_i^{j,R}$, the retail spending on intermediates.[24]

$$w_n^{j,M} l_n^{j,M} = (1-\beta_n) X_n^{j,M}, \quad w_n^{j,R} l_n^{j,R} = \gamma_n^j (1-\beta_n) X_n^{j,R}, \quad w_n^{j,B} l_n^{j,B} = \gamma_n^j (1-\beta_n) X_n^{j,B}, \quad (16)$$

The market clearing for primary factors including labor and structures requires that their returns equal the corresponding portion of value-added, as in the above equations.

3.5 Empirical Predictions

The spatial retail trade model outlined above provide four central empirical implications that we test in Section 4 and these predictions are formally derived and carefully proved in the Appendix B.1. As the bilateral iceberg trade costs for online shipments from origin m to destination n (κ_{nm}^R) fall—capturing the local effect of Amazon facility entry—the model predicts that regions hosting new facilities will experience:

(i) An expansion in the online retail presence, reflected in both an increase in per-retailer sales $X_{nm}^{j,R}$ and a higher equilibrium mass of online retailers O_m^j.

(ii) Higher bilateral online trade flows, indicated by an increase in the bilateral expenditure share $x_{nm}^{j,R}$ and the nominal trade flow $X_{nm}^{j,R}$.

(iii) An increase in local manufacturing output $X_m^{j,M}$ and manufacturing employment $l_m^{j,M}$.

[24] Accounting for regional trade deficits, the balance of trade requires that $\sum_{j=0}^{J} \sum_{i=1}^{N} (x_{ni}^{j,M} X_n^{j,M} + x_{ni}^{j,R} X_n^{j,R}) + \Omega_n = \sum_{j=0}^{J} \sum_{i=1}^{N} (x_{in}^{j,M} X_i^{j,M} + x_{in}^{j,R} X_i^{j,R})$.

The first two predictions follow directly. A reduction in κ^R_{nm} increases the profitability of serving region n, which raises both the demand faced by each seller and the likelihood that online retailers will locate in region m. As a result, sellers from m capture a larger share of retail spending in destination markets, increasing trade volumes between m and n. The third prediction builds on the role of retailers as intermediaries. As the number and scale of online sellers grow, their demand for upstream manufacturing inputs also rises. Given that trade frictions exist in the manufacturing sector, sellers naturally source more from nearby producers, which raises local manufacturing production. Higher output, in turn, directly increases labor demand in the manufacturing sector.

Two simplifying assumptions in the model warrant discussion. First, we assume in Assumption B.1 that wages, prices, and nominal incomes are locally fixed when analyzing the effects of lower shipping costs. Allowing these variables to adjust would likely strengthen the predicted growth in sales and manufacturing output. Second, we abstract from worker mobility, which would reduce wage changes across regions but would not overturn the predicted increases in trade flows, retailer entry, or local manufacturing. These simplifications are intentional to highlight that even without wage or population adjustments, reductions in shipping costs can generate meaningful variation in retailer concentration, trade patterns, and manufacturing outcomes—providing testable predictions for the empirical analysis.

4 Estimating the Effects of Amazon Facility

In this section, we test the model's four key empirical predictions. We begin by using detailed product and seller data to estimate the effects of Amazon facility entry on various seller outcomes, such as number of sellers, sales quantity, and pricing. We then turn to interregional trade flows to examine whether the expansion of Amazon's distribution network reshapes the geography of retail trade by reducing effective iceberge costs between regions. Finally, we analyze the employment effects of Amazon facility entry, with particular attention to local manufacturing employment, and compare these effects to the well-documented impact of the China shock. These estimates are not only of direct economic interest but also provide essential inputs for the subsequent quantitative evaluation of welfare.

4.1 Effect of Amazon Facility on Seller Outcomes

4.1.1 Baseline Results

Empirical Strategy. We estimate the following difference-in-differences specification:

$$\log(Y_{i,c,t}) = \alpha + \beta \cdot \text{PostFC}_{c,t} + \eta_i + \theta_{c,t} + \gamma_t + \epsilon_{i,c,t} \tag{17}$$

Table 2: Amazon Facility Entry and Seller Outcomes (in Log)

	Product Num.		Quantity		Price		Product Cat.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Actual entry	0.05***	0.05***	0.05**	0.05**	0.06**	0.06**	0.02**	0.03**
	[0.01]	[0.01]	[0.03]	[0.03]	[0.03]	[0.03]	[0.01]	[0.01]
Planned but unbuilt		0.01*		0.02		0.04		0.01
		[0.01]		[0.03]		[0.04]		[0.01]
Year-month FE	X	X	X	X	X	X	X	X
County-year FE	X	X						
Seller-county FE			X	X	X	X	X	X
Observations	176,127	176,127	704,404	704,404	678,439	678,439	704,404	704,404
R-squared	1.00	1.00	0.61	0.61	0.62	0.62	0.72	0.72

Notes: This table presents results from estimating equation (17). The dependent variables are various seller outcomes measured in logs. The key independent variable is an indicator for the presence of an Amazon distribution facility in the seller's county, which equals one since the first year of presence. Specifications include seller fixed effects, county-year fixed effects, and year-month fixed effects. Standard errors are clustered at the county level. For the specification where the outcome is the number of sellers, the regression is estimated at the county level and seller fixed effects are excluded.

where $Y_{i,c,t}$ represents the outcome of interest for seller i in county c at time t. The variable $\text{PostFC}_{c,t}$ is an indicator that takes the value of one if a fulfillment center is present in county c at time t and remains equal to one for all subsequent periods. We include seller-county fixed effects (η_i) to control for time-invariant seller-specific factors, county-year fixed effects ($\theta_{c,t}$) to absorb local shocks that vary over time, and year-month fixed effects (γ_t) to capture aggregate trends. Standard errors are clustered at the county level. The key coefficient of interest is β, which estimates the percentage change in seller outcomes attributable to the entry of an Amazon facility. When the outcome of interest is the number of sellers in a county, we estimate the same specification at the county level by aggregating the number of sellers within each county and time period. In this case, the unit of observation is the county the seller-county fixed effects are omitted accordingly.

Estimation Results. Baseline results in Table 2 (columnss 1, 3, 5, and 7) validate empirical prediction (i) and show that the establishment of an Amazon distribution facility significantly increases local seller activity across multiple outcomes. Following facility entry, the number of active sellers rises by about 5 percent, reflecting increased market entry, consistent with an increase in O_m^j . The quantity of products sold also grows by approximately 5 percent, and avegarge prices rise by 6 percent, both of which suggest higher sales. Additionally, the number of available product categories increases by 2 to 3 percent. These findings confirm that Amazon's distribution network expansion actively enhances local online retail presence.

4.1.2 Addressing Endogeneity: The Role of Planned but Unbuilt Facilities

A natural concern in this analysis is the potential endogeneity of fulfillment center placement. Amazon does not randomly assign its facilities across locations. It is plausible that Amazon targets counties that are already on a high-growth trajectory in terms of online sales. Despite controlling county-specific trends, aggregate year-month shocks, and seller-by-county fixed effects, concerns about potential bias from unobserved local shocks correlated with facility entry may still persist.

To address this concern, we follow an approach inspired by Donaldson (2018), who carefully tested the exogeneity of railroad construction using planned but unbuilt lines. In our setting, Amazon's internal decision-making provides a powerful placebo. Some projects advance through the company's planning process, are publicly announced, but ultimately remain unbuilt. Importantly, both built and unbuilt sites pass through Amazon's corporate selection filter. If Amazon systematically selects locations based on anticipated growth—visible only to Amazon's planners—then we would expect that both built and unbuilt facilities should exhibit similar effects on seller outcomes.

Our analysis shows that this is not the case. As shown in Table 2, coefficients on unbuilt sites (columns 2, 4, 6, and 8) are small and statistically insignificant. For example, while actual FC entry increases the number of sellers by about 5 percent, the coefficient on unbuilt facilities is only about 1 percent and is only marginally significant in one specification. The effects of unbuilt facilities on the quantity of goods sold, average price, and product variety are all close to zero and not statistically significant.

These findings show that counties where fulfillment centers were planned but not built did not experience the same changes in seller outcomes as those where facilities were actually constructed. This placebo analysis strengthens the credibility of our identification strategy. The sharp contrast in effects indicates that the observed gains follow the opening of the facility, rather than reflecting Amazon's ability to anticipate areas of future seller growth. The mechanism also aligns with documented reduction in shipping distances and delivery times after Amazon's expansion of its fulfillment network in Table 1.

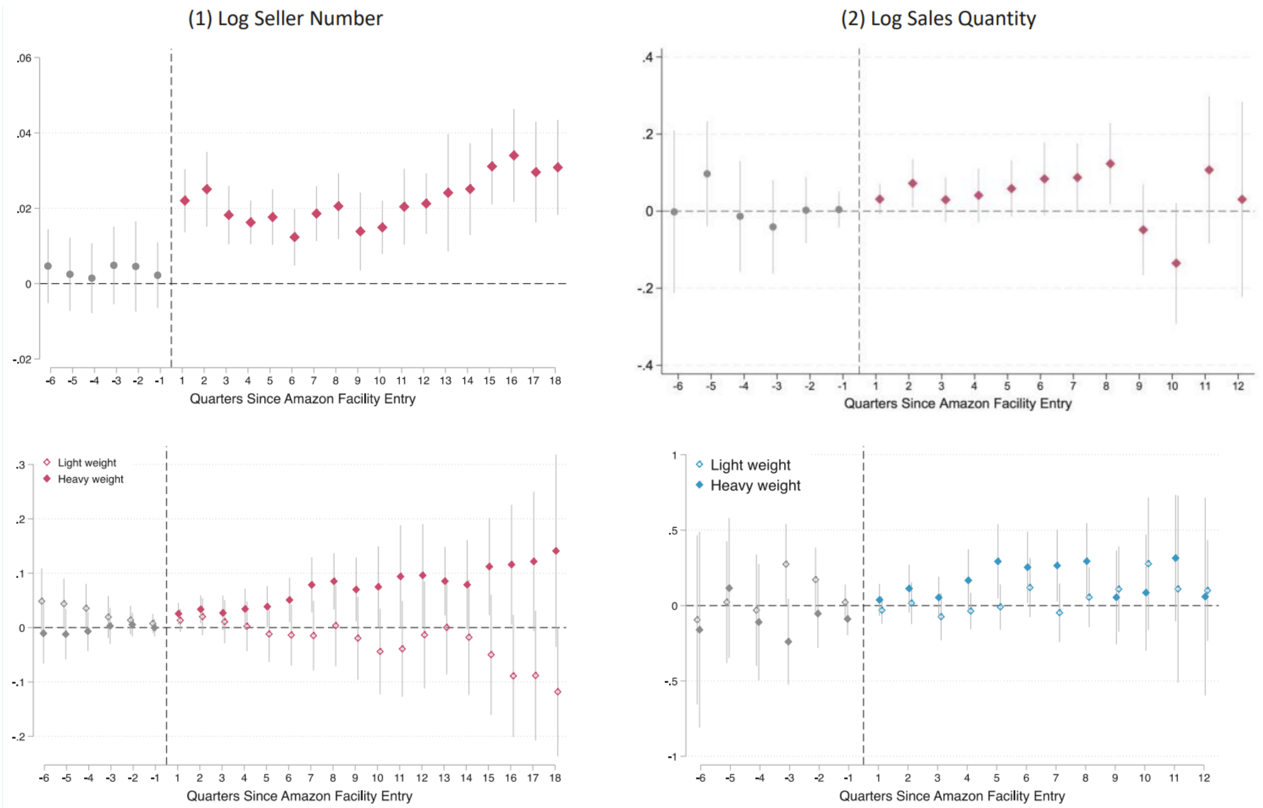
4.1.3 Event Study Results

To further validate our difference-in-differences estimates and ensure the parallel trends assumption holds, we estimate an event study specification with a full set of leads and lags:

$$\log(Y_{ict}) = \sum_{j=-10}^{10} \beta_j \cdot I(\text{MonthsSinceEntry}_{ct} = j) + \mu_i + \theta_t + \epsilon_{ict} \tag{18}$$

where $\log(Y_{ict})$ is one of four seller outcomes: number of sellers, sales quantity, seller prices, and the number of product categories. The indicator function $I(\cdot)$ equals one exactly j months

Figure 3: Event Study of Amazon Entry (2016-2025)



Notes: This figure plots dynamic event study estimates of the impact of Amazon fulfillment center (FC) entry on four seller outcomes: (i) number of sellers, (ii) quantity sold, (iii) average price, and (iv) number of product categories. The x-axis indicates months relative to FC opening (month 0), and the y-axis reports estimated log-point effects. Estimates are relative to the month before FC entry. All models include seller-county and year-month fixed effects. Confidence intervals are shown at the 95% level.

before or after Amazon opens a fulfillment center in county c. We use a window from 10 months before to 10 months after facility entry, with month zero being the exact month the FC begins operations. Seller-county fixed effects (μ_i) and year-month fixed effects (θ_t) absorb all time-invariant seller characteristics and common time trends, respectively.

