

## Internet Appendix for Online Publication Only

In this appendix, we provide evidence supporting our main results reported in the paper.

1. **Location Choice of Fulfillment Centers (FCs):** In Section IA1, we provide details on factors that may impact the location choice of fulfillment centers (FCs), including population density and fixed costs.
2. **Additional Details on Worker-Level Data:** In Section IA2, we provide additional details on worker data used in this study.
3. **Effect of FCs on Web Search Volume:** In Section IA3, we provide details on results showing how web search volume for the large e-commerce retailer increase after the establishment of an FC in the local area.
4. **Effect of FCs on Couriers, Messengers, and Support Activities:** In Section IA4, our results highlight an increase in demand for couriers and messengers after the establishment of an FC in the local area.
5. **Exposure to FC and Retailers' Firm Values:** In Section IA5, we show how publicly listed retail firms' performance is affected by FCs based on incumbent retail firms' exposure in the local area.
6. **Baseline Results with County-Level Controls:** In Section IA6, we report our baseline results where we control for various county-level time-varying observable economic factors that may be correlated with the FC dummy, like house price index, per capita annual income, unemployment rate, age composition, education composition, and costs of physical shopping.
7. **Matching Estimates:** In Section IA7, we report our results using matching estimates. We match counties based on population size, density, per capita income, unemployment rate, age composition, education composition, and retail spending per capita.
8. **Instrumental Variables Approach:** In Section IA8, we report results of our instrumental variables regression, where we instrument the FC with the interaction of the distance between the FCs and the closest US Postal Service (USPS) network facility and state-level generosity of corporate subsidies.
9. **Additional Robustness Tests:** In Section IA9, we report results of additional robustness tests on sample, dependent variable, and fixed effects.
10. **Robustness Tests: Two-way Fixed Effects Methodology:** In Section IA10, we report results of additional robustness tests on two-way fixed effects methodology.
11. **Occupation-Level Analysis:** In Section IA11, we report occupation-level analysis for treated counties and show how different occupations are affected by FCs.
12. **Additional Store-Level Results:** In Section IA12, we report additional results using store-level data. We find no evidence of increased relocation after FC entry for retail stores. Further, the entry of FCs has a larger impact on non-franchises than the franchises. Finally, after the establishment of an FC in the affected county, the entry rate for small stores is significantly reduced.
13. **Alternative Explanations:** In Section IA13, we show that our results are not driven by alternative theories like the largest e-commerce retailer choosing FC locations based on declining aggregate wages or declining retail growth.
14. **Effect of FCs on Unemployment Rate and Aggregate Consumption:** In Section IA14, we find weak evidence for a decline in the unemployment rate or an increase in aggregate consumption in FC counties.
15. **Alternative Identification Strategy:** In Section IA15, we use the entry of the major e-commerce retailer into different sectors as an alternative identification strategy and find consistent results.

## IA1 Location Choice of Fulfillment Centers (FCs)

The major e-commerce retailer opened its first fulfillment center (FC) in the state of Delaware in 1997 and later expanded its network of FCs in the state of Kentucky. By 2005, the major e-commerce retailer opened 4 FCs in the state of Kentucky and received a total of \$34.33 million in tax subsidy (*Good Jobs First*–Subsidy Tracker Database) from the Kentucky Economic Development Finance Authority. For example, in the year 2000, the large e-commerce retailer opened a fulfillment center in Taylor County, Kentucky, and received \$19,037,500 in tax credit for an estimated investment of \$38,075,000 (i.e., 50% of the investment cost). This pattern suggests that in the early stage of expansion, opening FCs in contiguous geography helps reduce distribution costs. At the same time, fixed costs play an important role in such decision making.<sup>1</sup>

During 2006-2010, the major e-commerce retailer opened 12 fulfillment centers: five in Pennsylvania, two in Indiana and Nevada, and one in Arizona, New Hampshire, and Kentucky. The counties in which the FCs are located are more densely populated and have a much larger population than the average county in the US. For example, counties with FCs have an average population of 615,495 with a density of 672 per square mile. In comparison, fewer than 100,000 people reside in the average county in the US, with a density of 260 per square mile. This suggests that population density played an important role in FC location decisions. From 2010 to 2016, the major e-commerce retailer expanded its network around the existing FCs.<sup>2</sup>

The major e-commerce expansion network is similar to Walmart’s expansion of stores. Holmes (2011) takes a revealed preference approach. He shows that the benefits of high store density have costs for Walmart, i.e., market areas overlap and new stores cannibalize sales from existing stores. In the case of the major e-commerce retailer, such cannibalization is not likely to happen. However, opening up a fulfillment center involves huge upfront fixed costs. For example, the initial investment for an FC with a land area of 1,017,600 square feet opened in 2014, located in Hillsborough, Florida, was around \$204,100,000. In the case of Walmart, Holmes (2011) assume fixed costs as a quadratic function of population density and with a constant term zero. However, for the major e-commerce retailer, upfront investment costs can be a binding constraint, especially when it takes months to build a new FC.

We do not attempt to solve the model because we do not have access to confidential data on major e-commerce expansion network logistics costs. Further, in addition to population density, many other factors like workforce availability, logistic infrastructure, and local government subsidies may impact the location decision. However, we do consider these factors in our analysis. For example, we construct a Bartik-style instrument composed of cross-sectional variation in the distance between the FCs and the closest postal network facility and its interaction with temporal variation in the generosity of the subsidies that local and state governments offer to corporations (Bartik, 1991). We discuss this in Section IA8.

## IA2 Additional Details on Worker-Level Data

A credit bureau provides our worker-level wage data. Many large companies voluntarily report payroll data to the credit bureau to expedite income verification for their employees when they apply for credit. Gopalan, Hamilton, Kalda, and Sovich (2020) and Zeng (2020) use the same data set and show that the data set is representative of the U.S. workforce. We focus on the impact of e-commerce on the retail sector. Therefore, we obtain data for companies in industries likely affected by e-commerce, leading to 57 companies in our worker sample. The median firm has more than 14,000 workers in the sample. The smaller companies in the sample have about 1000 employees. Overall, our work-level data contain large companies and do not cover workers in small local retail companies.

In terms of the type of workers, we do not have access to the occupation of workers. However, we know how they get paid (i.e., salaried vs. hourly), which is closely linked to the worker type and wage level. More than 85% of the observations are from hourly workers, who are likely low-skilled and low-wage workers. The

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<sup>1</sup>Using the *Good Jobs First*–Subsidy Tracker Database, we find that between 2000 and 2019, the major e-commerce retailer received \$2.4 billion in tax rebates, tax credits, and property tax abatement from various state and local governments.

<sup>2</sup>See: <https://logisticsviewpoints.com/2012/12/03/amazon-plans-carefully-its-distribution-capacity-growth/>

mean quarterly income of hourly workers is \$7,314. Annualized income is \$29,256, which is slightly higher than the mean income of 8.79 million retail sales workers (\$25,250) and the mean income of 4.53 million retail salespersons (\$27,180), as estimated by the BLS in May 2016. Salaried workers, who are likely high-skilled and high-wage, account for about 15% of the observations. The average annualized income is \$85,964. The majority of our worker-level analysis focuses on hourly workers because Table 2 shows that salaried workers are only slightly affected by the FC entry.

Further, we plot the average wage for each of the seven 3-digit NAICS industries as well as the average wage for each state using the worker level data in our sample. We also plot the same statistics using QCEW data. As shown in Figure IA1 and IA2, the average wage in our sample is close to, but slightly higher than the average wage in the QCEW data. This is because we have large retail firms in the sample, which have more salaried workers than small retail stores.

Although the worker-level data are from large retail companies, the establishment-level NETS data cover a wide range of retail companies, including mom and pop shops. In Tables 6 and 7 of the manuscript, where we analyze the impact of FCs along the extensive margin (employment, exit), we find that the effect is more significant for small retail stores compared to large retail stores. Unfortunately, we do not have worker-level data for medium and small retail stores, whose workers likely are more affected. These results suggest that the impact on income that we estimate using the worker-level data is likely a lower bound.

### IA3 Effect of FCs on Web Search Volume

We use monthly data from Google Trends for the e-commerce retailer (using its website URL as our search term) or its *Prime* service within the shopping category. There are 25 metropolitan statistical areas (MSAs) that have FCs of the e-commerce retailer opened after 2009 and have Google Trends data.<sup>3</sup> We estimate Equation (1) at the MSA-monthly level with the natural logarithm of web search index as the dependent variable ( $\text{Log}(Y_{i,t})$ ).

$$\text{Log}(Y_{i,t}) = \alpha + \sum_{j=2}^4 \beta_j \text{PreFC}_{i,t}(-j) + \sum_{j=0}^4 \gamma_j \text{PostFC}_{i,t}(j) + \eta_i + \theta_t + \epsilon_{it}. \quad (1)$$

Figure IA3, Panel A and Panel B plot the estimated coefficients and 95% confidence intervals. *PreFC* and *PostFC* dummies are defined at annual intervals. We include MSA ( $\eta_i$ ) and year-month fixed effects ( $\theta_t$ ). The variable  $\text{PreFC}_{i,t}(-j)$  ( $\text{PostFC}_{i,t}(j)$ ) is a dummy that takes a value of 1 if it is  $j$  years before (after) the establishment of FCs. Also,  $\text{PreFC}(-4)$  ( $\text{PostFC}(+4)$ ) equals 1 if it is four or more years before (after) the establishment of an FC.  $\text{PreFC}(-1)$  is dropped from the estimation so that all coefficient estimates can be treated as within MSA changes relative to the search index one year before the establishment of FCs in the MSA. We find that coefficients on  $\text{PreFC}(-4)$ ,  $\text{PreFC}(-3)$ , and  $\text{PreFC}(-2)$  are all statistically insignificant from the search index in  $\text{PreFC}(-1)$ . This suggests that no pre-trend exists in the search index data. Further, we find that within a year of the establishment of FCs, the local search activity for the e-commerce retailer (its *Prime* service) increased by 7% (by 20%), compared to one year before the establishment of FCs in the MSA.

If the timing and location of establishing an FC in the local area is simply a proxy of underlying expected growth in online sales, then we should find a similar trend for *eBay*, as we find for *Prime* service of the largest e-commerce retailer. We estimate Equation (1) at the MSA-monthly level for *eBay* web search index within the shopping category. Figure IA3, Panel C plot the estimated coefficients and 95% confidence intervals. We find that the estimated coefficients on *PreFC* and *PostFC* are statistically insignificant, and there is no effect of FCs on web search activity for *eBay*. The above results suggest that our results are not completely

<sup>3</sup>We use monthly data for a full window from January 2010 to August 2019, which is available only at the MSA level. More information about Google Trends data is available on Hal Varian's 2015 primer: <http://people.ischool.berkeley.edu/hal/Papers/2015/primer.pdf>.

driven by expected growth in online sales in the local area.

There is no publicly available data on shipping time and costs. However, anecdotal evidence from news articles suggests that these FCs can reduce shipping time and boost online consumption in the local areas. For example, the major e-commerce retailer spent \$1.5 billion to speed up its same-day delivery in a handful of states after bolstering its fulfillment centers<sup>4</sup>. In addition, same-day delivery can significantly impact the local retail store<sup>5</sup>. In 2012, the major e-commerce filed a patent for “anticipatory shipping” to ship the package to customers before they order it<sup>6</sup>. The above anecdotes suggest the importance of shipment and fulfillment centers for major e-commerce retailer’s expansion plans.

## IA4 Effect of FCs on Couriers, Messengers, and Support Activities

In this section, we use county-level Quarterly Census of Employment and Wages (QCEW) data on employment and total wages for each NAICS 3-digit sector to estimate the effect of FCs on employment and wages of couriers and messengers. First, we aggregate employment and total wages for the last month of the given quarter for the Support Activities for Transportation (NAICS 488), Postal Service (NAICS 491), and Couriers and Messengers (NAICS 492). Then, we estimate the employment and wage growth for the combined group for a given county. Here, we estimate Equation (1) with interaction terms. We also benchmark the regressions four years before the shock. All regressions include NAICS-3  $\times$  year-quarter and county  $\times$  year-quarter fixed effects. Thus, all effects are estimated within the same county. The coefficient represents the average quarterly growth rate during the year. We report the results in Figure IA4. We find positive growth (3% per quarter) in employment and wages in the focal county. These results suggest an increased demand for workers in support activities. We observe no impact in counties within 100 miles of FCs, which suggests that the establishment of FCs implies more demand for support activities only in the FC counties. The results for the Google search index and employment/wages of couriers and messengers suggest that the establishment of an FC encourages customers nearby to shop through the major e-commerce retailer.

## IA5 Exposure to FC and Retailers’ Firm Values

In this section, we show how publicly listed retail firms’ performance is affected by FCs based on retail firms’ exposure in the local area. If the FC effect is not local, all retailers should see a drop in performance regardless of where they operate. On the other hand, if an FC opening matters more for the local area, retailers that operate in FC areas (more exposed to FCs) should see a decline in performance. To test these competing hypotheses, we examine retailers’ stock returns around the establishment of FCs by exploiting retailers’ differential exposure to FCs. If the FC effect is local, retailers that have a larger exposure to FCs should have lower stock returns around the establishment of the FCs.

We run event-panel regressions by regressing stock returns on the retail firm’s exposure measure to FCs. We define the establishment of an FC as an event and conduct an event study for the affected retail firms. We utilize CRSP stock returns data for retail firms, where retail firms are identified using the list of NAICS codes in Table IA3. For each retail firm, cumulative returns from  $t$  ( $t = 1, 3, 6$ ) months before the event to  $t$  months after the event are calculated. Stock returns in the pre-event window are included because market participants may have incorporated the news of the establishment of FCs. To capture the exposure of retail firms to a given event, two measures are computed using NETS data. For a given retailer,  $Exposure_0$  is the fraction of retail sales in the FC county associated with the event in the year before the event.  $Exposure_{100}$  is the fraction of retail sales in counties within 100 miles of the FC county associated with the event.

