Center for Economic Institutions
Working Paper Series

No. 2020-7

"Diffusion of E-Commerce and Retail Job Apocalypse: Evidence from Credit Card Data on Online Spending"

Hyunbae Chun, Hailey Hayeon Joo, Jisoo Kang and Yoonsoo Lee

October, 2020

Institute of Economic Research
Hitotsubashi University
2-1 Naka, Kunitachi, Tokyo, 186-8603　JAPAN
http://cei.ier.hit-u.ac.jp/English/index.html
Tel:+81-42-580-8405/Fax:+81-42-580-8333

Diffusion of E-Commerce and Retail Job Apocalypse: Evidence from Credit Card Data on Online Spending*

Hyunbae Chun[†1], Hailey Hayeon Joo[1], Jisoo Kang[2] and Yoonsoo Lee[1]

[1] Department of Economics, Sogang University

[2] SNU Institute of Economic Research, Seoul National University

October 2020

Abstract

The rapid growth of e-commerce is widely blamed for job losses in brick-and-mortar retailers. We construct a unique measure of online spending share based on 30 billion transactions of credit cards in Korea. Using the geographic variation in online spending shares, we examine the causal effect of e-commerce on retail employment at the county level. We find that the rise in online spending share from 2010 to 2015 decreases the county-level offline retail employment by about 172 workers, which represents approximately 3% reduction in average retail employment. We also find that the employment shifts from offline retail to other local businesses, such as restaurants and personal services. However, such effects of employment shift are confined in metropolitan areas and fall far short of offsetting employment losses in non-metropolitan areas. Our finding implies a prospect of Retail Job Apocalypse in certain local labor markets (i.e., non-metropolitan areas), if not everywhere.

***JEL* codes**: J21, L81, R12

Keywords: E-Commerce, Employment, Local Labor Market, Retail, Credit Card

* We thank Emek Basker, Florin Maican, and the participants at the Annual Conference of the European Association for Research in Industrial Economics, Comparative Analysis of Enterprise Data Conference, Korea University, Seoul National University for their helpful comments. A part of this research was done while Hyunbae Chun was visiting the Institute of Economic Research at Hitotsubashi University. This work was supported by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2020S1A5A2A01043698). All results have been reviewed to ensure that no confidential information is disclosed.

† Corresponding author. Phone number: +82-2-705-8515. Address: 35 Baekbeom-ro, Mapo-gu, Seoul 04107, South Korea. E-mail: `hchun@sogang.ac.kr`

1 Introduction

The rapid growth of e-commerce has dramatically changed the modern retail sector over the past decades. The recent evolution of physical retail markets, driven by the shift of consumers shopping behavior favoring online over traditional shopping, has threatened an increasing number of traditional brick-and-mortar stores to shut down. Recently, a series of bankruptcies of major retail chains in the United States (Sears in 2018, ToysRus in 2017, and so forth) raised a concern about jobs lost in the so-called "Retail Apocalypse."[1] Some extreme view predicts "virtual extinction" of certain types of physical retail stores. However, our understanding of the ongoing restructuring process of the industry is still limited. For example, along with a great number of jobs destroyed at brick-and-mortar stores, as reported in major news media, job creation can also be involved in some local businesses (on which time and money saved from online shopping are spent).[2] Despite the importance of the impact such process would have on local labor markets, academic effort to quantify the effects of e-commerce is so far rare (Hortacsu and Syverson 2015).

As an initial step to examine the effect of the diffusion of e-commerce on local labor markets, we attempt to answer the following three questions:

(i) Does online shopping expansion affect local offline retail employment negatively, and how large is the effect?

(ii) Is there any employment shift from offline retail to other local sectors? (e.g., restaurants and personal services)

(iii) Does e-commerce ultimately lead to Retail Job Apocalypse? If so, is it common in every local labor market (i.e., metropolitan vs. non-metropolitan)?

In this paper, we construct a unique measure of online retail-spending share (hereafter, "online share") at the county level, based on more than 30 billion transactions of credit and debit cards (hereafter, "credit cards") in Korea. We match the county-level online share to the employment data constructed from the *Census on Establishments* (CE) and quantify the causal effect of e-commerce on the retail employment. Our findings are as follows.

---

[1] In addition to e-commerce growth, over-expansion of shopping malls and shift in consumer spending habits are suggested as key explanations for Retail Apocalypse.

[2] Recent papers studying the effect of e-commerce on retail pay attention to physical retail stores, which involve merchandise sales. In a broader sense, retail also includes restaurants, hairdressers, and personal services; in other words, services that still need a physical location to provide services. The diffusion of e-commerce accompanied changes in the functions of brick-and-mortar stores, about which we will discuss further in Section 5.