As shown in Figure 3, the pre-treatment dynamics across all four outcomes provide no evidence of differential trends prior to facility entry. In each panel, the coefficients for the ten months preceding the entry are statistically indistinguishable from zero and lie flat, suggesting that counties that eventually receive an Amazon FC do not exhibit anticipatory shifts in seller outcomes relative to those yet to be treated.

Post-entry, we observe immediate and persistent effects on seller number, sales quantity and product categories. Beginning in the month of amazonf facility entry (month 0), the number of sellers (Panel 1) and the sales quantity (Panel 2) increase sharply, by 18 and 8 percent with the first three months. These effects persist and appear to stabilize over the subsequent 6 to 10 months. Similarly, in Panel 4, we detect an increase in product variety offered by Amazon sellers of around 5 percent post entry. The price effect in Panel 3 appears to be more muted.

The flat pre-period combined with the abrupt and lasting post-period response is inconsistent with two common selection stories. First, if Amazon targeted counties experiencing rapid growth in online sales, one would observe positive coefficients in the months leading to entry. Second, if local policy makers accelerated facility approvals in response to emerging economic shocks, treatment dates would correlate with rising pre-trends. In the data, neither pattern appears. Instead, the evidence supports a timing mechanism driven by logistical and cost constraints rather than by local e-commerce conditions.[25]

4.2 Evidence of an Interregional Trade Channel

The preceding section presents that Amazon's distribution facility entry leads to significant increases in local seller entry and sales quantities. This section explores whether the observed effects stem from a reduction in domestic trade frictions, or whether alternative channels such as (i) local demand shocks or (ii) firm-level productivity shocks may be driving the results. I first provide two pieces of supporting evidence that reinforce the interpretation that a trade-based mechanism is central, before directly estimating the reduction in interregional trade friction motivated by the reduced-form specification derived from the model.

4.2.1 Channels at Work

To examine the channels, I first exploit heterogeneity in shipping frictions at the product level. The model implies that reductions in bilateral trade costs should have disproportionately larger effects on goods whose delivered costs are more sensitive to distance, weight, and handling, consistent with evidence that transportation costs shape trade flows through per-unit charges that scale with mass and distance (Hummels 2007). On the other hand, local demand shifts in differentiated-product markets could alter sales by changing consumer preferences or markups, but such effects need not correlate with product weight or shipping costs (Hottman et al. 2016). Likewise, firm-level productivity gains may enhance efficiency or scale but would not systematically predict stronger responses for heavier goods.

Figure 3 panels (3) and (4) implement this comparison by splitting categories a priori into heavy and light goods.[26] Post-entry, the effects are both immediate and more significant for heavy goods: the number of online sellers increases by about 3 percent on impact and by 5

[25] Unreported robustness checks replace month fixed effects with more granular region-by-month and county-size-by-month interactions and extend the window to twenty-four months before entry. Coefficient paths remain nearly identical, and the cumulative treatment effect on prices grows marginally from three to four percentage points. These findings confirm that finer control for local shocks or a longer pre-period does not alter the substantive conclusions.

[26] Heavy weight products: Tools & Home Improvement; Patio, Lawn & Garden; Home & Kitchen. Light weight products: Gift Cards; Movies & TV; CDs & Vinyl.

percent by the end of the first year. Log sales quantities increase more sharply—by about 10 percent in the first quarter and by nearly 30 percent within three to eight quarters—although confidence bands widen in later periods as markets scale up. In contrast, light categories display coefficients that are economically small and statistically indistinguishable from zero throughout. This heterogeneity is difficult to reconcile with local demand shocks or firm-level productivity improvements, as these explanations do not predict stronger effects for products with higher transport costs. Instead, the results support a mechanism driven by reductions in shipping frictions.

Second, the absence of any systematic change in seller prices or county GDP following facility entry as shown in Figure 4 suggests that the observed gains are not driven by local demand shocks or pricing power. This interpretation aligns with the structure of the model, which assumes CES preferences and monopolistic competition: when iceberg trade costs fall, trade volumes and product variety expand, while prices are determined by marginal costs and constant markups. If facility entry had instead operated through a local demand shock, one would expect prices to rise alongside quantities—patterns not observed in the data. Similarly, firm-level productivity improvements or learning-by-doing effects would generate price–quantity co-movements (Foster et al. 2008). The neutrality of both prices and county-level GDP thus reinforces the interpretation that Amazon's expansion primarily reduces bilateral trade frictions, rather than shifting local demand conditions or firm productivity.

4.2.2 Direct Evidence on Interregional Trade

Empirical Strategy. The spatial retail trade model predicts that Amazon's fulfillment centers reduce bilateral iceberg trade costs, denoted κ^R_{nm}, and expand interregional retail trade flows. This mechanism is consistent with standard trade models where lower trade frictions increase trade volumns. We test this core mechanism by estimating how the average number of Amazon facilities between two locations affects two outcomes: nominal bilateral trade flows, $x^{j,R}_{nm}$, and the relative trade share, $x^{j,R}_{nm}/x^{j,R}_{nn}$.

$$\ln\left(\frac{x^{j,R}_{nm}}{x^{j,R}_{nn}}\right) = (1-\sigma^j)\ln(\kappa^R_{nm}) + \delta^j_n + \delta^j_m + \epsilon^j_{nm} \tag{19}$$

In the model, relative trade share, $x^{j,R}_{nm}/x^{j,R}_{nn}$ can be expressed as $\frac{x^{j,R}_{nm}}{x^{j,R}_{nn}} = \frac{\Psi^j_m\left(\kappa^R_{nm}c^{j,R}_m/\mu\right)^{1-\sigma^j}}{\Psi^j_n\left(\kappa^R_{nn}c^{j,R}_n/\mu\right)^{1-\sigma^j}}$, which leads to the estimating equation 19. To empirically implement this, we model changes in iceberg costs $\ln(\kappa^R_{nm})$ explicitly as a function of average Amazon facility entry between regions m and n, as well as granular transportation infrastructure—airports, bridges, rail miles—and great-circle shipment distances: $\Delta\ln(\kappa^R_{nm}) = X'_{nm}\theta + \beta\text{AmzExposure}_{nm}$. Combining these two equations yields our main estimation specification, which connects Amazon entry directly to

Table 3: Amazon Facility Entry and Interregional Trade

	Wholesale		Manufacturing	
	$x^{j,R}_{nm}/x^{j,R}_{nn}$ (1)	d^{routed}_{nm} (2)	$x^{j,R}_{nm}/x^{j,R}_{nn}$ (3)	d^{routed}_{nm} (4)
Panel A. OLS Estimates				
Δ Amz Exposure	0.012***	-8.293**	0.013**	-5.831
	[0.003]	[3.867]	[0.005]	[3.837]
Observations	24,863	24,978	15,580	15,905
R-squared	0.078	0.328	0.101	0.340
Panel B. 2SLS Estimates				
Δ Amz Exposure	0.020***	-12.107**	0.025*	-8.271
	[0.007]	[4.698]	[0.012]	[8.482]
Observations	9,757	9,757	5,287	5,287
R-squared	-0.001	0.015	0.003	0.005
Origin, Dest., Ind. FE	X	X	X	X
Transportation controls	X	X	X	X

Notes: This table reports the effect of Amazon distribution facility exposure on interregional trade outcomes between U.S. states, using data from the Commodity Flow Survey (CFS). The dependent variables are the relative online trade share $x^{j,R}_{nm}/x^{j,R}_{nn}$ and routed shipment distance d^{routed}_{nm} between origin n and destination m. Results are shown separately for Wholesale and Manufacturing sectors. The main regressor is Δ Amz Exposure. Both OLS and 2SLS estimates are reported. All specifications include origin, destination, and industry fixed effects, as well as transportation controls. Standard errors clustered at the origin state level are reported in brackets. Asterisks denote significance at * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For the trade-share columns, coefficients can be mapped to the semi-elasticity parameter via the model relation $\delta^j = \beta(1-\sigma^j)$ if desired; β is not reported here.

trade outcomes:

$$\Delta \ln \left(\frac{x^{j,R}_{nm}}{x^{j,R}_{nn}} \right) = \delta^j \text{AvgCenter}_{nm} + X'_{nm}\theta + \delta^j_n + \delta^j_m + \epsilon^j_{nm}, \quad \delta^j = \beta \times (1-\sigma^j). \tag{20}$$

The empirical specification includes a rich set of fixed effects—origin, destination, and industry—to absorb persistent spatial comparative advantages. Using bilateral trade shares as the outcome also nets out destination-year shocks that raise inflows from all origins, not only those near new Amazon facilities. I further include detailed transportation controls (e.g., intermodal access, road quality, airport proximity) to improve the precision of the estimated coefficient on Amazon exposure.

Estimation Results. Turning to the estimation results in Table 3, the findings provide strong support for the model's prediction. Column (1) reports estimates for the relative bilateral expenditure shares, $x^{j,R}_{nm}/x^{j,R}_{nn}$, which correspond directly to the model's theoretical equation. The coefficients on Amazon facility exposure are positive and statistically significant, with a magnitude of 0.012, equivalent to about 1.2 percentage points, for both wholesale retail and manufacturing goods. Equation 20 links this estimated coefficient, δ^j, to the trade elasticity with respect to iceberg costs $\beta = \delta^j/(1-\sigma^j)$, which will be used in the model quantification in Section 5.

Column (2) provides direct evidence that Amazon facility entry reduces effective shipping frictions in the wholesale sector: a one-unit increase in Amazon exposure is associated with an 8.3 kilometer decline in actual routed distance between states—a proxy for realized shipping distance—conditioning on origin–destination, industry fixed effects, and transportation controls. This provides direct evidence that Amazon's expansion lowers effective shipping frictions beyond general transportation improvements. By contrast, Column (5) shows no significant effect for manufacturing. The insignificant coefficient in manufacturing serves as a placebo, consistent with the fact that fulfillment centers primarily handle retail and wholesale goods rather than industrial shipments.

Addressing Endogeneity with Historical Networks. One potential concern is that Amazon may endogenously expand its facility network along trade corridors that are already experiencing rapid growth. To address this, I implement an instrumental variables (IV) strategy that isolates exogenous variation in Amazon facility exposure by leveraging historical transportation networks, following the approach of Duranton, Morrow, and Turner (2014). The instrument is constructed from the interaction of historical transport routes—specifically, the 1898 U.S. railroad network and the 1947 planned interstate highway system—with a 30 (origin) × 26 (destination) matrix. These networks were developed under economic and strategic logics unrelated to contemporary e-commerce logistics: the rail network was built to support grain, livestock, lumber, and passenger movement in a predominantly agrarian economy, while the highway plan was designed for national defense and long-distance mobility rather than local trade flows. Given this historical context, these instruments are plausibly exogenous to current patterns of goods movement in the post-2012 CFS data.

5 The Aggregate Impact on Regional Economies

What are the general equilibrium effects of Amazon's distribution facility expansion on aggregate economic outcomes? In this section, we use the model to quantify the impacts of the Amazon facility expansion shock on welfare, employment, and regional inequality. We begin by outlining the quantification strategy, including the definition of welfare, the key fundamentals, and the parameters required to bring the model to the data. We then present the main results, followed by a discussion of the economic channels through which Amazon's expansion shapes these outcomes.

The counterfactual analysis begins with the 2007 initial equilibrium and introduces the Amazon expansion shock, represented by changes in the iceberg cost ($\hat{\kappa}^R_{nm}$), online match efficiency (μ), and the measure of online retailers (Ψ^j_m and O), while holding all other fundamentals constant.