Table IA4 reports the results. In Columns (4)-(6), we control for the natural logarithm of market capitalization and book-to-market ratio. Event fixed effects are included, and standard errors are clustered

<sup>4</sup><https://www.cnn.com/2020/03/03/amazon-expands-same-day-delivery-after-building-fulfillment-centers.html>

<sup>5</sup><https://slate.com/business/2012/07/amazon-same-day-delivery-how-the-e-commerce-giant-will-destroy-local-retail.html>

<sup>6</sup><https://www.wsj.com/articles/BL-DGB-32082>

at the event level. Therefore, these regressions exploit retailers’ differential exposure to FCs. The results indicate that there is a strong negative relationship between exposure measures and stock returns around events. Namely, retailers that have larger exposure to an FC opening have lower stock returns around the event. In Column (6), the coefficient estimate for  $Exposure_0$  is -0.712 and statistically significant at 1%. For one standard deviation increase in  $Exposure_0$ , where the standard deviation of  $Exposure_0$  is 0.022, the associated reduction is about 1.57 percentage points in the [-6,6]-window returns. For a median firm in the sample, this is equivalent to a reduction of \$18.67 million in market capitalization. Further, the results are robust to using the number of establishments to compute exposure measures. These results suggest that retailers that are more exposed to FCs have worse performance relative to retailers that are less exposed to FCs, highlighting the local effect of FCs.

## IA6 Baseline Results with County-Level Controls

This section presents baseline regression estimates for our strictest specification, where we control for local demand for online shopping due to time-varying socio-economic factors. Specifically, we add various control variables to regressions estimating the effect of FCs on employment and sales of retail stores (see Table IA5 for work-level income results, IA16, Panel A for establishment-level employment results, and Panel B for establishment-level sales results). In Column (1), we first add the house price index as a proxy for the average price level in the local area, as there is no county-level consumer price index. Counties with higher price levels may see higher demand for online shopping. We also add per capita income. Wealthy areas may have better internet access and have more white-collar households. Therefore, they may see stronger demand for online shopping. We also include the unemployment rate to control for the local labor market conditions. In Column (2), we add age composition in the local area (i.e., % below 20 years, % between 20 and 40 years, and % between 40 and 60 years), since young adults may prefer online shopping more than other adults. In Column (3), we add education composition in the local area (i.e., % with bachelor’s degree, % with masters degree, and % with professional degree) because highly educated people likely have a stronger demand for online shopping. In Column (4), we add proxies for the costs of physical shopping. We include time spent on work-related travel and time spent grocery travel. The idea is that if individuals spend more time on travel, there is likely more congestion in the local area or the driving distance is longer. Consumers in these areas may prefer online shopping more than consumers in other areas. The coefficient estimates in all four columns are very similar to the baseline estimates in the manuscript. These results mitigate the concern that omitted variables related to preference for online shopping bias our estimates.

## IA7 Matching Estimates

In this section, we describe our results using matching estimates. We use coarsened exact matching with five cut points and k2k match to find control counties. For each treated FC county, we identify the coarsened exact match. In coarsened exact matching models, we progressively add county-level characteristics that may be related to decisions of establishing FCs: 1) population size and population density; 2) per capita income and unemployment rate; 3) the percentage of the population with age below 18 and above 65, percentage of the population with high school and college degrees; 4) retail spending per capita; and 5) percentage of population with broadband access. Table IA6 provides the balance test for our different matching specifications. After matching, the differences between the treatment and control counties are statistically insignificant for most of the county characteristics.

We re-estimate our worker-level regression, where we add all the retail workers in the control counties to our analysis, estimating the effect of FCs on the worker income in FC counties. First, we add all retail stores in control counties to our analysis, estimating the effect of FCs on the employment/sales of retail stores in FC counties. We regress the logarithm of income of hourly workers on a  $PostFC \times Treated$  dummy and include worker and year quarter fixed effects. The fixed effects absorb the  $PostFC$  dummy and  $Treated$  dummy. Table IA7 reports the results. Panel A shows that the income of hourly retail workers in FC counties decreases by 1.7%–2.4% after the establishment of FCs relative to retail workers in control counties. The magnitude is comparable to our baseline estimates using only treated FC counties, -2.5%.

We also regress the logarithm of employment/sales on a  $\text{PostFC} \times \text{Treated}$  dummy and include establishment, industry-year, and region-year fixed effects. The fixed effects absorb the  $\text{PostFC}$  dummy and  $\text{Treated}$  dummy. Panel B shows that the employment of retail stores in FC counties decreases by 1.5%–1.8% after the establishment of FCs relative to retail stores in control counties. The magnitude is comparable to our baseline estimates using only treated FC counties, -2.1%. Panel C shows similar results for retail sales. The impact of FCs on sales is -2.4% to 2.7%. We find similar results for counties within 100 miles of FCs.

## IA8 Instrumental Variables Approach

In this subsection, we present results from an instrumental variables regression approach. We construct a Bartik-style instrument composed of cross-sectional variation in the distance between the FCs and the closest postal network facility and its interaction with temporal variation in the generosity of the subsidies that local and state governments offer to corporations (Bartik, 1991).

As discussed in Subsection 3.1, the choice of FC locations by the major e-commerce retailer is not random. To optimize fulfillment time, the major e-commerce retailer chooses locations that serve large populations and minimize long-zone shipping within the distribution network. This, in turn, utilizes existing logistics and shipping infrastructure. We use the distance of each county to the closest existing network facility of the US Postal Service (USPS) to proxy for shipping infrastructure. Among the 50 counties with at least one FC, we find that four of these counties contain a USPS network facility. For the remaining 46 FC counties, the median distance to the closest USPS network facility is less than 20 miles. Figure IA5 highlights the locations of the major e-commerce retailer’s fulfillment centers and USPS network facilities. The dark-shaded regions represent the counties with fulfillment centers, while the light-shaded regions represent the counties with USPS network facilities. The map shows the strong geographic correlation between FCs and USPS network facilities. However, this network of shipping infrastructure does not vary greatly over time.

Corporate subsidies offered by local and state governments may play an important role in determining the location of FCs. Using the *Good Jobs First*–Subsidy Tracker Database, we find that between 2000 and 2019, the major e-commerce retailer received \$2.4 billion in tax rebates, tax credits, and property tax abatement from various state and local governments. We calculate *State Generosity* as the logged value of cumulative corporate subsidies offered by the state from 1990 to 2016 (the end of our sample period) scaled by cumulative state revenue. In Figure IA6, the dark regions highlight more generous states, while the light regions highlight less generous states. We notice some overlap between state generosity and the location of FCs.

In conjunction, Figure IA5 and Figure IA6 suggest that both proximity to shipping infrastructure (in the form of USPS network facilities) and the willingness of state and local governments to provide corporate incentives may affect FC location decisions. Table IA8 presents the first stage in which the timing of the establishment of an FC is a function of the distance to a USPS network facility multiplied by the state corporate generosity. The sample consists of a balanced panel of the 50 counties where an FC was established between 2010 and 2016, inclusively. The dependent variable in our first-stage specification is *PostFC*, which changes from a value of 0 to a value of 1 in the year an FC is established in county  $c$ , and it remains equal to 1 for all subsequent years. In all regressions, we control for county-level and state-level local economic conditions by including the county’s unemployment rate, labor force, the state population, and the state revenue, all defined one year before the establishment of the FC. We report the coefficients of these control variables in Table IA8. We define  $\text{State Generosity}_{s,t-1}$  as the logged value of the cumulative corporate subsidies offered by the state starting in 1990 through the year  $(t-1)$  scaled by cumulative state revenue.  $\text{Log}(\text{Distance})$  is the logged value of the distance from the closest USPS network facility. In addition, we include region and year fixed effects to control for the region- and year-specific unobservables.

In Column (1), we find that the distance from a USPS network facility very weakly and negatively correlates with the *PostFC* dummy and is not statistically significant. Similarly, in Column (2), we find that state generosity does not significantly predict the choice of FC locations when entered as a level into the specification. However, when we include the interaction between state generosity and the distance from the nearest USPS facility (and adjust the sign so that the interaction can be thought of as proximity rather than

distance) as we do in Column (3), we see that it positively correlates with the *PostFC* dummy. These results suggest that within the same region, the major e-commerce retailer is more likely to open an FC *early* in the counties that are close to a network facility and where the state governments are ex-ante more generous in offering corporate subsidies. Note that the interaction term can be used as an appropriate instrument to identify the causal effect of *PostFC* on brick-and-mortar store performance as it (a) strongly correlates with our endogenous variable and does not suffer from a weak instrument problem (F-statistic is 14.18) and (b) the exclusion restriction is satisfied as the employment and wage *growth* in the retail sector are unlikely to be directly affected by the interaction of state generosity and distance from a USPS network facility.

Table IA9 we report the second stage of the two-stage regression for worker-level and county-industry level data. We use the estimated *PostFC* dummy for the FC counties and re-estimate 1 where we instrument (*PostFC*) with ( $\widehat{PostFC}$ ) and bootstrap the standard errors. We find a decline in income for hourly workers by almost 11.6% using instrumental variable regression. However, these results are weak statistically. In Column (3), we estimate regression with county-year quarter fixed effects, the first stage county and state-level control variables are absorbed in the fixed effects. Compared to the OLS regression, our estimate increases from -4.4% (Column (4), Table 3) to -7.7%.

In Panel B, we estimate our county-industry level regressions using the instrumental variable approach. We estimate all regressions with county-year quarter fixed effects, the first stage county and state-level control variables are absorbed in the fixed effects. In Column (1) of Table IA9 Panel B, we find a negative and significant impact of FCs on the retail sector employment growth. Compared to the OLS regression, our estimate increases from -2.9% to -5.6%. Similarly, we find a negative effect on total wage growth. Interestingly, with the instrumental variables approach, the magnitude of the increase in employment growth for the warehouse and transportation sector increases from 2.1% to only 2.5%. Overall, we find consistent and qualitatively similar results between the IV and OLS. In contrast, the OLS regression results may underestimate the negative effect of e-commerce on retail employment and wage growth due to the positive selection previously documented (refer to Table IA2).

## IA9 Additional Robustness Tests

We further conduct additional tests to ensure the robustness of the results reported so far. In our main analysis, we estimate our results with region-year-quarter fixed effects. In Panel A of Table IA10, we replace region-year-quarter with state-year-quarter fixed effects. The income effect is about -1.1% and still is significant.

In our baseline tests, we assigned FC treatment to workers based on the ZIP code of their residence in 2010 Q1. It is possible that some workers move to avoid the negative income shocks caused by FCs. Therefore, as a further robustness test, we remove migrants whose last observed ZIP code in the data is different from their first observed ZIP code. The results documented in Panel B of Table IA10 indicate that our main results remain unaffected.

In our analysis so far, we have used quarterly income computed from raw payroll data under the assumption that it is a timely reflection of the impact of FCs. However, it is possible that quarterly income is subject to seasonal variation. Since income is the key outcome measure in our analysis, we show robustness to our dependent variable by using an alternative income measure that is based on the projected annual income of a worker every month as computed by the credit bureau. We rerun our analysis with this projected annual income instead of the quarterly income we have used so far. The results, documented in Table IA10, Panel C, show a significant negative effect, suggesting that our analysis is robust to this measure of income.

## IA10 Robustness Tests: Two-Way Fixed Effects Methodology

A recent literature (Borusyak and Jaravel, 2017; De Chaisemartin and d’Haultfoeuille, 2020; Goodman-Bacon, 2021; Sun and Abraham, 2021) discusses some drawbacks to two-way fixed effects (TWFE) estimators when used in staggered Difference-in-Differences (DID) designs. Callaway and Sant’Anna (2021) provide an

approach for estimation and inference of causal parameters in staggered DID designs that allows for arbitrary treatment effect heterogeneity and dynamic effects. Their empirical approach avoids the issues of interpreting results of standard two-way fixed effects (TWFE) regressions as causal effects in DID setups, as highlighted in the above recent research. Table IA11 provides the comparison of TWFEs reported as baseline along with the Average Treatment effect on the Treated (ATT) estimates based on the weighted least square (WLS) outcome model and inverse probability tilting as treatment model as suggested by Callaway and Sant’Anna (2021). Finally, we also present treatment effects for each treated cohort, which allows us to examine the extent to which cohort-level heterogeneity exists – the very concern that has been the focus of the aforementioned literature. We find that, in our case, staggered DD estimates are conservative. For example, we find a beta estimate of -0.021 for employment in the retail sector using establishment fixed effects, industry-year fixed effects, and region-year fixed effects (Table IA11, Column (1)). Next, we show our estimates with TWFEs, i.e., only establishment fixed effects and year fixed effects. The estimate is similar to our baseline estimate. Next, we provide WLS-ATT estimates. We find a decline in employment by 4.5%, suggesting our TWFEs estimates are conservative. Finally, in Column (4), we show estimates for each cohort. We find that the estimates are largely homogeneous falling within the range of -3.7% and -5.3%. Overall, our DID TWFEs estimates can be interpreted as lower bounds of our parameter of interest. We find similar results for retail sales.

## IA11 Occupation-Level Analysis

Do incumbent retail firms shift their business models? Do they hire different workers as a result? As the worker-level data does not provide occupation information for workers, we cannot conduct this analysis using the worker-level data. Instead, we turn to publicly available Occupational Employment and Wage Statistics (OEWS) to understand the skill composition changes within the retail industry.

Ideally, we would like to have annual MSA-industry-occupation level data to know exactly how occupations shift within the retail industry. However, OEWS only provides annual MSA-occupation level employment data. Given these data constraints, we only can observe how each occupation changes over time in a given MSA. We focus on the top 20 occupations of the retail industry and analyze how FC entry affects employment in these occupations.<sup>7</sup> For each occupation, we estimate the following regression specification,

$$\text{Log}(Emp_{msa,t}) = \alpha + \beta \text{PostFC}_{msa,t} + \eta_{msa} + \theta_t + \epsilon. \quad (2)$$

As shown in Table IA12, FC entry has a significant negative impact on the employment of the largest occupation of the retail industry, retail salespersons. It also decreases the employment of general operations managers. On the other hand, we observe significant increases in the number of jobs related to e-commerce: stock clerks and order fillers; packers and packagers; bookkeeping, accounting, and auditing clerks; light truck drivers; delivery services truck drivers; shipping, receiving, and traffic clerks. However, we may not interpret these results as to how occupations change within the retail industry as the occupation data cover all industries.