First, we find that the increase in online shares indeed decreased the county-level offline retail employment. The magnitude of the effect is not catastrophic but substantial: one percentage point (pp) increase in online shares reduces half percent of employment. Our estimate implies that the rise in online share from 2010 to 2015 decreased about 172 workers in a typical county, which corresponds to approximately 3% reduction in retail employment. Our finding of the negative effect on physical retail stores is robust to various alternative analyses. To take into account the endogeneity problem, we use Barik instruments that exploit exogenous changes in local exposure to e-commerce across various goods. The results are also robust to the falsification test, alternative sets of instrumental variables, and various model specifications. Moreover, we find that the negative effect of online shopping on employment at brick-and-mortar stores is widespread across all locations.

Second, we find some evidence that the employment shifts from offline retail to other *local* businesses within a county, such as restaurants and personal services. This finding suggests a possibility that consumers who save time and money through online shopping shift their resources toward other local businesses such as coffee shops, restaurants, entertainment, aesthetics, and gyms. We believe that such a change in consumer behaviors created new jobs in other local sectors, possibly offsetting jobs that disappeared in the offline retail sector. However, such employment shift is not uniformly observed across all locations — local service jobs are more likely to be created in metropolitan areas but not necessarily in non-metropolitan ones.

Lastly, we find that Retail Job Apocalypse may occur in some, but not all, local labor markets. Both metropolitan and non-metropolitan labor markets suffered a decrease in offline retail employment. However, the benefit of new job creations in local services were unevenly shared between metropolitan and non-metropolitan areas. Although metropolitan areas have seen jobs growing in restaurants and personal services, those gains in jobs were not observed in non-metropolitan areas. This finding implies that the restructuring process, initiated by the diffusion of e-commerce, may evolve differently across local labor markets. In particular, local labor markets in non-metropolitan areas are likely to suffer from Retail Job Apocalypse.

We contribute to the literature by measuring the impact of e-commerce on local labor markets. We construct a unique measure of the online share using credit card transaction data and utilize the geographic variation in the degree of diffusion of e-commerce. To the best of our knowledge, this paper is the first empirical study to quantitatively evaluate the causal effects of the diffusion of e-commerce on local labor markets. More recently, economic literature began bringing out the issues of e-commerce impact on offline retail stores and employment (Goldmanis *et al.* 2009, Chava *et al.* 2018, Gebhardt 2018). Goldmanis *et al.* (2009) found that the growth of e-commerce decreases the number of small establishments and reallocates market shares from high to low cost producers. Gebhardt (2018) showed that areas with high-speed broadband access encounter job losses in offline retailers (e.g., electronics). Also, Chava *et al.* (2018) investigated whether retail stores near e-commerce fulfillment centers experience a reduction in sales and employees. However, previous studies had difficulties quantifying the e-commerce effect on local labor markets due to the lack of an appropriate measure of e-commerce spending. We thus contribute to the literature by overcoming the limitation of the previous studies.

Our finding is broadly related to the literature on the effects of new technologies on the labor market. Using a variation in exposure to industrial robots in the US local labor markets, Acemoglu and Restrepo (2020) found that robots take over the tasks that were previously performed by human workers. However, as Acemoglu and Restrepo (2018) highlighted, new technologies not only replace human labor but also create new tasks. For retail service, in which jobs in offline retail and service sectors are local in nature, whether creations and destruction of jobs occur in the same location has an important policy implication. Our study shows that new jobs were not necessarily created in the original locations where the retail jobs were lost. Although negative effects on jobs in physical stores are widely observed, the creation of new jobs in local services, which may have benefited from e-commerce, may not be equally distributed. For those areas that only shared the suffering of the negative effects, but not the benefit from the shifts in consumption patterns, the future of the local labor market is not very bright. Thus, identifying those locations is important for the labor market policy.

The remainder of this paper is organized as follows. Section 2 briefly reviews the diffusion of e-commerce and local labor markets in Korea. Section 3 describes our data set, and Section 4 provides the empirical specification and results. Section 5 presents the robustness checks for the results and discusses issues in local labor markets related to e-commerce. Section 6 concludes the paper.

2 E-Commerce and Local Labor Markets

2.1 Diffusion of E-Commerce

The structure of the retail industry has evolved since the 20^{th} century, thanks to a series of technological progress (Bronnenberg and Ellickson 2015). New technologies such as barcode scanners for inventory management have increased product variety, labor productivity, and firm size (Basker 2016). Moreover, e-commerce has fundamentally reshaped the retail environment, as consumers' shopping patterns have changed. E-commerce dramatically reduced search costs by providing detailed information about price and product quality online. Goods at online stores are often much cheaper than those at traditional offline stores (Brown and Goolsbee 2002). More importantly, the decrease in the need of consumers to visit physical stores to purchase merchandise has reformed the way brick-and-mortar stores operate (Smith and Zentner 2016).

E-commerce sales have grown fast worldwide. As of 2015, the online shares in UK, China, US, and Japan were 12.5%, 10.8%, 7.18%, and 4.75%, respectively.[3] The online share in Korea reached 11.7% in 2015, which is considerably higher than that in most countries. Both the fast internet connection and shipping at a relatively low cost, thanks to the relatively small country size, explain the fast diffusion of e-commerce in Korea.