5.1 Welfare Equation

I now define and derive the welfare changes and analyze the key channels. Welfare for a region is defined as real income per capita, $W_n = \frac{Y_n/L_n}{P_n}$, where $Y_n = I_n L_n + \Omega_n$ represents total income. Using the derived efficiency units of labor from equation (13), we can simplify Y_n as $Y_n = (\frac{1}{1-\beta_n})\Gamma(\frac{\nu_n-1}{\nu_n})\Phi_n^{1/\nu_n} L_n$. Next, using proportional changes or "hat algebra," welfare changes are expressed as $\hat{W}_n = \hat{\Phi}_n^{1/\nu_n}\Pi_{j=1}^J(\hat{P}_n^{j,R})^{-\eta_j}$. Labor market allocation gives $\hat{\Phi}_n^{1/\nu_n} = \hat{w}_n^{j,K}(\hat{\pi}_n^{j,K})^{\frac{-1}{\nu_n}}$ for any sector (j,K). For simplicity, I use the non-employment sector since it acts as an outside option: $\hat{\Phi}_n^{1/\nu_n} = \hat{w}_n^0(\hat{\pi}_n^0)^{\frac{-1}{\nu_n}}$. Finally, applying the retail trade share expression from equation (26) simplifies $\Pi_{j=1}^J(\hat{P}_n^{j,R})^{-\eta_j}$ to $\Pi_{j=1}^J(\hat{x}_{nn}^{j,R})^{\frac{-\eta_j}{\sigma^j-1}}(\hat{c}_n^{j,R})^{-\eta_j}$. These elements together yield the counterfactual welfare changes:

$$\hat{W}_n = \underbrace{\hat{w}_n^0(\hat{\pi}_n^0)^{\frac{-1}{\nu_n}}}_{\text{income effect}} \underbrace{\Pi_{j=1}^J(\hat{x}_{nn}^{j,R})^{\frac{-\eta_j}{\sigma^j-1}}(\hat{c}_n^{j,R/B})^{-\eta_j}}_{\text{price effect}}. \tag{21}$$

The expression for welfare changes highlights the general equilibrium channels through which e-commerce can affect an economy with interconnected regions and sectors. The term $\Pi_{j=1}^J(\hat{x}_{nn}^{j,R})^{\frac{-\eta_j}{\sigma^j-1}}(\hat{c}_n^{j,R})^{-\eta_j}$ reflects the price effects, derived from changes in the aggregated consumer retail price index. These effects depend on the region's share of local goods in consumer retail expenditure $\hat{x}_{nn}^{j,R}$ and are influenced by the demand elasticity σ^j and expenditure shares η^j at the sector level. A region's own-good expenditure share and demand elasticity serve as sufficient statistics for welfare change in many trade models, as discussed in Arkolakis et al. (2012). As e-commerce shifts demand toward non-local retailers, it increases welfare through this price channel. Sectoral differences in elasticities and expenditure shares further adjusts the welfare impact.

An additional term affecting price effects is the change in the unit cost of local retail production, $\hat{c}_n^{j,R}$, which reflects input-output linkages. This change affects both local retail prices and the expenditure share of a region's own retail goods, with consumers benefiting from a lower $\hat{c}_n^{j,R}$. As shown in equation (7), this effect is closely tied to input-output linkages. As the prices of intermediate goods adjust to wage changes, the price of local retail goods will shift based on γ_n^j, the value-added share of intermediate goods.

The income effects on welfare capture the forces of comparative advantage, under heterogeneous worker productivity and imperfect mobility across regions. The term $\hat{w}_n^0(\hat{\pi}_n^0)^{\frac{-1}{\nu_n}}$ suggests that as the non-employment rate decreases or returns for home production rise, welfare tends to increase. Although I focus on the non-employment sector to illustrate income effects, the change in total income is positively correlated with wage changes and negatively correlated with employment changes in any sector $\hat{\Phi}_n^{1/\nu_n} = \hat{w}_n^{j,K}(\hat{\pi}_n^{j,K})^{\frac{-1}{\nu_n}}, \forall(j,K)$, as shown in Galle et al. (2022). This indicates that welfare increases with the degree of worker specialization. Therefore, regions with a comparative advantage in sectors boosted by an e-commerce shock will see welfare gains, while those losing jobs to external competition will face welfare declines.

Taking stock, by explicitly accounting for demand shifts driven by consumer search, retailer location, shipping frictions, and heterogeneous labor supply, the model provides comparative statics that comprehensively reflect the general equilibrium mechanisms through which e-commerce impacts regional economic outcomes and welfare changes.

5.2 Calibration

The model is calibrated using data and variables from all 50 U.S. states. In this model, each market is defined as a region-sector pair, resulting in 400 markets in the quantification.[27] Table 4 outlines the parameters, fundamentals, and shocks across model sections that require calibration or estimation along with their sources of information, which I discuss below.

Consumption On the consumption side, I calibrate the expenditure shares for durable, non-durable, and service sector goods,η^j, using regional consumption data from the Bureau of Economic Analysis (BEA).

$$\Delta \ln(x_{nm}^{j,R}) = \delta + (1-\sigma)\Delta \ln(c_m^{j,R}) + \Delta \ln(\kappa_{nm}^R) + \epsilon_{nm}^{j,R} \tag{22}$$

For the elasticity of substitution between different retailers (σ^j), I calibrate using gravity trade flow equation (10), resulting in a log differences equation as in (22). This equation relates changes in bilateral retail expenditure shares to shifts in origination prices and iceberg costs. Origination prices are calculated from the CFS using per-unit prices—shipment value divided by shipment weight—for intra-regional shipments. Assuming iceberg costs are a flexible function of shipment distance, I then also control for changes in distances. To address potential price endogeneity, I apply a standard Hausman instrument to isolate prices from region-specific demand shocks, with results detailed in Appendix Table A1. The estimated elasticity of substitution is 1.8 for durable goods and 5.0 for non-durable goods. The non-durable elasticity aligns with existing estimates, such as 4.3 for brick-and-mortar versus online

[27] As outlined in Section 3, the model includes eight sectors: two tradable goods sectors (durable and non-durable), a service sector, and a non-employment sector. Each tradable sector contains three subsectors: manufacturing, online retail, and brick-and-mortar. Since the main dataset, CFS, uses the 3-digit North American Industry Classification System (NAICS), online Appendix Table 1 details the allocation of NAICS sectors into durable and non-durable categories, while the breakdown of online retail and brick-and-mortar sectors is discussed below.

Table 4: Parameters, Fundamentals and Shocks for Model Quantification

Section	Param.	Description	Estimation/Caliberation
Consumption	η_n^j	Sector share of consumption	CFS 2007
	σ^j	Elasticity of subs. across retailers	Keepa + IV
Labor Supply	π_n^j	Share of employment	CBP, ACS
	v^n	Fréchet shape of worker product.	Galle et al. (2022)
Production	β_n^j	Share of structures	BEA, Greenwood et al. (1997)
	θ^j	Fréchet shape of sector product.	Caliendo and Parro (2015)
	γ_n^j	Value-added share of retail goods	BEA, CFS
Expenditure	$x_{ni}^{j,M}$	Interm. expenditure share	CFS 2007
	$x_n^{j,B}$	Brick-and-motar expenditure share	CFS 2007, E-Stats
	$x_{nm}^{j,R}$	E-commerce expenditure share	CFS 2007, E-Stats
	$p_n^{j,B}$	Brick-and-motar price index	CFS 2007, E-Stats, CES
Amazon Expansion Shock	$\hat{\kappa}_{nm}^R$	Iceberg cost change	Amazon data + CFS 2007 + IV
	μ	Matching efficiency	E-stats + CES
	Ψ_m^j	Online retailer location probability	Keepa
	O_m^j	Measure of online retailers	E-stats
	T_n^j	Fréchet scale of sectoral product.	Assume constant
	A_n^j	Fréchet scale of labor product.	Assume constant

Notes: This table presents the model's calibration and details the sources of information for each parameter or fundamental.

retailers from Dolfen et al. (2019) and 5.5 across U.S. commuting zones from Gervais and Jensen (2019); as expected, the elasticity for durable goods is lower.[28]

Labor Supply. On the worker side, the Census County Business Patterns (CBP) data provide employment shares by region and sector, π_n^j, but do not separate online retail from brick-and-mortar employment. To distinguish these subsectors, I impute their regional output shares. First, I compute regional e-commerce output using E-Commerce Statistics (E-stats) for national e-commerce sales and the CFS to allocate trade flows based on seller origin, estimating each state's e-commerce output. Second, I compute regional total retail output by combining E-stats' national retail sales data with BEA value-added data to allocate output regionally. Finally, I calculate brick-and-mortar output as the difference between total retail output and regional e-commerce output, which allows me to divide the overall retail employment share accordingly between e-commerce and brick-and-mortar subsectors.

Regarding workers' labor supply elasticity, v^n, I adapt the value estimated by Galle et al. (2022), which presents a multi-sector Ricardian model with Roy (1951) type sorting

[28]Additionally, Hottman (2017) estimates an elasticity of substitution of 4.5 among stores within a county. Naturally, the elasticity of substitution among stores across different states is lower.

of heterogeneous workers whose productivities similarly characterized by joint Fréchet distributions.[29] Here I specify v^n equal to 1.5, which is the value from their preferred specification.

Production With regard to production, the share of structures in the structure-labor bundle β_n^j can be identified from the value-added share of labor over structure, which equals to $\frac{\beta_n^j}{1-\beta_n^j}$. BEA provides value-added and labor compensation, while Caliendo et al. (2018) derived value-added share of structures to be consistent with the share of capital estimates in Greenwood et al. (1997). I obtain the productivity dispersion parameter θ^j of different sectors directly from corresponding ones in Caliendo and Parro (2015), which used a multi-sector gravity equation to identify the values. For the value-added share of retail goods, γ_n^j, BEA provides the value-added for each sector, which divided by gross-output gives the share value.

Expenditure and Prices. To solve for changes in equilibrium economic variables, I calibrate three expenditure shares: the inter-regional intermediate expenditure share $x_{nm}^{j,M}$, the regional expenditure brick-and-mortar share $x_n^{j,B}$, and the inter-regional e-commerce expenditure share $x_{nm}^{j,R}$. I obtain $x_{ni}^{M,j}$ directly from the 2007 CFS data on durable and non-durable manufacturing goods. I calculate $x_n^{j,B}$ and $x_{nm}^{j,R}$ using data on total retail sales, e-commerce sales, and inter-regional retail trade. First, I distribute national e-commerce sales from E-stats to states based on inter-regional wholesale trade expenditure shares from the 2007 CFS data. Then, I distribute total retail sales from E-stats to states using state expenditure shares from the Consumer Expenditure Survey (CES), providing $x_n^{j,B}$. Lastly, I calculate $x_{nm}^{j,R}$ by allocating the remaining e-commerce retail share to various origins based on the 2007 CFS data.

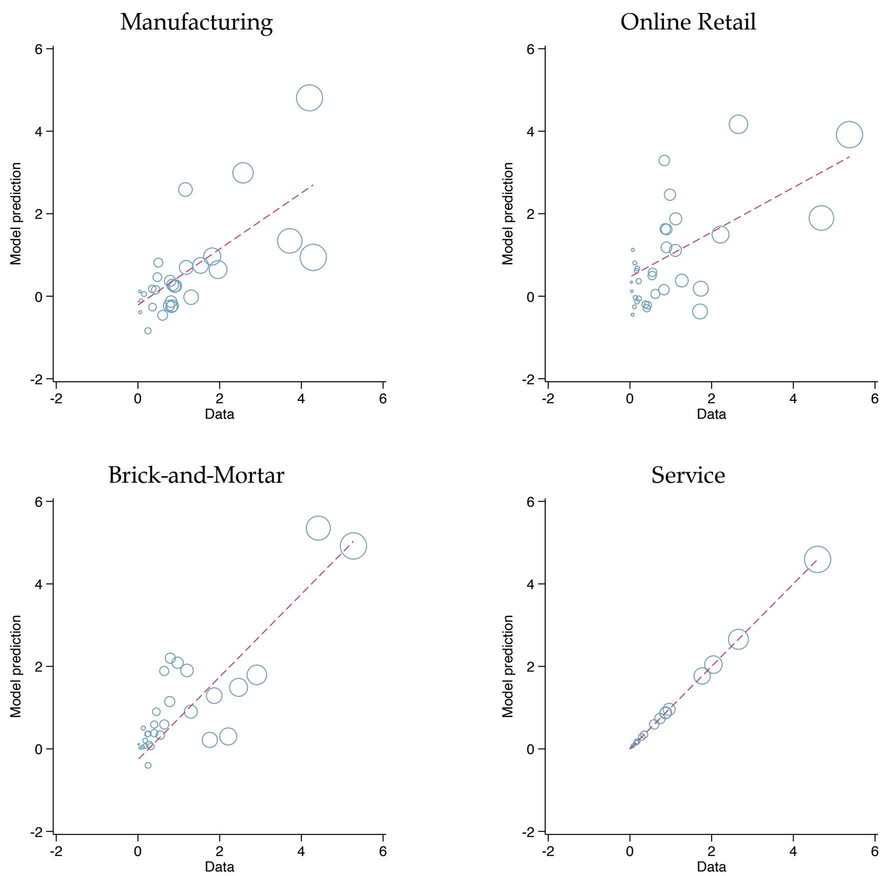
Further, I calibrate the price index of regional brick-and-mortar retail goods, $p_n^{j,B}$, for 2007 to use in solving counterfactual inter-regional trade flows, as in equation (10).[30] The CES data provide the regional price index for all retail goods. To isolate the brick-and-mortar price index, I use the regional ratio of e-commerce expenditure share to brick-and-mortar share, as derived in above steps. This ratio helps separates the brick-and-mortar price index $p_n^{j,B}$ from the overall price index P_n^j in the CES data. Specifically, I calculate $\frac{\sum_i x_{ni}^j}{x_n^{j,B}} = \left[\frac{(P_n^j)^{1-\sigma}}{(p_n^{j,B})^{1-\sigma}} - 1\right]$.[31] This approach imputes the model-consistent brick-and-mortar price indices by aligning them with the observed brick-and-mortar to e-commerce expenditure shares in the data.