## IA12 Additional Store-Level Results

We further study how FC entry affects retail stores’ relocation decisions. We define two dummy variables as dependent variables: relocation out of county and relocation out of state. The dummy variable is set to 0 before relocation and set to 1 once relocated. Table IA17 reports the results. In Panel A, where we examine stores in counties with FCs, the results do not indicate that retail stores are more likely to be relocated out of county or state after FC entry. As shown in Panel B, there is no evidence of more relocation after FC entry for retail stores within 100 miles of FCs.

We also analyze who gets affected by estimating the impact of FCs on employment and sales of retail

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<sup>7</sup>OEWS provides a separate industry-occupation level employment dataset, which allows us to identify the top 20 occupations in the retail industry.

stores using sub-samples (franchise versus non-franchise). Table IA18 reports the results. Panel A includes counties with FCs. The employment of non-franchise decreases by 2.8%, while the employment of franchise decreases by 1.3%. In Panel B, where we include counties within 100 miles of FCs but not counties with FCs, the employment effect on non-franchise is -1.5%, while there is no impact on franchises. The table shows that the impact on sales is similar. Overall, these results indicate that the entry of FCs has a larger impact on non-franchises than franchises.

In all our previous analyses, we focus on the effect of the establishment of FCs on incumbent brick-and-mortar retail stores. However, it is possible that entry into the local retail sector is discouraged by the establishment of the FC due to the consequent increase in competition, the decline in sales, and the closure of some incumbent brick-and-mortar retail stores. We analyze the impact of the establishment of the FC on entry into the local retail market in Table IA19. We find that after the establishment of an FC in the affected county, the entry rate for small stores is significantly reduced by 8.1% in counties within 100 miles of an FC.

## IA13 Alternative Explanations

It is possible that the major e-commerce retailer decisions are made based on forecasts that these FC counties are expecting lower labor costs in the future. We test this hypothesis by estimating how FCs correlate with the average income level of other workers in FC counties relative to other counties. For each county-year, we compute the average income of workers (excluding retail, transportation & warehousing) using publicly available QCEW data.<sup>8</sup> Then we estimate the following county-year level panel regressions:

$$\text{Log}(Average Wage_{c,t}) = \alpha + \sum_{j=2}^4 \beta_j \text{PreFC}_{c,t}(-j) + \sum_{j=0}^4 \gamma_j \text{PostFC}_{c,t}(j) + \eta_c + \theta_t + \epsilon_{c,t}. \quad (3)$$

We include all non-treated counties as a control group. PreFC(-1) is dropped from the estimation so that all coefficient estimates can be treated as changes relative to average wages one year before the establishment of FCs. Figure IA9 plots the estimated coefficients for PreFC(j = -4 to j = -2) and PostFC (j=1 to j = 4). In Panel A, counties with FCs are treated. The figure shows that the treated counties and control counties have similar pre trends in average wages. More importantly, there is no evidence that treated counties have a decline in average wages after the establishment of FCs compared to control counties. Panel B shows similar patterns where counties within 100 miles of FCs are treated. Overall, although it is possible that labor availability and costs are important factors in determining FC, it is unlikely these factors confound our findings.

It is also possible that the e-commerce retailer may choose a location that may not be ideal for the retail sector. For example, the e-commerce retailer may choose FCs locations that are close to airports and other transportation hubs, which likely have low population density. As a result, these areas (e.g., within a few miles of FCs) are not good for the growth of retail stores. However, this study includes all retail stores in the counties that have FCs and counties within 100 miles of FCs instead of just stores within a few miles of FCs. As shown in Table IA1, these counties have larger populations, higher population densities, and greater retail sales compared to an average U.S. county. For example, the average population is 615,495 and the average population density is 672 for FC counties. In contrast, an average U.S. county has a population of 98,460 and a population density of 259. This mitigates concerns that stores in our analysis are located in areas with low population density. Therefore, the empirical design in this study is unlikely to be contaminated by geographical factors related to transportation.

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<sup>8</sup>We take the average of the average income for each NAICS 2-digit sector.

## IA14 Effect of FCs on Unemployment Rate and Aggregate Consumption

We also test if FCs have any positive or negative effect on the overall county. We use BLS unemployment rate data and find a mildly negative effect on the unemployment rate. We find similar but weak results when we use matched counties as a control group. Table IA21 report the regression results. Further, we test if the increased convenience of purchasing via e-commerce increases aggregate total consumption (Dolfen, Einav, Klenow, Klopach, Levin, Levin, and Best, 2019; Agarwal, Qian, Ren, Tsai, and Yeung, 2020). More specifically, we test how total consumption changes after the establishment of an FC. We collect MSA-level total consumption data from CES. One caveat is that CES only provides this data for less than 20 MSAs. We focus on MSAs that have an FC from 2010 to 2016. To quantify the effect, we estimate the following regression specifications.

$$\text{Log}(Y_{msa,t}) = \alpha + \text{PostFC}_{msa,t} + \eta_{msa} + \theta_t + \epsilon_{msa,t}. \quad (4)$$

Table IA22 reports the regression results. Column (1) shows no increase in total consumption expenditures after the establishment of FCs. However, the total consumption expenditures might be a noisy measure for our purpose. It includes some major components unrelated to e-commerce, such as housing, health care, and education. Therefore, we also investigate the impact of FCs on a few subcategories that are more exposed to e-commerce. As shown in the rest of the table, the coefficient estimates for expenditures on food, apparel, and entertainment (including electronics) appear to be positive but statistically insignificant. The lack of statistical significance could be due to the small sample size and the noise of aggregate consumption data. It is possible that the convenience effect could increase consumption levels in categories that are more affected by e-commerce.

## IA15 Alternative Identification Strategy

We use an alternative identification strategy to assess the impact of e-commerce on retail sector workers. We analyze the impact of the major e-commerce retailer on the retail sector using its staggered entry into different sectors, which is another important dimension of the major e-commerce retailer's expansion. We do not use this as our main identification strategy in the paper because our worker-level data starts in 2010, which is after all these entries. This test intends to further support the idea that the expansion of the major e-commerce retailer negatively impacts the retail sector. To conduct the test, we hand collect the announcement dates for the entry into industries from the major e-commerce retailer's news announcements. We report these dates in Table IA23. The earliest entry (book stores) is in 1995, while the latest entry (office supplies and stationery stores) is in 2008. Since the major e-commerce retailer does not enter all the 6-digit NAICS industries within the retail sector, some industries are treated, while other industries are in the control group.

To quantify the effect, we estimate the following regression specification using NETS data from 1990 to 2012,

$$\text{Log}(Y_{i,j,c,t}) = \alpha + \text{Post}_{j,t} * \text{Treated}_j + \eta_i + \theta_{c,t} + \epsilon_{i,j,c,t}, \quad (5)$$

Where  $i$ ,  $j$ ,  $c$ , and  $t$  denotes establishment, industry, county, and time, respectively. We include establishment fixed effects ( $\eta_i$ ) and county  $\times$  year fixed effects ( $\theta_{c,t}$ ). These fixed effects absorb both the Post dummy and the Treated dummy.

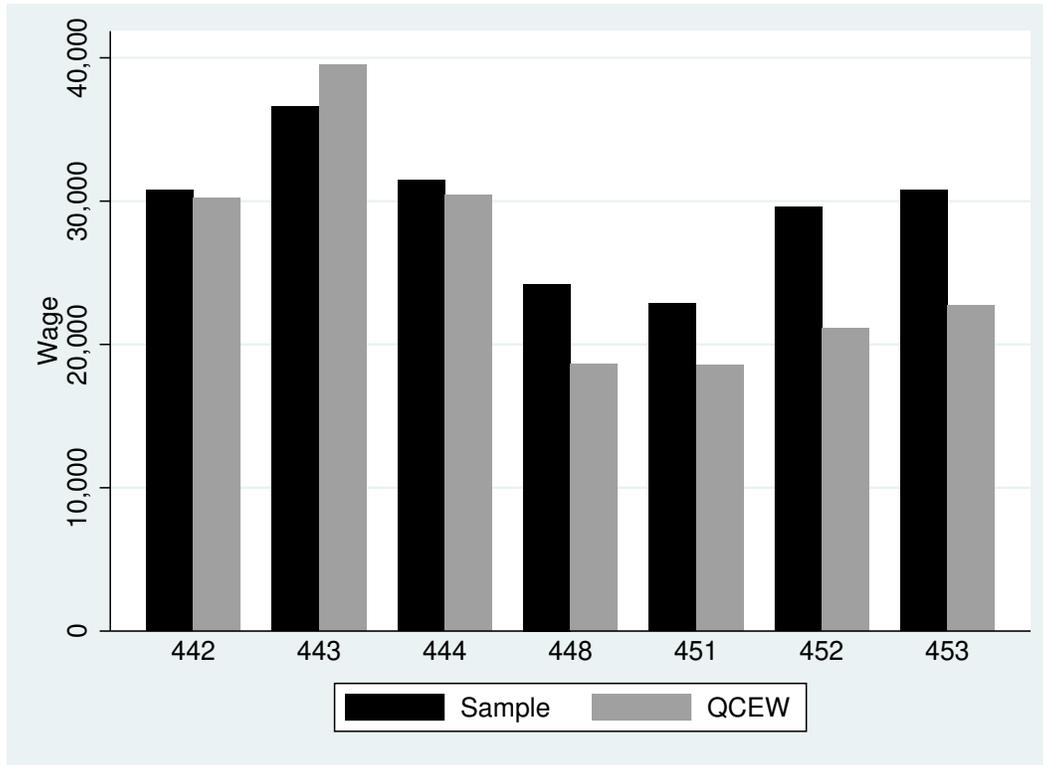
The results in Table IA24 indicate that the employment of treated retail stores decreases significantly after the entry of the major e-commerce retailer. To avoid the impact of the financial crisis on the estimation, we repeat the analysis using pre-crisis data from 1990 to 2006. The results from Columns (3)-(4) are similar to what we find in Columns (1)-(2).

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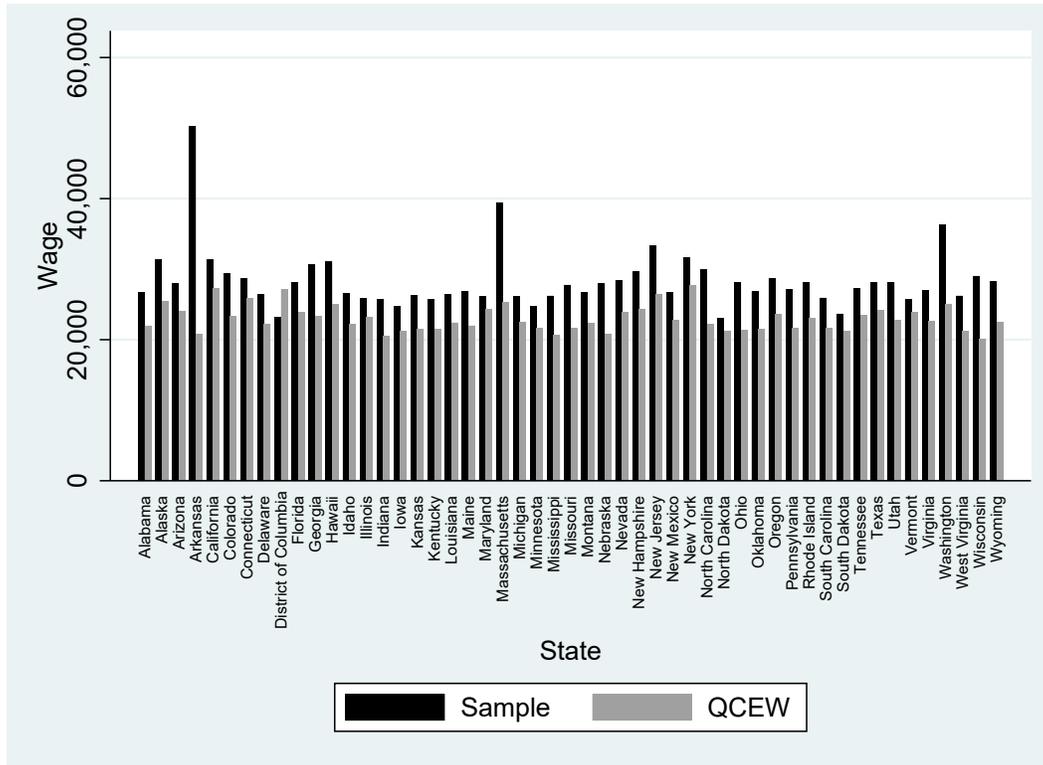
**Figure IA1: Average Wage Across Industries**

This figure presents the average wage of the worker-level data in the sample and the average wage of the QCEW data for each industry.



**Figure IA2: Average Wage Across States**

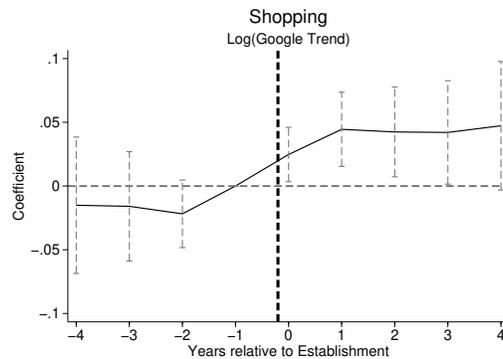
This figure presents the average wage of the worker-level data in the sample and the average wage of the QCEW data in each state for the industries we analyze in the paper.



### Figure IA3: Effect of FCs on Web Search Volume

These figures present the dynamic effect of FCs on the local web search activity. We use monthly data from Google Trends for shopping categories for 25 MSAs that have FCs of the e-commerce retailer. We estimate Equation (1) at the MSA-monthly level and plot the estimated coefficients and 95% confidence intervals. *PreFC* and *PostFC* dummies are defined at annual intervals. We include MSA and year-month fixed effects. *PreFC*(-1) is dropped from the estimation so that all coefficient estimates can be treated as within MSA changes relative to the search index one year before the establishment of FCs in the MSA. Panel A reports results for web activity of the e-commerce retailer (we use website URL of the e-commerce retailer) within the shopping category in MSAs with FCs. Panel B reports results for web activity of *Prime* service of the e-commerce retailer within the shopping category in MSAs with FCs. Panel C reports results for web activity of eBay.com, the second-largest e-commerce website, in MSAs with FCs.

