Effects of E-commerce on Local Labor Markets

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Abstract

This paper studies the effect of e-commerce on local labor markets. We exploit cross-market variation in e-commerce price advantage stemming from the enactment of the Amazon Tax—state-level legislation that mandates state sales taxes collection to out-of-state online retailers. Introducing out-of-state sales taxes lowered employment and reduced wages in transportation and warehousing, industries complementary to e-commerce. Within the in-state retail sector, the decline in brick-and-mortar employment is somewhat offset by an increase in employment in warehouse clubs and supercenters. Our results are consistent with a general equilibrium model in which consumers substitute e-commerce for big-box purchases, crowding out brick-and-mortar retail.

Keywords: E-commerce, Retail, Employment, Amazon Tax
JEL: H71; J2; L81; O33

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1 Introduction

In the last decade, the increase in the presence of online retailers (Amazon, eBay, Alibaba, Zappos, Newegg, Safeway, etc.) has led to the rapid growth of e-commerce transactions from 4 percent of total sales in the first quarter of 2010 to 11 percent of total sales in the first quarter of 2019 in the United States.[1] Retail is a key local economic activity and its workforce represents 11 percent of the total workforce in the US. Thus, the expansion of e-commerce may have important distributional consequences in local labor markets, primarily attributable to changes employment and wages in retail and retail-related industries.

There is no consensus on what the labor market adjustment to the shift in the patterns of online versus in-store retail will be. On the one hand, Gebeloff and Russell (2017), Kane and Tomer (2017) and Tomer and Kane (2021) suggest the expansion of e-commerce may harm the retail workforce, especially outside of metropolitan areas. On the other hand, Hortaçsu and Syverson (2015) casts doubt on e-commerce driving force due to its smaller size compared to Warehouse Clubs and Supercenters, and Mandel (2017) associates e-commerce with job creation and wage growth. Better understanding when and where e-commerce is costly, and how and why it may be beneficial, are key items for policy design. However, causal evidence on the effect of e-commerce on local labor markets is limited.

This paper investigates the effects of changes in e-commerce on retail and retail-related industries in US local labor markets between years 2010 and 2016. The main identification challenge to evaluate the effects of the e-commerce expansion on local labor market outcomes is that e-commerce sales grow everywhere at a pace given by local economic conditions. Hence, it is hard to distinguish changes in local labor markets that are attributable to e-commerce exposure from those that are due to changes in local economic conditions. To address this empirical challenge, we exploit the fact that out-of-state e-commerce retailers were initially not required to collect sales taxes. Thus, out-of-state e-commerce retailers had a price advantage over in-state retailers. In 2013, four US states (i.e., Maine, Minnesota, Missouri, and West Virginia) passed legislation requiring state sales tax collection by online retailers. We exploit this plausibly exogenous variation in the timing of the enactment of the Amazon Tax and use a difference-in-differences design to evaluate the effects of changes in e-commerce competition on local labor markets.

The intuition behind our analysis is that the growth of e-commerce was fueled partially by out-of-state e-commerce retailers having a price advantage over in-state retailers. We consider the enactment of the Amazon Tax as a partial or total removal of such price advantage. This idea is in line with previous work documenting the negative impact of the Amazon Tax on online sales (Baugh et al., 2018). We focus on the effects of the Amazon Tax on employment and wages in in-state Retail (i.e., 'Brick-and-Mortar' and 'Warehouse Clubs and Supercenters', also known as 'Big-Box') and Retail-related

[1]From Annual Retail Trade Survey years 2003-2017. Moreover, during the COVID-19 pandemic e-commerce has reached 15 percent of total retail sales according to the Quarterly Retail E-Commerce Sales Report, U.S. Census Bureau.

industries (i.e., 'Transportation and Warehousing') at commuting zone level.[2] We use employment data from the County Business Patterns (CBP), and wages and occupational employment shares from the American Community Survey (ACS). We compare the evolution of these labor market outcomes in commuting zones (CZs) located in states that enacted the Amazon Tax relative to CZs in states that did not pass this piece of legislation.

Using the cross-market variation in out-of-state online retailers' price advantage over in-state retailers, we document several key findings. First, rising state sales taxes on purchases from out-of-state retailers causes lower employment and reduced wages in 'Transportation and Warehousing', which are industries complementary to e-commerce. We find that the employment-to-working-age-population ratio decreases by 10 percent (i.e., -40 workers per 100 thousand working age population) on average in CZs located in states that enacted the Amazon tax. We also find a 5.9 percent decline in wages in this complementary sector. These results are statistically significant at 10 percent, and are in line with the 9 percent decline in e-commerce sales documented by Baugh et al. (2018).

Second, mandating sales tax collection to out-of-state online retailers also leads to a net decline in local retail employment of 0.8 percent (somewhat imprecisely estimated, though). Within the local retail sector, we find a 2 percent decline in Brick-and-Mortar employment (i.e., -144 workers per 100 thousand working age population), which represents 83 percent of the retail sector at baseline. This decline is somewhat offset by an 8 percent increase in Warehouse Clubs and Supercenters or 'Big-Box' employment (+88 workers per 100 thousand working age population), which represents 15 percent of the retail sector at baseline. The point estimates for the sub-sectoral employment effects described are statistically significant at 5 percent and 10 percent, respectively. The effects of the Amazon Tax on retail wages are imprecisely estimated. Our employment results point to a certain degree of substitution between local retail sub-sectors, which explains the net changes in overall in-state retail employment that we observe.

Third, we explore this substitution channel further by studying whether the labor demand response that we find is driven only by changes in the levels of employment or also by changes in the composition of employment in these sectors. Our results suggest that, when the out-of-state price advantage is removed, in-state retailers reorganize their occupational structure by reducing the share of employees in sales occupations while increasing the share of employees in service, office, professional and managerial occupations. The estimated changes in occupational shares have the expected sign, but are sometimes somewhat imprecisely estimated when averaging all post-Amazon-Tax years. These results may indicate sluggish changes in the composition of employment within the retail sub-sectors.

Fourth, we study whether the local labor market response that we find is heterogeneous in urban and non-urban CZs to account for differences in internet penetration

[2] We acknowledge that 'Warehouse Clubs and Supercenters' or 'Big-Box' retailers technically belong to the Brick-and-Mortar Retail category. To facilitate the discussion of our results, hereon, we use the term offline retailers when we refer to both groups of retailers and Brick-and-Mortar to refer to any type of in-state offline retail industry other than Warehouse Clubs and Supercenters.

and additional city sales taxes. Our main findings on retail employment and wages are driven by urban markets. Regarding the composition of employment, we find stronger evidence of changes in the occupational structure in non-urban markets, with office and service-related occupations replacing those in sales.

To investigate the potential channels leading to the in-state offline retail response to changes in the e-commerce price advantage, we also provide a conceptual framework. Through a four-sector general equilibrium model analysis, we find that our empirical results can be explained (i) by consumers' decisions being more responsive to price changes than workers', and (ii) by consumers' decisions being more responsive to price changes from big-box retail than from e-commerce retail when compared to brick-and-mortar retail. The first condition is derived from the relative difference in consumption preferences for different types of retail being larger than the relative difference in labor preferences for working in different retail sectors or last-mile transportation and warehousing. The second condition is derived from two separate assumptions: First, how much consumers substitute between big-box and e-commerce is bounded by how much consumers substitute between brick-and-mortar and big-box retail, and by how much consumers substitute between brick-and-mortar and e-commerce retail. Second, how much workers substitute between employment at big-box retailers and at last-mile transportation and warehousing is bounded by how much workers substitute between employment at brick-and-mortar and at big-box retail, and by how much workers substitute between employment at brick-and-mortar and at last-mile transportation and warehousing. Through the use of a general equilibrium model, we recognize which substitution patterns can predict different changes in employment, which in turn helps us to identify employers and employees more likely to be affected by future growth of e-commerce. Hence, with the use of the model, one could potentially predict future employment patters by looking at consumers' and workers' preferences.

This paper contributes to a growing literature that explores the role of e-commerce in the economy with a new identification strategy. By exploiting the enactment of the Amazon Tax as a source of exogenous variation, this paper evaluates how the removal of a price advantage changes incentives for both online and offline retailers which may lead to changes in the retail market structure. In that sense, this paper extends the literature evaluating e-commerce effects on market structure, competition, prices, entrance and exit, and spatial distribution (Goldmanis et al., 2010; Bar-isaac et al., 2012; Cavallo, 2017; Vitt, 2020; Pozzi, 2013; Wu, 2020; Fang, 2020; Chung, 2023). As this literature is mostly descriptive and theoretical, by exploiting the Amazon Tax in our identification strategy, this paper is the first to explore e-commerce causal effects on the economy.

Furthermore, this paper adds to the recent literature studying the effects of e-commerce on labor market outcomes. Chun et al. (2019) finds that increases in online spending are associated with local retail employment decline in Korea. The authors propose instrumenting the geographic variation in online spending with the local age distribution and online penetration rates, but they do not take into account that unobserved economic conditions may simultaneously affect online penetration rates and employment. Chava et al. (2023) finds that the staggered rollout of a major e-commerce firm's fulfillment centers reduces traditional retail employment and wages in US counties. A major drawback of this approach is that a fulfillment center opening in a county may lead to spillover effects in neighbouring counties that are considered as controls. While both Chun et al. (2019) and Chava et al. (2023) introduce innovative strategies to evaluate the effects of e-commerce effects on employment, their empirical strategies cannot overcome endogeneity issues that stem from the fact that local economic conditions may affect e-commerce retailers' decisions. Our contribution to this literature is twofold: First, by exploiting exogenous variation in the timing of the enactment of sales tax legislation, the Amazon Tax, we causally identify changes in the local labor market due to a reduction in e-commerce retailers' price advantage. Second, we extend the analysis of local labor market effects of e-commerce by exploring changes the retail occupational structure.

Lastly, this paper contributes to the literature that studies the effects of the Amazon Tax on a variety of outcomes. Baugh et al. (2018) finds that the Amazon Tax reduces online sales, while Afonso (2019) shows that it increases tax revenue. Kaçamak and Wilking (2020) shows that the Amazon Tax leads to the presence of a pass-through to consumers as well as to a reduction in online expenditure. This paper is the first to evaluate the effects of the Amazon Tax on the local retail labor market and explore the mechanisms behind these changes with a general equilibrium model.

This paper proceeds as follows. In the next section, we explore the institutional background regarding the changes in the retail sector and retail labor market as well as the history of the Amazon Tax. In Section 3 we describe the data sources. In Section 4, we describe our empirical strategy. In Section 5, we present our estimation results on the effects of Amazon tax on employment in retail and complementary sectors of e-commerce, distinguishing between retail sub-sectors in urban and non-urban areas. In Section 6, we describe a series of robustness checks. Section 7 introduces a conceptual general equilibrium framework that investigates the potential channels leading to the observed effects. Section 8 concludes.

2 Institutional Background

2.1 The Retail Sector and the Retail Labor market

In this section, we document changes in the retail sector sales and employment patterns using data from the County Business Patterns (CBP), the American Community Survey (ACS), the Annual Retail Trade Survey, the Monthly Retail Trade and Food Service Survey, and the Occupational Employment and Wages Survey (OEWS).

The retail industry is present in almost all local markets within United States, with 99.81 percent of U.S. counties having at least one retail establishment in 2003 according to the CBP. The sector has experienced several major changes in the last thirty years. First, the decline in small family owned brick-and-mortar stores due to the entrance of 'Warehouse Clubs and Supercenters' (or 'Big-Box Stores') has been widely studied as the "Walmart effect"(Fishman, 2006). Second, department stores have experienced a sharp decline in their number of establishments, that the media has denominated as the"Retail

Apocalypse". Third, the development of new technologies has enabled safely purchasing goods online with the emergence of 'E-commerce retailers'. Fourth, the sector has been widely affected by the COVID-19 pandemic, with significant drops in employment and output possibly related to the accelerated adoption of contactless shopping and curbside pickup by retailers and consumers (Dorfman, 2022).

The North American Industry Classification System (NAICS) identifies as e-commerce retailers as those retailers that do not have a store, perform most of their sales online, and are included into "Electronic Shopping and Mail Order Housing (NAICS 4541)".[3] The remaining retailers, also known as brick-and-mortar retailers, may also sell online, but are classified according to their primary business activity. [4]

While the origins of e-commerce can be traced back to the early 1980s, it was not until the mid 1990s, when the first web browsers were launched, that companies started developing e-commerce platforms. The first e-commerce companies like Book Stacks Unlimited and Amazon.com, Inc. focused on the online book market. Figure A.1a shows the evolution of the share of online sales with respect to sales in the electronic commerce and mail order houses industry. Online sales reach more than half of the total sales of the sector in the year 2009, reaching up to 80 percent in the year 2018. Hence, we consider the electronic commerce and mail order houses industry equivalent to the e-commerce sector.

Not only online sales had an immense growth in the e-commerce sector, but also the share of the e-commerce sector as part of retail experienced a substantial growth. The share of the Electronic Shopping and Mail-Order Houses sector in total retail sales went from 5 percent in 2005 to more 10 percent in 2016. The increasing importance of e-commerce is also observable through the growth rate of sales. Figure A.1b shows that the growth rate of sales of e-commerce retailers is several times the growth rate of sales of offline retailers between years 2003 and 2017.

Turning to the retail labor market, Figure A.2 shows that employment is highly correlated with sales in both e-commerce and brick-and-mortar retail. However, e-commerce is less labor-intensive compared to brick-and-mortar. Figure A.3a shows the number of employees per 100,000 USD in sales for both sectors for years 2010-2017. While in 2010 e-commerce retailers employed 1.19 workers per 1 USD in sales, brick-and-mortar retailers employed 2.98 times the number of workers relative to e-commerce retailers. By the year 2017, that difference has grown to 3.48 times. Furthermore, e-commerce labor composition is different from that of brick-and-mortar retail. Figure A.3b Panel A presents the occupational structure in retail, grouped for the main three sectors, in the year 2007 using OEWS data. Both E-commerce and Warehouse clubs and supercenters employ more employees from office and service occupations that general brick-and-mortar

[3]We use the 2012 NAICS revision. The 2017 revision eliminated the sub-category NAICS 4541.

[4]In our analysis, we also distinguish between two sub-sectors that are technically within the overall brick-and-mortar (or offline) category: (1) 'Warehouse Clubs and Supercenters' or 'Big-Box' (NAICS 4529) and (2) 'Brick-and-Mortar' retail (NAICS 44 net of NAICS 4529 and NAICS 4541).[5] To facilitate the discussion of our results, we use the term Brick-and-Mortar to refer to any type of in-state offline retail industry other than Warehouse Clubs and Supercenters. We acknowledge that 'Warehouse Clubs and Supercenters' or 'Big-Box' technically belong to the Brick-and-Mortar Retail category.

sectors. In turn, e-commerce retailers employ less employees of sales and related occupations, but require services from the last-mile transportation and warehousing sector. Figure A.4 shows how the growth rate of e-commerce retail sales is highly correlated with the growth rate of employment in last-mile transportation and warehousing in the period studied.

Finally, there is also evidence that the retail sector is moving to a hybrid retail model: an increase in brick-and-mortar online sales combined with changes in the retail occupational structure. First, the share of online sales from offline retailers have more than double between 2005 and 2016. Even when those shares remain small, the changes preempt the COVID-19 pandemic (see Figure A.5a). Second, the number of establishments from offline retailers has decline more than 7 percent in the same period. Third, the occupational structure of retail has experienced several changes. Figure A.6 presents the changes in retail occupational shares for the 4 major occupational groups with respect to the corresponding shares in 2005 from the American Community Survey (ACS). The retail sector in 2005 represents around 10 percent of the total employed population, and the share of sales and related occupations is 53 percent of the retail employees. Hence, a reduction in the share of sales and related occupations in retail of 5 percent from 2005 to 2017 represents 1 percent less employees in sales and related occupations, or more than 1M employees not working in sales and related occupations anymore. This descriptive evidence suggests that brick-and-mortar retailers may have made some adjustments to sell online and adopt a hybrid model.

In order to explain these changes in the retail sector sales and in the retail labor market outcomes, first and foremost, we consider the evolution of retail competition. The first indicator of the type of competition is that prices from websites and physical stores are similar in US 69 percent of the time (Cavallo, 2017). However, Cavallo's (2017) analysis of US prices does not include tax rates or contemplate tax rates differences due to state legislation. As out-of-state online retailers were initially exempt from collecting sales taxes, they had a price advantage over brick-and-mortar retailers. With a sufficient price advantage, more consumers may choose to buy online. Hence, the price advantage could have accelerated the growth of e-commerce and could have lead the changes in the retail labor market. Leveling the playing field, as out-of-state e-commerce retailers are being required to collect sales taxes by new state legislation, results a reduction of out-of-state online sales documented by (Baugh et al., 2018; Einav et al., 2014). In the next section, we introduce the details of what the legislation change entailed, to later focus on the effects of the Amazon Tax on local labor markets.

2.2 The Amazon Tax

The enactment of the Amazon Tax by state legislators mandates that out-of-state retailers are to collect state sales taxes for purchases realized in state. To provide some context, consumers across the US are responsible for paying sales taxes for out-of-state purchases, also known as "use taxes". Use taxes are set to discourage circumventing sales taxes through out-of-state consumption. Consumers are required to remit use taxes on the income tax returns annually. However, Manzi (2010) finds that only 27 states that have sales and income taxes include a line on the income tax return to report use tax. Furthermore, he finds that more than 89 percent of the of income tax returns of those states do not report any use tax. Low compliance on use tax reporting could be explained due to use taxes not being collected at the time of the purchase and consumers relying on retailers to collect sales taxes.[6]

Moreover, in the 1992 case *Quill v. North Dakota*, the US Supreme Court ruled that out-of-state retailers cannot be required to collect state sales taxes due to lack of nexus (physical presence) in the state. The reason sustained by the Court was that otherwise collecting sales taxes would impermissibly burden interstate commerce due to many diverse taxing jurisdictions (Lunder and Pettit, 2014). Hence, since 1992, the US Supreme Court ruling has given a price advantage to out-of-state online retailers over brick-and-mortar retailers. Furthermore, several researchers estimate and forecast revenue losses from uncollected state sales taxes due to e-commerce. Bruce and Fox (2001) estimates these losses were $7B in 2001 and forecasts those losses to be $29.17B in 2011 (2.83 percent of total sales tax collection). As estimates and forecasts have been updated the revenue losses have increased.[7]

As state government's concerns increased, in 2008, the state of New York enacted the first legislation that changed the definition of nexus to require sales tax collection from out-of-state retailers. The definition of nexus as physical presence was replaced by "having a constitutionally sufficient connection between the state and business". The new legislation considers retailers that have affiliates, associates or subsidiaries in state to have a sufficient connection with the state, and hence being required to collect sales taxes.[8]

In the following years, 28 states have implemented sales taxes on out-of-state e-commerce sales by making the definition of nexus broader. These legislation changes, also known as the "Amazon Tax", have been associated to increases in sales tax collection and declines in consumption. Afonso (2019) finds that the Amazon Tax increases local sales tax revenue while comparing tax revenue collection in North Dakota counties with South Dakota counties after North Dakota enacted the Amazon Tax. Moreover, he finds that the policy change benefits urban jurisdictions more so than rural or tourism-rich

[6]Since the difference between sales taxes and use taxes relies on the location of the retailer, on the remaining of the paper, we will use sales taxes and use taxes interchangeably.