[29] In their model, worker differ not only by region and sector, but also by groups that can be categorized by education level and demographics etc., leading to a more nuanced picture of welfare. Bringing the model to data on U.S. commuting zones and other countries for 13 manufacturing and a nonmanufacturing sector and using a model implied Bartick type identification, they estimate the labor supply elasticity (analogous to v^n) to range from 1.42 to 2.79, which are close to the across occupation elasticities estimated in Burstein et al. (2019) and Hsieh et al. (2019) ranging from 1.2 to 3.44.

[30] The inter-regional e-commerce price index, $p_{nm}^{j,R}$, is also needed and is calculated as $p_m^{j,B} \cdot \kappa_{mn}^{j,R}$.

[31] Expanded as $\frac{\sum_i x_{ni}^j}{x_n^{j,B}} = \frac{\sum_{i=1}^N (\frac{p_{ni}^j}{\mu})^{1-\sigma}}{(p_n^{j,B})^{1-\sigma}} = \frac{(P_n^j)^{1-\sigma} - (p_n^{j,B})^{1-\sigma}}{(p_n^{j,B})^{1-\sigma}} = \left[\frac{(P_n^j)^{1-\sigma}}{(p_n^{j,B})^{1-\sigma}}\right] - 1$.

Figure 4: Predicted and Observed Sectoral Value Added in 2007



Notes: This figure compares model predictions against observed BEA data for value added in various sectors. The data of the regional expenditure change (y-axis) predicted by the model comes from the model calculation, which is obtained by applying market clearance conditions and other calculations. The observed data (x-axis) comes from BEA directly. This figure evaluates model accuracy regarding sectoral income distribution within regional economies.

Amazon Expansion Shock. The Amazon expansion shock is captured through changes in iceberg costs ($\hat{\kappa} nm^R$), online match efficiency (μ), and the distribution of online retailers (Ψ_m^j and O). First, I estimate the change in $\kappa_{nm}^{j,R}$ using the coefficients from Table 3. Equation 20 links the estimated coefficient, δ^j, to the trade elasticity with respect to iceberg costs. Given the estimated elasticity of $1 - \sigma^j = -4.05$ for durable goods, the corresponding semi-elasticity is $\beta = \delta^j/(1 - \sigma^j) \approx 0.30$ percentage points. This value provides a direct estimate of the reduction in trade costs resulting from Amazon facility entry.

Second, I compute the distribution of online retailers directly from the 2017 Keepa data, as shown in Figure 2. Third, I impute the change in μ based on observed expenditure shares between local online and brick-and-mortar retailers and the estimated trade costs. In the model, μ enters the CES consumption function as a demand shifter. I isolate μ using the ratio of expenditure shares, which simplifies to equation (23):

$$\frac{x_{nn}^{j,R}}{x_{n}^{j,B}} = \frac{\Psi_n^j (c_n^{j,R}/\mu)^{1-\sigma}}{\frac{1}{O}(c_n^{j,B})^{1-\sigma}} = \mu^{1-\sigma} \cdot \psi_n^j (\frac{w_n^{j,R}}{w_n^{j,B}})^{1-\sigma}. \tag{23}$$

This equation shows that, given unit costs and online retailer locations, the regional e-commerce share reflects only match efficiency. With all terms in equation (23) calibrated—except for the regional wage ratio, which can be computed using CBP data—I estimate μ and find that consumers in 2017 were 27 percent more likely to buy from online retailers due to Amazon's match efficiency.

Non-targeted Moments. I now present the baseline equilibrium quantified through the model and compare it with data for non-targeted moments. As shown in Table 4, the model is calibrated to precisely match inter-regional trade shares across sectors as well as the value-added share in production. Starting with an initial guess, I apply the market-clearing conditions in equations (14) and (15) to calculate model-predicted regional expenditures by sector, which are non-targeted.[32] Figure 4 shows the model-predicted regional variations in expenditures (y-axis) alongside observed BEA data (x-axis), both normalized by mean and standard deviation, with circle sizes representing observed data.[33] As shown, the model closely aligns with regional expenditure patterns across sectors based on the data. For the service sector, which is modeled as a fixed share of total income and directly taken from BEA data, the model matches the data perfectly.

5.3 Welfare and Employment Outcomes

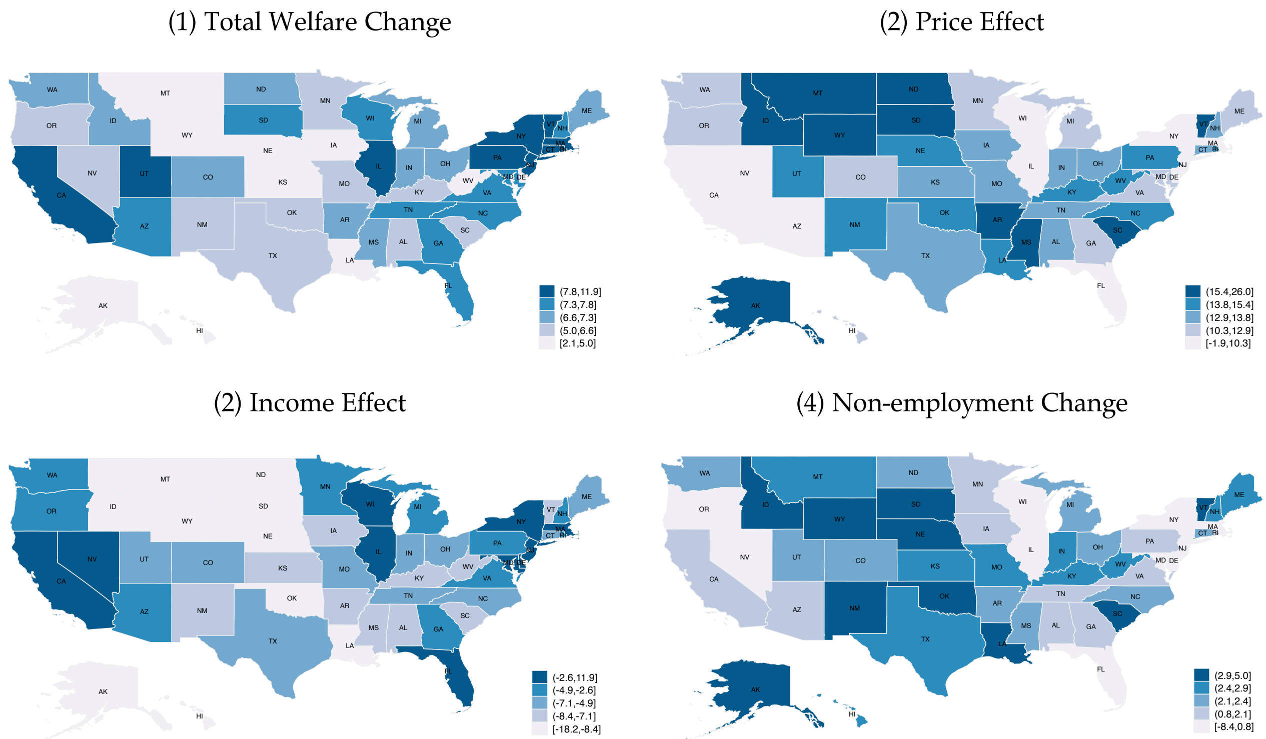
Welfare: Starting with welfare changes from the Amazon shock, Figure 5 panels (A) to (C) show state-level changes in total welfare, with separate decompositions into price and income effects. On average, total welfare across states increases by 6.7 percent–this is primarily due to price effects, while income effects have a negative impact on welfare. Specifically, price reductions from Amazon's expansion alone would have led to a 13.1 percent welfare increase. However, Amazon's growth also reallocates economic activities and labor, resulting in differential income changes across regions. This income effect alone would have reduced total welfare by 5.4 percent.

The aggregate welfare changes and their components reveal a significant variation across regions. As shown in Figure 5, states on the East and West Coasts generally experience larger

[32] Market clearing conditions described in equations (14) and (15) present a fixed-point problem. To address this, I use functional iteration to determine the equilibrium expenditures predicted by the model.

[33] Since the BEA data does not segregate retail value added between online and brick-and-mortar retailers, I employ a similar method used in estimating the ratio of e-commerce retail output to total retail output to impute regional employment share π_n^j. This output share is used to separate the BEA retail sector value added and serves as the initial guess for the model's imputation.

Figure 5: Welfare, Employment Changes and Decompositions



Notes: This figure shows state-level changes in welfare, its decomposition into price effects and income effects, as well as non-employment due to Amazon's expansion. Welfare changes and employment changes are calculated from model counterfactual analysis using hat algebra.

welfare gains, while Midwestern states see smaller increases. Breaking down to the sources, we observe that income effects exhibit greater dispersion than price effects, indicating that income changes drive much of the regional heterogeneity in welfare outcomes.

Focusing more specifically on the underlying mechanisms, states with a comparative advantage in online retailing—such as New York, Massachusetts, Wisconsin, California, and Florida—see positive income effects due to employment gains, which boost their overall welfare. These states also benefit from a diverse industrial composition, supporting wage growth across all sectors. In contrast, Midwestern states like North Dakota, Montana, and Wyoming face negative income effects from retail sector competition and worker shifts to lower-wage sectors. However, as these regions initially have lower consumer spending on online retail goods, they experience significant positive price effects, which help to offset the income-related welfare losses.

Employment: I now turn to discuss the employment changes implied by the Amazon shock and the model. Table 5 illustrates the average sectoral employment changes due to the Amazon shock in percentages. As can be seen from the table, the overall picture of employment changes due to Amazon is characterized by reallocation from all other sectors to the growing online

Table 5: Employment Changes by Sector and State Groups

	All States		Below 50th Percentile Online Sales Density	
Sector	Mean	Std. Dev.	Mean	Std. Dev.
Manufacturing	-4.3	(7.6)	-1.8	(1.1)
Online Retail	109.8	(97.8)	63.3	(64.8)
Brick-and-Mortar	-11.1	(8.0)	-8.6	(1.2)
Service	-1.6	(7.9)	1.2	(1.2)
Non-Employment	-1.3	(8.1)	1.7	(0.8)

Notes: This table summarizes the sectoral employment shifts in response to Amazon's expansion based on the model counterfactual analysis. The data on online sales density comes from Keepa. The units are ratio relative to the 2007 baseline economy.

retail sector, particularly from brick-and-motor and manufacturing. Non-employment has also declined by 1.3 percent. Since in 2007 the average non-employment rate was 38.5 percentage points, which implies that non-employment has declined by 0.5 percentage points due to the Amazon shock.

Beneath the overall rise in non-employment, there is significant regional variation. As illustrated in Figure 5, Midwestern states, which lack a comparative advantage in online retailing and have less industrial diversity, show a stronger shift toward non-employment and service sectors. The last two columns of Table 5 reveal that in states where online seller density is below the 50th percentile, online retail employment has grown by about 63.3 percent, which is 46.5 percentage points lower than the overall increase. At the same time, these states have seen higher reallocation to service and non-employment sectors, with rates increasing by 1.2 and 1.7 percent, respectively.

Implications for Inequality: As discussed above, the impacts of an Amazon shock carry significant distributional implications. Although total welfare has increased and non-employment has decreased, substantial disparities exist across states. To quantify this dispersion, I examine changes in the Gini index. Between 2007 and 2017, Amazon's expansion led the Gini index of welfare or GDP per capita to rise from 0.11 to 0.13, a 20 percent increase. Meanwhile, the Gini index for non-employment grew from 0.05 to 0.25, a fourfold increase. These results indicate a widening gap in both welfare levels and employment opportunities across regions due to Amazon's influence.

6 Conclusion

The expansion of e-commerce, exemplified by Amazon's growth, has significantly reshaped regional economies, creating both opportunities and challenges. This paper leverages data on the universe of products and retailers on Amazon, combined with detailed information on Amazon's fulfillment and distribution facilities, to provide new empirical insights into the spatial dynamics of e-commerce. The data reveal five key patterns pointing to differential spatial agglomeration of online retailers associated trade flows. These findings, which are new to the literature, highlight how e-commerce influences trade and regional economic structures.

Using these empirical insights, the paper develops a multi-sector spatial trade framework incorporating consumer search, retailer location decisions, and regional comparative advantages. Quantitative counterfactual results demonstrates that while e-commerce has driven price reductions, more consumption varieties, and improved overall welfare, it has also deepened regional disparities and altered labor market dynamics. States with a comparative advantage in online retailing and diverse industrial structures, such as New York and California, experienced welfare gains due to positive income and price effects. In contrast, Midwestern states, like Wyoming and Montana, faced income losses and increased reliance on lower-wage sectors, despite benefiting from price reductions. Employment patterns also shifted, with workers moving away from brick-and-mortar retail and manufacturing toward online retail, contributing to a 1.3 percent decline in non-employment nationally. However, less advantaged regions saw higher shifts to non-employment and service sectors. These dynamics exacerbated inequality, with the Gini index of welfare and non-employment increasing significantly. To address these disparities, I introduce a revenue redistribution policy, reallocating regional incomes to equalize welfare changes while remaining budget-neutral.