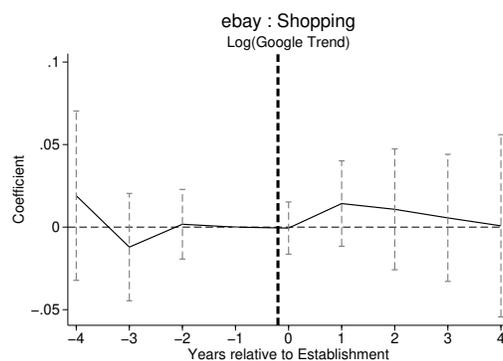
#### Panel A: Website URL of the E-commerce Retailer



#### Panel B: Prime Service

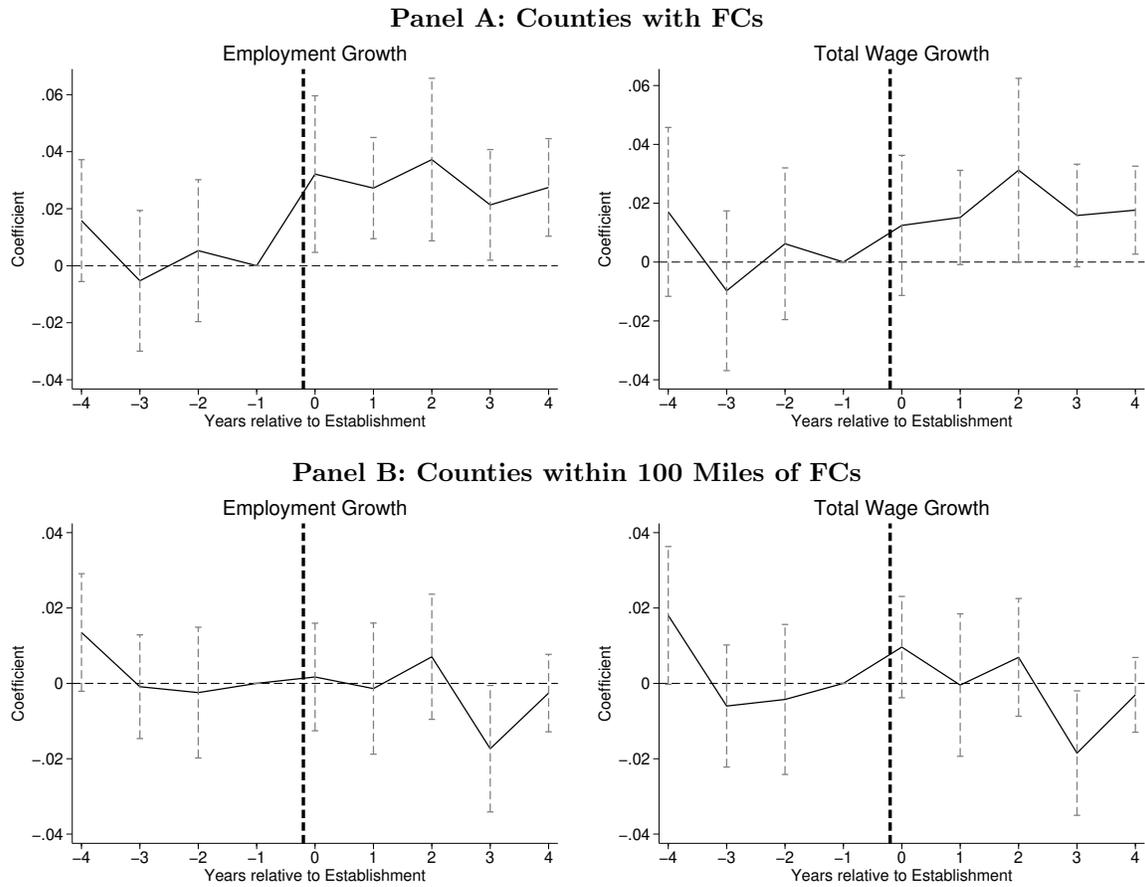


#### Panel C: eBay



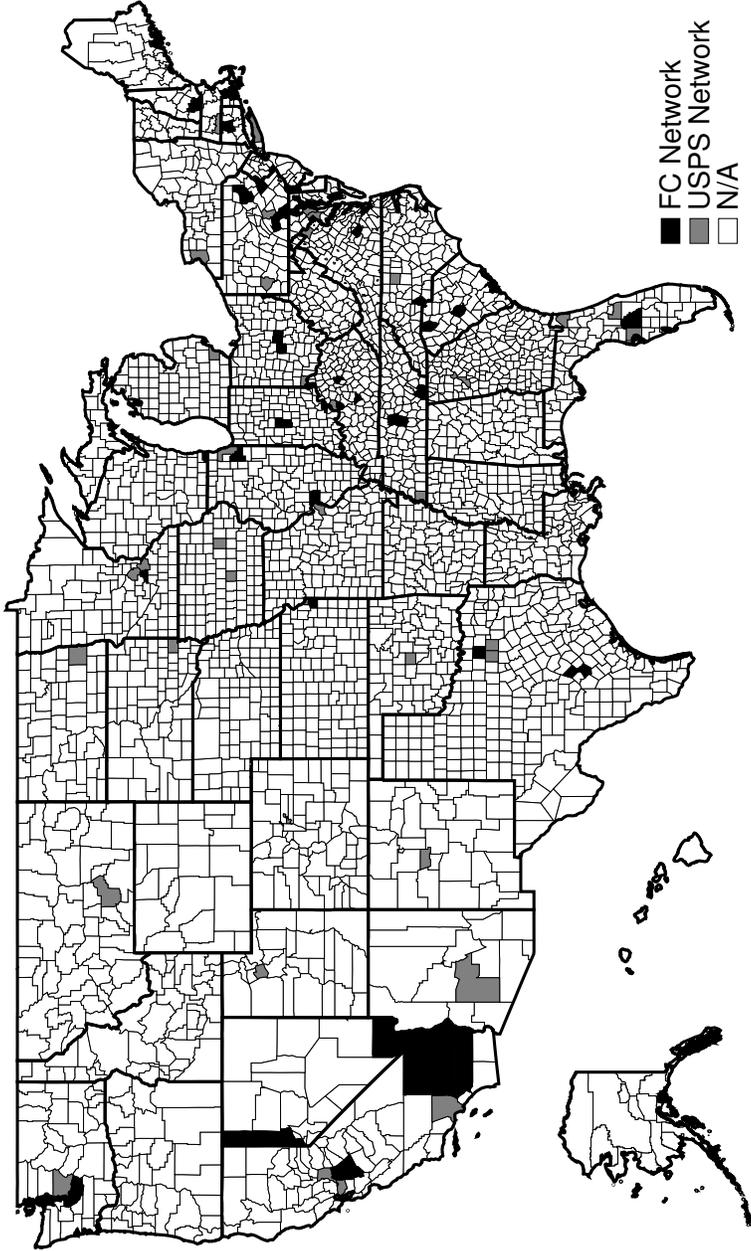
**Figure IA4: Effect of FCs on Couriers, Messengers, and Support Activities**

These figures present the dynamic effect of FCs on the employment and wage growth for couriers, messengers, and other support activities. We use county-level QCEW data for each NAICS 3-digit sector, and we use aggregate employment and total wages for the last month of the given quarter for Support Activities for Transportation (NAICS 488), Postal Service (NAICS 491), and Couriers and Messengers (NAICS 492). Then, we estimate the employment and wage growth for the combined group for a given county. We estimate Equation (1) and plot the estimated coefficients from the *PreFC* ( $j=-4$  to  $j=-2$ ) and *PostFC* ( $j=0$  to  $j=4$ ) dummies, which are defined at an annual frequency. *PreFC*(-1) is dropped from the estimation so that all coefficient estimates can be treated as percentage changes relative to the employment and wage growth one year before the establishment of FCs. All regressions include NAICS-3  $\times$  year-quarter and county  $\times$  year-quarter fixed effects. The broken lines around the coefficients represent 95% confidence intervals. Panel A includes data for counties with FCs. Panel B includes data for counties within 100 miles of FCs but not counties with FCs.



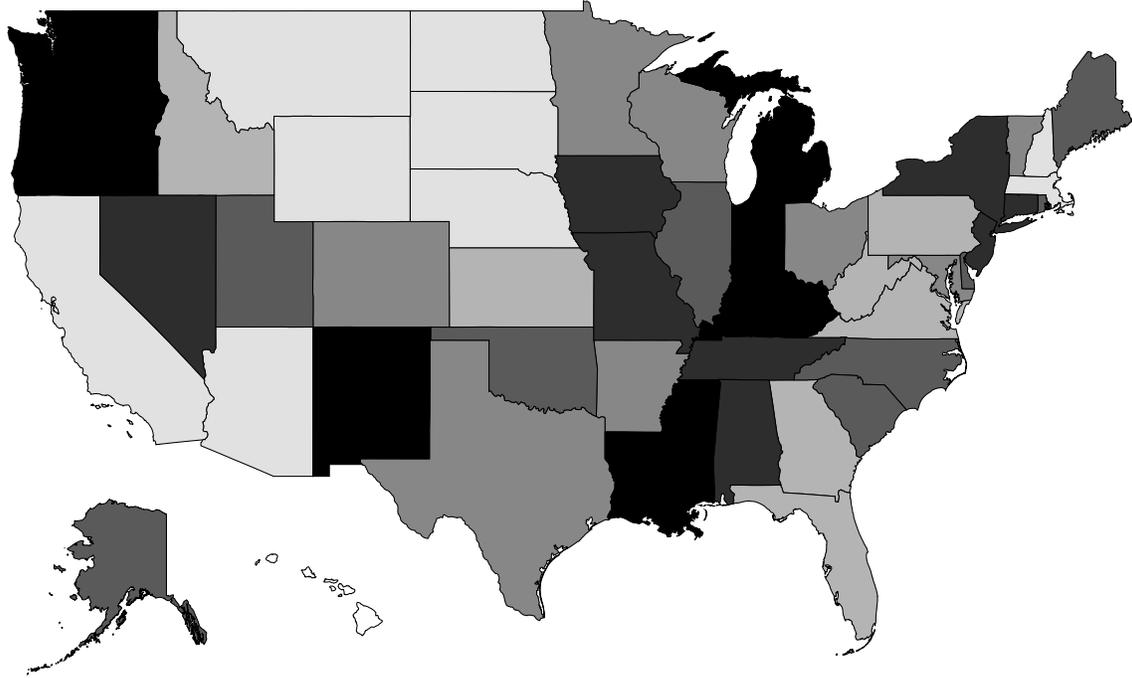
**Figure IA5:** Major E-Commerce Retailer's FC Network and USPS Network

The map highlights the locations of the major e-commerce retailer's FCs and USPS Network Facilities. The dark regions highlight the counties with FCs, while the light regions highlight the counties with USPS network facilities.



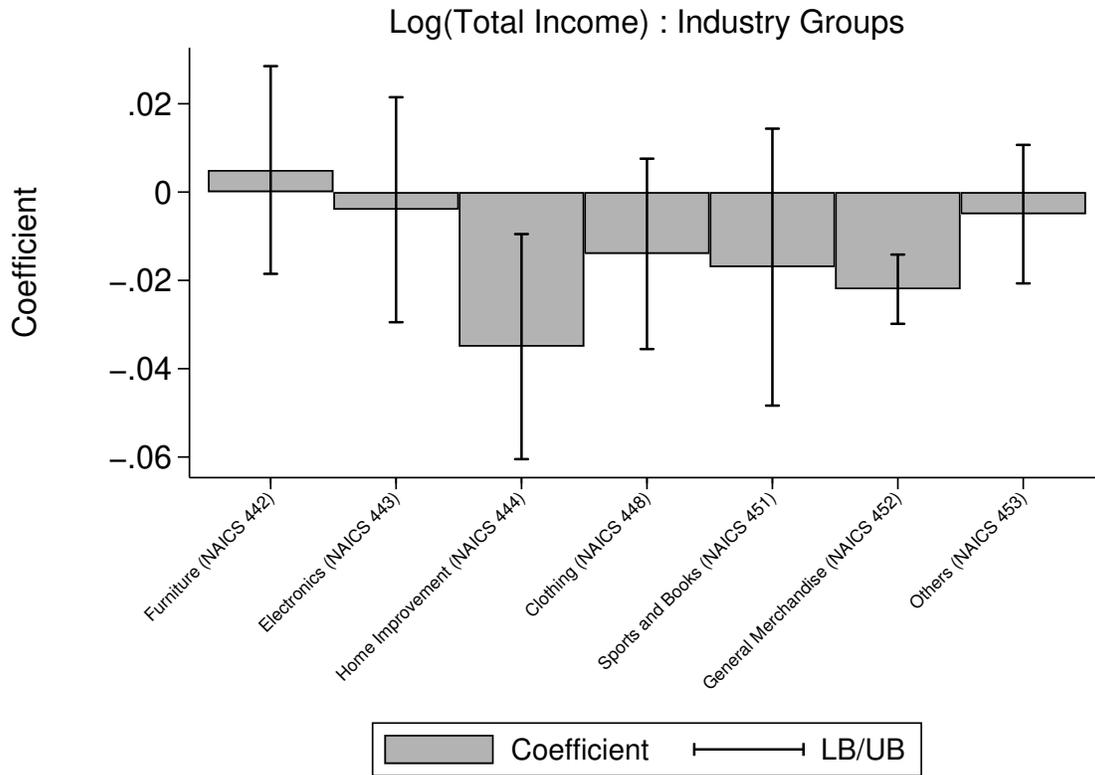
**Figure IA6: State Generosity**

The map highlights states that are generous in giving corporate subsidies. *State Generosity<sub>s</sub>* is defined as the logged value of the cumulative corporate subsidies offered by the state from 1990 to 2016 scaled by cumulative state revenue. The darker regions highlight more generous states, while the lighter regions highlight less-generous states.