[7]Bruce and Fox (2004) estimate the losses as $15.5B in 2003 and forecast them as $21.5B in 2008. Bruce et al. (2009) update the estimates to $23.39B in 2008 and the forecast to $30.67B in 2011 with an high growth sales scenario of $40.82B for the same year. Additionally, Omar et al. (2008) estimates that the revenue losses would rise to $62.1B by 2011.

[8]A previous attempt to increase and simplify sales tax collection, in 2005, 13 state governments signed the Streamline Sales and Use Tax Agreement (SSUTA), while 10 additional states were incorporated as full members at a later date. The agreement is meant to ease the registration process for businesses operating in multiple sales tax-levying states, as well as set common sales tax-related definitions and rules, simplifying rate structures. The agreement also provides exemptions for smaller remote sellers from tax collection responsibilities, even though they were already exempt from collecting due to *Quill*. Finally, the agreement proposes providing all participating remote sellers free tax software. Nevertheless, as the definition of nexus requires physical presence, in SSUTA states, out-of-state retailers collect tax voluntarily. Hence, the effect of SSUTA on tax revenue collection is not clear.

jurisdictions due to the urban jurisdiction also collecting local sales taxes. Additionally, Baugh et al. (2018) estimates a reduction of Amazon purchases by 9.4 percent due to Amazon sales tax collection. These findings are supported by Kaçamak and Wilking (2020), which finds that consumers face higher prices and in turn reduce their online expenditures.

These papers focus on the year in which Amazon.com, Inc. starts collecting sales taxes (as opposed to considering the year when the legislation is introduced). The timing of Amazon's decision to start collecting sales taxes may be correlated with local economic conditions that also affect other retailers decisions, leading to possible endogeneity issues. As previous papers study the effect of taxes on consumer behavior, relying on Amazon Tax collection does not bring the same endogeneity issues that it would when studying labor market outcomes. Contrary to previous work, we focus on the Amazon Tax enactment dates from state legislation to avoid any type of anticipation that retailers and consumers may face.

The Amazon Tax definition of nexus only allowed state governments to collect sales taxes from out-of-state retailers that were selling their own goods. However, some online retailers, like Amazon, act both as retailers and a marketplace. In a further effort to reduce tax revenue losses, state governments enacted new legislation in the years 2017 and 2018, that broadened the definition of nexus to include marketplace collection. Hence, we restrict the analysis to the period 2010-2016.

Finally, in the 2018 case *South Dakota v. Wayfair, Inc*, the US Supreme Court overruled *Quill* stating not only that physical presence was no longer needed, but also highlights "the inherently unfair competitive advantage of online retailers over retailers with a physical presence in a state and the economic distortions caused by businesses who intentionally avoid any physical presence in a state." (Newmark et al., 2019). In other words, the *Wayfair* ruling supports the idea that before the enactment of the Amazon Tax, out-of-state retailers had a price advantage over brick-and-mortar retailers. Removing that price advantage through sales tax collection affected consumption patterns and helped the states recover tax revenue losses, however, it is unclear how it affected local business in particular and local labor markets in general.

3 Data

This section describes the data we use to investigate the effect of removing the out-of-state online retailers price advantage on in-state retail and retail-related labor market outcomes between 2010 and 2016.

First, we obtain data on employment for selected industries from the County Business Patterns (CBP).[9] The CBP data is elaborated by the U.S. Census Bureau from the Business Register (BR), which combines several data sources: the Economic Census, the Annual Survey of Manufactures and Current Business Surveys, and IRS administrative records. The CBP county-level annual data includes the number of establishments and

[9]We focus on industries NAICS 44, 4529, 4541 and 49. We also look at establishment counts for those industries from CBP in Appendix A.2

employment during the week of March 12, first quarter payroll, and annual payroll of each 6-digit industry. To preserve the confidentiality of individual employers, the U.S. Census Bureau suppressed the number of employees for the majority of county-industry cells. Accordingly, a flag is provided indicating the bin in which the suppressed number belongs to. Bartik et al. (2018) and Eckert et al. (2021) both overcome this suppression by developing linear programming methods that impute the suppressed values. We use the Eckert et al. (2021) imputed version because it harmonizes industry codes to NAICS 2012, and bridges county codes making them consistent over time.[10]

Second, we combine the CBP data on employment with population data from the Census Intercensal Population Estimates for the periods 2000-2010 and 2010-2020 to construct two outcome variables: employment-to-working-age-population.[11] The Census Intercensal Population Estimates is a product from the U.S. Census Bureau, which reconcile the population and housing units post-censal estimates with the census counts at the county, state and national level. The annual population county estimates account for births, deaths and migration patterns and are constructed using the Das Gupta method, confirming that the sum of county estimates amounts to the national level.

Third, we obtain data on wages and occupational structure from the IPUMS-USA version of the American Community Survey (ACS). This dataset, collected yearly since 2005, consists of a yearly 1-in-100 nationally representative sample and contains questions regarding employment status, occupation and pre-tax wages and salaries received in the previous calendar year (annual income wages). We deflate wages and salaries to 2014 USD and measure changes in the occupational structure through changes in occupational shares. We harmonize occupational codes to the 2010 Standard Occupational Classification System (SOC). We focus on annual income wages of employees in retail and last-mile transportation and warehousing. We examine changes in 4 occupational shares: share of sales and related occupations (SOC 41-), share of office and service occupations (SOC 43-, and 3X-), share of managerial and professional occupations (SOC 1X- and 2X-) and share of production, construction and transportation and material moving occupations (SOC 53-, 51-, 45-, 47- and 29-).[12] The smallest identifiable geographical unit in ACS data is the Public-Use Microdata Area (PUMA) defined by the Census Bureau every 10 years.

Fourth, we identify dates of enactment of the Amazon Tax from state legislation. We complement this information with dates in which one of the biggest e-commerce retailers, Amazon, started to collect sales taxes in each state from Baugh et al. (2018) and Amazon own reports on its website by using Wayback Machine. We also review the

[10]Eckert et al. (2021) imputes 1975-2016 CBP employment values with an algorithm that relies on linear programming. The algorithm minimizes the distance to the midpoint of the flagged bin, conditional on being inside the interval and all values adding to the parent category both by industry and geography. The algorithm also accounts for inconsistent bounds due to possible errors either in the employment of disclosed cells or in the employment bounds of the suppressed cells.

[11]To evaluate changes in establishment counts in Appendix A.2 we look at the number of establishments per capita.

[12]We will label the "share of production, construction and transportation and material moving occupations" as the "occupational share of construction, production and transportation" from now on.

dates in which state governments signed Voluntary Collection Agreements (VCA) with Amazon, Inc from Kaçamak and Wilking (2020) and records from newspaper articles.

Fifth, to assess the effect of e-commerce on local labor markets, we use commuting zones (CZs) as units of observation. The concept of CZ to define regional economies is commonly used in previous work, and has the advantage of relying in economic geography as opposed to state borders or population (Dorn, 2009; Autor et al., 2013, 2019). We collapse the CPS and population data to the CZ level using crosswalks from CBP county 2000 and CBP county 2010 definitions provided by Autor et al. (2013). We collapse the ACS data to the CZ level using crosswalks from PUMA 2000 and PUMA 2010 definitions to CZ definition provided in Autor and Dorn (2013). Our analysis includes 229 CZs that cover both urban and non-urban areas in thirteen US states, four of which enacted the Amazon Tax in 2013.[13] We consider a CZ as urban if it is above the percentile 75 of the population distribution from year 2000 Census. Exploring whether there are heterogeneous effects of e-commerce across urban and non-urban CZs is informative because urban areas are more likely to be subject to additional local sales taxes and to have better access to high-speed internet.

Finally, in the sensitivity analysis, we use additional sources of data to check that our results are robust to controlling for a series of consumption predictors (i.e., median household income, location Amazon fulfillment centers, industry GDP distribution, sales tax levels across states, and CZs' demographic characteristics) because the effects of the Amazon Tax in local labor markets may be mediated by shifts in consumption patters. We describe these data sources in detail in the Appendix A.3.

4 Empirical Strategy

The main objective of our analysis is to identify the effects of changes in e-commerce on local labor market outcomes. The main empirical challenge is that the evolution of online and offline retail are not exogenous to local economic conditions. To causally identify the effect of e-commerce on employment and wages, we leverage the idea that the e-commerce growth was fueled, in part, by the price advantage that out-of-state e-commerce retailers had over in-state retailers who were subject to the sales tax. In an ideal experiment, we would randomly remove this price advantage in treated states and compare their labor market outcomes evolution relative to control states. In the absence of such experiment, we use a difference-in-differences (DID) approach that allows us to estimate the effect of a change in tax policy at state level—the Amazon Tax—on local labor market outcomes at CZ level.

We use this quasi-experimental setting to compare the evolution of labor market

[13]We divide the 7 percent of the 216 CZs in our sample that cross state borders leading to a total of 229 CZ-state observations. One advantage of splitting CZs by states is that the partition of a CZ in an untreated state is a good comparison of the partition of the same CZ in a treated state. However, if the local markets are integrated, spillovers may occur, leading to the violation of stable unit treatment value assumption (SUTVA). We show that our results are robust to excluding CZs that cross state borders.

outcomes in CZs located in states that enacted the Amazon Tax relative to CZs located in states that did not pass this state tax legislation. Contrary to previous work, we define the treatment as the enactment of an the Amazon Tax by a state government. In our view, defining treatment when Amazon actually starts collecting sales taxes is subject to biases that arise from anticipation from consumers and retailers.[14]

We make a series of sample restrictions: (i) we start our period of analysis in 2010 to avoid overlap with the Great Recession in years 2008-2009; (ii) we exclude New York state, which passed the Amazon Tax in 2008 due to the same reason; (iii) we exclude states that enacted the Amazon Tax to close to the start (end) of our period of analysis because we would not have enough pre-treatment (post-treatment) years; (iv) we exclude states that signed voluntary collection agreements (VCA) to avoid selection bias and anticipation. These VCA would have involved negotiation between state officials and Amazon; (v) we exclude from states with no state sales tax; and (vi) we exclude the analysis of the effects of follow-up legislation that broadened the definition of nexus to include marketplace collection in 2017 and 2018. Our final sample is a panel of 216 CZs, located in 13 US states, spanning the period between 2010 and 2016. Figure 1 shows our sample of treated and control states. Our treated states are those that enacted the Amazon Tax in 2013: Maine, Minnesota, Missouri, and West Virginia. Our sample of control states are those that did not enact the Amazon Tax between 2010 and 2016 (i.e., never treated): Hawaii, Idaho, Iowa, Mississippi, Nebraska, New Mexico, Utah, Wisconsin, and Wyoming.

Table 1 shows a comparison of some baseline observable characteristics in CZs located in treated and control states. CZs in states that enacted the Amazon Tax have higher sales tax rates, lower household income, and higher rate of older, and more educated population. Moreover, the industry composition is different across CZs in treated and control states. While the DID approach does not require that treated and control units are similar in characteristics, it relies on the assumption that the outcome variables in treated and control units would have evolved similarly in the absence of treatment. In the robustness checks, we show that our results are robust to controlling for a series of baseline characteristics and we formally test the parallel trends assumption.

4.1 Econometric Specification

In this section, we explain the specifications we use to estimate the effect of the Amazon Tax on local labor markets, and we discuss our identification assumptions.

Local labor markets may differ in level and trend before the enactment of the Amazon Tax, meaning that any direct comparison between CZs in states where the price advantage was removed and those where it was not removed would be biased. To address pre-existing differences and to be able to explore within-CZ variation in labor market outcomes, we estimate the following difference-in-differences model:

[14] Baugh et al. (2018) and Afonso (2019) assume that consumers cannot anticipate Amazon decision to collect sales taxes even though multiple news articles announced the changes.

$$Y_{cy} = \alpha_c + \gamma_y + \delta D_{sy} + \epsilon_{cy} \tag{1}$$

where the dependent variable Y_{cy} is a labor market outcome of CZ c in year y, D_{sy} is a dummy variable that equals one after the Amazon Tax is enacted in state s in year 2013, and ϵ_{cy} is the error term. The specification includes CZ fixed effects, α_c, to account for time-invariant unobserved determinants of labor market outcomes at CZ level, and time fixed effects, γ_y, to control for time-specific factors that are common across CZs. The coefficient of interest δ estimates the causal effect of the Amazon Tax on local labor market outcomes. The regressions are weighted by the initial CZ's population, and we cluster standard errors at the level at which treatment takes place (i.e., state).

Our main outcomes of interest are employment-to-working-age-population ratios, wages, and retail occupational shares. For the latter, we define the shares of employment in occupations i in CZ c and year y, $Y_{cyi} = \frac{Emp_c yi}{Emp_c y}$. We focus on the following four retail occupations: (i) sales (SOC 41-), (ii) office and service (SOC 43-, and 3X-), (iii) construction, production and transportation (SOC 53-, 51-, 45-, 47- and 29-), and (iv) managerial and professional (SOC 1X- and 2X-).

We use Equation 1 to estimate the effect of removing the price advantage of out-of-state online retailers on three in-state retail (NAICS 44) and retail-related industries: (i) last-mile transportation and warehousing (NAICS 49), a sector complementary to e-commerce; (ii) warehouse clubs and supercenters, also known as big box (NAICS 4529); and (iii) brick-and-mortar retail. We also show the overall effect on in-state retail (i.e., the sum of in-state e-commerce, brick-and-mortar retail, and big-box retail).[15]

Equation 1 consistently estimates the causal effect of D_{sy} under the assumption that CZs in states where the legislation was enacted and CZs in states which did not enact the Amazon Tax would have had common changes in outcomes in the absence of the shift in tax policy. Our main identification assumption is that CZs in treated and control states had pre-Amazon-Tax parallel trends in employment, wages, and occupational shares that would have continued in the absence of the treatment.

In order to test for the parallel trend assumption we also estimate the following event study model:

$$Y_{cy} = \alpha_c + \gamma_y + \sum_k \psi_k D_{sy}^k + \epsilon_{cy} \tag{2}$$

where the main parameters of interest, ψ_k, capture the difference in the average of Y_{cy} that is due to comparing between CZs in treated and control states at each moment in time with respect to the year before treatment (2012). We pay special attention to the estimates of ψ_k for $k < -1$. If those estimates are deemed non-statistically different from zero, we fail to reject the hypothesis of parallel trends. Additionally, we perform an F test to evaluate if the linear trends in the outcome variable of control and treatment

[15] The definition of transportation and warehousing (NAICS 49) does not include freight or transportation of passengers, only postal services and courier messengers which represents last-mile transportation. We define brick-and-mortar retail as offline retailers in the category NAICS 44, excluding warehouse clubs and supercenters (NAICS 4529) and in-state e-commerce retailers (NAICS 4541).

groups are parallel during the pre-treatment period. We report the p-values of the F-test together with the main results. Figures 2, 3 and 4 show the event studies for our main outcome variables; we do not find evidence of violation of the parallel trends assumption. Additionally, in Section 6 we include a sensitivity analysis to evaluate the existence of effects when relaxing the parallel trend assumption, following Rambachan and Roth (2023).

Finally, for the baseline analysis, we assume that there are no spillover effects between CZs located on state borders. One possible threat to this assumption is that in those CZs, the enactment of the Amazon Tax in a particular state affects not only the employment in the CZs in that state, but also employment in neighbouring CZs out of that state. Additionally, CZs that are located in more than one state may violate this assumption if their markets are integrated, leading to spillover effects to the area located in control state. In order to evaluate these threats to the stable unit treatment value assumption (SUTVA), we exclude from the specification all CZs that cross state borders as a robustness check.

5 The Effects of the Amazon Tax on Local Labor Markets

Thus far, the empirical evidence on the adjustment of the retail sector to the expansion of e-commerce highlights the following stylized facts: (i) e-commerce is less labor-intensive compared to traditional retail; (ii) e-commerce is associated with increased labor demand in transportation and warehousing—a retail-related sector; (iii) e-commerce still represents a very small fraction of the total retail sector despite its considerable growth; (iv) there is a high correlation between sales and employment in the overall retail sector; (v) traditional retail has the technological capabilities to adapt their selling model and compete with e-commerce by selling its products online and in stores.

We consider the Amazon Tax as a plausibly exogenous negative shock to the e-commerce sector because it removed the price advantage it had over in-state retail. In line with this idea, previous work shows that the Amazon Tax is associated with declines in online sales (Baugh et al., 2018). A reduction in online sales could be driven by (a) consumers substituting out-of-state online purchases with offline in-state purchases, or (b) consumers narrowing their overall consumption. In scenario (a), the negative product-demand shock to out-of-sales e-commerce implies a positive product-demand shock for in-state retail, but a negative service-demand shock for transportation and warehousing—a sector complementary to e-commerce. In scenario (b), there is a negative shock to the overall retail sector; its sub-sectors (i.e., e-commerce, brick-and-mortar, and big box) may respond to lower sales by adjusting their competition strategies. For example, in-state retailers may switch to a hybrid sales model (i.e., click-and-brick) to compete with e-commerce.