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Appendix

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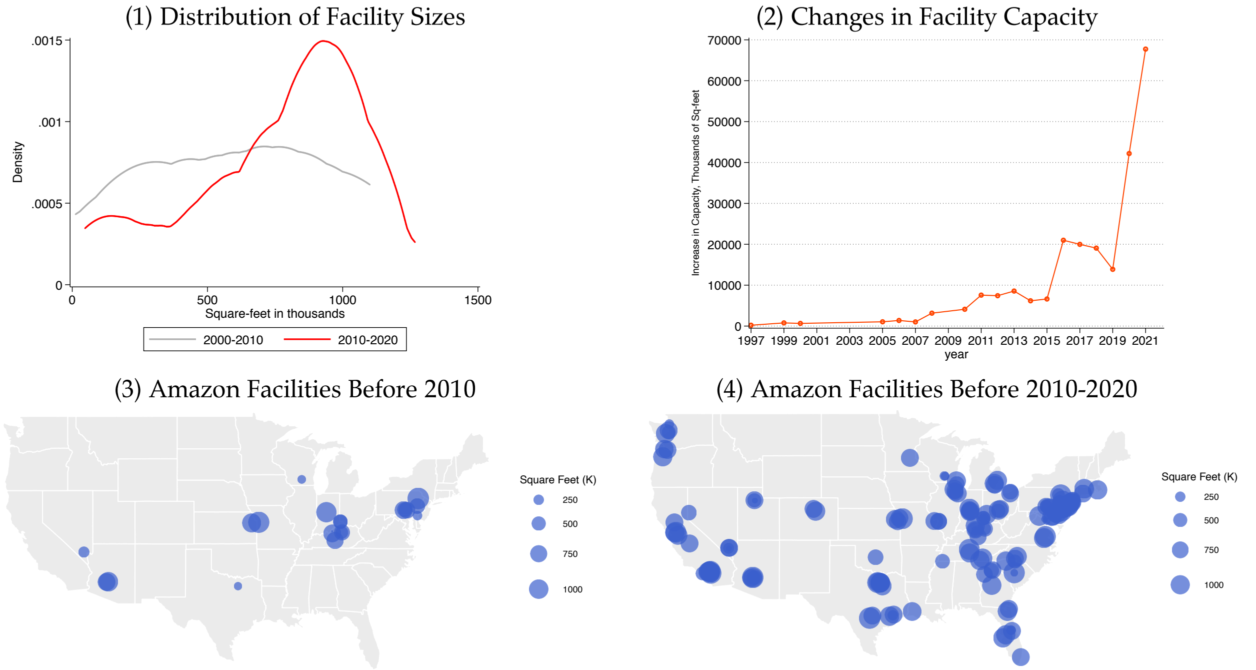
A ADDITIONAL EMPIRICAL RESULTS

Table A1: OLS and IV Estimates for σ

	OLS - Dur (1)	**OLS - Non-dur** (2)	**IV - Dur** (3)	**IV - Non-dur** (4)
$1-\sigma$	0.05***	-0.02	-0.76**	-4.05**
	[0.02]	[0.03]	[0.36]	[1.69]
Distance control	X	X	X	X
F-Stats			62.0	4.3
Observations	15,183	10,889	15,183	10,889
R-squared	0.00	0.00	-0.10	-2.06

Notes: This table displays regression results for the logarithmic difference in a destination state's expenditure share across various origin states from 2007 to 2017, based on the logarithmic difference in prices, and accounting for changes in shipping distances using CFS data. The regression coefficient for log prices indicates the value of $1-\sigma$ as per equation 22. For the instrumental variable (IV) specifications, I employ the Hausman instrument, which uses contemporaneous price changes of the same industrial goods in different geographic markets (states) to account for price changes.

Figure A1: Expansion of Amazon Facilities



Notes: This figure presents Amazon's facility growth, differentiated by facility sizes and distribution across regions. The data comes from MWPV, a supply chain consulting company (www.mwpvl.com). The focus is on large fulfillment centers that handle non-perishable goods, which are more likely to influence retail patterns and regional economies.

B THOERY AND QUANTITATIVE

B.1 Propositions and Proofs

Assumptions (Short-run Equilibrium)**.** *Comparative statics with respect to κ^R_{nm} hold the endogenous objects $w^{j,K}_n \quad (K = \{M, R, B\})$, P_n, and Y_n locally fixed. In other words, these derivatives are evaluated at a short-run equilirbrium.*

Proposition 1 (Trade Costs Reduction Seller Outcomes)**.** *Consider a reduction in the bilateral iceberg cost for online shipments from origin m to destination n, $\kappa^R_{nm} \to \kappa^R_{nm}(1-\varepsilon)$, $0 < \varepsilon < 1$. Under Assumptions B.1 and the parameter restrictions $\sigma^j > 1$, $\tau > 0$, $0 \leq \rho < 1$, the following results obtain for every tradable sector j:*

(i) *For every destination n, the sales by any online retailer in m increases, $\frac{\partial X^{j,R}_{nm}}{\partial \kappa^R_{nm}} < 0$.*

(ii) *The probability of online retailers located in m rises, $\frac{\Psi^j_m}{\partial \kappa^R_{nm}} < 0 \; \forall \, n$.; the mass of online retailers located in m rises, $\frac{\partial O^j_m}{\partial \kappa^R_{nm}} < 0 \; \forall \, n$ under the calibrated parameters in Section **??**.*

Proof of Proposition 1:

We start by proving Result (i) of Proposition 1.

For any retailer among the measure O^j_m from region m, its total sales to region n can be derived as:

$$X^{j,R}_{nm} = \eta^j X_n \left(P^{j,R}_n\right)^{\sigma^j - 1} \left(\tilde{\sigma}^j c^{j,R}_m\right)^{-\sigma^j} \left(\kappa^R_{nm}\right)^{-\sigma^j}.$$

The derivative with respect to κ^R_{nm} is

$$\frac{\partial X^{j,R}_{nm}}{\partial \kappa^R_{nm}} = -\sigma^j \cdot \eta^j X_n \left(P^{j,R}_n\right)^{\sigma^j - 1} \left(\tilde{\sigma}^j c^{j,R}_m\right)^{-\sigma^j} \left(\kappa^R_{nm}\right)^{-\sigma^j - 1} = -\sigma^j \cdot X^{j,R}_{nm} \cdot \kappa^{R\,-1}_{nm}.$$

Given $\sigma^j > 1$, $X^{j,R}_{nm} > 0$, and $\kappa^R_{nm} > 0$, it follows that $\frac{\partial X^{j,R}_{nm}}{\partial \kappa^R_{nm}} < 0$. Therefore, a reduction in κ^R_{nm} strictly increases per-firm sales to n, establishing Result (i).

Now, turning to Result (ii). We want to prove that the equilibrium measure of online retailers in region m, O^j_m, strictly decreases in response to a reduction in κ^R_{nm} (i.e., $\partial O^j_m / \partial \kappa^R_{nm} < 0$). Recall that the mass of online retailers is given by:

$$O^j_m = O \cdot \Psi^j_m \cdot \left(\bar{c}^{j,R}_m\right)^{\tau},$$

where O is exogenous, Ψ^j_m is the location choice probability, $\bar{c}^{j,R}_m$ is the cost cutoff, and $\tau > 0$. The objective is to show $\frac{\partial O^j_m}{\partial \kappa^R_{nm}} < 0 \to$ a fall in κ^R_{nm} raises O^j_m.

Step 1. Differentiate the cost cut-off $\bar{c}_m^{j,R}$. From equation **??**, we know that

$$\bar{c}_m^{j,R} \; = \; \frac{\mu z_m^{j,R}}{\tilde{\sigma}^j} \left[\frac{\sigma^j}{\eta^j} \frac{w_m^{j,R} f_m}{\sum_{g=1}^{N} \left(\kappa_{mg}^R / P_g^{j,R} \right)^{\sigma^j - 1} X_g^{-1}} \right]^{\frac{1}{1-\sigma^j}} , \qquad \sigma^j > 1.$$

Let $D_m \equiv \sum_g \left(\kappa_{mg}^R / P_g^{j,R} \right)^{\sigma^j - 1} X_g^{-1}$, $\quad \gamma \equiv \frac{1}{1-\sigma^j} = -\frac{1}{\sigma^j - 1} < 0$. Then $\bar{c}_m^{j,R} = K_m D_m^{-\gamma}$ with $K_m = \frac{\mu z_m^{j,R}}{\tilde{\sigma}^j} \left(\frac{\sigma^j}{\eta^j} w_m^{j,R} f_m \right)^{\gamma} > 0$ independent of κ_{nm}^R.

Differentiate with respect to κ_{nm}^R:

$$\frac{\partial \bar{c}_m^{j,R}}{\partial \kappa_{nm}^R} = -\gamma\,(\sigma^j - 1) \bar{c}_m^{j,R} \, \frac{(\kappa_{nm}^R / P_n^{j,R})^{\sigma^j - 1} X_n^{-1}}{D_m} \frac{1}{\kappa_{nm}^R} = \bar{c}_m^{j,R} \, \frac{(\kappa_{nm}^R / P_n^{j,R})^{\sigma^j - 1} X_n^{-1}}{D_m} \frac{1}{\kappa_{nm}^R},$$

Hence $\partial \bar{c}_m^{j,R} / \partial \kappa_{nm}^R > 0$. Consequently $\frac{\partial \left(\bar{c}_m^{j,R} \right)^{\tau}}{\partial \kappa_{nm}^R} = \tau \left(\bar{c}_m^{j,R} \right)^{\tau - 1} \frac{\partial \bar{c}_m^{j,R}}{\partial \kappa_{nm}^R} > 0$.

Step 2. Differentiate the location probability Ψ_m^j. Define

$$\Psi_m^j = \Gamma_m / \mathcal{D}, \qquad \Gamma_m \; \equiv \; T_m^{j,R} \left(\xi_m^j \right)^{-\tau/(1-\rho)}, \qquad \mathcal{D} \; \equiv \; \sum_{h=1}^{N} \Gamma_h,$$

with

$$\xi_m^j \; = \; \sum_{g=1}^{N} \left(\frac{c_m^{j,R} \kappa_{mg}^R}{P_g^{j,R}} \right)^{\sigma^j - 1} X_g^{-1}.$$

Because $\partial \mathcal{D} / \partial \kappa_{nm}^R = \partial \Gamma_m / \partial \kappa_{nm}^R$, the quotient rule gives

$$\frac{\partial \Psi_m^j}{\partial \kappa_{nm}^R} \; = \; \frac{\mathcal{D} - \Gamma_m}{\mathcal{D}^2} \frac{\partial \Gamma_m}{\partial \kappa_{nm}^R}.$$

Moreover,

$$\frac{\partial \xi_m^j}{\partial \kappa_{nm}^R} = (\sigma^j - 1)\,(c_m^{j,R} / P_n^{j,R})^{\sigma^j - 1} X_n^{-1} (\kappa_{nm}^R)^{\sigma^j - 2} > 0,$$

$$\frac{\partial \Gamma_m}{\partial \kappa_{nm}^R} \; = \; -\frac{\tau}{1-\rho} \, \Gamma_m \, \frac{1}{\xi_m^j} \frac{\partial \xi_m^j}{\partial \kappa_{nm}^R} \; < \; 0.$$

Since $\mathcal{D} - \Gamma_m > 0$, we have $\frac{\partial \Psi_m^j}{\partial \kappa_{nm}^R} < 0$. Hence probability of online retailers located in m rises when κ_{nm}^R decreases.

Step 3. Sign of $\frac{\partial O_m^j}{\partial \kappa_{nm}^R}$. Differentiate with the product rule:

$$\frac{\partial O_m^j}{\partial \kappa_{nm}^R} \;=\; O\Big[\frac{\partial \Psi_m^j}{\partial \kappa_{nm}^R}\big(\bar{c}_m^{j,R}\big)^{\tau} \;+\; \Psi_m^j\,\tau\,\big(\bar{c}_m^{j,R}\big)^{\tau-1}\frac{\partial \bar{c}_m^{j,R}}{\partial \kappa_{nm}^R}\Big].$$

From Steps 1 and 2, we have explicit expressions:

$$\frac{\partial \Psi_m^j}{\partial \kappa_{nm}^R} = -\frac{\tau}{1-\rho}(\sigma^j-1)\Psi_m^j(1-\Psi_m^j)\frac{s_{nm}}{\kappa_{nm}^R},$$

$$\frac{\partial\left(\bar{c}_m^{j,R}\right)^{\tau}}{\partial \kappa_{nm}^R} = \tau\left(\bar{c}_m^{j,R}\right)^{\tau}\frac{s_{nm}}{\kappa_{nm}^R},$$

where $s_{nm} = \frac{(\kappa_{nm}^R/P_n^{j,R})^{\sigma^j-1}X_n^{-1}}{\sum_g(\kappa_{mg}^R/P_g^{j,R})^{\sigma^j-1}X_g^{-1}} \in (0,1)$ is a share term.