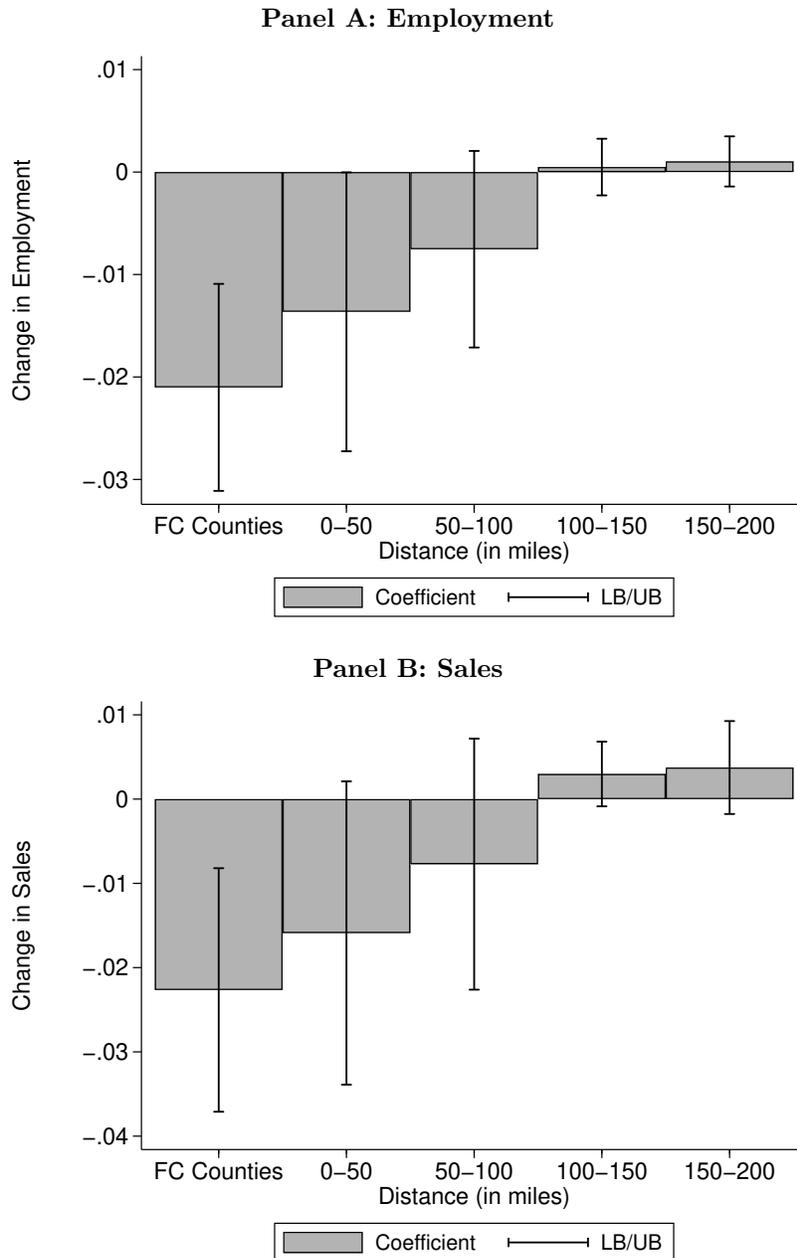
**Figure IA7:** Heterogeneous Effect of FCs on Income of Retail Workers – By Industry

This figure presents the heterogeneous effect of FCs on the income of retail workers based on their industries. The analysis includes workers in counties with FCs. All regressions include worker and year-quarter fixed effects. Standard errors are clustered by FC. We plot coefficients and 95% confidence intervals.



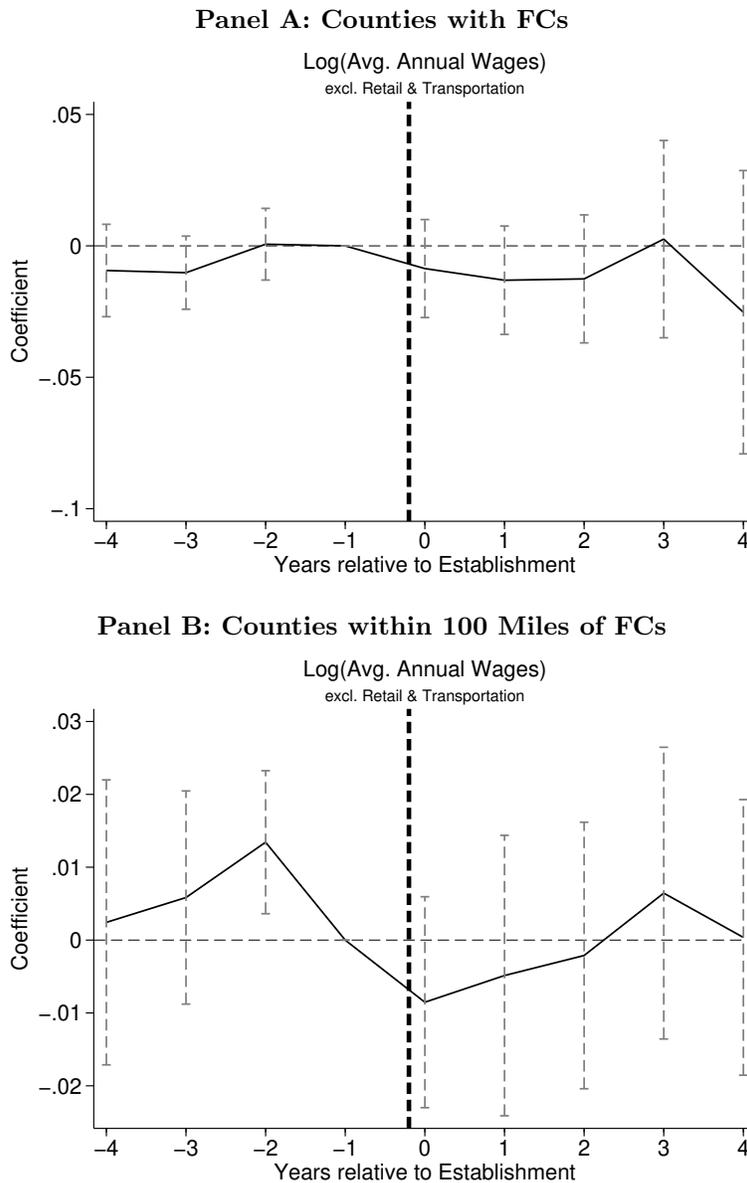
**Figure IA8: Distance to FC and Effect of FCs on Employment and Sales**

This figure presents the heterogeneous effect of FCs on the employment and sales of retail stores based on the distance between a given county and its closest FC. U.S. counties without FCs are placed into one of four groups based on the distance to the closest FC (i.e., 0-50 miles, 50-100 miles, 100-150 miles, and 150-200 miles). We drop counties that are served by an FC within 500 miles before the establishment of the closest FC. We estimate Equation (1) using subsamples. Standard errors are clustered by FC. We plot coefficients and 95% confidence intervals.



**Figure IA9: Effect of FCs on Income of All Workers (excl. Retail and Transportation)**

These figures present the dynamic effect of FCs on the average annual wage of all workers, excluding workers in retail (NAICS code 44–45) and transportation & warehousing (NAICS code 48–49). We use county-level QCEW data for each NAICS 2-digit sector and calculate the average annual wage income at the county level. We estimate Equation (3) and plot the estimated coefficients from the *PreFC* ( $j=-4$  to  $j=-2$ ) and *PostFC* ( $j=0$  to  $j=4$ ) dummies, which are defined at an annual frequency. *PreFC*(-1) is dropped from the estimation so that all coefficient estimates can be treated as changes relative to average wages one year before the establishment of FCs. All regressions include county fixed effects and year-quarter fixed effects. We include all non-treated counties as a control group. The broken lines around the coefficients represent 95% confidence intervals. Panel A includes data for counties with FCs. Panel B includes data for counties within 100 miles of FCs but not in counties with FCs.



**Table IA1: County Demographics**

This table presents demographic statistics of 3,135 counties based on the 2010 Census.

	Full Sample	Counties with FCs	Counties within 50 Miles of FCs	Counties within 100 Miles of FCs
N	3,135	50	445	1,141
Total Population	308,674,608	30,774,770	86,724,715	163,939,679
Population	98,460.80	615,495.40	194,887.00	143,680.70
Population Density	259.49	672.84	698.24	531.76
Retail Sales (in millions)	431.71	2,827.55	821.65	615.01
Retail Sales per Capita	3,552.72	4,623.48	3,692.95	3,679.81
Median Household Income	43,419.43	56,220.34	51,179.56	47,123.08
Unemployment Rate	9.36	9.64	10.17	10.27
Percent Age under 18	23.49	24.80	23.77	23.22
Percent Age over 65	15.93	12.16	14.08	15.31
Percent High School Graduate or Higher	82.51	85.84	83.04	82.31
Percent Bachelor's Degree or Higher	18.73	27.52	21.74	19.73

**Table IA2: Determinants of FC Locations: OLS**

This table presents the results for determinants of an FC's location. The dependent variable indicates whether the county has an FC in the post-2010 period. In Panel A, the independent variables represent 2010 US levels. In Panel B, the independent variables are measured as long differences computed from 2000 to 2010. Retail sales are aggregated at the county level using NETS data. Other independent variables are county-level census data.

**Panel A: Levels**

	FC				
	(1)	(2)	(3)	(4)	(5)
Log(Retail Sales)	0.013*** (0.002)	0.008*** (0.002)	0.007*** (0.002)	0.007*** (0.002)	0.007*** (0.002)
Log(Population Density (per sq mile))		0.009*** (0.003)	0.009*** (0.003)	0.006** (0.003)	0.007** (0.003)
Unemployment Rate			-0.001** (0.001)	-0.000 (0.001)	-0.000 (0.001)
Log Median Household Income				0.038*** (0.014)	0.038*** (0.014)
Perc. Age 18 to 65					-0.000 (0.000)
Observations	3130	3111	3111	3111	3111
R <sup>2</sup>	0.07	0.07	0.07	0.07	0.07
State FE	✓	✓	✓	✓	✓

**Panel B: Long-Differences**

	FC				
	(1)	(2)	(3)	(4)	(5)
$\Delta \text{Log(Retail Sales)}$	0.012*** (0.004)	0.005 (0.003)	0.005 (0.003)	0.005 (0.003)	0.005 (0.003)
$\Delta \text{Log(Population Density (per sq mile))}$		0.114*** (0.025)	0.115*** (0.025)	0.115*** (0.025)	0.116*** (0.025)
$\Delta \text{Unemployment Rate}$			-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)
$\Delta \text{Log Median Household Income}$				-0.008 (0.019)	-0.008 (0.019)
$\Delta \text{Perc. Age 18 to 65}$					0.000 (0.001)
Constant	0.013*** (0.002)	0.009*** (0.002)	0.009*** (0.002)	0.011** (0.004)	0.010** (0.005)
Observations	3128	3109	3109	3109	3109
R <sup>2</sup>	0.04	0.05	0.05	0.05	0.05
State FE	✓	✓	✓	✓	✓

**Table IA3:** List of Retail Sectors

This table presents the 6-digit NAICS industries that we include in our analysis.

NAICS	Industry Name
441310	Automotive parts and accessories stores
441320	Tire dealers
442110	Furniture stores
442210	Floor covering stores
442291	Window treatment stores
442299	All other home furnishings stores
443141	Household appliance stores
443142	Electronics stores
444110	Home centers
444120	Paint and wallpaper stores
444130	Hardware stores
444190	Other building material dealers
444210	Outdoor power equipment stores
444220	Nursery, garden, and farm supply stores
446120	Cosmetic and beauty supply stores
446191	Food, health, supplement stores
446199	All other health and personal care stores
448110	Men's clothing stores
448120	Women's clothing stores
448130	Children's and infants' clothing stores
448140	Family clothing stores
448150	Clothing accessories stores
448190	Other clothing stores
448210	Shoe stores
448310	Jewelry stores
448320	Luggage and leather goods stores
451110	Sporting goods stores
451120	Hobby, toy, and game stores
451130	Sewing, needlework, and piece goods stores
451140	Musical instrument and supplies stores
451211	Book stores
451212	News dealers and newsstands
451220	Precorded tape, CD, and record stores
452111	Department stores, except discount
452112	Discount department stores
452910	Warehouse clubs and supercenters
452990	All other general merchandise stores
453110	Florists
453210	Office supplies and stationery stores
453220	Gift, novelty, and souvenir stores
453310	Used merchandise stores
453910	Pet and pet supplies stores
453920	Art dealers
453930	Manufactured, mobile, home dealers
453991	Tobacco stores
453998	Store retailers not specified elsewhere

**Table IA4:** Exposure to FC and Retailers' Firm Values

This table presents the results of event panel regressions that assess the impact of the establishment of FCs on retailers' firm values. The establishment of a FC is an event. For a given retail firm,  $[-t, t]$  is the cumulative return from  $t$  months before the event to  $t$  months after the event.  $Exposure_0$  is the fraction of retail sales in the FC county associated with the event.  $Exposure_{100}$  is the fraction of retail sales in counties within 100 miles of the FC county associated with the event. Firm controls include the logarithm of market capitalization and book-to-market ratio. Event fixed effects are included. Standard errors clustered by event are reported in parentheses. \*, \*\*, \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively.