In this section, we present our estimation results of the effects of the Amazon Tax on local labor market outcomes in retail and retail-related industries. We guide our interpretation of the results taking into account the five stylized facts mentioned above, and in Section 7, we complement our empirical evidence with a general equilibrium model to help rationalize our findings.

5.1 The effects of the Amazon Tax on Local Employment

We start by examining the effect of the Amazon Tax on in-state employment in retail and retail-related sectors in Table 2. First, Panel A presents DID estimates of Equation 1 using our sample of 229 urban and non-urban CZs. Column 1 shows that the employment-to-working-age-population ratio in transportation and warehousing decreases by 10 percent (i.e., -40 workers per 100 thousand working age population) on average in CZs located in states that enacted the Amazon tax. This effect represents a 10 percent decrease from the pre-period baseline mean; the coefficient is statistically significant at 10 percent. This result is in line with the idea that e-commerce retailers experienced a negative product-demand shock when their price advantage was removed, and in turn, they decreased the demand for transportation and warehousing.

Second, we explore the effects of the Amazon Tax on employment in the overall retail sector (Column 2) and in two offline retail sub-sectors: warehouse clubs and supercenters (Column 3) and traditional brick-and-mortar (Column 4).[16] Mandating sales tax collection to out-of-state online retailers also leads to a net decline in local retail employment of 0.8 percent (somewhat imprecisely estimated, though). Within the local retail sector, we find a 2 percent decline in brick-and-mortar employment (i.e., -144 workers per 100 thousand working age population). This decline is somewhat offset by an 8 percent increase in warehouse clubs and supercenters employment (88 workers per 100 thousand working age population). The point estimates for the sub-sectoral employment effects described are statistically significant at 5 percent and 10 percent, respectively. Our results suggest that once the out-of-state price advantage is removed, competition between in-state offline retailers increases: Big-box retailers increase labor demand while other brick-and-mortar retailers reduce it.

Third, we examine whether there are heterogeneous employment responses across urban CZs (Panel B) and non-urban CZs (Panel C). This distinction is important because urban areas have higher access to internet and also collect local sales taxes. Our main employment results are driven by urban CZs.

Fourth, in the last row of each panel we report p-values corresponding to an F-test to assess the presence of parallel trends in the outcome variables in the pre-period. All p-values are larger than 0.05, which means that we fail to reject the null hypothesis that test for the presence of parallel trends. In Section 6, we perform a sensitivity analysis following Rambachan and Roth (2023) honest parallel trends design.

Finally, we examine the dynamic effects of the Amazon Tax on the same outcomes in the event studies presented in Figure 2. We observe no pre-period differences in employment between CZs in treated and controls states. Overall, the panels show that

[16] The brick-and-mortar sub-sector represents 83 percent of the retail employment at baseline; the warehouse clubs and supercenters sub-sector represents 15 percent of the retail employment at baseline.

the post-treatment response in employment outcomes occurs one or two years after the Amazon Tax is enacted. Panel (b) shows a net decline in employment in the overall retail sector two years after the tax enactment, followed by a recovery in the fourth year, which is driven by brick-and-mortar retail. We take this result as suggestive evidence that the traditional brick-and-mortar retail sector adjustment to the Amazon Tax may have involved switching to a hybrid model (e.g., click-and-brick). Our results imply that once the price advantage of out-of-state online retailers is removed, in-state brick-and-mortar retailers may have incentives to enter to the online retail market to compete against out-of-state e-commerce.

5.2 The effects of the Amazon Tax on Local Wages

The expansion of e-commerce may have additional consequences on retail and transportation and warehousing employees. Several claims have been made on how e-commerce can harm employees in the retail sector (Gebeloff and Russell, 2017; Kane and Tomer, 2017; Tomer and Kane, 2021). Chava et al. (2023) finds that after Amazon opens a fulfillment center, wages of brick-and-mortar employees decrease, mostly due to a reduction in working hours. The intuition behind our empirical analysis and conceptual framework is that, once the e-commerce price advantage is removed, general brick-and-mortar retailers may have incentives to covert to a hybrid system and compete with e-commerce retailers at the same prices. Also, e-commerce retailers may have incentives to locate closer to consumers, given that now they have to collect taxes everywhere. Thus, a priori the effects of the Amazon Tax on wages could go in either direction.

Next, we explore whether the negative shock to e-commerce has effects on retail and retail-related wages in Table 3. First, we find a 5.9 percent decline in annual income wages in the transportation and warehousing sector in Column 1 in Panel A. This result is statistically significant at 10 percent, and it is in line with the 9 percent decline in e-commerce sales documented in Baugh et al. (2018), and the 10 percent decline in employment we find in this sector.

Second, coefficient estimates in Column 2 point to a 2 percent decline in wages in the retail sector in CZs where the Amazon Tax was enacted. However, this estimate is not statistically significant. Third, coefficient estimates on the effect of the Amazon Tax on hourly wages in retail and retail-related sectors, presented in Columns 3 and 4, also have the expected sign, but are not statistically significant.

Fourth, we do not find statistically significant differences in annual wages and hourly wages when exploring urban and non-urban CZs separately. The magnitude of the coefficients is similar across urban and non-urban CZs, with the exception of annual wages in the transportation and warehousing sector. The coefficients in Column 1 imply that the decline in annual wages is four times larger in non-urban CZs, though imprecisely estimated.

Finally, the last row in each panel shows the p-values for the F-test to evaluate the parallel trends assumption. For these outcomes, the p-values are not small enough to reject the null hypothesis. Figure 3 presents the event study estimates; we do not find visual evidence of pre-trends, however, the pre-period estimates are noisy. In the robustness checks, we present additional sensitivity analyses.

5.3 The effects of the Amazon Tax on the Retail Occupational Structure

Online retail and offline retail are different in their labor demand both in levels and in composition. E-commerce is less labor intensive, but also its labor demand is different in terms of skills and occupations. In Section 5.1, we document a decline in employment in in-state transportation and warehousing, a sector complementary to e-commerce. We also find evidence of an increase in employment in warehouse clubs and supercenters, and a decline in employment of general brick-and-mortar retail. In addition to the effects of the Amazon Tax in employment levels, we may expect changes in the composition of labor if in-state offline retailers adjust to the removal of the out-of-state online retailers' price advantage by selling online in state. For example, we may expect a decrease in the labor demand of sales occupations, and an increase in the labor demand of professional, office and transportation occupations.

In this section, we explore the effects of the Amazon Tax on the overall retail occupational structure. Our outcomes of interest in Table 4 are the shares of employment in four occupations within the retail sector: Construction, production and transportation (Column 1)); Office and services (Column 2); Sales (Column 3); and Managerial and professional (Column 4)).[17]

First, we present the effects of the Amazon Tax on these retail occupational shares across all CZs in our sample in Panel A. We find that the retail share of office and service occupations is 0.73 percentage points higher in CZs in states that enacted the Amazon Tax (see Column 2). This effect represents a 3.4 percent increase from its baseline mean, and it is statistically significant at 10 percent. The signs of the other coefficient estimates presented in Panel A support the intuition we describe above, but are imprecisely estimated.

Second, we explore the substitution channel within retail further by examining changes in the composition of employment in urban CZs (Panel B) and in non-urban CZs (Panel C). We find stronger evidence of changes in the occupational structure in non-urban markets, with office and service-related occupations replacing those in sales. The share of retail sales occupations declines 2.6 percentage points, which represents 5 percent less of its baseline mean. The share of office and services occupations increases 2.1 percentage points, which represents 9.87 percent of its baseline mean. Both these effects are statistically and economically significant, pointing to changes in the different occupational labor demands in in-state non-urban retail that move in the direction of incorporating an occupational structure more similar to that of the e-commerce retail sector. Third, the last row in each panel presents the p-values of the F-test to evaluate the parallel trend assumption. We fail to reject the null hypothesis about the presence of parallel trends. In Section 6, we present results of additional sensitivity checks.

[17] Construction, production and transportation occupational share also includes material moving occupations.

Our results suggest that, when the out-of-state price advantage is removed, in-state retailers reorganize their occupational structure by reducing the share of employees in sales occupations while increasing the share of employees in service, office, professional and managerial occupations. The estimated changes in occupational shares have the expected sign, but are sometimes imprecisely estimated when averaging all post-Amazon-Tax years. These results may indicate sluggish changes in the composition of employment within the retail sub-sectors, which can be also observed in the event studies in Figure 4.

6 Robustness Checks

In this section, we show that our results are robust to a series of sensitivity checks. First, we test for violations of the parallel trends assumption and study their impacts on the point estimates and confidence intervals of interest following the approach proposed by Rambachan and Roth (2020). The honest parallel trends design consists on evaluating how different violations of the parallel trends assumption will affect the parameter of interest. It allows us to evaluate confidence intervals for our estimated parameter of interest when the maximum post-treatment violation of parallel trends is up to $\bar{M}$ times larger than the maximum pre-treatment violation for different values of $\bar{M}$. We include this sensitivity analysis for the average treatment effect for each outcome discussed in Section 5.

Regarding employment levels, Figure A.7 shows that our statistically significant results in transportation and warehousing and retail are robust to allowing for violations of parallel trends up to 0.3 times as big as the maximum violation in the pre-treatment period. The result in general brick-and-mortar retail is robust to allowing for violations of parallel trends up to 0.5 times as large as the maximum violation in the pre-treatment period. Regarding wages, Figure A.8 shows that significant results in transportation and warehousing wages are robust to allowing for violations of parallel trends up to 0.1 times as big as the maximum violation in the pre-treatment period. Regarding occupational shares, Figure A.9, we find that the significant result in office and services occupations is robust to allowing for violations of parallel trends up to 0.3 times as big as the maximum violation in the pre-treatment period. The effect on sales occupations is robust to allowing for violations of parallel trends up to 0.1 times as big as the maximum violation in the pre-treatment period.

Second, out of the 229 CZs in our sample, 12 percent cross state borders, hindering the distinction between treated and control areas due to the Amazon Tax legislation being enacted by states. Table A.1 shows that our results are robust to excluding CZs that cross state borders.

Third, we check that our results are robust to controlling for a series of consumption predictors (i.e., median household income, location Amazon fulfillment centers, industry GDP distribution, sales tax levels across states, and CZs' demographic characteristics) because the effects of the Amazon Tax in local labor markets may be mediated by shifts in consumption patters.[18] We include CZ-level consumption predictors measured at baseline interacted with time dummies. These interactions allow for the possibility that the relationship between the outcome variables and the CZ's baseline consumption predictors changes in the post-2013 period. We avoid including the post-treatment consumption predictors covariates as they can potentially be affected by the treatment (Wooldridge, 2005; Callaway and Sant'Anna, 2021). We estimate the following difference-in-differences model:

$$Y_{cy} = \alpha_c + \gamma_y + \delta D_{sy} + \sum_{k=2010}^{2016} X_{c,2010} \times T_k + \epsilon_{cy} \tag{3}$$

where X_c is a vector including the following covariates: median household income, state tax rate, industry GDP shares at 1 digit, number of Amazon fulfillment center located in the CZ, rate of white population, rate of black population and rate of female population. Tables A.2, A.3 and A.4 show that our main results are robust to the inclusion of these consumption predictors. Moreover, this specification improves the precision of our estimates in some cases.

In Column 2 of Panel A in Table A.2, we find that the decline 1.2 percent (with respect to the baseline mean) in overall retail is statistically significant when controlling for consumption predictors. Consistent with our main results, we find a 7.6 percent decline in transportation and warehousing. The decline in retail employment is explained by the 2.6 percent decline in general brick-and-mortar retail that is not fully compensated by the 5.6 percent increase in employment in warehouse clubs and supercenters, given that the former represents more than 83 percent of the retail sector. The changes in the precision of the estimated effects on wages and occupational shares are mixed after the inclusion of covariates. In Table A.3, we find that effects on annual income wages and hourly wages for transportation and warehousing and retail sectors are statistically significant in non-urban CZs, but not in urban CZs. Finally, the results presented in Panel A of Table A.4 point to a different occupational substitution channel, with a decline of 1.5 percent in the retail share of sales employees with respect to the baseline mean, and an increase of 10 percent in the retail share of managerial and professional employees with respect to the baseline mean. While the effects in office and service occupational share is no longer statistically significant, it is still sizable, especially in non-urban areas—4.2 percent of its baseline mean.

7 Discussion of Effects of E-commerce

In Section 5, we show that reducing the price advantage of out-of-state e-commerce retailers not only generates changes in employment levels, but also in the employment composition across retail sub-industries. While employment in warehouse clubs and supercenters increases, employment in general brick-and-mortar retailers decreases. In

[18] See the Appendix A.3 for a description of the additional data sources used here.

this section, we present a four-sector general equilibrium model to rationalize the effects of rising e-commerce taxes on local labor markets.

7.1 The Basic Model

The economy has four sectors: general brick-and-mortar retail (B), warehouse clubs and supercenters (S), out-of-state e-commerce retail (E) and transportation and warehousing (T). The only production factor is labor (L). The production of the three types of retail (B, S, E) occurs in a constant returns to scale environment:

$$B = L_B, \qquad S = L_S, \qquad E = T = L_T \tag{I}$$

Additionally, out-of-state e-commerce retail is produced in state with transportation and warehousing services (T), which in turn are produced with labor. To simplify notation we label it as $L_T = L_E$.

In this setup, labor has a fixed total supply, but workers can freely move between sectors (with no unemployment). Thus:

$$L_B + L_S + L_E = \bar{L} \tag{II}$$

In each sector, labor is paid the value of its marginal product in competitive markets (zero profit condition)[19]:

$$p_B B = w_B L_B, \qquad p_S S = w_S L_S, \qquad p_E E = w_E L_E \tag{III}$$

Workers' decision regarding how much labor they want to allocate in each sector is given by their corresponding wages, w_B, w_S, w_E and their indirect utility $V(w_B, w_S, w_E)$, which is reflected in the following elasticities of substitution: η_1, workers' elasticity of substitution between warehouse clubs and supercenters (S) and general brick-and-mortar retail (B); η_2, workers' elasticity of substitution between transportation and warehousing (T) and general brick-and-mortar retail (B); and η_3, workers' elasticity of substitution between warehouse clubs and supercenters (S) and transportation and warehousing (T).

We assume that workers preferences for working in the different sectors are well-behaved (complete, transitive, monotonic and convex). We also assume that workers see the different sectors as substitutes ($\eta_1 > 0, \eta_2 > 0$, $\eta_3 > 0$), and that they see working at B and working at S as the most substitutable jobs, and that they see working at T and working at B as the least substitutable jobs, while the elasticity of substitution between working at T and working at S is between the others ($\eta_1 > \eta_3 > \eta_2$). This assumption comes from the fact that B and S have similar occupational structures, that is they require similar occupations and skills, while B and T have dissimilar occupational structures.

Finally, consumers maximize their utility $U(B, S, E)$. Consumer's preferences are characterized by the elasticity of substitution between demands of B, S and E: σ_1,

[19] While these markets rarely behave as perfectly competitive markets, this simplifying assumption allows us to focus on the competition across sectors instead of the competition within each sector

elasticity of substitution between warehouse clubs and supercenters (S) and general brick-and-mortar retail (B); σ_2, workers' elasticity of substitution between out-of-state e-commerce retail (E) and general brick-and-mortar retail (B); and σ_3, workers' elasticity of substitution between warehouse clubs and supercenters (S) and out-of-state e-commerce retail (E).

Consumer face price $p_i(1+\tau_i)$ and an *ad valorem* tax τ_i for $i = B, S, E$. We assume that consumers' preferences are well-behaved (complete, transitive, monotonic and convex), and they see retail from different sectors as substitutes ($\sigma_1 > 0, \sigma_2 > 0$, $\sigma_3 > 0$). We also assume that consumers see purchasing at B and purchasing at S as the most substitutable purchases, and that they see purchasing at E and purchasing at B as the least substitutable purchases, while the elasticity of substitution between purchasing from E and purchasing at S is between the others ($\sigma_1 > \sigma_3 > \sigma_2$). This assumption is consistent with the idea of all in-state offline retailers (B and S) requiring trips to the shop, hence once consumers are already outside the house they will prefer purchasing at the cheapest places (prices matter more), while E and B being completely different purchasing experiences. [20]

In this economy, with pre-existing tax rates τ_B, τ_S and τ_E, we evaluate the effect of a small increase in the tax rate of out-of-state e-commerce retail (E).

7.2 The effects of the Amazon Tax

We solve for the effects of an increase in the *ad valorem* tax rate on sales of out-of-state e-commerce retail, sector E, while the remaining tax rates do not change, $\widehat{\tau_B} = 0$,$\widehat{\tau_S} = 0$. Since we focus on real behavior, we choose S as numeraire, hence $\widehat{p_S} = 0$. The general solutions are:[21]

$$\widehat{w_S} = \widehat{p_S} = 0 \tag{14a}$$

$$\widehat{w_E} = \widehat{p_E} = \widehat{w_T} = \widehat{p_T} = -A\widehat{\tau_E} \tag{14b}$$

$$\widehat{w_B} = \widehat{p_B} = -A\epsilon_L\widehat{\tau_E} \tag{14c}$$

$$\widehat{L_E} = \widehat{E} = \widehat{L_T} = \widehat{T} = [\underbrace{\lambda_S\sigma_1\epsilon_U A}_{\text{Indirect Effect}} + \underbrace{(\lambda_E - 1)\sigma_2(\epsilon_U - 1)A}_{\text{Direct Effect}}]\widehat{\tau_E} \tag{14d}$$

$$\widehat{L_B} = \widehat{L_B} = [\lambda_S\sigma_1\epsilon_U A + \lambda_E\sigma_2(\epsilon_U - 1)A]\,\widehat{\tau_E} \tag{14e}$$

$$\widehat{L_S} = \widehat{L_S} = [(\lambda_S - 1)\sigma_1\epsilon_U A + \lambda_E\sigma_2(\epsilon_U - 1)A]\,\widehat{\tau_E} \tag{14f}$$

where ϵ_U and ϵ_L are the relative differences in preferences for consumers and workers respectively: $\epsilon_U = \frac{\sigma_3 - \sigma_2}{\sigma_1 - \sigma_2}$ and $\epsilon_L = \frac{\eta_3 - \eta_2}{\eta_1 - \eta_2}$, $A \equiv \frac{1}{1 - \frac{\epsilon_L}{\epsilon_U}}$, and $\lambda_i = \frac{L_i}{L}$.