Substitute these into the product rule:

$$\frac{\partial O_m^j}{\partial \kappa_{nm}^R} = O\left[\left(-\frac{\tau}{1-\rho}(\sigma^j-1)\Psi_m^j(1-\Psi_m^j)\frac{s_{nm}}{\kappa_{nm}^R}\right)\left(\bar{c}_m^{j,R}\right)^{\tau} + \Psi_m^j\left(\tau\left(\bar{c}_m^{j,R}\right)^{\tau}\frac{s_{nm}}{\kappa_{nm}^R}\right)\right].$$

Factor out common positive terms O, τ, $\left(\bar{c}_m^{j,R}\right)^{\tau}$, Ψ_m^j, s_{nm}, and κ_{nm}^{-R}:

$$\frac{\partial O_m^j}{\partial \kappa_{nm}^R} = O\tau\left(\bar{c}_m^{j,R}\right)^{\tau}\Psi_m^j\frac{s_{nm}}{\kappa_{nm}^R}\left[-\frac{\sigma^j-1}{1-\rho}(1-\Psi_m^j)+1\right].$$

Define the bracketed term:

$$b = 1 - \frac{(\sigma^j-1)(1-\Psi_m^j)}{1-\rho}.$$

Under $\sigma^j > 2, 1 > \rho, \Psi_m^j < 0.5$ (calibrated): $\frac{\partial O_m^j}{\partial \kappa_{nm}^R} \;<\; 0$. Q.E.D.

Proposition 2 (Trade Costs Reduction and Trade Flows). *Consider a reduction in the bilateral iceberg cost for online shipments from origin m to destination n, $\kappa_{nm}^R \to \kappa_{nm}^R(1-\varepsilon)$, $0<\varepsilon<1$. Under Assumptions B.1 and the parameter restrictions $\sigma^j>1,\ \tau>0,\ 0\le\rho<1$, the following results obtain for every tradable sector j:*

(i) *The bilateral online retail expenditure share $x_{nm}^{j,R}$ strictly increases.*

(ii) *Nominal bilateral trade flows $X_{nm}^{j,R} \equiv x_{nm}^{j,R}X_n^j$ strictly increase.*

Proof of Proposition 2:

Recall the bilateral expenditure share is given by Equation 10:

$$x_{nm}^{j,R} = \frac{\Psi_m^j (\kappa_{nm}^R c_m^{j,R}/\mu)^{1-\sigma^j}}{\mathcal{D}_n^j},$$

where $\mathcal{D}_n^j \equiv \sum_{h=1}^N \Psi_h^j (\kappa_{nh}^R c_h^{j,R}/\mu)^{1-\sigma^j} + O^{-1}(c_n^{j,B})^{1-\sigma^j}$ and $\sigma^j > 1$.

Define $A_{nm} \equiv \Psi_m^j (\kappa_{nm}^R c_m^{j,R}/\mu)^{1-\sigma^j}$ and $B_n \equiv \mathcal{D}_n^j - A_{nm}$. Note $B_n > 0$ is independent of κ_{nm}^R (only A_{nm} depends on κ_{nm}^R). Rewrite:

$$x_{nm}^{j,R} = \frac{A_{nm}}{B_n + A_{nm}}.$$

The derivative with respect to κ_{nm}^R is:

$$\frac{\partial x_{nm}^{j,R}}{\partial \kappa_{nm}^R} = \frac{\frac{\partial A_{nm}}{\partial \kappa_{nm}^R}(B_n + A_{nm}) - A_{nm}\frac{\partial A_{nm}}{\partial \kappa_{nm}^R}}{(B_n + A_{nm})^2} = \frac{\frac{\partial A_{nm}}{\partial \kappa_{nm}^R} B_n}{(B_n + A_{nm})^2}.$$

Since $\sigma^j > 1$:

$$\frac{\partial A_{nm}}{\partial \kappa_{nm}^R} = \Psi_m^j (c_m^{j,R}/\mu)^{1-\sigma^j}(1-\sigma^j)(\kappa_{nm}^R)^{-\sigma^j} < 0.$$

As $B_n > 0$, $(B_n + A_{nm})^2 > 0$, and $\partial A_{nm}/\partial \kappa_{nm}^R < 0$, it follows that:

$$\frac{\partial x_{nm}^{j,R}}{\partial \kappa_{nm}^R} < 0.$$

Thus, a reduction in κ_{nm}^R increases $x_{nm}^{j,R}$.

Nominal trade flows are $X_{nm}^{j,R} = x_{nm}^{j,R} X_n^j$, where $X_n^j = \eta^j Y_n$ is constant under Assumptions B.1. Thus:

$$\frac{\partial X_{nm}^{j,R}}{\partial \kappa_{nm}^R} = X_n^j \frac{\partial x_{nm}^{j,R}}{\partial \kappa_{nm}^R}.$$

From above, $\partial x_{nm}^{j,R}/\partial \kappa_{nm}^R < 0$ and $X_n^j > 0$, so: $\frac{\partial X_{nm}^{j,R}}{\partial \kappa_{nm}^R} < 0$. Q.E.D.

Proposition 3 (Trade Costs Reduction and Manufacturing Output and Employment)**.** *Consider a reduction in the bilateral iceberg cost for online shipments from origin m to destination n,* $\kappa_{nm}^R \to \kappa_{nm}^R(1-\varepsilon),\ \ 0 < \varepsilon < 1$. *Under Assumptions B.1 and the parameter restrictions* $\sigma^j > 1,\ \tau > 0,\ 0 \le \rho < 1$*, the following results obtain for the manufacturing sector M:*

- ***(i)*** *The manufacturing (intermediate-goods) output* $X_m^{j,M}$ *and manufacturing employment* $l_m^{j,M}$ *in the host region for every tradable sector j strictly increase.*

Proof of Proposition 3:

From Proposition 1 we have $\frac{\partial X_{nm}^{j,R}}{\partial \kappa_{nm}^{R}} < 0$. Since Total retail revenue in m is $X_m^{j,R} = \sum_n X_{nm}^{j}$, we have $\frac{\partial X_m^{j,R}}{\partial \kappa_{nm}^{R}} < 0$.

From market clearing condition 14, local manufacturing revenue is $X_{mm}^{j,M} = (1-\gamma_m^j)x_{mm}^{j,M}X_m^{j,R}$. Since $x_{mm}^{j,M}$ is independent of κ_{nm}^{R} (the shock is downstream), we obtain

$$\frac{\partial X_m^{j,M}}{\partial \kappa_{nm}^{R}} = (1-\gamma_m^j)x_{mm}^{j,M}\frac{\partial X_m^{j,R}}{\partial \kappa_{nm}^{R}} < 0.$$

Turning to manufacturing employment, using the market clearing condition 14, we have $l_m^{j,M} = \frac{1-\beta_m}{w_m^{j,M}} X_m^{j,M}$. Under Assumptions B.1, we have

$$\frac{\partial l_m^{j,M}}{\partial \kappa_{nm}^{R}} = \frac{1-\beta_m}{w_m^{j,M}}\frac{\partial X_m^{j,M}}{\partial \kappa_{nm}^{R}} < 0.$$

Q.E.D.

B.2 Derivation of Demand Function

Proof of Theorem 1: In a sequential ordered search model, consumers in region n optimally choose or purchase a good from sector j at retailer i where $\omega_{ni}^j - p_{ni}^j$ is maximized. Denoting this demand as D_{ni}^j, it can be expressed as $D_{ni}^j = P(\omega_{ni}^j - \ln p_{ni}^j > \max_g \ \omega_{ng}^j - \ln p_{ng}^j) = \int \Pi_{g\neq i} F_{\omega_{ng}^j}(\epsilon - \ln p_{ng}^j) f_{\omega_{ni}^j}(\epsilon - \ln p_{ni}^j) d\epsilon$. This demand D_{ni}^j equates to a discrete choice model with indirect utility $v_{ni}^j = -\ln p_{ni}^j + \epsilon_{ni}^{j,DC}$ if $F_{\omega_{ni}^j} = F_{\epsilon_{ni}^{j,DC}}$, where $\epsilon_{ni}^{j,DC}$ is the random utility a consumer derives from the retailer.

To transition from a discrete choice model to CES demand, we note that the average ϵ_{ni}^j is zero for brick-and-mortar stores and $\ln(\mu)$ for online retailers. Therefore, we can express $\epsilon_{ni}^{j,DC}$ as $\ln(\mu) + \chi^j \tilde{\epsilon}_{ni}^j$ where $\tilde{\epsilon}_{ni}^j$ has mean zero and unit variance, and χ^j is the variance of the effective match value ω_{ni}^j, assumed to vary across sectors but not regions. The demand then becomes $D_{ni}^j = \int \Pi_{g\neq i} F_{\epsilon_{ng}^{j,DC}}(\epsilon - \ln p_{ng}^j) f_{\epsilon_{ni}^{j,DC}}(\epsilon - \ln p_{ni}^j) d\epsilon$.

Assuming $F_{\omega_{ni}^j} = F_{\epsilon_{ni}^{j,DC}}$ follows an extreme type I distribution, the demand for retailer i if i is an online retailer becomes

$$D_{ni}^j = \frac{(p_{ni}^j/\mu)^{\frac{-1}{\chi^j}}}{\sum_{g=1}^{N}(p_{ng}^j/\mu)^{\frac{-1}{\chi^j}} + (p_{n0}^j)^{\frac{-1}{\chi^j}}}.$$

If i is brick-and-mortar, then

$$D^j_{ni} = \frac{p^j_{n0})^{\frac{-1}{\chi^j}}}{\sum_{g=1}^N (p^j_{ng}/\mu)^{\frac{-1}{\chi^j}} + (p^j_{n0})^{\frac{-1}{\chi^j}}}.$$

Denote the elasticity of substitution among retailers by σ_j, then $\sigma_j = \frac{1+\chi^j}{\chi^j}$. This demand function leads to sector j's demand as $C^j_n = \left[(c_{n0})^{\frac{\sigma-1}{\sigma}} + \mu \sum_{i=1}^N (c_{ni})^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma_j}{\sigma_j-1}}$. Given that the consumer's expenditure share is controlled by η^j in a Cobb-Douglas manner, the final demand function is $C_n = \Pi_{j=1}^J (C^j_n)^{\eta^j}$.

B.3 Comparative Statics in Hat Algebra

Comparative Statics. Computing the equilibrium outcomes out of the model requires solving a system of nonlinear equations (10), (12), (3), (4), and (**??**) to (**??**), which requires pinning down the levels of a large number of fundamentals and parameters. To ease the comparative statics analysis, we adopt the "exact hat algebra" method (Dekle et al. 2008) to characterize the equilibrium variables and solve for the economy in proportional changes, which greatly reduces the number of fundamentals and parameters to identify. Below we first give the definition of the competitive equilibrium of the economy.

Definition 1 (Competitive Equilibrium). *Given the fundamentals Ψ and labor supply L_n, a competitive equilibrium for this economy is a vector of wages $\mathbf{w} = \{w^j_n\}^{N,J}_{n=1,j=0}$ such that the optimality conditions are satisfied and all markets clear – equations (10), (12), (3), (4), as well as (**??**) to (**??**) hold.*

Now we turn to characterize the model equilibrium using hat algebra. Specifically, define $\hat{x}\ equivx'/x$ the relative change of any variable from its original to counterfactual equilibrium values, x and x' respectively. Since e-commerce shocks function in three channels relating to search and transportation frictions and capital capacity, proportional changes in these fundamentals can be expressed as $\hat{\mu}^j_{ni}$, $\hat{\kappa}^R_{ni}$, and $\hat{\rho}^j_n$. The equilibrium in relative changes under the e-commerce shock can be characterized by the following equations.