Window (in months)	Return					
	[-1,1] (1)	[-3,3] (2)	[-6,6] (3)	[-1,1] (4)	[-3,3] (5)	[-6,6] (6)
$Exposure_0$	0.115 (0.155)	-0.232*** (0.082)	-0.691*** (0.134)	0.113 (0.162)	-0.237** (0.091)	-0.712*** (0.133)
$Exposure_{100}$	-0.048** (0.023)	-0.077 (0.046)	-0.037 (0.127)	-0.047* (0.024)	-0.077 (0.048)	-0.041 (0.126)
Observations	3,143	3,143	3,143	3,143	3,143	3,143
Adjusted R <sup>2</sup>	0.120	0.095	0.063	0.121	0.095	0.066
Event FE	✓	✓	✓	✓	✓	✓
Firm Controls				✓	✓	✓

**Table IA5: Effect of FCs on Income of Retail Workers – With Controls**

This table presents the results of worker-level regressions that assess the effect of FCs on the income of retail workers, where we control for various county-specific characteristics. In Column (1), we control for unemployment rate, house price index, and per capita income. In Column (2), we also control for percentage of population in different age groups. In Column (3), we control for education characteristics. In Column (4), we use American Time Survey data and control for average time travel for work and grocery shopping. All regressions include worker, firm-yearqtr, and region-yearqtr fixed effects. Standard errors clustered by FC are reported in parentheses. \*, \*\*, \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively.

	Log(Total Income)			
	<i>Hourly Workers</i>			
	(1)	(2)	(3)	(4)
PostFC	-0.013*** (0.003)	-0.013*** (0.003)	-0.010** (0.004)	-0.011*** (0.004)
Log(House Price Index) <sub>c,t-1</sub>	-0.024 (0.022)	-0.030 (0.020)	-0.015 (0.021)	-0.009 (0.022)
Log(Per Capita Income) <sub>c,t-1</sub>	0.041 (0.027)	0.016 (0.023)	0.011 (0.018)	0.006 (0.021)
Unemployment Rate <sub>c,t-1</sub>	-0.387 (0.252)	-0.337 (0.251)	-0.156 (0.216)	-0.109 (0.230)
% Below 20 Years <sub>c,t-1</sub>		1.280** (0.599)	1.920*** (0.633)	2.010*** (0.674)
% Between 20 and 40 Years <sub>c,t-1</sub>		0.165 (0.621)	0.359 (0.736)	0.355 (0.724)
% Between 40 and 60 Years <sub>c,t-1</sub>		1.010 (0.663)	1.630** (0.708)	1.620** (0.711)
% with Bachelors Degree <sub>c,t-1</sub>			0.167 (0.117)	0.171 (0.128)
% with Masters Degree <sub>c,t-1</sub>			0.279 (0.258)	0.266 (0.265)
% with Professional Degree <sub>c,t-1</sub>			0.042 (0.525)	-0.044 (0.559)
Log(Work Travel(hrs/week)) <sub>cb,t-1</sub>				-0.005 (0.003)
Log(Grocery Travel(hrs/week)) <sub>cb,t-1</sub>				-0.001 (0.003)
Worker FE	✓	✓	✓	✓
Firm-YearQtr FE	✓	✓	✓	✓
Region-YearQtr FE	✓	✓	✓	✓
Observations	1,812,662	1,812,662	1,504,887	1,447,177
Adjusted R <sup>2</sup>	0.840	0.840	0.837	0.836

**Table IA6: Balance Tests: CEM Matched Sample**

This table presents balance tests of FC counties and matched counties. We use coarsened exact matching with five cut points and k2k match. This table provide the univariate balance test for matching variables. In Panel A, we report a balance test where we identify control counties based on population size and population density. In Panel B, in addition to population size and population density, we include per capita income and unemployment rate in the matching model. In Panel C, we also add percentage of population with age below 18 and above 65, along with percentage of population with high school and college degree to the matching model. In Panel D, we further include retail spending per capita in the matching model. Finally, in Panel E we include percentage of population with broadband access in our matching model.

	Before Matching (Means)				After Matching (Means)			
	FC Counties (1)	All Counties (2)	Diff (3)	t-stat (4)	FC Counties (5)	Matched Counties (6)	Diff (7)	t-stat (8)
<b>Panel A: Table IA7, Column 1</b>								
Observations	50	3,086			50	50		
Log Population	12.82	10.24	2.38	12.87	12.82	12.62	0.2	0.98
Log Population Density	6.19	3.78	2.41	10.13	6.19	6.06	0.13	0.69
<b>Panel B: Table IA7, Column 2</b>								
Observations	50	3,086			47	47		
Log Population	12.82	10.24	2.38	12.87	12.77	12.53	0.23	1.14
Log Population Density	6.19	3.78	2.41	10.13	6.21	6.22	-0.01	-0.06
Per Capita Income(\$)	56,220	43,186	13,034	8.06	56,358	54,154	2,204	0.87
Unemployment Rate (%)	9.64	9.36	0.28	0.63	9.25	9.34	-0.09	-0.23
<b>Panel C: Table IA7, Column 3</b>								
Observations	50	3,086			43	43		
Log Population	12.82	10.24	2.38	12.87	12.64	12.52	0.12	0.52
Log Population Density	6.19	3.78	2.41	10.13	6.21	6.13	0.07	0.37
Per Capita Income(\$)	56,220	43,186	13,034	8.06	56,304	56,200	103	0.04
Unemployment Rate (%)	9.64	9.36	0.28	0.63	8.98	9.33	-0.35	-0.86
Age Below 18 (%)	24.8	23.45	1.35	2.89	24.44	24.30	0.14	0.28
Age Above 65 (%)	12.16	16.01	-3.85	-6.57	12.49	12.79	-0.3	-0.51
High School(%)	85.84	82.45	3.39	3.15	86.62	86.90	-0.28	-0.26
Bachelor Degree(%)	27.52	18.59	8.93	7.41	27.83	27.46	0.37	0.23
<b>Panel D: Table IA7, Column 4</b>								
Observations	50	3,086			41	41		
Log Population	12.82	10.24	2.38	12.87	12.63	12.34	0.29	1.22
Log Population Density	6.19	3.78	2.41	10.13	6.17	6.00	0.16	0.94
Per Capita Income(\$)	56,220	43,186	13,034	8.06	56,246	54,769	1,476	0.58
Unemployment Rate (%)	9.64	9.36	0.28	0.63	8.99	9.29	-0.3	-0.64
Age Below 18 (%)	24.8	23.45	1.35	2.89	24.36	24.41	-0.04	-0.09
Age Above 65 (%)	12.16	16.01	-3.85	-6.57	12.6	12.36	0.24	0.41
High School(%)	85.84	82.45	3.39	3.15	86.48	86.87	-0.39	-0.34
Bachelor Degree(%)	27.52	18.59	8.93	7.41	27.7	27.68	0.02	0.01
Retail Sales per Capita(\$)	4,492.7	3,542.8	949.9	2.98	4,446.85	4,297.80	149.05	0.57

	Before Matching (Means)				After Matching (Means)			
	FC Counties (1)	All Counties (2)	Diff (3)	t-stat (4)	FC Counties (5)	Matched Counties (6)	Diff (7)	t-stat (8)

**Panel E: Table IA7, Column 5**

Observations	50	3,086			40	40		
Log Population	12.82	10.24	2.38	12.87	12.61	12.33	0.28	1.29
Log Population Density	6.19	3.78	2.41	10.13	6.14	6.07	0.07	0.38
Per Capita Income(\$)	56,220	43,186	13,034	8.06	56,068	55,723	345	0.12
Unemployment Rate (%)	9.64	9.36	0.28	0.63	9.00	9.35	-0.35	-0.79
Age Below 18 (%)	24.8	23.45	1.35	2.89	24.42	24.52	-0.1	-0.17
Age Above 65 (%)	12.16	16.01	-3.85	-6.57	12.55	12.3	0.25	0.43
High School(%)	85.84	82.45	3.39	3.15	86.45	86.95	-0.5	-0.47
Bachelor Degree(%)	27.52	18.59	8.93	7.41	27.55	27.55	0	0
Retail Sales per Capita(\$)	4,492.7	3,542.8	949.9	2.98	4,436.61	4,637.2	-200	-0.76
Broadband Access (%)	79.78	77.32	2.45	2.1	76.16	76.18	-0.02	-0.01

**Table IA7:** Effect of FCs on Worker Income, Employment, and Sales of Retail Stores – CEM Matching Sample

This table presents results of worker-level and establishment-level panel regressions that assess the effect of FCs on worker income, employment, and sales of retail establishments/stores using a matched sample. We use coarsened exact matching with five cut points and k2k match. Table IA6 provide the balance tests. In Column (1), we identify control counties based on population size and population density. In Column (2), in addition to population size and population density, we include per capita income and unemployment rate in the matching model. In Column (3), we also add percentage of population with age below 18 and above 65, along with percentage of population with high school and college degrees to the matching model. In Column (4), we further include retail spending per capita in the matching model. In Column (5), we include percentage of population with broadband access in our matching model. All worker-level regression include worker and yearqtr fixed effects. All store level regressions include establishment, industry-year, and region-year fixed effects. For counties within 100 Miles of FCs, we re-estimate coarsened exact matching model and for each treated county within 100 Miles of FCs (excluding counties with FCs) we find a control county based on coarsened exact matching. We report regression results in Panel D, E and F. Standard errors clustered by FC are reported in parentheses. \*, \*\*, \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Log(1+Income) Hourly Workers-Counties with FCs					
Matching Variables	Population Size &	Add Per Capita Income &	Add Age &	Add Retail Spending	Add Broadband
	Density	Unemployment Rate	Education Demographics	Per Capita	Access
	(1)	(2)	(3)	(4)	(5)
PostFC × Treated	-0.017*** (0.005)	-0.015*** (0.005)	-0.023*** (0.005)	-0.021*** (0.004)	-0.024*** (0.003)
Observations	3,045,998	2,966,435	2,640,053	2,204,839	2,237,053
Adjusted R <sup>2</sup>	0.815	0.822	0.825	0.832	0.823
Worker FE	✓	✓	✓	✓	✓
YearQtr FE	✓	✓	✓	✓	✓

Panel B: Log(1+Employment)-Counties with FCs					
Matching Variables	Population Size &	Add Per Capita Income &	Add Age &	Add Retail Spending	Add Broadband
	Density	Unemployment Rate	Education Demographics	Per Capita	Access
	(1)	(2)	(3)	(4)	(5)
PostFC × Treated	-0.018*** (0.004)	-0.015*** (0.005)	-0.015*** (0.005)	-0.016*** (0.006)	-0.018*** (0.005)
Observations	917279	1042981	847679	645603	597924
Adjusted R <sup>2</sup>	0.978	0.976	0.977	0.978	0.977
Establishment FE	✓	✓	✓	✓	✓
Ind-Year FE	✓	✓	✓	✓	✓
Region-Year FE	✓	✓	✓	✓	✓

Panel C: Log(1+Sales)-Counties with FCs					
Matching Variables	Population Size &	Add Per Capita Income &	Add Age &	Add Retail Spending	Add Broadband
	Density	Unemployment Rate	Education Demographics	Per Capita	Access
	(1)	(2)	(3)	(4)	(5)
PostFC × Treated	-0.027*** (0.006)	-0.024*** (0.007)	-0.024** (0.009)	-0.024** (0.009)	-0.024** (0.009)
Observations	917279	1042981	847679	645603	597924
Adjusted R <sup>2</sup>	0.973	0.971	0.972	0.973	0.972
Establishment FE	✓	✓	✓	✓	✓
Ind-Year FE	✓	✓	✓	✓	✓
Region-Year FE	✓	✓	✓	✓	✓

Panel D: Log(1+Income)-Counties within 100 Miles of FCs					
<i>Matching Variables</i>	Population Size & Density (1)	Add Per Capita Income & Unemployment Rate (2)	Add Age & Education Demographics (3)	Add Retail Spending Per Capita (4)	Add Broadband Access (5)
PostFC × Treated	-0.013*** (0.002)	-0.016*** (0.002)	-0.015*** (0.002)	-0.017*** (0.003)	-0.016*** (0.002)
Observations	18,750,507	18,167,363	11,382,211	10,656,182	8,623,011
Adjusted R <sup>2</sup>	0.829	0.828	0.830	0.820	0.829
Worker FE	✓	✓	✓	✓	✓
YearQtr FE	✓	✓	✓	✓	✓

Panel E: Log(1+Employment)-Counties within 100 Miles of FCs					
<i>Matching Variables</i>	Population Size & Density (1)	Add Per Capita Income & Unemployment Rate (2)	Add Age & Education Demographics (3)	Add Retail Spending Per Capita (4)	Add Broadband Access (5)
PostFC × Treated	-0.017*** (0.002)	-0.016*** (0.002)	-0.014*** (0.004)	-0.014*** (0.003)	-0.014*** (0.003)
Observations	3528676	3161864	2212512	2087021	1933818
Adjusted R <sup>2</sup>	0.979	0.979	0.979	0.980	0.979
Establishment FE	✓	✓	✓	✓	✓
Ind-Year FE	✓	✓	✓	✓	✓
Region-Year FE	✓	✓	✓	✓	✓

Panel F: Log(1+Sales)-Counties within 100 Miles of FCs					
<i>Matching Variables</i>	Population Size & Density (1)	Add Per Capita Income & Unemployment Rate (2)	Add Age & Education Demographics (3)	Add Retail Spending Per Capita (4)	Add Broadband Access (5)
PostFC × Treated	-0.031*** (0.003)	-0.029*** (0.004)	-0.025*** (0.005)	-0.025*** (0.005)	-0.024*** (0.005)
Observations	3528676	3161864	2212512	2087021	1933818
Adjusted R <sup>2</sup>	0.972	0.972	0.973	0.973	0.973
Establishment FE	✓	✓	✓	✓	✓
Ind-Year FE	✓	✓	✓	✓	✓
Region-Year FE	✓	✓	✓	✓	✓

**Table IA8: Instrumental Variables: First Stage**

This table presents the results for the first stage of the instrumental variable regression, i.e., determinants of an FC's location. The dependent variable  $PostFC$  is an indicator that equals 1 beginning in the year an FC is established in county  $c$ ; it remains 1 for all subsequent years. The independent variables are state- and county-level variables defined one year before the establishment of an FC.  $State\ Generosity_{s,t-1}$  is defined as the logged value of the cumulative corporate subsidies offered by the state from 1990 until that year scaled by cumulative state revenue.  $Log(Distance)_c$  is the logged value of the distance from the closest USPS network facility. We use the following categories for regions: East North Central, East South Central, Middle Atlantic, Mountain, New England, Pacific, South Atlantic, West North Central, and West South Central. Standard errors clustered by FC are reported in parentheses. The data period is 2010-2016. \*, \*\*, \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively.