[20] The consumer budget constraint here is implied by the assumption that the tax revenues are rebated lump sum to consumers and equations in (III).

[21] See Appendix A.1.1 for derivations

From (14a), wages in sector S do not change. The change of wages and price in sector E is proportional with respect to A, which measures the relation between relative differences in preferences for consumption and labor, from (14b).

The effects of increasing the tax rate on sales of E on the production of both B, S and E and their respective labor requirements can be split in two effects: Direct effects and Indirect effects. The Direct effect reflects the trade-off that the consumer faces when substituting between general brick-and-mortar retail (B) and out-of-state e-commerce retail(E). The Direct Effect from both (14d), (14e) and (14f) consists of an effect given by the elasticity of substitution σ_2 between consumption of B and E, which is in turn weighted by a function of share of labor used in the production of E and the ratio of elasticity differences for consumption, ϵ_U, and the relation between relative differences in preferences for consumption and labor, A.

The Indirect effect reflects the trade-off that the consumer faces when substituting across in-state retailers, that is between general brick-and-mortar retail (B) and warehouse clubs and supercenters (S). The Indirect Effect from both (14d), (14e) and (14f) consists of an effect given by the elasticity of substitution σ_1 between consumption of B and S, which is in turn weighted by a function of share of labor used in the production of S and the ratio of elasticity differences for consumption (ϵ_U) and A, the relation between relative differences in preferences for consumption and labor. Both the Direct effect and the Indirect effect are a result of changes in relative prices of e-commerce p_E, since they both include the change in prices and wages in sector E from equation (14b).

The following proposition shows in which cases a rise on the tax rate on out-of-state e-commerce sales, $\widehat{\tau_E} > 0$, leads to the observed effects present in the empirical results: declines in employment and wages in last-mile transportation and warehousing, declines in employment in general brick-and-mortar retail, and increases in employment in warehouse clubs and supercenters.

Proposition 1 *Let ϵ_U and ϵ_L be the relative differences in preferences for consumers and workers respectively: $\epsilon_U = \frac{\sigma_3 - \sigma_2}{\sigma_1 - \sigma_2}$ and $\epsilon_L = \frac{\eta_3 - \eta_2}{\eta_1 - \eta_2}$. Let Ψ_B be the relative subsitutability of brick-and-mortar retail in the economy: $\Psi_B = \frac{\lambda_S \sigma_1}{\lambda_E \sigma_2}$. Both wages and employment in transportation and warehousing and general brick-and-mortar retail will fall $\widehat{w_T} = \widehat{w_E} < 0, \widehat{w_B} < 0, \widehat{L_T} = \widehat{L_E} < 0, \widehat{L_B} < 0$, while employment in warehouse clubs and supercenters will rise, $\widehat{L_S} > 0$, if an only if:*
$\frac{1}{1+\Psi_B} > \epsilon_U > \epsilon_L > 0$, and $\frac{1-\lambda_E}{\lambda_E} > \Psi_B > \frac{\lambda_S}{1-\lambda_S}$

In the Appendix A.1, we present Propositions 2-6 which build up to Proposition 1. Under Proposition 1, Propositions 2-6 hold simultaneously. Proposition 1 consists of two main blocks. The first block refers to the relationship between the relative differences in preferences for consumers and workers, ϵ_U and ϵ_L respectively. Due to workers seeing the different sectors as substitutes, with B and S the most subsitutable and B and T the least substitutable ($\eta_1 > \eta_3 > \eta_2 > 0$), the relative difference in workers preferences is larger than 0. This assumption is derived from the differences in occupational structures, with B and S having a similar occupational structure and B and T a dissimilar occupational structure.

As consumers also see purchasing at retail sectors as substitutes, with purchases at B and S being the most substitutable and purchases at B and E being the least substitutable ($\sigma_1 > \sigma_3 > \sigma_2 > 0$), the relative difference in consumers preferences is also larger than 0. But for the first block of Proposition 1 to hold, the relative difference in consumers preferences has to be larger than the relative difference in workers preferences. By definition of relative differences in preferences, this condition is equivalent to consumers being more sensitive to changes in prices than workers to changes in wages.[22] Additionally, the relative difference in consumers preferences has to be bounded by the inverse of the relative substitutability of brick-and-mortar retail in the economy Ψ_B, which refers to the ratio of elasticities of substitution of brick-and-mortar retail by the other sectors, σ, each weighted by the size of their respective sector in the economy, measured by the share of labor in their sector, λ.

Finally, for Proposition 1 to hold, the relative substitutability of brick-and-mortar retail in the economy Ψ_B has to be bounded by the relative size of e-commerce retail and the relative size of warehouse clubs and supercenters retail. If the e-commerce sector is too small ($\lambda_E \to 0$), then Ψ_B has to be at most 1, and the relative difference in consumers preferences has to be at most 0.5.

7.3 Substitution in the Retail Market

In this section, we explore the determinants of the elasticities of substitution. As mentioned before, a consumer can either buy from a in-state offline retailer, either a general brick-and-mortar or a big box retailer, or buy online from an out-of-state e-commerce retailer. We assume consumers buy multiple goods, and for each good acquisition they decide from the three purchasing options.

Each purchasing option involves a cost $C_{ij} = h(\cdot)$ associated with the type of retailer j and how the consumer i perceives the purchase. The first difference in purchasing costs between buying from a offline retailer and buying from an e-commerce retailer comes from the searching time that consumers spend on selecting the product. Searching times, $t_j = g(\theta_j, \psi_j)$ are affected by how well the retailer shows the product characteristics, θ_j, and how much variety,ψ_j, they offer. For example, through e-commerce, consumers face lower costs associated to accessing detailed information of the characteristics of the products, comparing across products, comparing prices across different sites and buying with a click in their computer or mobile device. Although a offline store offers limited product variety, by searching online the vast product variety can obfuscate the consumer.

Offline retailers' proximity to each other creates an environment where consumers can visit many stores and purchase all the goods in the same visit, similar to searching online and comparing many websites. Hence, distance to the store, d_j, is a key cost associated to purchases from offline retailers. The lack of proximity to consumers of some offline stores, like outlet malls, creates a challenge for consumers without transportation means.

[22] Relative differences in preferences can be expressed not only as differences in elasticities of substitution but also as differences in price elasticities. For example $\epsilon_U = \frac{\sigma_3 - \sigma_2}{\sigma_1 - \sigma_2} = \frac{\gamma_S - \gamma_E}{\gamma_B - \gamma_E}$ with γ_i the price elasticity of sector $i = B, S, E$. See Gørtz (1977) for further details.

The distance costs associated with purchasing experiences, therefore, are different for the two types of offline retailers. Big box retailers allow consumers for the possibility of trip bundling, effectively reducing the purchasing costs due to distance. However, the options for general brick-and-mortar retailers' locations are limited. While they could be placing themselves close to one another in an attempt to reduce traveling costs for consumers, they have less control on how consumers' preferences are regarding their neighbour stores and which complementarities or substitutabilities there are between the goods they sell and other goods offered nearby.

Another difference between buying online and offline is that while delivery is not needed in offline stores, it is required for online purchases, adding waiting time, m_j, and shipping costs, s_j, to the associated purchasing costs. Although consumers could reduce both waiting time and shipping costs by subscribing to some e-commerce retailers' member programs, like Amazon Prime, these costs remain somewhat present, while there are no such costs when buying at local retail stores. Additionally, pre-purchase interactions at offline stores reduce consumption costs related to measurements, touch, smell, try, and feel, which are not possible online. We consider this cost as experience-related costs X, where $X = 0$ at the store and $X = 1$ online.

Finally, there are some learning costs, L_{ij} associated with purchasing in general. For instance, when buying in the offline store the consumer learns where the products are located; if those products are moved to different shelves the consumer will have to re-learn the products location. Furthermore, buying online requires developing certain skills such as internet browsing skills and how to recognize safe sites and platforms from scams.

Consumers then maximize utility given by:

$$U_{ij} = v_i - p_j - C_{ij}$$

depending on how much their value the good v_i, the price they face at each purchasing option p_j, and the associated cost from the purchase, $C_{ij} = h(t_j, s_j, m_j, d_j, X_j, L_{ij})$.

As out-of-state e-commerce retailers do not collect sales taxes, consumers buying from them pay a price p, while consumers buying from general brick-and-mortar retailers pay the price $p(1 + \tau)$, with τ being the *ad valorem* sales tax. As warehouse clubs and supercenters usually offer discounts due to buying in bulk, consumers buying from them pay the price $p'(1+\tau)$.[23] For simplicity, we assume $p < p'(1+\tau) < p(1+\tau)$ and that the associated purchasing cost at both offline retail options are the same (C_{is}). Even though some e-commerce retailers and some warehouse clubs offer memberships, the decision of acquiring the membership and paying the fixed fee occurs only once a year, so it could be considered part of the associated cost of purchase.

In this setting, the elasticities of substitution between purchasing channels are functions of both the price advantage and consumers' purchasing associated costs. In that sense, as urban and non-urban areas have observable characteristics that lead to differences in both the type of price advantage and the determinants of purchasing associated costs, we expect differences in consumers' substitution patterns. For example, urban

[23] See Volpe and Boland (2022) for evidence of Walmart offering lower prices to households

areas not only have state sales taxes, they also have local sales taxes (Propheter, 2019). Hence, in urban areas the price advantage is not removed when the Amazon Tax is enacted, only reduced, which may lead to a smaller substitution between e-commerce purchases and offline purchases by consumers. Alternatively, consumers in non-urban areas may face lower product variety, higher distance to the stores, waiting times, shipping costs, and learning costs due to lack of access to internet. While lower product variety and higher distance to the stores imply higher associated costs for purchases from offline retailers, higher waiting times, shipping costs, and learning costs due to lack of access to internet imply higher associated costs for purchases from e-commerce retailers. Therefore, we may expect larger or smaller substitution from consumers depending which mechanisms prime.

Additionally, once the price advantage is removed, general brick-and-mortar retailers may have incentives to enter to the e-commerce retail market, given that now they compete with e-commerce retailers at the same prices, while e-commerce retailers may have incentives to locate closer to consumers, given that now they have to collect taxes everywhere.

7.4 Retail Production and Substitution in the Labor Market

In the previous section, we assume that retailers in each sector produce retail using only labor. However, from the empirical analysis, the retail production functions require different combinations of tasks performed by employees from a variety of occupations (skills) according to the type of retail. Let's consider the main four occupational groups present in the retail sector: sales employees L_{si}, professional and managerial employees L_{pi}, production, construction, transportation and material moving employees L_{ti}, office and service employees L_{oi}. Let θ_{hi} be the share of each occupation h required for the production in sector $i = B, S, T$, and L_i be the vector of retail employment required to produce in such sector.

Notice that while out-of-state e-commerce retail only demands last-mile transportation and warehousing services in the local labor market (i.e., in state), when located in-state e-commerce retail also requires employees from the main four occupations. For the following analysis, we focus on in-state e-commerce requirements since general brick-and-mortar retailers may have incentives to enter into e-commerce retail market and out-of-state e-commerce retailers may have incentives to locate closer to consumers. To make the distinction clear, we label in-state e-commerce retail sector as O.

In line with the observations from the data, we assume that e-commerce retailers require fewer employees than general brick-and-mortar retailers and warehouse clubs and supercenters.[24] We also assume that general brick-and-mortar retailers require larger shares of sales and related occupations and smaller shares of the remaining occupations than e-commerce retailers, and that warehouse clubs and supercenters require a larger share of service and office occupations than general brick-and-mortar retailers, but smaller than e-commerce retailers. Finally, we assume that warehouse clubs and su-

[24]This means that $L_S > L_B > L_O$

percenters require smaller shares of production, construction and transportation occupations and professional and managerial occupations than both general brick-and-mortar and e-commerce retailers.[25]

Here, in-state e-commerce retail requirements for transportation and related occupations are considering both in-house and out-sourced. Previously, we chose to consider that out-of-state e-commerce retailers outsource last-mile transportation and warehousing instead of conducting these processes in-house as that was how major e-commerce retailers conducted the last-mile transportation and warehousing during the period studied.

For the following analysis let's consider a labor market problem as a simplification of Bartik and Rinz (2018). In this framework, in-state occupational wages are determined by the inverse labor-demand elasticity σ_h and a labor productivity shifter α_h such that the inverse-labor demand for a given occupation is $w_h = \alpha_h LD_h^{-\sigma_h}$, where the in-state labor demand LD_h for each occupation h is $LD_h = \sum_j l_{hj}$, with $j = B, S, O$ representing the in-state retail sectors, general brick-and-mortar retail, warehouse clubs and supercenters, and e-commerce retail.

In the baseline model, workers chose how much of their work was allocated to each sector. However, as sectors have different requirements for occupations, it is reasonable to assume that workers are in fact choosing between different occupations. In this framework, each worker k has a bundle of skills, Θ_k, to perform several tasks. We assume all bundles can be placed on a line such that different intervals belong to different occupations. For example, transportation and material moving occupations require less complex skills than sales and related occupations or professional occupations. While employees that require less complex skills can acquire additional skills and access to other occupations, skill acquisition is costly because it requires human capital accumulation. Also, workers with more complex skills can perform occupations that require less complex skills, however, as they are not the best match to those occupations, they face costs related to adaptation and lower wages.

For a given set of distributions of wages, skill bundles, initial occupation h_0 and vacancies, workers place themselves into occupations such that they maximize their indirect utility over occupation h:

$$v_{kh} = \ln(w_h) - s^H c_k^H \times 1(h \neq h_0)$$

Where w_h is the occupational wage, c_k^H is an idiosyncratic moving cost which is a function of the bundle of skills that the worker has $c_k^H(\Theta_k)$, and s^H is a measure of the importance of this cost. This setup is a particular case of Bartik and Rinz (2018) in which workers do not move across locations (location moving cost is set to infinity).

The labor supply for each occupation will depend on the vector of wages w, the initial number of workers in each occupation N_{h_0}, and a function $G(\cdot)$ that assigns probabilities of choosing each occupation based on w and the distribution function of moving costs $F(c_i^H)$:

[25] This is equivalent to assuming
$\theta_{sS} > \theta_{sB} > \theta_{sO}$, $\theta_{pO} > \theta_{pB} > \theta_{pS}$, $\theta_{oO} > \theta_{oS} > \theta_{oB}$ and $\theta_{tO} > \theta_{tB} > \theta_{tS}$.

$$LS_h(w) = \sum_{h_0} N_{h_0} G(F(c_i^H), w)$$

The equilibrium in the labor market is characterized by the aggregate labor demand being equal to the aggregate labor supply for each occupation:

$$LD_h(w) = LS_h(w)$$

The labor demand for each occupation is the sum of all retailers labor demands for such occupation. The labor demand in a given occupation will be affected by both the importance of each retailer in the total labor demand, previously defined as λ_j, and the shares that the occupation represents in each retailer labor demand, θ_{hj}. An increase in the sales tax rate for out-of-state e-commerce retailers reduces their demand of last-mile transportation and warehousing services. This reduction will lead to a decline of the labor demand and wages of transportation employees in that sector.

If in response to the removal of the price advantage there is an increase in employment in warehouse clubs and supercenters and a decrease in employment of general brick-and-mortar retail, we may expect a decline in the labor demand of transportation and professional occupations, and an increase in the labor demand of sales and office occupations. Finally, as general brick-and-mortar retailers now have incentives to start selling online, and out-of-state e-commerce retailers now have incentives to locate themselves in the local economy, we may expect a decrease in the labor demand of sales occupations, and an increase in the labor demand of professional, office and transportation occupations. Due to wages and occupational moving costs, transportation employees may be underqualified to work in sales or office occupations, and professional employees may be underqualified to work in sales or office occupations, leading to mismatches in the retail local labor market. Similarly, sales employees may be overqualified to work in transportation occupations, or underqualified to work in professional or office occupations, leading to additional mismatches in the retail local labor market.

8 Conclusion

In this paper, we present evidence of a non-neutral role for e-commerce on local labor markets. We investigate the effects of changes in e-commerce on retail and retail-related industries in US local labor markets between years 2010 and 2016. Our identification strategy exploits exogenous variation in the timing of the enactment of the Amazon Tax—legislation requiring out-of-state online retailers to collect state sales tax. The intuition behind our analysis is that the growth of e-commerce was fueled partially by out-of-state e-commerce retailers having a price advantage over in-state retailers. We consider the enactment of the Amazon Tax as a partial or total removal of such price advantage.

Using the cross-market variation in out-of-state online retailers' price advantage over in-state retailers, we document several key findings. First, introducing state sales taxes on online purchases from out-of-state retailers causes lower employment and reduced wages in transportation and warehousing, which are industries complementary to e-commerce. Second, within the in-state offline retail sector, the decline in brick-and-mortar employment is somewhat offset by an increase in employment in warehouse clubs and supercenters. This substitution between in-state retail sub-sectors leads to a net decline in local retail employment (somewhat imprecisely estimated, though). Our results are consistent with a general equilibrium model in which consumers substitute e-commerce for big-box purchases, crowding out brick-and-mortar retail.

Third, we explore this substitution channel further by studying whether the labor demand response that we find is driven only by changes in the levels of employment or also by changes in the composition of employment in these sectors. Our results suggest that, when the out-of-state price advantage is removed, in-state retailers reorganize their occupational structure by reducing the share of employees in sales occupations while increasing the share of employees in service, office, professional and managerial occupations. Our main findings on retail employment and wages are driven by urban markets, but we find stronger evidence of changes in the occupational structure in non-urban markets, with office and service-related occupations replacing those in sales.

Our results imply that in-state retailers change their competition strategies and switch to a hybrid sales model to compete with e-commerce once the price advantage of the latter is removed. To rationalize the channels behind our main findings, we develop a conceptual framework. Through a general equilibrium model, we connect the differential effects on local labor markets with consumers' and workers' elasticities of substitution. Our main model predictions are consistent with previous studies.

Although e-commerce retail still represents only a small portion of the retail sector, it plays an important role in the local economy. Furthermore, the results may indicate the ineffectiveness of an increase in sales taxes, such as the enactment of the Amazon Tax, in terms of slowing down or stopping the "Retail Apocalypse". The inefficacy of this policy may be caused by erroneous perceptions of elasticities of substitution sizes. Additional research is needed regarding both consumers' and workers' preferences to better identify policies that protect retail employees from the changes caused by e-commerce growth.