The share of labor in different sectors is given by:

$$\hat{\pi}^0_n = \frac{\hat{A}^0_n(\hat{w}^0_n)^{\nu_n}}{\hat{\Phi}_n},\ \hat{\pi}^{j,K}_n = \frac{\hat{A}^{j,K}_n(\hat{w}^{j,K}_n)^{\nu_n}}{\hat{\Phi}_n},\ \text{where } \hat{\Phi}_n = \sum_{h=0}^J \sum_{K=M,R} \pi^{K,h}_n \hat{A}^{K,h}_n (\hat{w}^{K,h}_n)^{\nu_n}. \tag{24}$$

The input costs are given by:

$$\hat{c}^{j,M}_n = \hat{\omega}^{j,M}_n, \quad \hat{c}^{j,R}_n = (\hat{\rho}^{j,R}_n \hat{\omega}^{j,R}_n)^{\gamma^j_n} (\hat{P}^{j,M}_n)^{1-\gamma^j_n}, \tag{25}$$

$$\text{where } \hat{\omega}_n^{j,K} = \hat{w}_n^{j,K}(\hat{l}_n^{j,K})^{\beta_n} = (\hat{w}_n^{j,K})^{1+\beta_n}(\hat{\pi}_n^{j,K})^{\frac{(\nu_n-1)\beta_n}{\nu_n}},$$

$$\text{and } \hat{P}_n^{j,M} = \left(\sum_{i=1}^{N} x_{ni}^{j,M}(\hat{\kappa}_{ni}^{M}\hat{c}_i^{j,M})^{-\theta^j}\hat{T}_i^j\right)^{\frac{-1}{\theta^j}}$$

The trade shares are given by:

$$x_{ni}^{\prime j,M} = x_{ni}^{j,M}(\frac{\hat{\kappa}_{ni}^{M}\hat{c}_i^{j,M}}{\hat{P}_n^{j,R}})^{-\theta_j}\hat{T}_i^j, \quad x_{ni}^{\prime j,R} = x_{ni}^{j,R}(\frac{\hat{\kappa}_{ni}^{R}\hat{c}_i^{j,R}}{\hat{\mu}_{ni}^{j}\hat{P}_n^{j,R}})^{1-\sigma^j}, \tag{26}$$

$$\text{where } \hat{P}_n^{j,R} = \left(\sum_{i=1}^{N} x_{ni}^{j,R}(\frac{\hat{\kappa}_{ni}^{R}\hat{c}_i^{j,R}}{\hat{\mu}_{ni}^{j}})\right)^{\frac{1}{1-\sigma^j}}.$$

Market clearing conditions now become:

$$X_n^{\prime j,R} = \sum_{i=1}^{N} x_{in}^{\prime j,R}\eta^j\left[\sum_{k=0}^{J}\sum_{K=M,R}(\frac{1}{1-\beta_i})\hat{\rho}_i^{K,k}\hat{w}_i^{K,k}\hat{l}_i^{K,k}\rho_i^{K,k}w_i^{K,k}L_i^{K,k} - \Omega_i\right], \tag{27}$$

$$X_n^{\prime j,M} = \sum_{i=1}^{N}(1-\gamma_i^j)x_{ni}^{\prime j,M}X_n^{\prime j,R}, \tag{28}$$

$$\hat{w}_n^{j,M}\hat{l}_n^{j,M}w_n^{j,M}L_n^{j,M} = \beta_n\hat{X}_n^{j,M}, \quad \hat{w}_n^{j,R}\hat{l}_n^{j,R}w_n^{j,R}L_n^{j,R} = \frac{1}{\hat{\rho}_i^{j,R}}\gamma_n^j\beta_n\hat{X}_n^{j,R} \tag{29}$$

Equations (24)-(27) from above illustrate that given the e-commerce shock $(\hat{\mu}_{ni}^j, \hat{\kappa}_{ni}^R, \hat{\rho}_n^j)$, solving for the equilibrium in proportional changes only requires information on initial allocations $(x_{ni}^{j,K}, X_{ni}^{j,K}, K = \{M, R\})$, value-added and capital capacities $(w_n^{j,K}, L_n^{j,K}, \rho_n^{j,K}, K = \{M, R\})$, exogenous trade deficits (Ω_n), as well as parameters with respect to value-added shares (β_n and γ_n^j), consumption shares (η_n^j), and trade elasticities (σ^j and θ^j). All other equilibrium variables, economic fundamentals, and parameters turn out to be irrelevant for computing real wage changes – this significantly reduces the estimation burden of conducting counterfactual analysis of the e-commerce shock.

B.4 Alternative Model with Endogenous Entry

In the previous section, I introduced a model in which an exogenous measure of online retailers choose locations across regions based on multi-variate Pareto productivity draws. In this section, I present an alternative model in which regional retailers decide whether to enter the online retail market, and the measure of entrants will endogenously determined by regional conditions. I begin by detailing the structure of this alternative model, after which I discuss the quantitative implications. Further details on the model derivation and quantitative results are provided in Appendix B.5.

B.4.1 Endogenous Local Online Retail Entry

We begin by considering a group of regional retailers that decide entering online retail, some of which may be existing brick-and-mortar retailers.[34] Following Chaney (2008), the productivity distribution of these retailers is Pareto: $P\left(Z^j < z\right) = G^j(z) = 1 - z^{-\rho}$. Retailers decide to enter the online retail market based on the profitability condition that requires that the expected revenue from selling to different destination markets n must be at least equal to the costs of entering the local region f_m: $\sum_n \left(\frac{p_{nm}^{j,R}/\mu}{P_n^{R,j}}\right)^{1-\sigma} \eta^j Y_n \geq \sigma w_m^{j,R} f_m$. Using this condition, we can derive the threshold cost $\bar{c}_m^j$, below which retailers will choose to enter the online retail market.

$$\bar{c}_m^j = \frac{\mu}{\tilde{\sigma}} \left(\frac{\sigma}{\eta^j}\right)^{\frac{1}{1-\sigma}} \left[\frac{w_n^{j,R} f_m}{\sum_n \left(\kappa_{nm}^R / P_n^{R,j}\right)^{1-\sigma} Y_n}\right]^{\frac{1}{1-\sigma}}. \tag{30}$$

The trade flow equation can be derived based on two key factors: the probability of entering online retailing, which depends on the threshold productivity, and the measure of potential entrants, which is assumed to be proportional to a region's total nominal income Y_m.[35] The bilateral export $X_{nm}^{j,R}$ from region m to region n as shown in equation 31 extends Chaney (2008) by incorporating online matching efficiency μ and vertical production factors ($P_m^{j,M}$, γ^j), which influence trade flows.[36] Similar to Chaney (2008), the regional incomes of both origin and destination regions, Y_m and Y_n, play a role, as well as the remoteness of region m to all other regions, represented by $\sum_n \left(\frac{\kappa_{nm}^R}{P_n^{R,j}}\right)^{1-\sigma} Y_n$. However, here, the remoteness reflects the threshold profitability of selling from region m to various regions, rather than being part of the price index. Local brick-and-mortar (BM) sales $X_n^{j,B}$ in region n is also modeled in

[34]Each region has a representative brick-and-mortar retailer and a measure of potential online retail entrants, which could represent either "online departments" of existing brick-and-mortar stores or a separate group of online retailers.

[35]By equating the unit cost derived from the online retail production function with the threshold cost $\bar{c}_m^j = \frac{1}{z_m^j}\left(w_m^{j,R}\right)^{\gamma^j}\left(P_m^{j,M}\right)^{(1-\gamma^j)}$, we can obtain the threshold productivity $\bar{z}_m^j = \left(w_m^{j,R}\right)^{\nu_i^j}\left(P_m^{j,M}\right)^{\left(1-\gamma_i^j\right)} \frac{\tilde{\sigma}}{\tilde{\mu}}\left(\frac{\sigma}{\eta^j}\right)^{\frac{1}{\sigma-1}}\left[\frac{w_m^{j,R} f_m}{\sum_n \left(\kappa_{nm}^R P_n^{R,j}\right)^{1-\sigma} Y_n}\right]^{\frac{1}{\sigma-1}}$.

[36]In this equation $\lambda \equiv \tilde{\sigma}^{-\rho}\left(\frac{\sigma}{\eta^j \mu^{1-\sigma}}\right)^{\frac{\sigma-\rho-1}{1-\sigma}} \frac{-\rho}{\sigma-\rho-1}$.

below.

$$X_{nm}^{j,R} = \lambda Y_m \left(\left(w_m^{j,R} \right)^{\gamma^j} \left(P_m^{j,M} \right)^{\left(1-\gamma^j\right)} \frac{\kappa_{nm}^R}{\mu} \right)^{-\rho} \times \left[\frac{w_m^{j,R} f_m}{\sum_n \left(\frac{\kappa_{nm}^R}{P_n^{R,j}} \right)^{1-\sigma} Y_n} \right]^{\frac{\sigma-\rho-1}{1-\sigma}} \eta^j Y_n \left(P_n^j \right)^{\sigma-1}. \quad (31)$$

$$X_{nn}^{j,B} = \left(\left(\omega_n^{j,B} \right)^{\gamma^j} \left(P_n^{j,M} \right)^{\left(1-\gamma^j\right)} \right)^{1-\sigma} \eta^j Y_n \left(P_n^j \right)^{\sigma-1} \quad (32)$$

Finally, the price index P_n^j is derived using the threshold cost condition, while the expenditure share of region m in n, for both retail and brick-and-mortar sales, follows from the trade flow equations. Appendix B.5 contains the full mathematical derivation. These shares capture the distribution of consumption across regions and sectors.

B.4.2 Discussion of Counterfactual Results

Appendix B.5 presents counterfactual quantitative results from the alternative model with endogenous entry, which suggests different regional economic outcomes compared to the baseline model. This alternative model indicates a welfare gain of 7.7 percent across all states, for which is comparable to the baseline. However, decomposition shows significantly stronger driving forces: the price effect alone increases welfare by 30 percent, whereas the income effect reduces welfare by 22.3 percent. In terms of employment, there is a smaller shift from brick-and-mortar and services to e-commerce, but a more pronounced decline in manufacturing employment and an increase in non-employment.

The differences in welfare and employment outcomes observed in the alternative entry model can be explained by higher price competition and market concentration. Endogenous entry introduces additional "love-of-variety" and pro-competitive effects, which amplify the price-reducing impact of improved online retail efficiency and lower shipping costs, leading to a higher welfare. Since the entry decisions and regional distribution of online retailers are influenced by local income and cost structures, the model predicts a greater reliance on comparative advantage, resulting in a more concentrated e-commerce sector. Table B1 shows that the correlation between cost changes and welfare changes is significantly stronger in the alternative entry model compared to the baseline. Additionally, Appendix B.5 reports the HHI of online retail concentration at 0.26, substantially higher than the 0.16 observed in Keepa data as shown in Figure **??**.

While greater concentration in online retailing increases overall welfare, it slows average employment growth in the sector across regions and limits labor reallocation from the service and brick-and-mortar sectors. Additionally, higher concentration in downstream retail markets intensifies the selection of cost-advantaged manufacturers, leading to greater concentration

Table B1: Reliance on Costs for Entry and Baseline Models

	Entry Model		Baseline Model	
Variables	$\hat{W}_n$	$\hat{L}_n^M$	$\hat{W}_n$	$\hat{L}_n^M$
$\hat{c}_r^{avg}$	46.8***	-21.7***	0.2	-0.3***
	[7.9]	[3.7]	[0.1]	[0.0]
Observations	50	50	50	50
R-squared	0.6	0.6	0.2	0.7

Notes: This table presents the correlation between average cost changes in both the durable and non-durable goods sectors ($\hat{c}_r^{avg}$) and regional welfare changes ($\hat{W}_n$), as well as regional changes in manufacturing employment ($\hat{L}_n^M$). The correlations are derived from the quantitative results of both the baseline model in Section 3 and the alternative endogenous entry model in Section B.4.

and reallocation in the upstream manufacturing sector. Table B1 shows that in the endogenous entry model, the negative association between cost changes and manufacturing employment is significantly stronger than the baseline model.

Another source of differences between the two models arises from their focus on different moments. The entry model incorporates additional parameters compared to the location choice model, including iceberg cost levels κ_{nm}^R, retail sector price indices $p_n^{j,R}$, regional income Y_n, changes in e-commerce efficiency $\hat{\mu}$, and the Pareto shape parameter ρ. As a result, the entry model must account for additional extensive-margin features. In the data, there is significant cross-regional differences in prices and income, which contribute to the model's prediction of higher concentration.