	PostFC			
	(1)	(2)	(3)	(4)
State Generosity $_{s,t-1} \times (-1) \times Log(Distance)_c$ from Closest USPS Network			0.110*** (0.029)	0.116*** (0.033)
State Generosity $_{s,t-1}$		-0.029 (0.027)	0.303*** (0.099)	0.321*** (0.109)
Log(Distance) $_c$ from Closest USPS Network $_c$	-0.005 (0.029)	-0.006 (0.030)	-0.016 (0.029)	-0.018 (0.034)
County Unemployment Rate $_{c,t-1}$	-0.055*** (0.018)	-0.054*** (0.019)	-0.071*** (0.018)	-0.081*** (0.021)
Log(County Labor Force) $_{c,t-1}$	-0.094*** (0.031)	-0.099*** (0.032)	-0.104*** (0.032)	-0.131*** (0.035)
Log(State Population) $_{s,t-1}$	0.450* (0.266)	0.406 (0.262)	0.337 (0.252)	0.431 (0.311)
Log(State Revenue) $_{s,t-1}$	-0.621** (0.247)	-0.591** (0.243)	-0.486** (0.232)	-0.629** (0.285)
County Agg. Retail Sales Growth $_{c,t-1}$				1.017*** (0.345)
County Agg. Sales Growth $_{c,t-1}$				0.289 (0.262)
Region FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Adjusted R <sup>2</sup>	0.49	0.49	0.51	0.55
No. of Counties	50	50	50	50
Observations	350	350	350	250
F-stat (State Generosity $_{s,t-1}$ $\times Log(Distance)_c \times (-1) = 0$ )			14.18	12.25
p-value			0.0001	0.0001

**Table IA9: Instrumental Variables: Second Stage**

This table presents the results for the second stage of the instrumental variable regression. We use the estimated  $\widehat{PostFC}$  dummy for the FC counties, and we re-estimate Equation (1), where we instrument  $PostFC$  with  $\widehat{PostFC}$  and adjust standard errors accordingly. Standard errors clustered by FC are reported in parentheses. Panel A reports results for worker-level data. Panel B reports results for county-industry level data. \*, \*\*, \*\*\* indicate significance at the 10%, 5%, and 1% level, respectively.

<b>Panel A: Second Stage: Worker-Level</b>			
	Log(1+ Total Income): <i>Hourly Workers</i>		
	(1)	(2)	(3)
$\widehat{PostFC}$	-0.116*	-0.106*	
	(0.060)	(0.057)	
$\widehat{PostFC} \times \text{Retail}$			-0.077***
			(0.017)
Worker FE	✓	✓	✓
Year-Qtr FE	✓		
Region-YearQtr FE		✓	
First Stage Controls	✓	✓	
County-YearQtr FE			✓
Observations	1,408,358	1,408,358	5,592,239

<b>Panel B: Second Stage: County-Level</b>						
	Employment Growth			Total Wage Growth		
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{PostFC} \times \text{Retail}$	-0.056***			-0.056***		
	(0.007)			(0.008)		
$\widehat{PostFC} \times \text{Warehouse}$		0.025***			0.017**	
		(0.008)			(0.008)	
$\widehat{PostFC} \times \text{Restaurant}$			0.009**			0.004
			(0.004)			(0.004)
County-YearQtr FE	✓	✓	✓	✓	✓	✓
Ind-YearQtr FE	✓	✓	✓	✓	✓	✓
Observations	1,178,424	1,178,424	1,178,424	1,179,161	1,179,161	1,179,161

**Table IA10: Robustness Check**

This table presents robustness checks for the effect of FCs on the income of hourly retail workers using Equation (1). Panel A replaces region-year-quarter fixed effects with state-year-quarter fixed effects. Panel B excludes migrants whose first and last ZIP codes in the data are different. Panel C uses the modeled annualized income as an alternative measure of income. All regressions include worker, firm-year-quarter, and region-year-quarter fixed effects. Standard errors clustered by FC are reported in parentheses. \*, \*\*, \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively.

	Log(Total Income): <i>Hourly Workers</i>	
	Counties with FCs	Counties within 100 Miles of FCs
	(1)	(2)
<b>Panel A: State-Year-Quarter Fixed Effects</b>		
PostFC	-0.011*** (0.002)	-0.013*** (0.001)
Observations	1,880,155	9,544,422
Adjusted R <sup>2</sup>	0.842	0.854
<b>Panel B: Excluding Migrants</b>		
PostFC	-0.016*** (0.003)	-0.015*** (0.003)
Observations	1,631,114	8,204,088
Adjusted R <sup>2</sup>	0.848	0.859
<b>Panel C: Alternative Measure of Income</b>		
PostFC	-0.013*** (0.001)	-0.011*** (0.002)
Observations	1,884,907	9,565,115
Adjusted R <sup>2</sup>	0.911	0.914
Worker FE	✓	✓
Firm-YearQtr FE	✓	✓
Region-YearQtr FE	✓	✓

**Table IA11:** Two Way Fixed Effects (TWFEs) v/s Average Treatment Effect on Treated (ATT) based on Callaway and Sant’Anna (2021)

This table presents results of establishment-level panel regressions based on Two Way Fixed Effects (TWFEs) and Average Treatment Effect on Treated (ATT) based on Callaway and Sant’Anna (2021). Column (1) provides our baseline estimates with restrictive establishment, industry  $\times$  year, and region  $\times$  year fixed effects. In Column (2), we provide our less restrictive model with only establishment and year fixed effects. In Column (3), we provide ATT estimates based on Callaway and Sant’Anna (2021) estimation methodology with bootstrapped standard errors. Finally, in Column (4), we provide estimates for each cohort. Standard errors clustered by FC are reported in parentheses. \*, \*\*, \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively. Panel A provides results for retail employment, and Panel B report results using retail sales as a dependent variable.

Panel A: Log(1+Employment)-Counties with FCs				
	Baseline (1)	TWFEs (2)	WLS-ATT (3)	Cohorts (4)
PostFC	-0.021*** (0.005)	-0.023*** (0.007)		
ATT			-0.045*** (0.002)	
G2011				-0.041*** (0.003)
G2012				-0.053*** (0.003)
G2013				-0.048*** (0.003)
G2014				-0.037*** (0.002)
Adj.-R <sup>2</sup>	0.968	0.967		
Obs.	142824	142824	130526	130526
Establishment FE	✓	✓	✓	✓
Year FE		✓	✓	✓
Ind-Year FE	✓			
Region-Year FE	✓			

Panel B: Log(1+Sales)-Counties with FCs				
	Baseline	TWFES	WLS-ATT	Cohorts
	(1)	(2)	(3)	(4)
PostFC	-0.023*** (0.007)	-0.024** (0.009)		
ATT			-0.053*** (0.003)	
G2011				-0.037*** (0.007)
G2012				-0.067*** (0.004)
G2013				-0.062*** (0.005)
G2014				-0.046***
Adj.-R <sup>2</sup>	0.956	0.955		
Obs.	142824	142824	130526	130526
Establishment FE	✓	✓	✓	✓
Year FE		✓	✓	✓
Ind-Year FE	✓			
Region-Year FE	✓			

**Table IA12: Effect of FCs on Employment by Occupation**

This table presents the results of 20 separate MSA-occupation-level panel regressions that assess the effect of FCs on the employment for a given occupation. We identify the top 20 occupations in the retail industry. For each occupation, we estimate Equation 2 and report coefficient estimates  $\beta$ . All regressions include MSA and year fixed effects. Standard errors are clustered by MSA. \*, \*\*, \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively.

Occupation	Emp in Retail	Fraction of Total Retail Emp (%)	Estimated Effect
Retail salespersons	3891310	25.99	-0.022**
Cashiers	2828730	18.89	0.024
Stock clerks and order fillers	1303730	8.71	0.037*
First-line supervisors/managers of retail sales workers	1037570	6.93	0.026
Laborers and freight, stock, and material movers, hand	351870	2.35	0.040
Automotive service technicians and mechanics	294290	1.97	0.015
Pharmacy technicians	245680	1.64	0.049**
Customer service representatives	243080	1.62	-0.023
Packers and packagers, hand	206860	1.38	0.101**
Bookkeeping, accounting, and auditing clerks	192230	1.28	0.063***
General and operations managers	190980	1.28	-0.063**
Truck drivers, light or delivery services	186480	1.25	0.056**
Office clerks, general	185090	1.24	-0.022
Combined food preparation and serving workers, including fast food	183080	1.22	-0.020
Pharmacists	177720	1.19	0.011
First-line supervisors/managers of office and administrative support workers	168940	1.13	0.024
Shipping, receiving, and traffic clerks	159440	1.06	0.087***
Food preparation workers	155160	1.04	0.175***
Parts salespersons	141650	0.95	0.075*
Butchers and meat cutters	105880	0.71	0.028

**Table IA13: Effect of FCs on Sales of Retail Stores**

This table presents the results of establishment-level panel regressions that assess the heterogeneous effect of FCs on the sales of retail establishments/stores based on the size of stores. Panel A includes establishments in counties with FCs. Panel B includes establishments in counties within 100 miles of FCs but not in counties with FCs. Column (1) reports results for all stores, while Columns (2)-(4) report results for terciles based on sales one year before the establishment of FCs in the county or neighboring county. All regressions include establishment, industry-year, and region-year fixed effects. Standard errors clustered by FC are reported in parentheses. \*, \*\*, \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively.

	Log(1+Sales)			
	All	Small	Medium	Large
	(1)	(2)	(3)	(4)
<b>Panel A: Counties with FCs</b>				
PostFC	-0.023*** (0.007)	-0.017 (0.012)	-0.020*** (0.005)	-0.032*** (0.009)
Observations	142,824	51,722	44,949	46,153
Adjusted R <sup>2</sup>	0.956	0.793	0.652	0.907
<b>Panel B: Counties within 100 Miles of FCs</b>				
PostFC	-0.011* (0.006)	-0.005 (0.009)	-0.009* (0.005)	-0.019 (0.012)
Observations	852,556	304,575	271,331	276,644
Adjusted R <sup>2</sup>	0.956	0.770	0.656	0.910
Establishment FE	✓	✓	✓	✓
Ind-Year FE	✓	✓	✓	✓
Region-Year FE	✓	✓	✓	✓

**Table IA14:** Placebo Tests: Sales of Full-Service Restaurants

This table presents the results of establishment-level panel regressions that assess the heterogeneous effect of FCs on the sales of full-service restaurants (NAICS 722511) based on the size of restaurants. Panel A includes establishments in counties with FCs. Panel B includes establishments in counties within 100 miles of FCs but not in counties with FCs. Column (1) reports results for all restaurants, while Columns (2)-(4) report results for terciles based on sales one year before the establishment of FCs in the county or neighboring county. All regressions include establishment and region-year fixed effects. Standard errors clustered by FC are reported in parentheses. \*, \*\*, \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively.

	Log(1+Sales)			
	All	Small	Medium	Large
	(1)	(2)	(3)	(4)
<b>Panel A: Counties with FCs</b>				
PostFC	0.001 (0.002)	0.012*** (0.004)	-0.000 (0.002)	-0.000 (0.004)
Observations	91,748	30,673	35,520	25,555
Adjusted R <sup>2</sup>	0.977	0.881	0.816	0.933
<b>Panel B: Counties within 100 Miles of FCs</b>				
PostFC	-0.000 (0.001)	0.001 (0.004)	0.000 (0.001)	-0.004 (0.005)
Observations	555,996	177,524	210,874	167,594
Adjusted R <sup>2</sup>	0.979	0.873	0.778	0.949
Establishment FE	✓	✓	✓	✓
Region-Year FE	✓	✓	✓	✓

**Table IA15:** Placebo Tests – Effect of FCs on Sales of Retail Stores

This table presents the results of placebo tests that assess the effect of placebo FCs on the sales of retail establishments/stores using a matched control sample. We match each treated county to a control county using coarsened exact matching (CEM), and assign the FC establishment date to the corresponding control county. In Column (1), we identify control counties based on population size and population density. In Column (2), in addition to population size and population density, we include per capita income and unemployment rate in the matching model. In Column (3), we also add percentage of population with age below 18 and above 65, along with percentage of population with high school and college degree to the matching model. In Column (4), we further include retail spending per capita in the matching model. All regressions include establishment fixed effects, industry-year fixed effects, and region-year fixed effects. Standard errors clustered by FC are reported in parentheses. \*, \*\*, \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively.

<i>Matching Variables</i>	Dependent Variable: Log(1+Sales)			
	Populations Size & Density (1)	Add Per Capita Income & Unemployment Rate (2)	Add Age & Education Demographics (3)	Add Retail Spending Per Capita (4)
Placebo PostFC	-0.001 (0.003)	-0.005 (0.004)	-0.003 (0.002)	-0.001 (0.002)
Observations	600019	547565	775184	716695
Adjusted R <sup>2</sup>	0.969	0.971	0.969	0.970
Establishment FE	✓	✓	✓	✓
Ind-Year FE	✓	✓	✓	✓
Region-Year FE	✓	✓	✓	✓

**Table IA16:** Effect of FCs on Employment and Sales of Retail Stores – With Controls

This table presents the results of establishment-level panel regressions that assess the effect of FCs on the employment and sales of retail establishments/stores where we control for various county-specific characteristics. In Column (1), we control for unemployment rate, house price index and per capita income. In Column (2), we also control for percentage of population in different age groups. In Column (3), we control for education characteristics. In Column (4), we use American Time Survey data and control for average time travel for work and grocery shopping. All regressions include establishment, industry-year, and region-year fixed effects. Standard errors clustered by FC are reported in parentheses. \*, \*\*, \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively.