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9 Tables

Table 1: Balance Table - State characteristics before the Amazon Tax enactment

	Without Amazon Tax	With Amazon Tax	Difference
Number of Amazon FC	0.01	0.00	0.01
State sales tax rate	5.56	5.58	-0.01
Median HHD income	46868.26	43898.20	2970.06***
GDP share industry 1	0.07	0.06	0.02*
GDP share industry 2	0.11	0.10	0.01
GDP share industry 3	0.12	0.13	-0.01
GDP share industry 4	0.12	0.12	0.00
GDP share industry 5	0.23	0.25	-0.01**
GDP share industry 6	0.06	0.08	-0.02***
GDP share industry 7	0.04	0.03	0.01**
GDP share industry 8	0.02	0.02	-0.00***
Rate of white population	0.87	0.94	-0.07***
Rate of black population	0.07	0.03	0.04***
Rate of female population	0.50	0.50	-0.00**

The table presents a comparison of selected characteristics for the period 2010 and 2012 between CZ in states that enacted Amazon Tax in 2013 and in states that did not enact Amazon Tax or signed Voluntary Collection Agreements. GDP shares by industries grouped at 1 digit code: Agriculture, forestry, fishing and hunting (industry 1), Mining, Utilities and Construction (industry 2), Manufacturing (industry 3), Wholesale trade, Retail, Transportation and Warehousing (industry 4), FIRE and Professional and Business Services (industry 5), Education, Health Care, and Social Assistance (industry 6), Arts, Entertainment, Recreation, Accommodation, and Food Services (industry 7) and Other services (industry 8). Sources: American Community Survey (ACS) years 2010-2016, Census Intercensal Population Estimates 2010-2020, Bureau of Economic Analysis data, Small Area Income and Poverty Estimates Program, MWPVL International and TaxFoundation.org

Table 2: Employment

	Transportation & Warehousing	Retail	Warehouse Clubs & Supercenters	General Brick-and-Mortar Retail
Panel A: Sample all commuting zones				
Enactment Amazon Tax	-39.667*	-56.682	87.955*	-143.544**
	(13.57)	(31.12)	(33.48)	(43.00)
Baseline mean	396.48	7420.12	1142.41	6169.09
SD	747.47	1773.99	615.06	1544.33
Observations	1603	1603	1603	1603
Parallel trends	0.343	0.376	0.0862	0.940
Panel B: Sample urban commuting zones				
Enactment Amazon Tax	-37.105	-77.230	108.075*	-177.964**
	(18.83)	(39.19)	(41.84)	(48.80)
Baseline mean	499.45	7883.95	1149.49	6574.26
SD	394.13	1004.99	384.74	1026.99
Observations	441	441	441	441
Parallel trends	0.118	0.477	0.0604	0.845
Panel C: Sample non-urban commuting zones				
Enactment Amazon Tax	-44.969	3.214	3.056	-10.811
	(30.45)	(62.68)	(31.28)	(75.18)
Baseline mean	357.39	7244.08	1139.72	6015.32
SD	840.75	1961.85	682.75	1675.36
Observations	1162	1162	1162	1162
Parallel trends	0.176	0.586	0.686	0.691

This table presents the estimates of the difference-in-differences model, where Enactment of Amazon Tax refers to the estimation coefficient (δ) from $Y_{cy} = \alpha_c + \gamma_y + \delta D_{sy} + \epsilon_{cy}$, where outcome variable is $\frac{Emp_{cy}}{Pop_{cy}} \times 100000$ for both each corresponding sector (columns). All specifications include year and commuting zone fixed effects and standard errors clustered at the state level.

Table 3: Annual wages and hourly wages

	ln(annual income wages)		ln(hourly wages)	
	Transportation & Warehousing	Retail	Transportation & Warehousing	Retail
Panel A: Sample all commuting zones				
Enactment Amazon Tax	-0.059*	-0.020	-0.006	-0.054
	(0.02)	(0.02)	(0.02)	(0.03)
Baseline mean	10.45	9.95	2.70	2.91
SD	0.36	0.17	0.17	0.12
Observations	1603	1603	1603	1603
Parallel trends	0.278	1.000	0.0275	0.212
Panel B: Sample urban commuting zones				
Enactment Amazon Tax	-0.035	-0.020	-0.005	-0.040
	(0.03)	(0.02)	(0.03)	(0.03)
Baseline mean	10.50	9.99	2.75	2.99
SD	0.32	0.15	0.22	0.12
Observations	441	441	441	441
Parallel trends	0.0676	0.951	0.0715	0.348
Panel C: Sample non-urban commuting zones				
Enactment Amazon Tax	-0.137	-0.024	-0.007	-0.090
	(0.10)	(0.02)	(0.02)	(0.08)
Baseline mean	10.43	9.93	2.68	2.88
SD	0.38	0.18	0.15	0.10
Observations	1162	1162	1162	1162
Parallel trends	0.789	0.962	0.686	0.185

This table presents the estimates of the difference-in-differences model, where Enactment of Amazon Tax refers to the estimation coefficient (δ) from $Y_{cy} = \alpha_c + \gamma_y + \delta D_{sy} + \epsilon_{cy}$, where outcome variable is annual wages and hourly wages for each corresponding sector (columns). All specifications include year and commuting zone fixed effects and standard errors clustered at the state level.

Table 4: Retail occupational shares

	Construction, Production & Transportation	Office & Services	Sales	Managerial & Professional
Panel A: Sample all commuting zones				
Enactment Amazon Tax	-0.517	0.734*	-0.896	0.679
	(0.54)	(0.26)	(0.54)	(0.41)
Baseline mean	16.63	21.56	52.60	9.21
SD	4.94	5.22	6.80	4.08
Observations	1603	1603	1603	1603
Parallel trends	0.875	0.281	0.937	0.186
Panel B: Sample urban commuting zones				
Enactment Amazon Tax	-0.720	0.368	-0.377	0.729
	(0.59)	(0.35)	(0.50)	(0.34)
Baseline mean	15.40	21.29	53.35	9.96
SD	4.25	4.94	6.34	3.72
Observations	441	441	441	441
Parallel trends	0.853	0.148	0.554	0.341
Panel C: Sample non-urban commuting zones				
Enactment Amazon Tax	0.034	2.137***	-2.623*	0.453
	(0.63)	(0.49)	(1.18)	(0.82)
Baseline mean	17.10	21.66	52.31	8.93
SD	5.10	5.33	6.95	4.17
Observations	1162	1162	1162	1162
Parallel trends	0.988	0.651	0.277	0.248

This table presents the estimates of the difference-in-differences model, where Enactment of Amazon Tax refers to the estimation coefficient (δ) from $Y_{cy} = \alpha_c + \gamma_y + \delta D_{sy} + \epsilon_{cy}$, where outcome variable is $Y_{cyi} = \frac{Emp_{cyi}}{Emp_{cy}}$ for each occupational group: transportation and material moving occupations, production and construction occupations (SOC 53-, 51-, 45-, 47- and 29-), office and service occupations (SOC 43-, and 3X-), sales and related occupations (SOC 41-), and managerial and professional occupations (SOC 1X- and 2X-). All specifications include year and commuting zone fixed effects and standard errors clustered at the state level.

10 Figures

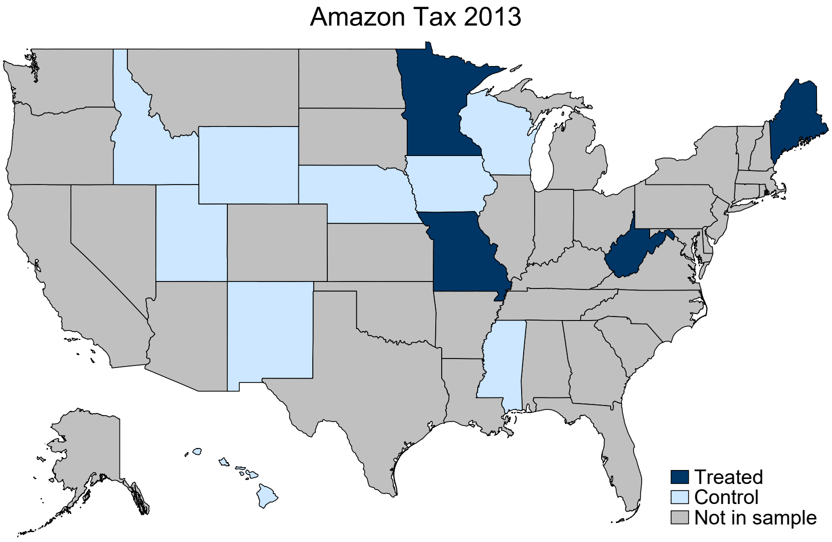
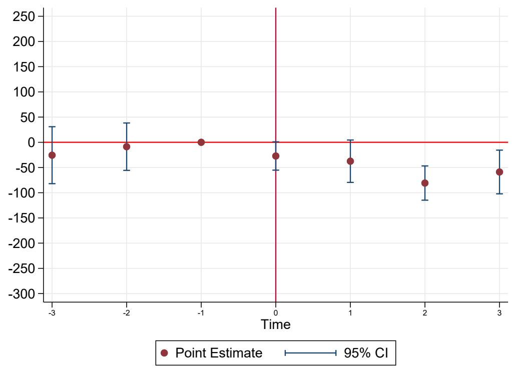
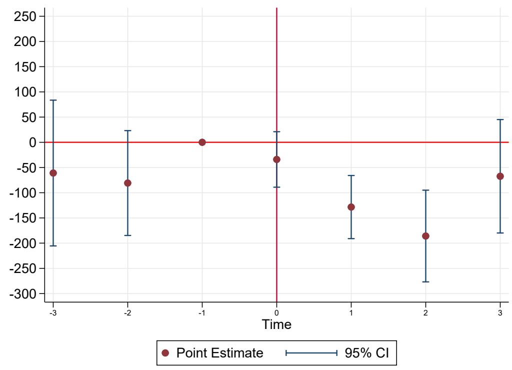


Figure 1: States in sample

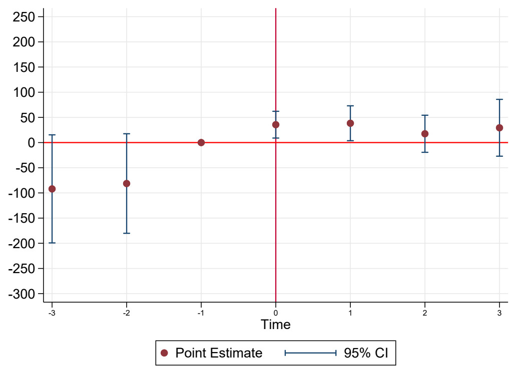
Note: This figure presents in dark blue states that enacted the Amazon Tax in 2013, in light blue states that never enacted the Amazon Tax, in gray states excluded from sample because: enacted the Amazon Tax in other years,signed voluntary collection agreements with Amazon, Amazon was already collecting sales taxes due to physical presence.



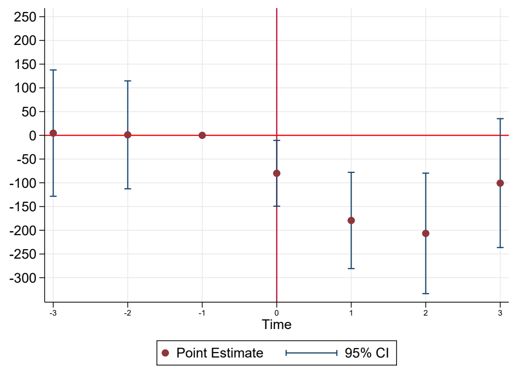
(a) Transportation & warehousing



(b) Retail



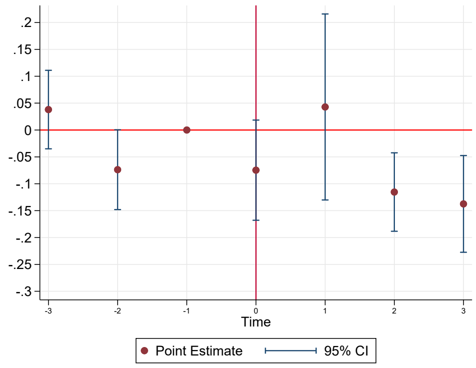
(c) Warehouse clubs & supercenters



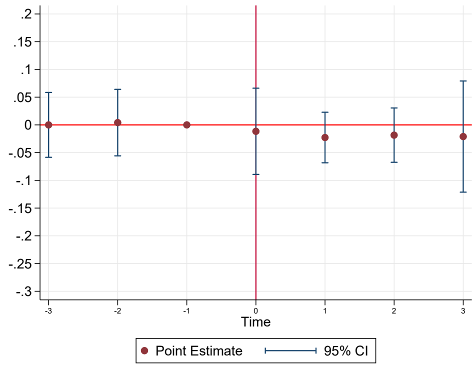
(d) General brick-and-mortar retail

Figure 2: Employment/working age population by sector

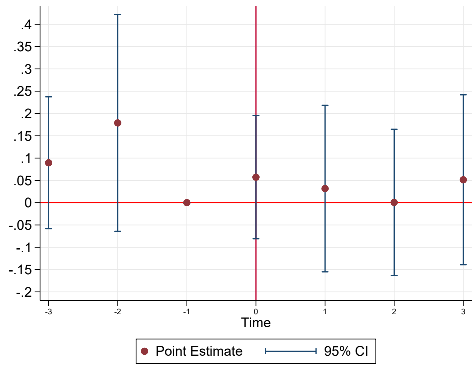
Note: This figure shows on each panel the coefficients (per 100,000 working age population) and 95% confidence interval for separate event study regressions of the ratio between each sector employment and working age population. Regression coefficients are weighted by 2010 population and the standard errors are clustered at the state level.



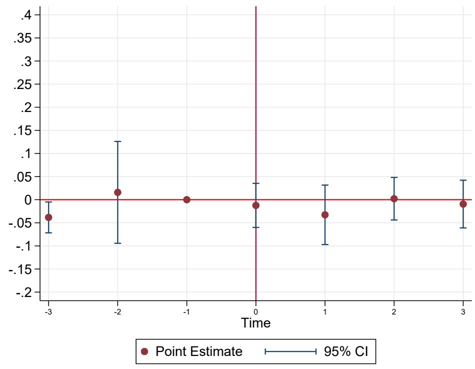
(a) Transportation & warehousing annual income wages



(b) Retail annual income wages



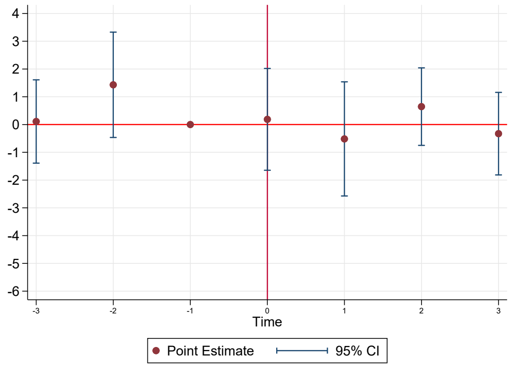
(c) Transportation & warehousing hourly wages



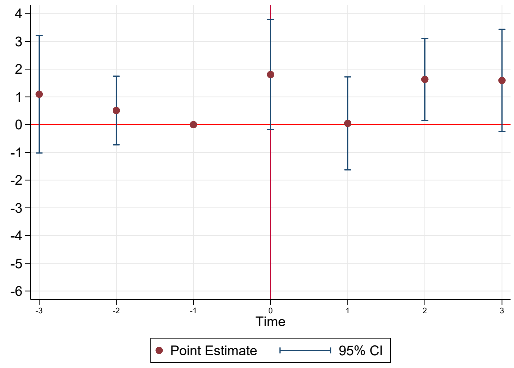
(d) Retail hourly wages

Figure 3: log(annual income wages) and log(hourly wages) by sector

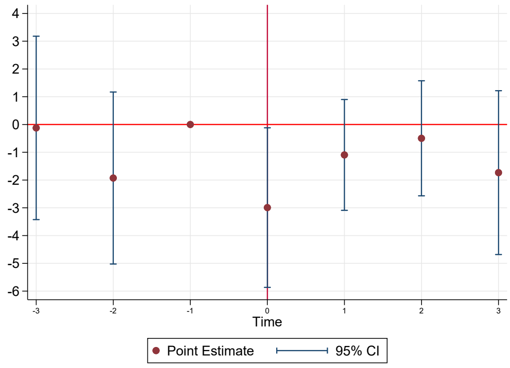
Note: Each panel of this figure shows the coefficients and 95% confidence interval for separate event study regressions of the logarithm of each sector annual wages. Regression coefficients are weighted by 2010 population and the standard errors are clustered at the state level.



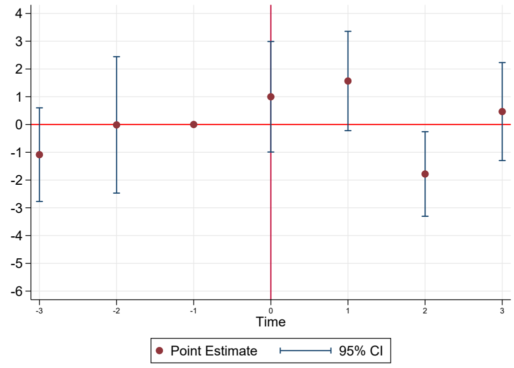
(a) Production, construction & transportation



(b) Office & service



(c) Sales



(d) Managerial & professional

Figure 4: retail occupational shares by occupation groups

Note: Each panel on this figure shows the coefficients and 95% confidence interval for separate event study regressions of the retail occupational shares. Regression coefficients are weighted by 2010 population and the standard errors are clustered at the state level. Occupational shares classified as: transportation and material moving occupations, production and construction occupations (SOC 53-, 51-, 45-, 47- and 29-), office and service occupations (SOC 43-, and 3X-), sales and related occupations (SOC 41-), and managerial and professional occupations (SOC 1X- and 2X-)

A Appendix

A.1 Appendix Model

A.1.1 Solving for Equilibrium Effects

In this section, we present the equations of change of the model following the log-linearization method of Jones (1965), and solve for the effects of a small increase in the tax rate of out-of-state e-commerce retail. Totally differentiating the production functions from equations in (I):

$$\widehat{B} = \widehat{L_B} \tag{4}$$

$$\widehat{S} = \widehat{L_S} \tag{5}$$

$$\widehat{E} = \widehat{L_E} \tag{6}$$

Where $\widehat{i}$ is the proportional change of $i = B, S, E$, $\widehat{i} \equiv di/i$, and $\widehat{L_i}$ is the proportional change of labor in sector $i = B, S, E$, $\widehat{L_i} \equiv dL_i/L_i$

From differentiating the resource constraint:

$$\lambda_X \widehat{L_X} + \lambda_Y \widehat{L_Y} + \lambda_Z \widehat{L_Z} = 0 \tag{7}$$

Here, the fraction of labor supplied used in the production of retail is given by λ_i for $i = B, S, E$, with $\lambda_i = \frac{L_i}{\bar{L}}$. As before, $\widehat{L_i} \equiv \frac{dL_i}{L_i}$ is the proportional change in L_i.