B.5 Alternative Modeling Details

The price index P_n^j for sector j in region n is a function of the aggregated price levels of imports from other regions and the local price level for brick-and-mortar (BM) stores. It integrates over all possible productivity levels z above a certain threshold $\bar{z}_m^j$, weighted by the productivity distribution $G(z)$, and sums up contributions from all other regions m to region n. The equation is expressed as:

$$
\begin{aligned}
P_n^j &= \left[\sum_{m=1}^{N} Y_m \int_{\bar{z}_m^j} \left(\tilde{\sigma}\frac{\left(w_m^{j,R}\right)^{\gamma^j}\left(P_m^{j,M}\right)^{(1-\gamma^j)} k_{nm}^R}{\mu z_m^j}\right)^{1-\sigma} dG(z) + \left(\left(\omega_n^{j,B}\right)^{\gamma^j}\left(P_n^{j,M}\right)^{(1-\gamma^j)}\right)^{1-\sigma}\right]^{\frac{1}{1-\sigma}} \\
&= \left[\sum_{m=1}^{N} Y_m \left(\tilde{\sigma}\left(w_m^{j,R}\right)^{\gamma^j}\left(P_m^{j,M}\right)^{(1-\gamma^j)}\frac{\kappa_{nm}^R}{\mu}\right)^{1-\sigma}\frac{-\rho}{\sigma-\rho-1}\bar{z}_m^{j\;\sigma-\rho-1} + \left(\left(\omega_n^{j,B}\right)^{\gamma^j}\left(P_n^{j,M}\right)^{(1-\gamma^j)}\right)^{1-\sigma}\right]^{\frac{1}{1-\sigma}} \\
&= \left[\tilde{\sigma}^{1-\sigma}\frac{-\rho}{\sigma-\rho-1}\sum_{m=1}^{N} Y_m \left(\left(w_m^{j,R}\right)^{\gamma^j}\left(P_m^{j,M}\right)^{(1-\gamma^j)}\frac{\kappa_n^R}{\mu}\right)^{1-\sigma}\left[\left(w_m^{j,R}\right)^{\gamma^j}\left(P_m^{j,M}\right)^{(1-\gamma^j)}\frac{\tilde{\sigma}}{\mu}\left(\frac{\sigma}{\eta^j}\right)^{\frac{1}{\sigma-1}}\left[\frac{w_m^{j,R} f_m}{\sum_n \left(\frac{R_{nm}^R}{P_n^{R,j}}\right)^{1-\sigma} Y_n}\right]^{\frac{1}{\sigma-1}}\right]^{\sigma-\rho-1}\right. \\
&= \left[\lambda \sum_{m=1}^{N} Y_m \left(\left(w_m^{j,R}\right)^{\gamma^j}\left(P_m^{j,M}\right)^{(1-\gamma^j)}\frac{\left(\kappa_{nm}^R\right)^{\frac{\sigma-1}{\rho}}}{\mu}\right)^{-\rho}\left[\frac{w_m^{j,R} f_m}{\sum_n \left(\frac{\kappa_{nm}^R}{P_n^{R,j}}\right)^{1-\sigma} Y_n}\right]^{\frac{\sigma-\rho-1}{\sigma-1}} + \left(\left(\omega_n^{j,B}\right)^{\gamma^j}\left(P_n^{j,M}\right)^{(1-\gamma^j)}\right)^{1-\sigma}\right]^{\frac{1}{1-\sigma}} \\
&= \left[\lambda \sum_{m=1}^{N} Y_m \left(\left(w_m^{j,R}\right)^{\gamma^j}\left(P_m^{j,M}\right)^{(1-\gamma^j)}\frac{\left(k_{nm}^R\right)^{\frac{\sigma-1}{\rho}}}{\mu}\right)^{-\rho}\left[\frac{w_m^{j,R} f_m}{\theta_m^j}\right]^{\frac{\sigma-\rho-1}{\sigma-1}} + \left(\left(\omega_n^{j,B}\right)^{\gamma^j}\left(P_n^{j,M}\right)^{(1-\gamma^j)}\right)^{1-\sigma}\right]^{\frac{1}{1-\sigma}}
\end{aligned}
$$

The second part of the model deals with the total exports from region m to n, denoted as $X_{nm}^{j,R}$. This equation calculates the aggregate value of goods from sector j that are exported from region m to region n. The exports are determined by the productivity threshold, wage rates, prices, and sectoral income levels in both the exporting and importing regions:

$$
\begin{aligned}
X_{nm}^{j,R} &= \int_{\bar{z}_m^j} w_m^{j,B} l_m^{j,B} X_{nm}(\phi) dG(\phi) = \int_{\bar{z}_m^j} Y_m \left(\frac{p_{nm}^j(\phi)}{P_n^j} \right)^{1-\sigma} \eta^j Y_n dG(\phi) \\
&= \int_{\bar{z}_m^j} Y_m \left(\tilde{\sigma} \frac{\left(w_m^{j,R}\right)^{\gamma^j} \left(P_m^{j,M}\right)^{\left(1-\gamma^j\right)} \kappa_{nm}^R}{z_m^j \mu P_n^j} \right)^{1-\sigma} \eta^j Y_n dG(\phi) \\
&= Y_m \left(\tilde{\sigma} \frac{\left(w_m^{j,R}\right)^{\gamma^j} \left(P_m^{j,M}\right)^{\left(1-\gamma^j\right)} \kappa_{nm}^R}{\mu P_n^j} \right)^{1-\sigma} \eta^j Y_n \frac{-\rho}{\sigma-\rho-1} \bar{z}_m^{j\,\sigma-\gamma-1} \\
&= Y_m \left(\tilde{\sigma} \frac{\left(w_m^{j,R}\right)^{\gamma^j} \left(P_m^{j,M}\right)^{\left(1-\gamma^j\right)} \kappa_{nm}^R}{\mu P_n^j} \right)^{1-\sigma} \eta^j Y_n \frac{-\rho}{\sigma-\rho-1} \left[\left(w_m^{j,R}\right)^{\gamma^j} \left(P_m^{j,M}\right)^{\left(1-\gamma^j\right)} \frac{\tilde{\sigma}}{\mu} \left(\frac{\sigma}{\eta^j}\right)^{\frac{1}{\sigma-1}} \left[\frac{w_m^{j,R} f_m}{\sum_n \left(\frac{\kappa_{nm}^R m}{P_n^{R,j}}\right)^{1-\sigma} Y_n} \right]^{\frac{1}{\sigma-1}} \right]^{\sigma-\rho-1} \\
&= \tilde{\sigma}^{-\rho} \left(\frac{\sigma}{\eta^j}\right)^{\frac{\sigma-\rho-1}{1-\sigma}} \frac{-\rho}{\sigma-\rho-1} Y_m \left(\left(w_m^{j,R}\right)^{\gamma^j} \left(P_m^{j,M}\right)^{\left(1-\gamma^j\right)} \frac{\left(\kappa_{nm}^R\right)^{\frac{\sigma-1}{\rho}}}{\mu} \right)^{-\rho} \left[\frac{w_m^{j,R} f_m}{\sum_n \left(\frac{\kappa_{nm}^R m}{P_n^{R,j}}\right)^{1-\sigma} Y_n} \right]^{\frac{\sigma-\rho-1}{\sigma-1}} \eta^j Y_n \left(P_n^j\right)^{\sigma-1} \\
&= \lambda_2 Y_m \left(\left(w_m^{j,R}\right)^{\gamma^j} \left(P_m^{j,M}\right)^{\left(1-\gamma^j\right)} \frac{\left(\kappa_{nm}^R\right)^{\frac{\sigma-1}{\rho}}}{\mu} \right)^{-\rho} \left[\frac{w_m^{j,R} f_m}{\sum_n \left(\frac{\kappa_{nm}^R m}{P_n^{R,j}}\right)^{1-\sigma} Y_n} \right]^{\frac{\sigma-\rho-1}{\sigma-1}} \eta^j Y_n \left(P_n^j\right)^{\sigma-1}
\end{aligned}
$$

The total BM sales in region n, $X_{nn}^{j,B}$ can then be expressed as:

$$
X_{nn}^{j,B} = \left(\frac{p_{nn}^{j,B}}{P_n^j} \right)^{1-\sigma} \eta^j Y_n = \left(\left(\omega_n^{j,B}\right)^{\gamma^j} \left(P_n^{j,M}\right)^{\left(1-\gamma^j\right)} \right)^{1-\sigma} \eta^j Y_n \left(P_n^j\right)^{\sigma-1}
$$

Finally, the model considers the expenditure share of region m in region n and how it changes over time that reflects how shifts in variables like wages, prices, and productivity can impact the flow of goods and services between regions:

$$x_{nm}^{j,R} = \frac{\lambda Y_m \left(\left(w_m^{j,R}\right)^{\gamma^j} \left(P_m^{j,M}\right)^{\left(1-\gamma^j\right)} \frac{\left(\kappa_{nm}^R\right)^{\frac{\sigma-1}{\rho}}}{\mu} \right)^{-\rho} \left[\frac{w_m^{j,R} f_m}{\sum_n \left(\frac{\kappa_{nm}^R}{P_n^{R,j}}\right)^{1-\sigma} Y_n} \right]^{\frac{\sigma-\rho-1}{\sigma-1}}}{\sum_h \lambda Y_h \left(\left(w_h^{j,R}\right)^{\gamma^j} \left(P_h^{j,M}\right)^{\left(1-\gamma^j\right)} \frac{\left(\kappa_{nm}^R\right)^{\frac{\sigma-1}{\rho}}}{\mu} \right)^{-\rho} \left[\frac{w_h^{j,R} f_h}{\sum_n \left(\frac{\kappa_{nh}^R}{P_n^{R,j}}\right)^{1-\sigma} Y_n} \right]^{\frac{\sigma-\rho-1}{\sigma-1}} + \left(\left(\omega_n^{j,B}\right)^{\gamma^j} \left(P_n^{j,M}\right)^{\left(1-\gamma^j\right)} \right)^{1-\sigma}}$$

$$x_{nn}^{j,B} = \frac{\left(\left(\omega_n^{j,B}\right)^{\gamma^j} \left(P_n^{j,M}\right)^{\left(1-\gamma^j\right)} \right)^{1-\sigma}}{\sum_h \lambda Y_h \left(\left(w_h^{j,R}\right)^{\gamma^j} \left(P_h^{j,M}\right)^{\left(1-\gamma^j\right)} \frac{\left(\kappa_{nm}^R\right)^{\frac{\sigma-1}{\rho}}}{\mu} \right)^{-\rho} \left[\frac{w_h^{j,R} f_h}{\sum_n \left(\frac{\kappa_{nh}^R}{P_n^{R,j}}\right)^{1-\sigma} Y_n} \right]^{\frac{\sigma-\rho-1}{\sigma-1}} + \left(\left(\omega_n^{j,B}\right)^{\gamma^j} \left(P_n^{j,M}\right)^{\left(1-\gamma^j\right)} \right)^{1-\sigma}}$$

Finally, in time difference, the price index becomes:

$$\hat{P}_n^j = \left[\sum_m x_{nm}^{j,R} \widehat{Y}_m \left(\left(\widehat{w}_m^{j,R}\right)^{\gamma^j} \left(\widehat{P}_m^{j,M}\right)^{\left(1-\gamma^j\right)} \frac{\left(\hat{\kappa}_{nm}^R\right)^{\frac{\sigma-1}{\rho}}}{\hat{\mu}} \right)^{-\rho} \left[\frac{\widehat{w}_m^{j,R} \widehat{\hat{f}}_m}{\widehat{\theta}_m^j} \right]^{\frac{\sigma-\rho-1}{\sigma-1}} + x_{nn}^{j,B} \left(\left(\widehat{\omega}_n^{j,B}\right)^{\gamma^j} \left(\widehat{P}_n^{j,M}\right)^{\left(1-\gamma^j\right)} \right)^{1-\sigma} \right]^{\frac{1}{1-\sigma}},$$

where $\hat{\theta}_m^j = \frac{\sum_n \left(\kappa_{nh}^{\prime R} / P_n^{\prime R,j}\right)^{1-\sigma} Y_n^{\prime}}{\sum_n \left(\kappa_{nm}^R / P_n^{R,j}\right)^{1-\sigma} Y_n}$.

The expenditure share of destination n from orgin m for online retailers, as well the expenditure share of brick-and-motar sales in time difference becomes:

$$x_{nm}^{j,R} = x_{nm}^{j,R} \frac{\hat{Y}_m \left(\left(\widehat{w}_m^{j,R}\right)^{\gamma^j} \left(\widehat{P}_m^{j,M}\right)^{\left(1-\gamma^j\right)} \frac{\left(\hat{\kappa}_{nm}^R\right)^{\frac{\sigma-1}{\rho}}}{\hat{\mu}} \right)^{-\rho} \left[\frac{\widehat{w}_m^{j,R} \widehat{f}_m}{\hat{\theta}_m^j} \right]^{\frac{\sigma-\rho-1}{\sigma-1}}}{\left(\hat{P}_n^j\right)^{1-\sigma}}$$

$$x_{nm}^{\prime j,B} = x_{nm}^{j,B} \left(\frac{\left(\widehat{\omega}_n^{j,B}\right)^{\gamma^j} \left(\widehat{P}_n^{j,M}\right)^{\left(1-\gamma^j\right)}}{\hat{P}_n^j} \right)^{1-\sigma}$$

Table B2: Employment Changes Based on Alternative Endogeneous Entry Model

Sector	All States		Below 50th Percentile Online Sales Density	
	Mean	Std. Dev.	Mean	Std. Dev.
Manufacturing	-44.9	(1.4)	-44.5	(1.4)
Online Retail	39.3	(3.4)	40.2	(3.6)
Brick-and-Mortar	-1.1	(2.4)	-2.0	(2.4)
Service	-1.5	(2.4)	-2.4	(2.4)
Non-Employment	6.3	(2.6)	7.1	(2.7)

Notes: This table summarizes the sectoral employment shifts in response to Amazon's expansion based on endogenous entry model. The data on online sales density comes from Keepa. The units are ratio relative to the 2007 baseline economy.