	Panel A: Log(1+Employment)			
	(1)	(2)	(3)	(4)
PostFC	-0.025*** (0.005)	-0.021*** (0.005)	-0.021*** (0.006)	-0.022*** (0.006)
Log(House Price Index) <sub>c,t-1</sub>	-0.026 (0.071)	-0.057 (0.049)	-0.076 (0.073)	-0.087 (0.071)
Log(Per Capita Income) <sub>c,t-1</sub>	0.058 (0.059)	0.018 (0.054)	-0.003 (0.068)	0.015 (0.071)
Unemployment Rate <sub>c,t-1</sub>	-0.956* (0.516)	-0.541 (0.631)	-0.882 (0.853)	-0.988 (0.811)
% Below 20 Years <sub>c,t-1</sub>		2.899* (1.558)	4.475* (2.335)	4.015 (2.415)
% Between 20 and 40 Years <sub>c,t-1</sub>		2.416** (1.020)	2.791 (1.773)	2.966 (1.783)
% Between 40 and 60 Years <sub>c,t-1</sub>		4.729*** (1.680)	6.164** (2.350)	6.089** (2.297)
% with Bachelors Degree <sub>c,t-1</sub>			-0.126 (0.223)	-0.137 (0.222)
% with Masters Degree <sub>c,t-1</sub>			-0.590 (0.745)	-0.520 (0.753)
% with Professional Degree <sub>c,t-1</sub>			0.024 (1.298)	0.038 (1.325)
Log(Work Travel(hrs/week)) <sub>cb,t-1</sub>				0.008* (0.004)
Log(Grocery Travel(hrs/week)) <sub>cb,t-1</sub>				0.000 (0.006)
Establishment FE	✓	✓	✓	✓
Ind-Year FE	✓	✓	✓	✓
Region-Year FE	✓	✓	✓	✓
Observations	139,198	139,198	110,777	104,288
Adjusted R <sup>2</sup>	0.968	0.968	0.970	0.970

	Panel B: Log(1+Sales)			
	(1)	(2)	(3)	(4)
PostFC	-0.025*** (0.006)	-0.021*** (0.006)	-0.026*** (0.007)	-0.026*** (0.008)
Log(House Price Index) <sub>c,t-1</sub>	-0.069 (0.068)	-0.089 (0.057)	-0.112 (0.091)	-0.125 (0.087)
Log(Per Capita Income) <sub>c,t-1</sub>	0.025 (0.079)	0.024 (0.075)	0.005 (0.086)	0.035 (0.091)
Unemployment Rate <sub>c,t-1</sub>	-1.007 (0.905)	-0.598 (0.959)	-1.151 (1.137)	-1.291 (1.070)
% Below 20 Years <sub>c,t-1</sub>		2.243 (2.271)	4.631 (3.053)	3.816 (3.153)
% Between 20 and 40 Years <sub>c,t-1</sub>		3.092** (1.351)	3.480 (2.177)	3.775* (2.195)
% Between 40 and 60 Years <sub>c,t-1</sub>		3.906* (1.943)	6.955** (3.001)	6.676** (2.909)
% with Bachelors Degree <sub>c,t-1</sub>			-0.002 (0.275)	0.005 (0.266)
% with Masters Degree <sub>c,t-1</sub>			-0.728 (1.040)	-0.599 (1.041)
% with Professional Degree <sub>c,t-1</sub>			-0.320 (1.602)	-0.242 (1.657)
Log(Work Travel(hrs/week)) <sub>cb,t-1</sub>				0.013** (0.006)
Log(Grocery Travel(hrs/week)) <sub>cb,t-1</sub>				-0.001 (0.009)
Establishment FE	✓	✓	✓	✓
Ind-Year FE	✓	✓	✓	✓
Region-Year FE	✓	✓	✓	✓
Observations	139,198	139,198	110,777	104,288
Adjusted R <sup>2</sup>	0.955	0.955	0.968	0.968

**Table IA17: Effect of FCs on Store Relocations**

This table presents the results of establishment-level panel regressions that assess the effect of FCs on the relocation of retail establishments/stores. Panel A includes establishments in counties with FCs. Panel B includes establishments in counties within 100 miles of FCs but not in counties with FCs. The Relocation Out of County/State dummy variable is equal to one if a firm moves out of county/state in a given year and stays one after the move; otherwise, it equals zero. All regressions include establishment, industry-year, and region-year fixed effects. Standard errors clustered by FC are reported in parentheses. \*, \*\*, \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively.

	Relocation Out of County (1)	Relocation Out of State (2)
<b>Panel A: Counties with FCs</b>		
PostFC	0.003 (0.002)	0.002 (0.002)
Observations	142,824	142,824
Adjusted R <sup>2</sup>	0.691	0.456
Establishment FE	✓	✓
Ind-Year FE	✓	✓
Region-Year FE	✓	✓
<b>Panel B: Counties within 100 Miles of FCs</b>		
PostFC	-0.001 (0.001)	-0.001 (0.001)
Observations	852,556	852,556
Adjusted R <sup>2</sup>	0.714	0.442
Establishment FE	✓	✓
Ind-Year FE	✓	✓
Region-Year FE	✓	✓

**Table IA18:** Effect of FCs on Employment and Sales of Retail Stores – Franchise vs. Non-Franchise

This table presents the results of establishment-level panel regressions that assess the heterogeneous effect of FCs on the employment and sales of retail establishments/stores for franchises and non-franchises. Panel A includes establishments in counties with FCs. Panel B includes establishments in counties within 100 miles of FCs but not in counties with FCs. All regressions include establishment, industry-year, and region-year fixed effects. Standard errors clustered by FC are reported in parentheses. \*, \*\*, \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively.

	Log(1+Employment)		Log(1+Sales)	
	Non-Franchises	Franchises	Non-Franchises	Franchises
	(1)	(2)	(3)	(4)
<b>Panel A: Counties with FCs</b>				
PostFC	-0.028*** (0.005)	-0.013** (0.005)	-0.029*** (0.008)	-0.015** (0.007)
Observations	75,535	67,289	75,535	67,289
Adjusted R <sup>2</sup>	0.951	0.965	0.921	0.964
<b>Panel B: Counties within 100 Miles of FCs</b>				
PostFC	-0.015*** (0.005)	-0.002 (0.003)	-0.017** (0.007)	-0.003 (0.004)
Observations	491,502	361,054	491,502	361,054
Adjusted R <sup>2</sup>	0.957	0.975	0.918	0.971
Establishment FE	✓	✓	✓	✓
Ind-Year FE	✓	✓	✓	✓
Region-Year FE	✓	✓	✓	✓

**Table IA19: Opening of Retail Stores**

This table presents the results of county-level panel regressions that assess the heterogeneous effect of FCs on the entry rates of retail establishments/stores based on the size of stores. Here, we define *entry rate* as the logged value of the number of entrants in a given county. Panel A includes entrants in counties with FCs. Panel B includes entrants in counties within 100 miles of FCs but not in counties with FCs. Column (1) reports results for all stores, while Columns (2)-(4) report results for terciles based on the first-year sales after entry. All regressions include county and region-year fixed effects. Standard errors clustered by FC are reported in parentheses. \*, \*\*, \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively.

	Log(1+Entrants)			
	All	Small	Medium	Large
	(1)	(2)	(3)	(4)
<b>Panel A: Counties with FCs</b>				
PostFC	0.012 (0.051)	-0.007 (0.070)	0.081 (0.076)	0.001 (0.072)
Observations	190	190	190	190
Adjusted R <sup>2</sup>	0.982	0.967	0.972	0.965
<b>Panel B: Counties within 100 Miles of FCs</b>				
PostFC	-0.081** (0.032)	-0.118*** (0.041)	-0.015 (0.053)	-0.051 (0.068)
Observations	4045	4045	4045	4045
Adjusted R <sup>2</sup>	0.953	0.919	0.915	0.912
County FE	✓	✓	✓	✓
Region-Year FE	✓	✓	✓	✓

**Table IA20: Robustness Check: Full Sample**

This table presents the results of robustness checks using the full sample of data and including FC shocks during the full sample period. Column (1) replicates results in Table 6, Column (1); Column (2) replicates results in Table IA13, Column (1); and Column (3) replicates results in Table 8, Column (3). Column (1) and Column (2) use NETS data from 1995 to 2014. Column (3) uses QCEW data from 1995 to 2016. \*, \*\*, \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively.

	Log(1+Employment) (1)	Log(1+Sales) (2)	Employment Growth (3)
<b>Panel A: Counties with FCs</b>			
PostFC	-0.021*** (0.005)	-0.026*** (0.005)	
PostFC × (Retail + Warehouse + Restaurant)			-0.028*** (0.003)
Observations	597,681	597,681	3,084,198
Adjusted R <sup>2</sup>	0.896	0.897	0.162
<b>Panel B: Counties within 100 Miles of FCs</b>			
PostFC	-0.019*** (0.007)	-0.025*** (0.008)	
PostFC × (Retail + Warehouse + Restaurant)			-0.007 (0.005)
Observations	3,828,487	3,828,487	3,084,198
Adjusted R <sup>2</sup>	0.894	0.896	0.162
Establishment FE	✓	✓	
Ind-Year FE	✓	✓	
Region-Year FE	✓	✓	
County-YearQtr FE			✓
Ind-YearQtr FE			✓

**Table IA21: Effect of FCs on Unemployment Rate – Matching Sample**

This table presents results of county-level panel regressions that assess the effect of FCs on the unemployment rate using a matched sample. We match each treated county to a control county using coarsened exact matching (CEM). In Column (1) we report results for FC counties. In Column (2), we identify control counties based on population size and population density. In Column (3), in addition to population size and population density, we include per capita income and unemployment rate in the matching model. In Column (4), we also add percentage of population with age below 18 and above 65, percentage of population with high school and college degree to the matching model. In Column (5), we further include retail spending per capita in the matching model. All regressions include county and region-year fixed effects. Standard errors clustered by FC are reported in parentheses. \*, \*\*, \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable: Unemployment Rate					
	<i>Matching Variables</i>				
	<i>FC Counties</i>	Populations Size & Density	Add Per Capita Income & Unemployment Rate	Add Age & Education Demographics	Add Retail Spending Per Capita
	(1)	(2)	(3)	(4)	(5)
Post FC	-0.003* (0.001)				
PostFC × Treated		-0.003 (0.002)	-0.004* (0.002)	-0.002 (0.002)	-0.002 (0.002)
Observations	266	511	511	567	525
Adjusted R <sup>2</sup>	0.970	0.954	0.961	0.952	0.940
County FE	✓	✓	✓	✓	✓
Region-Year FE	✓	✓	✓	✓	✓

**Table IA22:** Effect of FCs on Consumer Expenditures

This table presents the results of MSA-level panel regressions that assess the effect of FCs on consumer expenditures. The analysis includes MSAs with FCs. All regressions include MSA and year fixed effects. Standard errors clustered by MSA are reported in parentheses. \*, \*\*, \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively.

	Log(Total)	Log(Food)	Log(Apparel)	Log(Entertainment)	Log(Reading)
	(1)	(2)	(3)	(4)	(5)
PostFC	-0.022 (0.031)	0.019 (0.033)	0.031 (0.077)	0.013 (0.041)	-0.010 (0.044)
Observations	98	98	98	98	98
Adjusted R <sup>2</sup>	0.858	0.714	0.407	0.825	0.865
MSA FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓

**Table IA23: Online Store Announcements by the Major E-commerce Retailer**

This table presents the online store announcement by the major e-commerce retailer.

NAICS Code	Industry Name	Announcement Date
451211	Book stores	10/4/1995
451140	Musical instrument and supplies stores	6/11/1998
451220	Precorded tape, CD, and record stores	6/11/1998
453220	Gift, novelty, and souvenir stores	11/17/1998
443142	Electronics stores	6/13/1999
451120	Hobby, toy, and game stores	6/13/1999
453910	Pet and pet supplies stores	6/14/1999
444110	Home centers	11/9/1999
444120	Paint and wallpaper stores	11/9/1999
444130	Hardware stores	11/9/1999
444190	Other building material dealers	2/9/2000
444210	Outdoor power equipment stores	2/9/2000
446120	Cosmetic and beauty supply stores	4/17/2000
446199	All other health and personal care stores	4/17/2000
453991	Tobacco stores	4/17/2000
442110	Furniture stores	5/19/2000
442210	Floor covering stores	5/19/2000
442291	Window treatment stores	5/19/2000
442299	All other home furnishings stores	5/19/2000
443141	Household appliance stores	5/19/2000
444220	Nursery, garden, and farm supply stores	5/19/2000
451130	Sewing, needlework, and piece goods stores	5/19/2000
453920	Art dealers	10/10/2000
453310	Used merchandise stores	11/1/2000
451212	News dealers and newsstands	10/30/2001
448110	Men's clothing stores	11/7/2002
448120	Women's clothing stores	11/7/2002
448130	Children's and infants' clothing stores	11/7/2002
448140	Family clothing stores	11/7/2002
448150	Clothing accessories stores	11/7/2002
448190	Other clothing stores	11/7/2002
448210	Shoe stores	11/7/2002
448320	Luggage and leather goods stores	11/7/2002
451110	Sporting goods stores	9/22/2003
448310	Jewelry stores	4/22/2004
446191	Food, health, supplement stores	7/17/2006
453110	Florists	7/17/2006
441310	Automotive parts and accessories stores	10/26/2006
441320	Tire dealers	10/26/2006
453210	Office supplies and stationery stores	6/23/2008

**Table IA24:** Effect of E-commerce Online Store on Retail Sector: NETS Data

This table presents the results of establishment level panel regressions that assess the effect of the entry into 6-digit industries by the major e-commerce retailer on the employment of those industries. We include all establishments within the retail sector. All regressions include establishment and county  $\times$  year fixed effects. Standard errors clustered by 6-digit industry are reported in parentheses. \*, \*\*, \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively.

	Log(Employment)			
	Sample Period: 1990-2012		Sample Period: 1990-2006	
	(1)	(2)	(3)	(4)
Post $\times$ Treated	-0.014*** (0.003)	-0.015*** (0.003)	-0.007** (0.003)	-0.008** (0.003)
Observations	17,995,768	17,995,216	13,739,998	13,739,602
Adjusted R <sup>2</sup>	0.92	0.92	0.92	0.92
Establishment FE	✓	✓	✓	✓
Year FE	✓		✓	
County $\times$ Year FE		✓		✓