We totally differentiate the equations in (III)to obtain:

$$\widehat{p_B} + \widehat{B} = \widehat{w_B} + \widehat{L_B} \tag{8}$$

$$\widehat{p_S} + \widehat{S} = \widehat{w_S} + \widehat{L_S} \tag{9}$$

$$\widehat{p_E} + \widehat{E} = \widehat{w_E} + \widehat{L_E} \tag{10}$$

From the definition of workers' elasticity of substitution between sectors:

$$\widehat{L_B} - \widehat{L_S} = \eta_1 \left(\widehat{w_S} - \widehat{w_B}\right) \tag{11}$$

$$\widehat{L_B} - \widehat{L_E} = \eta_2 \left(\widehat{w_E} - \widehat{w_B}\right) \tag{12}$$

$$\widehat{L_E} - \widehat{L_S} = \eta_3 \left(\widehat{w_S} - \widehat{w_E}\right) \tag{13}$$

Finally, from the definition of consumer' elasticity of substitution for types of retail(B, S, E):

$$\widehat{B} - \widehat{S} = \sigma_1 \left(\widehat{p_S} + \widehat{\tau_S} - \widehat{p_B} - \widehat{\tau_B}\right) \tag{14}$$

$$\widehat{B} - \widehat{E} = \sigma_2 \left(\widehat{p_E} + \widehat{\tau_E} - \widehat{p_B} - \widehat{\tau_B}\right) \tag{15}$$

$$\widehat{E} - \widehat{S} = \sigma_3 \left(\widehat{p_S} + \widehat{\tau_S} - \widehat{p_E} - \widehat{\tau_E}\right) \tag{16}$$

With $\widehat{\tau_i} = \frac{d\tau_i}{1+\tau_i}$

This model is characterized by the assumptions of perfect competition, perfect mobility, perfect information and perfect certainty, and defined by equations (4)-(18).

We solve for the effects of an increase in the ad valorem tax rate on sales of out-of-state e-commerce retail, sector E, while the remaining tax rates do not change, $\widehat{\tau_B} = 0, \widehat{\tau_S} = 0$. Since we focus on real behavior, we choose S as numeraire, hence $\widehat{p_S} = 0$. Combining equations I, II, III and 4, 5, 6, I find:

$$\hat{p_B} = \hat{w_B}, \hat{p_S} = \hat{w_S}, \hat{p_E} = \hat{w_E} \tag{15}$$

As $\hat{p_S} = 0$ due to S being the numeraire, hence:

$$\widehat{w_S} = \widehat{p_S} = 0 \tag{14a}$$

Combining equations 9,10 and 11, we obtain the expression:

$$\hat{p_B} = \frac{\sigma_3 - \sigma_2}{\sigma_1 - \sigma_2}(\hat{p_E} + \hat{\tau_E}) = \epsilon_U(\hat{p_E} + \hat{\tau_E}) \tag{16}$$

Combining equations 6,7 and 8, we obtain the expression:

$$\hat{p_B} = \frac{\eta_3 - \eta_2}{\eta_1 - \eta_2}\hat{p_E} = \epsilon_L \hat{p_E} \tag{17}$$

Combining expressions 15, 16 and 17, I find 14b and 14c

$$\widehat{w_E} = \widehat{p_E} = \widehat{w_T} = \widehat{p_T} = -A\widehat{\tau_E} \tag{14b}$$

$$\widehat{w_B} = \widehat{p_B} = -A\epsilon_L\widehat{\tau_E} \tag{14c}$$

Combining equation 9 with 14b and 14c, we obtain:

$$\hat{S} = \hat{B} + \frac{\sigma_1 \epsilon_L \epsilon_U}{\epsilon_L - \epsilon_U}\hat{\tau_E} \tag{18}$$

Combining equation 10 with 14b and 14c, we obtain:

$$\hat{E} = \hat{B} + \frac{\sigma_2 \epsilon_L(\epsilon_U - 1)}{\epsilon_L - \epsilon_U}\hat{\tau_E} \tag{19}$$

Combining expressions 18 and 19 with equation 4 and I, we find:

$$\widehat{L_B} = \widehat{L_B} = [\lambda_S \sigma_1 \epsilon_U A + \lambda_E \sigma_2(\epsilon_U - 1)A]\,\widehat{\tau_E} \tag{14e}$$

Combining equation II, 14e and expression 18, we obtain

$$\widehat{L_S} = \widehat{L_S} = [(\lambda_S - 1)\sigma_1 \epsilon_U A + \lambda_E \sigma_2(\epsilon_U - 1)A]\,\widehat{\tau_E} \tag{14f}$$

Finally, combining equations III, 14e and expression 19 we find

$$\widehat{L_E} = \widehat{E} = \widehat{L_T} = \widehat{T} = [\lambda_S \sigma_1 \epsilon_U A + (\lambda_E - 1)\sigma_2(\epsilon_U - 1)A]\widehat{\tau_E} \tag{14d}$$

A.1.2 Derivations of Proposition 1

To derive Proposition 1, we evaluate each of the effects separately. We present the conditions that lead to Proposition 1 through Propositions 2-6.

Proposition 2 *The wage, and price, of E will fall if an only if:*

$$\epsilon_L = \frac{\eta_3 - \eta_2}{\eta_1 - \eta_2} < \frac{\sigma_3 - \sigma_2}{\sigma_1 - \sigma_2} = \epsilon_U$$

That is, wages in transportation and warehousing will fall if and only if the relative differences in preferences for consumers, ϵ_U , is larger than the relative differences in preferences for workers, ϵ_L.

An example where this proposition holds is a case where consumers' elasticity of substitution between e-commerce retail and warehouse clubs and supercenter retail, σ_3, is larger than consumers' elasticities of substitution for both types of retail with respect of general brick-and-mortar retail, σ_2 and σ_1, while the workers' elasticities of substitutions are similar across the three sectors.

Proposition 3 *The wage, and price, of B will fall if an only if:*

$$\frac{1}{\epsilon_U} = \frac{\sigma_1 - \sigma_2}{\sigma_3 - \sigma_2} < \frac{\eta_1 - \eta_2}{\eta_3 - \eta_2} = \frac{1}{\epsilon_L}$$

Hence, wages in general brick-and-mortar retail will fall if and only if the inverse of relative differences in preferences for consumers, ϵ_U , is larger than the inverse of relative differences in preferences for workers, ϵ_L. Proposition 2 also holds with the previous example.

The following propositions show under which conditions a rise on the tax rate on out-of-state e-commerce sales, $\widehat{\tau_E} > 0$, leads to a rise or fall of the labor requirements of the three sectors.

Proposition 4 *Let ϵ_U and ϵ_L are the relative differences in preferences for consumers and workers respectively: $\epsilon_U = \frac{\sigma_3-\sigma_2}{\sigma_1-\sigma_2}$ and $\epsilon_L = \frac{\eta_3-\eta_2}{\eta_1-\eta_2}$, and $C = \frac{\lambda_S\sigma_1}{(\lambda_E-1)\sigma_2}$. E-commerce consumption,E, as well as labor requirements in transportation and warehousing,L_W, will fall if an only if either one of these cases holds:*

Case I: $0 < \epsilon_L < \epsilon_U$ and $\epsilon_U < \frac{1}{1+C}$
Case II: $\epsilon_L < \epsilon_U$, $\epsilon_L < 0$ and $\epsilon_U > \frac{1}{1+C}$
Case III: $\epsilon_L > \epsilon_U$, $\epsilon_L > 0$ and $\epsilon_U > \frac{1}{1+C}$
Case IV: $0 > \epsilon_L > \epsilon_U$ and $\epsilon_U < \frac{1}{1+C}$

Under cases I and II, Propositions 2 and 3 also hold. The additional requirement for Proposition 4 to hold is given by the consumers' relative elasticity of substitution of general brick-and-mortar retail with respect to other retail sectors, σ_1/σ_2, weighted by the ratio of labor shares in warehouse clubs and supercenters and e-commerce retail, $\lambda_S/(\lambda_E - 1)$. Notice that as $\lambda_E - 1 < 0$, C is also negative. Hence, for case I to hold, it must be the case that $0 \leq |C| < 1$ and larger enough such that $\epsilon_U < \frac{1}{1+C}$.The underlying condition such that the absolute value of C is smaller than 1 is given by $\lambda_S/(1-\lambda_E) < \sigma_1/\sigma_2$, where $\lambda_S/(1-\lambda_E) = \lambda_S/(\lambda_S+\lambda_B) < 1$. An example in which case I may be true is if consumers' elasticity of substitution between general brick-and-mortar and warehouse clubs and supercenters is smaller than their elasticity of substitution between general brick-and-mortar and e-commerce retail. For case II to hold, it must be true that either $\leq |C| > 1$ or $\epsilon_U > \frac{1}{1+C}$; then a sufficient condition is that $\lambda_S/(1-\lambda_E) > \sigma_1/\sigma_2$ which holds with σ_1 sufficiently small.

Under cases III and IV, Propositions 2 and 3 don't hold, which implies that wages in transportation and warehousing and general brick-and-mortar retail increase when the tax on e-commerce increase. Moreover, case III and IV only require $\epsilon_U > \frac{1}{1+C}$ and $\epsilon_U < \frac{1}{1+C}$ respectively, without any boundary restriction for C.

Proposition 5 *Let ϵ_U and ϵ_L are the relative differences in preferences for consumers and workers respectively: $\epsilon_U = \frac{\sigma_3-\sigma_2}{\sigma_1-\sigma_2}$ and $\epsilon_L = \frac{\eta_3-\eta_2}{\eta_1-\eta_2}$, and $D = \frac{(\lambda_S-1)\sigma_1}{\lambda_E\sigma_2}$. Retail warehouse clubs and supercenters consumption, S, as well as its labor requirements will rise if an only if either one of these cases holds:*

Case V: $0 < \epsilon_L < \epsilon_U$ *and* $\epsilon_U > \frac{1}{1+D}$
Case VI: $\epsilon_L < \epsilon_U$, $\epsilon_L < 0$ *and* $\epsilon_U < \frac{1}{1+D}$
Case VII: $\epsilon_L > \epsilon_U$, $\epsilon_L > 0$ *and* $\epsilon_U < \frac{1}{1+D}$
Case VIII: $0 > \epsilon_L > \epsilon_U$ *and* $\epsilon_U > \frac{1}{1+D}$

Under cases V and VI, Propositions 2 and 3 also hold. The additional requirement for Proposition 5 to hold is given by the consumers' relative elasticity of substitution of general brick-and-mortar retail with respect to other retail sectors, σ_1/σ_2, weighted by the ratio of labor shares in warehouse clubs and supercenters and e-commerce retail, $(\lambda_S-1)/\lambda_E$. Notice that as $\lambda_S - 1 < 0$, D is also negative. Hence, for case V to hold, it can be true that either $\leq |D| > 1$ or $\epsilon_U > \frac{1}{1+D}$; then a sufficient condition is that $(1-\lambda_S)/\lambda_E = (\lambda_B+\lambda_E)/\lambda_E > \sigma_1/\sigma_2$ which holds with σ_1 sufficiently small, since $(1-\lambda_S)/\lambda_E > 1$. For case VI to hold, it must be the case that $0 \leq |D| < 1$ and larger enough such that $\epsilon_U < \frac{1}{1+D}$.The underlying condition such that the absolute value of D is smaller than 1 is given by $(1-\lambda_S)/\lambda_E < \sigma_1/\sigma_2$, where $(1-\lambda_S)/\lambda_E = \lambda_E + \lambda_B/\lambda_E > 1$. An example in which case VI may be true is if consumers' elasticity of substitution between general brick-and-mortar and warehouse clubs and supercenters is smaller than their elasticity of substitution between general brick-and-mortar and e-commerce retail.

Under cases VII and VIII, Propositions 2 and 3 don't hold, which implies that wages in transportation and warehousing and general brick-and-mortar retail increase when the tax on e-commerce increase. Moreover, case VII and VIII only require $\epsilon_U < \frac{1}{1+D}$ and $\epsilon_U > \frac{1}{1+D}$ respectively, without any boundary restriction for D.

Proposition 6 *Let ϵ_U and ϵ_L are the relative differences in preferences for consumers and workers respectively: $\epsilon_U = \frac{\sigma_3-\sigma_2}{\sigma_1-\sigma_2}$ and $\epsilon_L = \frac{\eta_3-\eta_2}{\eta_1-\eta_2}$, and $F = \frac{\lambda_S\sigma_1}{\lambda_E\sigma_2}$. Retail consumption from general brick-and-mortar retailers, B, as well as their labor requirements will fall if an only if either one of these cases holds:*

Case IX: $\frac{1}{1+F} > \epsilon_U > \epsilon_L > 0$
Case X: $\epsilon_U > \frac{1}{1+F} > 0 > \epsilon_L$
Case XI: $\epsilon_L > \epsilon_U > \frac{1}{1+F} > 0$
Case XII: $0 > \epsilon_L > \epsilon_U$ *and* $\epsilon_U < \frac{1}{1+F}$

Under cases IX and X, Propositions 2 and 3 also hold. The additional requirement for Proposition 6 to hold is given by the consumers' relative elasticity of substitution of general brick-and-mortar retail with respect to other retail sectors, σ_1/σ_2, weighted by the ratio of labor shares in warehouse clubs and supercenters and e-commerce retail, λ_S/λ_E. Notice that as both λ_S and λ_E are shares of labor employed in each sector, $\lambda_S/\lambda_E > 0$, then F is also positive and $1/(1+F) < 1$. For case IX to hold, it must be true that $\epsilon_U < 1$; then a necessary condition is that either $\sigma_3 < \sigma_1$ with σ_2 sufficiently small or $\sigma_3 > \sigma_1$ with σ_2 sufficiently large. The opposite is true for cases X and XI.

Under cases XI and XII, Propositions 2 and 3 don't hold, which implies that wages in transportation and warehousing and general brick-and-mortar retail increase when the tax on e-commerce increase. Moreover, case XI and XII only require $\epsilon_U < \frac{1}{1+F}$ and $\epsilon_U > \frac{1}{1+F}$ respectively. Case XII requires then that $\epsilon_U < 1$, or equivalently either $\sigma_3 < \sigma_1$ with σ_2 sufficiently small or $\sigma_3 > \sigma_1$ with σ_2 sufficiently large, while case XI does not impose any additional boundary restriction for F.

A.2 The Effects of the Amazon Tax on Other Outcomes

In the main analysis, we study the effect of the Amazon Tax on the employment, wages, and occupational structure at CZ level. In this section we explore the effects of removing the out-of-state e-commerce price advantage on two additional set of outcomes.

First, we investigate if the Amazon Tax changes the number of establishments per capita at CZ level. A major concern when discussing the effects of e-commerce on the economy has been the chance that it would crowd out local brick-and-mortar stores. The increasing trend in brick-and-mortar establishment closures was referred to in the news as the "Retail Apocalypse". In Table A.5, we present the results of estimating Equation 1 using the establishments-to-population ratio as outcome variable at CZ level. We do not find statistically significant changes in the number establishments per capita in retail and retail-related sectors. Consequently, we do not find evidence supporting the idea that removing the price advantage that out-of-state online retailers had over in-state retailers would prevent e-commerce from crowding out brick-and-mortar. A possible explanation remains that the in-state retailers adapted their business models to compete online retailers.

Second, we study whether there are effects of the Amazon Tax on the overall local labor market. We estimate Equation 1 using total employment over working age population, total number of establishments over population and total annual income wages (in logs) in all sectors as outcome variables at CZ level. A priori, we would not expect the Amazon Tax to affect these outcomes of interest in industries other than retail or directly related to retail. We present the results in Table A.6. None of the coefficient are statistically significant.

A.3 Data Appendix

In the sensitivity analysis, we check that our results are robust to controlling for consumption predictors (i.e., median household income, location Amazon fulfillment centers, industry distribution, sales tax levels across states, and CZs' demographic characteristics) because the effects of the Amazon Tax in local labor markets may be mediated by shifts in consumption patters.

Given that effects of the Amazon Tax on local labor markets may be mediated by shifts in consumption patterns, we control for predictors of changes in consumption and e-commerce consumption in the robustness checks. Our main results are robust to controlling for differential consumption trends at CZ level. We include CZ-level consumption predictors measured at baseline interacted with time dummies. These interactions allow for the possibility that the relationship between the outcome variables and the CZ's baseline consumption predictors changes in the post-2013 period. We avoid including the post-treatment consumption predictors covariates as they can potentially be affected by the treatment (Wooldridge, 2005; Callaway and Sant'Anna, 2021).

Median Household Income: we obtain estimates from the Small Area Income and Poverty Estimates (SAIPE) Program. The SAIPE Program is conducted by the US Census Bureau, which combines data from administrative records, survey data and population estimates to produce median household income estimates at the county level.

Amazon Fulfillment Centers: To predict changes in e-commerce consumption patterns, we obtain location records of Amazon.com, Inc fulfillment centers from MWPVL International. MWPVL International is a firm that provides services on supply chain and logistics network strategy. As part of their research analysis of the current Amazon.com logistics network they collected Amazon.com fulfillment center's locations.

The reasons behind using Amazon locations as a predictor of e-commerce consumption patterns are twofold: Amazon is one of the biggest e-commerce retailers in the period studied; and Amazon sets locations such that it minimizes shipping costs according to consumption patterns (Houde et al., 2017). We complement data on the location of Amazon fulfillment centers from MWPVL International with information on fulfillment centers from newspaper articles.

Industry Distribution: we calculate the share of the the GDP of each industry at a given county in a given year using data from the Bureau of Economic Analysis (BEA). The GDP is computed as the sum of employees' compensations, proprietors' income and other income payments and costs (OIC). The total compensation to employees is calculated from wages, salaries and supplements to wages and salaries, as part of the county personal income statistics. The main sources of data behind BEA's computations are BEA county-level compensation and proprietors' income data. To distribute state-level OIC to counties, BEA uses Quarterly Census of Employment and Wages (QCEW) data, National Establishment Time Series (NETS) sales data, Economic Census data, and various sources industry-specific data. For more details on the county GDP computations see Aysheshim et al. (2020).

State and Local Sales Tax Rates: To account for differences in sales tax rates across regions, we control for the sales tax rates differences with data collected from TaxFoundation.org reports on State and Local Sales Tax Rates. TaxFoundation.org collects historical records on state and local sales tax rates from the Federation of Tax administrators.

Demographic Characteristics: Finally, we also control for relevant population characteristics (e.g., white rate, black rate, female rate) that may shape consumption patterns. Such rates were constructed with data from Census Intercensal Population Estimates for the period 2010-2020.

A.4 Appendix Tables

Table A.1: Sample all commuting zones - excluding CZ in state borders

	Transportation & Warehousing	Retail	Warehouse Clubs & Supercenters	General Brick-and-Mortar Retail
Panel A: Employment / WA population				
Enactment Amazon Tax	-38.093*	-55.468	57.567*	-94.998*
	(15.26)	(37.81)	(25.82)	(33.73)
Baseline mean	332.51	7342.94	332.51	6184.39
SD	583.00	1792.09	648.31	1616.58
Observations	1400	1400	1400	1400
Parallel trends	0.812	0.448	0.219	0.755
Panel B: Annual wages and hourly wages				
	ln(annual income wages)		ln(hourly wages)	
	Transportation & Warehousing	Retail	Transportation & Warehousing	Retail
Enactment Amazon Tax	-0.063*	-0.030	-0.028*	-0.026
	(0.03)	(0.02)	(0.01)	(0.04)
Baseline mean	10.44	9.96	2.71	2.92
SD	0.35	0.18	0.15	0.12
Observations	1400	1400	1400	1400
Parallel trends	0.0954	0.588	0.0394	0.242
Panel D: Retail Occupational Shares				
	Construction, Production & Transportation	Office & Services	Sales	Managerial & Professional
Enactment Amazon Tax	-0.520	0.818*	-0.757	0.458
	(0.50)	(0.36)	(0.48)	(0.48)
Baseline mean	17.35	21.12	52.80	8.73
SD	5.02	5.16	6.60	4.19
Observations	1400	1400	1400	1400
Parallel trends	0.652	0.440	0.640	0.428

This table presents the estimates of the difference-in-differences model, where Enactment of Amazon Tax refers to the estimation coefficient (δ) from $Y_{cy} = \alpha_c + \gamma_y + \delta D_{sy} + \epsilon_{cy}$, where outcome variable is $\frac{Emp_{cy}}{Pop_{cy}} \times 100000$ for both each corresponding sector (columns). The sample excludes all CZs that cross state borders. All specifications include year and commuting zone fixed effects and standard errors clustered at the state level.

Table A.2: Employment (controlling for consumer predictors)

	Transportation & Warehousing	Retail	Warehouse Clubs & Supercenters	General Brick-and-Mortar Retail
Panel A: Sample all commuting zones				
Enactment Amazon Tax	-30.183*	-97.969**	64.402*	-157.300***
	(12.94)	(26.92)	(28.71)	(32.04)
Baseline mean	396.48	7420.12	1142.41	6169.09
SD	747.47	1773.99	615.06	1544.33
Observations	1603	1603	1603	1603
Parallel trends	0.141	0.142	0.192	0.140
Covariates × time FE	YES	YES	YES	YES
Panel B: Sample urban commuting zones				
Enactment Amazon Tax	-28.831	-125.281**	63.910	-188.669**
	(15.13)	(29.64)	(45.31)	(49.12)
Baseline mean	499.45	7883.95	1149.49	6574.26
SD	394.13	1004.99	384.74	1026.99
Observations	441	441	441	441
Parallel trends	0.135	0.227	0.337	0.237
Covariates × time FE	YES	YES	YES	YES
Panel C: Sample non-urban commuting zones				
Enactment Amazon Tax	-61.465	-17.633	-18.905	-16.415
	(39.30)	(48.92)	(31.60)	(45.18)
Baseline mean	357.39	7244.08	1139.72	6015.32
SD	840.75	1961.85	682.75	1675.36
Observations	1162	1162	1162	1162
Parallel trends	0.238	0.238	0.472	0.102
Covariates × time FE	YES	YES	YES	YES

This table presents the estimates of the difference-in-differences model, where Enactment of Amazon Tax refers to the estimation coefficient (δ) from $Y_{cy} = \alpha_c + \gamma_y + \delta D_{sy} + \epsilon_{cy}$, where outcome variable is $\frac{Emp_{cy}}{Pop_{cy}} \times 100000$ for both each corresponding sector (columns). All specifications include year and commuting zone fixed effects and standard errors clustered at the state level.

Table A.3: Annual wages and hourly wages (controlling for consumer predictors)

	ln(annual income wages)		ln(hourly wages)	
	Transportation & Warehousing	Retail	Transportation & Warehousing	Retail
Panel A: Sample all commuting zones				
Enactment Amazon Tax	-0.069	-0.012	0.011	-0.087**
	(0.04)	(0.01)	(0.02)	(0.03)
Baseline mean	10.45	9.95	2.70	2.91
SD	0.36	0.17	0.17	0.12
Observations	1603	1603	1603	1603
Parallel trends	0.325	0.225	0.00183	0.731
Covariates x time FE	YES	YES	YES	YES
Panel B: Sample urban commuting zones				
Enactment Amazon Tax	-0.033	-0.015	0.003	-0.076
	(0.04)	(0.01)	(0.02)	(0.04)
Baseline mean	10.50	9.99	2.75	2.99
SD	0.32	0.15	0.22	0.12
Observations	441	441	441	441
Parallel trends	0.613	0.0249	0.0197	0.746
Covariates x time FE	YES	YES	YES	YES
Panel C: Sample non-urban commuting zones				
Enactment Amazon Tax	-0.147*	-0.008	-0.002	-0.106*
	(0.06)	(0.02)	(0.02)	(0.05)
Baseline mean	10.43	9.93	2.68	2.88
SD	0.38	0.18	0.15	0.10
Observations	1162	1162	1162	1162
Parallel trends	0.603	0.669	0.472	0.0559
Covariates x time FE	YES	YES	YES	YES

This table presents the estimates of the difference-in-differences model, where Enactment of Amazon Tax refers to the estimation coefficient (δ) from $Y_{cy} = \alpha_c + \gamma_y + \delta D_{sy} + \epsilon_{cy}$, where outcome variable is annual wages and hourly wages for each corresponding sector (columns). All specifications include year and commuting zone fixed effects and standard errors clustered at the state level.

Table A.4: Retail occupational shares (controlling for consumer predictors)

	Construction, Production & Transportation	Office & Services	Sales	Managerial & Professional
Panel A: Sample all commuting zones				
Enactment Amazon Tax	-0.542	0.383	-0.780*	0.939**
	(0.44)	(0.32)	(0.35)	(0.31)
Baseline mean	16.63	21.56	52.60	9.21
SD	4.94	5.22	6.80	4.08
Observations	1603	1603	1603	1603
Parallel trends	0.142	0.188	0.766	0.216
Covariates x time FE	YES	YES	YES	YES
Panel B: Sample urban commuting zones				
Enactment Amazon Tax	-0.890	0.235	-0.229	0.884*
	(0.56)	(0.44)	(0.47)	(0.35)
Baseline mean	15.40	21.29	53.35	9.96
SD	4.25	4.94	6.34	3.72
Observations	441	441	441	441
Parallel trends	0.108	0.0779	0.956	0.197
Covariates x time FE	YES	YES	YES	YES
Panel C: Sample non-urban commuting zones				
Enactment Amazon Tax	0.598	0.915	-1.942	0.429
	(0.99)	(0.66)	(1.23)	(0.63)
Baseline mean	17.10	21.66	52.31	8.93
SD	5.10	5.33	6.95	4.17
Observations	1162	1162	1162	1162
Parallel trends	0.135	0.538	0.129	0.0350
Covariates x time FE	YES	YES	YES	YES

This table presents the estimates of the difference-in-differences model, where Enactment of Amazon Tax refers to the estimation coefficient (δ) from $Y_{cy} = \alpha_c + \gamma_y + \delta D_{sy} + \epsilon_{cy}$, where outcome variable is $Y_{cyi} = \frac{Emp_{cyi}}{Emp_{cy}}$ for each occupational group: transportation and material moving occupations, production and construction occupations (SOC 53-, 51-, 45-, 47- and 29-), office and service occupations (SOC 43-, and 3X-), sales and related occupations (SOC 41-), and managerial and professional occupations (SOC 1X- and 2X-). All specifications include year and commuting zone fixed effects and standard errors clustered at the state level.

Table A.5: Establishments

	Transportation & Warehousing	Retail	Warehouse Clubs & Supercenters	General Brick-and-Mortar Retail
Panel A: Sample all commuting zones				
Enactment Amazon Tax	-0.178	-2.663	0.514	-2.901
	(0.23)	(2.50)	(0.42)	(2.27)
Baseline mean	8.54	431.12	21.45	403.95
SD	7.10	116.16	12.11	110.94
Observations	1603	1603	1603	1603
Parallel trends	0.320	0.465	0.142	0.472
Panel B: Sample urban commuting zones				
Enactment Amazon Tax	-0.307	-4.044	0.661	-4.396
	(0.20)	(2.39)	(0.43)	(2.04)
Baseline mean	9.73	377.24	15.15	354.80
SD	3.53	64.87	7.25	62.92
Observations	441	441	441	441
Parallel trends	0.412	0.268	0.360	0.184
Panel C: Sample non-urban commuting zones				
Enactment Amazon Tax	0.257	1.786	0.157	2.017
	(0.43)	(3.70)	(0.54)	(3.80)
Baseline mean	8.10	451.57	23.85	422.61
SD	8.01	124.54	12.71	119.25
Observations	1162	1162	1162	1162
Parallel trends	0.603	0.530	0.250	0.425

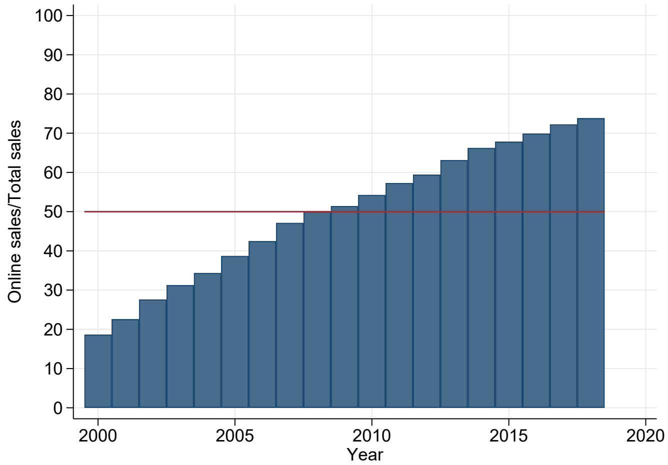
This table presents the estimates of the difference-in-differences model, where Enactment of Amazon Tax refers to the estimation coefficient (δ) from $Y_{cy} = \alpha_c + \gamma_y + \delta D_{sy} + \epsilon_{cy}$, where outcome variable is $\frac{Emp_{cy}}{Pop_{cy}} \times 100000$ for both each corresponding sector (columns). All specifications include year and commuting zone fixed effects and standard errors clustered at the state level.

Table A.6: Overall activity

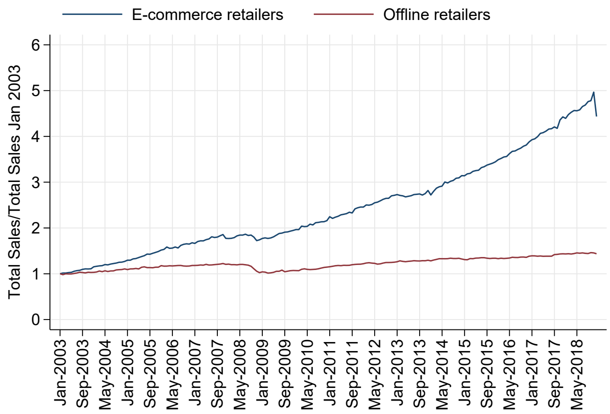
	Employment / WA Pop	ln(annual income wages)	ln(hourly wages)	N Establishments / Pop
Panel A: Sample all commuting zones				
Enactment Amazon Tax	447.504	0.005	-0.011	57.043
	(510.39)	(0.01)	(0.01)	(47.22)
Baseline mean	47061.22	10.10	2.91	2615.54
SD	13129.17	0.18	0.12	763.90
Observations	1603	1603	1603	1603
Parallel trends	0.345	0.445	0.0180	0.216
Panel B: Sample urban commuting zones				
Enactment Amazon Tax	620.963	0.007	-0.009	64.812
	(563.59)	(0.01)	(0.01)	(51.24)
Baseline mean	54174.45	10.18	2.99	2402.04
SD	10332.15	0.17	0.12	360.71
Observations	441	441	441	441
Parallel trends	0.329	0.640	0.0498	0.167
Panel C: Sample non-urban commuting zones				
Enactment Amazon Tax	-427.509	-0.000	-0.010	26.345
	(350.51)	(0.02)	(0.01)	(32.04)
Baseline mean	44361.62	10.07	2.88	2696.57
SD	13076.72	0.18	0.10	855.75
Observations	1162	1162	1162	1162
Parallel trends	0.793	0.212	0.134	0.683

This table presents the estimates of the difference-in-differences model, where Enactment of Amazon Tax refers to the estimation coefficient (δ) from $Y_{cy} = \alpha_c + \gamma_y + \delta D_{sy} + \epsilon_{cy}$, where outcome variable is $\frac{Emp_{cy}}{Pop_{cy}} \times 100000$ for both each corresponding sector (columns). All specifications include year and commuting zone fixed effects and standard errors clustered at the state level.

A.5 Appendix Figures



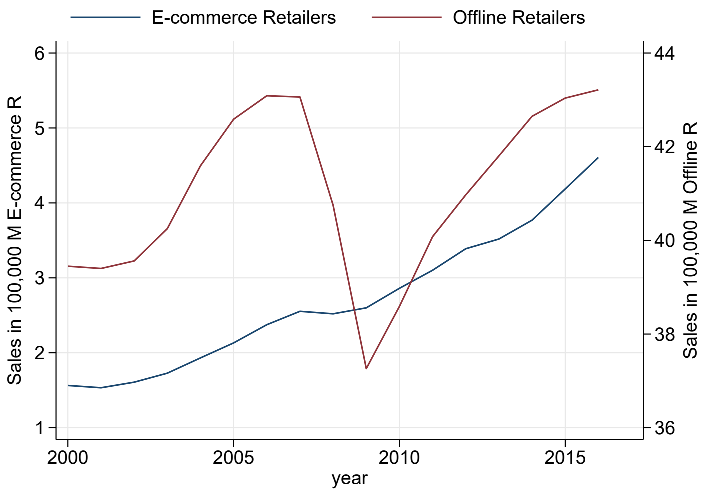
(a) Online sales share from e-commerce retail sales



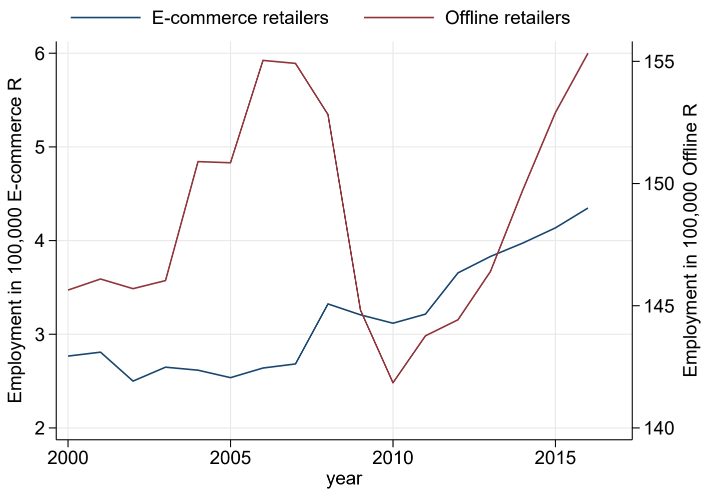
(b) Sales growth e-commerce vs offline retailers

Figure A.1: The growth of online and e-commerce in the economy

Note: These figures show the growth of online sales for the e-commerce retail sector as well as the growth of the e-commerce sector in the economy. Figure A.1a shows the share of online sales from total sales for e-commerce retailers computed from Annual Retail Trade Survey years 2000-2017. Figure A.1b presents the evolution of sales of e-commerce retailers (blue) and offline retailers (red) computed from from Monthly Retail Trade and Food Services Survey years 2003-2018. E-commerce retail here refers to electronic commerce and mail order houses industry (NAICS 4541), offline retailers are the remaining retailers.



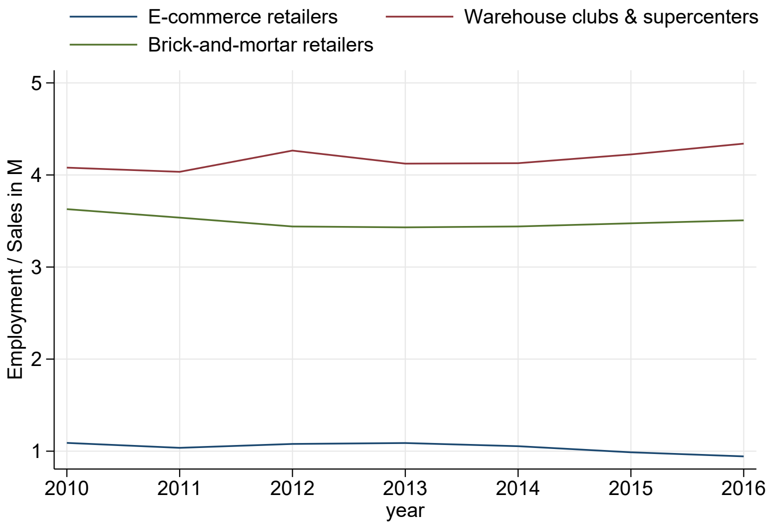
(a) Sales



(b) Employment

Figure A.2: Sales vs Employment in retail

Note: These figures show employment and sales for e-commerce and offline retailers. Both figures exhibit similar patterns, which suggest a strong correlation between employment and sales for both sectors. Total sales in 100,000 M are computed from Annual Retail Trade Survey years 2000-2016. Employment in 100,000 is computed from County Business Patters data. E-commerce and mail Retailers (blue) axis is on the left, while offline retailers (red) axis is on the right. Offline retailers are retailers that are not in the electronic commerce and mail order houses industry (NAICS 4541).



(a) Employment per 100,000 M retail sales

(b) Retail Occupational Structure 2007

Figure A.3: The retail labor market structure

Note: These figure show the labor market structure of the retail sector by sub-sector. Figure A.3a shows shows total employment from County Business Patterns data divided by total sales from Monthly Retail Trade and Food Services Survey years 2010-2017 deflated to 2014 usd. Figure A.3b presents the share of occupations by sub-industry from Occupational Employment and Wage Statistics (OEWS) May 2007. Industries: E-commerce (NAICS 4541), Warehouse Clubs and Supercenters (NAICS 4529), General Brick-and-mortar (NAICS 441, 442, 443, 444, 445, 446, 447, 448, 451, 4521, 453, 4542 and 4543). The occupational share represents Emp_{iR}/Emp_R where Emp is employment, i is the occupational group and R is retail. Occupational shares for major retail occupations: production, construction and transportation and material moving occupations (SOC 53-, 51-, 45-, 47- and 49-), office and service occupations (SOC 43-, and 3X-), sales and related occupations (SOC 41-), and managerial and professional occupations (SOC 1X- and 2X-)

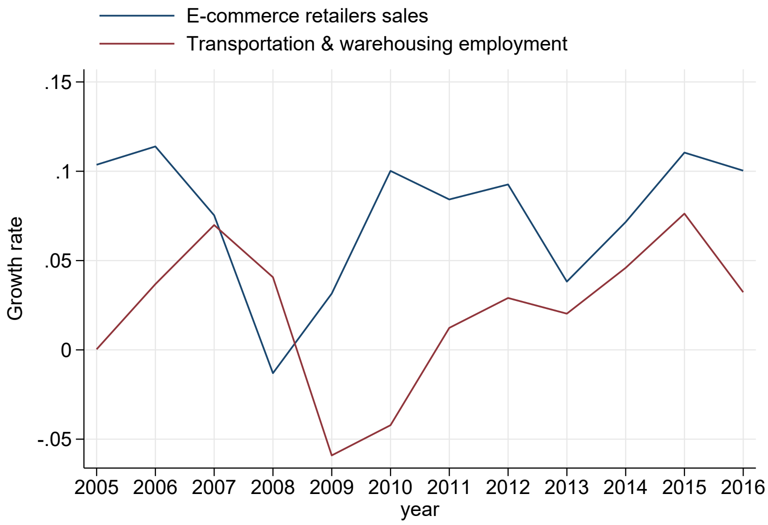
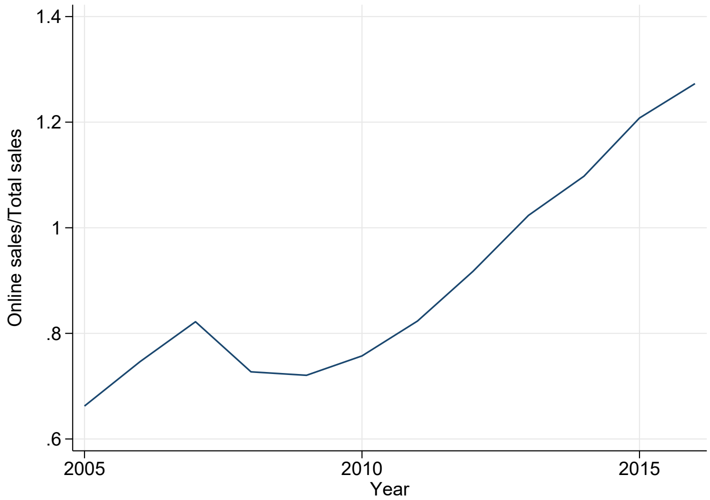
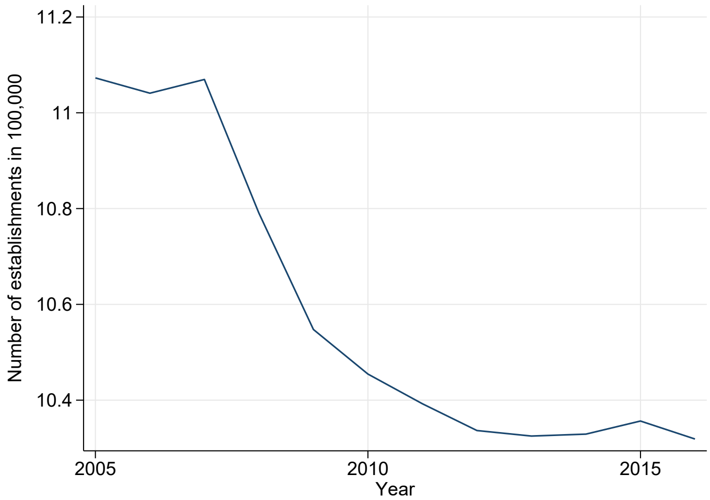


Figure A.4: Online retail sales growth vs warehousing and transportation employment growth
Note: This figure shows warehousing and transportation employment growth rate and e-commerce retail sales growth rate during the years 2005-2017. Both growth rates exhibit similar patterns, which suggest a high correlation. Employment growth rate is computed from County Business Patterns data. Sales growth rate is computed from Annual Retail Trade Survey.



(a) Online sales share from offline retailers' sales



(b) Number of establishments of offline retailers

Figure A.5: Changes for offline retailers

Note: These figures document changes for offline retailers: (1) the share of online sales has double in the last decade and (2) the number of establishments has decrease more than 7 percent. Figure A.5a the share of online sales from offline retailers' total sales computed from Annual Retail Trade Survey years 2005-2017. Figure A.5b presents the evolution of the number of establishments of offline retailers from County Business Patterns 2005-2016. Offline retailers are retailers that are not in the electronic commerce and mail order houses industry (NAICS 4541).

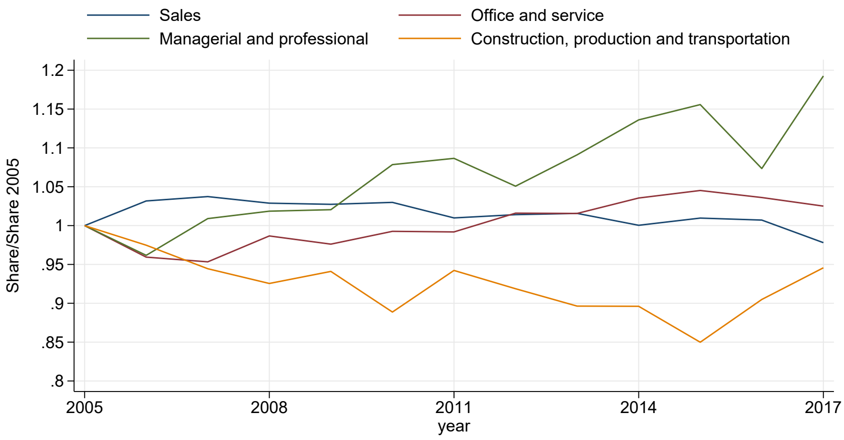
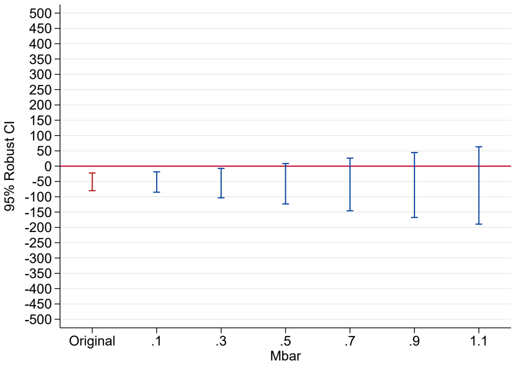
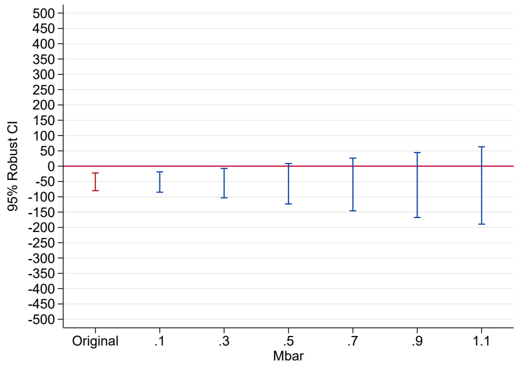


Figure A.6: Changes in retail occupational structure

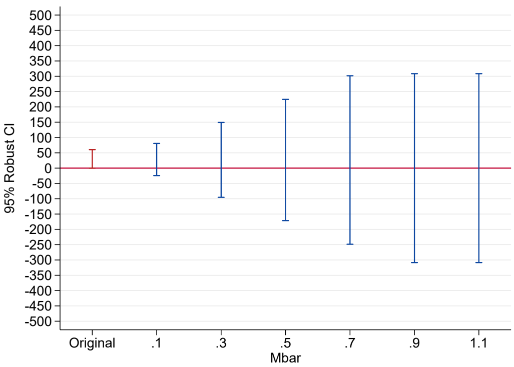
Note: This figure documents the changes in retail occupational shares for major occupations in years 2005-2017. Occupational shares are calculated using the American Community Survey (ACS). The occupational share represents Emp_{iR}/Emp_R where Emp is employment, i is the occupational group and R is the retail sector. Changes are measured with respect to 2005, as $share_{iR,t}/share_{iR,2005}$. Occupational shares for major occupations: production, construction and transportation and material moving occupations (SOC 53-, 51-, 45-, 47- and 49-), office and service occupations (SOC 43-, and 3X-), sales and related occupations (SOC 41-), and managerial and professional occupations (SOC 1X- and 2X-)



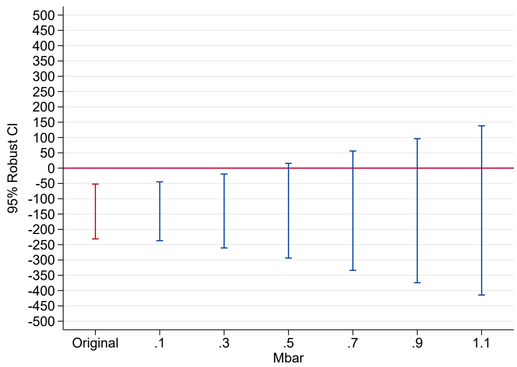
(a) Transportation & warehousing



(b) Retail



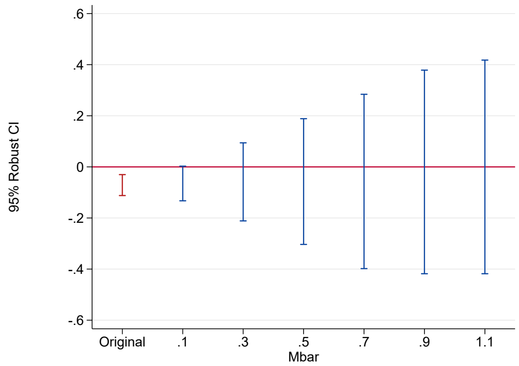
(c) Warehouse clubs & supercenters



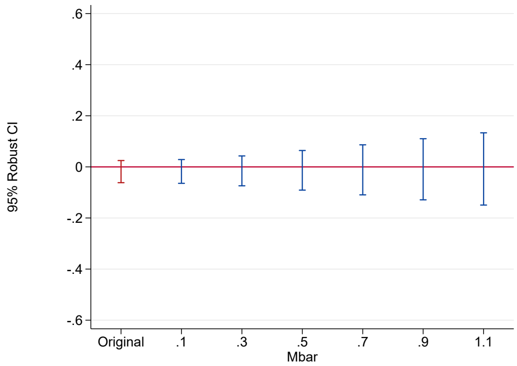
(d) General brick-and-mortar retail

Figure A.7: Sensitivity analysis - Employment/working age population by sector

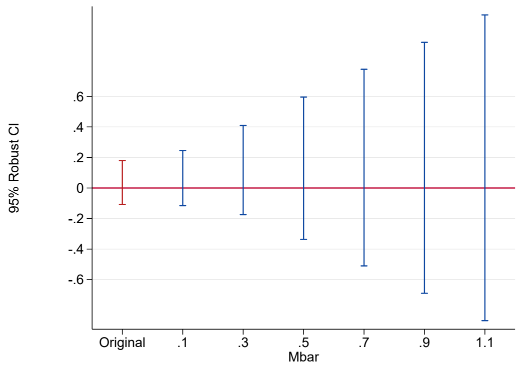
Note: This figure shows on each panel the sensitivity analysis of the difference-in-differences coefficients (per 100,000 working age population) and 95% confidence interval for separate regressions of the ratio between each sector's employment and working age population. Regression coefficients are weighted by 2010 population and the standard errors are clustered at the state level.



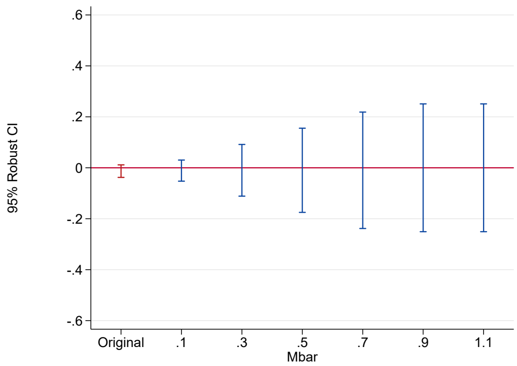
(a) Transportation & warehousing annual income wages



(b) Retail annual income wages



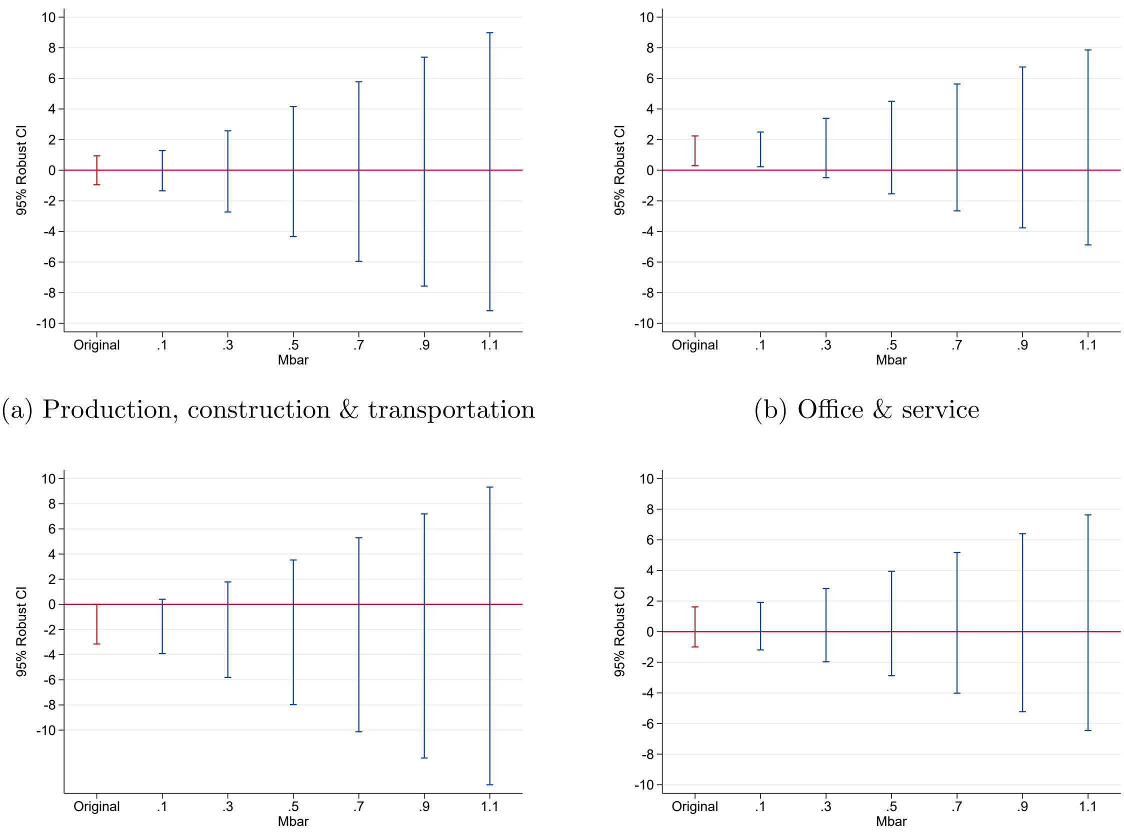
(c) Transportation & warehousing hourly wages



(d) Retail hourly wages

Figure A.8: Sensitivity analysis - log(annual income wages) and log(hourly wages) by sector

Note: This figure shows on each panel the sensitivity analysis of the difference-in-differences coefficients and 95% confidence interval for separate regressions of the ratio between each sector's employment and working age population. Regression coefficients are weighted by 2010 population and the standard errors are clustered at the state level.



(a) Production, construction & transportation

(b) Office & service

(c) Sales

(d) Managerial & professional

Figure A.9: Sensitivity analysis - Retail occupational shares by occupation groups

Note: This figure shows on each panel the sensitivity analysis of the difference-in-differences coefficients and 95% confidence interval for separate regressions of the ratio between each sector's employment and working age population. Regression coefficients are weighted by 2010 population and the standard errors are clustered at the state level.