[Insert Figure 1 About Here]

As seen in Figure 1, e-commerce, measured as the online shares, dramatically increased in Korea between 2010 and 2015. However, although the increase in online shares was widely observed in most counties in Korea, the degree of increase was not uniform across the counties. Specifically, the increase in online shares among metropolitan areas was higher by 6.5 pp, on average, compared with non-metropolitan areas during the same period. Nonetheless, notably, online shopping has become a major shopping method nationwide despite some differences across locations.

2.2 Technological Progress in Retail and Local Labor Markets

Offline retail stores, along with restaurants and personal services, are key employers in local labor markets. Technological progress and structural changes in the retail sector have affected local labor markets *worldwide*. The effect of such changes on the labor market has received much attention from economists and policymakers. Since the 1990s, the expansion of large discount stores (e.g., Wal-Mart) has significantly influenced the local labor market (Basker 2005, Neumark *et al.* 2008, Cho *et al.* 2015). They substituted and complemented stores in the neighborhood by securing low

[3] Sources: UK: Office for National Statistics "Internet Sales as a Percentage of Total Retail Sales"; US: US Census Bureau "Estimated Quarterly US Retail Sales (Adjusted): Total and E-commerce"; China: National Bureau of Statistics of China, China Statistical Yearbook 2016; Japan: Ministry of Economy, Trade and Industry "Results Compiled of the E-Commerce Market Survey"; Korea: Statistics Korea, "Monthly Online Shopping Survey"

prices and high productivity based on information and communication technology (Foster et al. 2006, Haltiwanger *et al.* 2010).

Although those changes occurred between "physical" stores in local markets, replacing jobs at traditional stores with those at the big-box or new chain stores, the impact of e-commerce on local labor markets is fundamentally different. The penetration of e-commerce did not necessarily create physical establishments at the locale. Moreover, the closings of numerous brick-and-mortar retail chain stores have raised a social issue on whether a further increase in online sales would lead to Retail Apocalypse (Economist 2017, New York Times 2017). Nonetheless, academic studies were only limitedly conducted due to difficulty in measuring the impact of e-commerce at individual local markets (Chava *et al.* 2018, Gebhardt 2018).

Local labor markets in Korea also went through dramatic changes with the fast diffusion of e-commerce. The average growth rate of retail trade employment was slow at approximately 2.5% from 2010 to 2015, which was lower than that of the total employment in all industries. Slow employment growth in the offline retail sector was widely observed across counties.

However, not all retail industries went through a path of decline. For example, the restaurant sector, which is another main axis of the local brick-and-mortar stores, recorded a solid growth. The growth rate of restaurant (including food and beverage) employment was faster than that of total employment during the same period (annually 4.2%). The number of food restaurants increased in all counties. In particular, in metropolitan areas, that of non-alcoholic beverage places (so-called *cafés*) substantially increased.[4] These employment changes in the local brick-and-mortar stores may be associated with the change in consumption patterns. Presumably, the saved time and money from online shopping could play a role in such changes, shifting the spending from purchasing merchandise to local services. We will analyze and quantify the causal effect of e-commerce on the local labor market in the regression framework in Section 4.

3 Data

3.1 Measuring Online Shares from the Credit Card Data

To measure the annual online shares by county, we use the credit card transaction data provided from Shinhan Card Co. (hereafter, "the Company"). Our dataset is representative of credit card

[4] In metropolitan areas, the employment growth rate of non-alcoholic beverage places is quite high (annually more than 20%).

transactions in Korea in terms of the coverage. The Company is the largest credit and debit card company in Korea in terms of both the number and amount of transactions.[5] The dataset provided by the Company contains more than 30 billion transactions, which occurred from January 1, 2010, to December 31, 2015. Those transactions were made by approximately 21 million (credit or debit) cardholders, which correspond to about two-thirds of the adult population.

We briefly explain the data structure and variable construction process (Appendix A provides further details). Each transaction in the data (i.e., the point of sales) includes information about the amount and date of the transaction, the type of card (credit or debit), address of merchants and cardholders, and industry classification of merchants. To identify whether transactions are made online, we use the industry classification of merchants. We classify online transactions that are made by merchants whose industry classification is e-commerce (KSIC 4791 excluding mail order). An online transaction, by definition, is made through the Internet and is not involved with a physical point of purchase. Meanwhile, an offline transaction is, in general, made at a physical brick-and-mortar store at which a consumer visits and swipes his/her card. As in Einav *et al.* (2017), online transactions in our study exclude home shopping (TV or phone orders).[6]

The county-level annual online share can be defined as follows:

$$Online\ Share_{jt} = \frac{\text{Online spending in county } j \text{ in year } t}{\text{Total spending in county } j \text{ in year } t},$$

where total spending in county j in year t is the sum of both online and offline spending in county j in year t. The geographic market for an offline transaction can be identified by the physical point of purchase, that is, the location of the retail store at which the card is swiped. Offline spending in county j in year t can be measured as the total amount of all brick-and-mortar retail stores' transactions located in county j in year t.[7] Online spending in county j in year t can be measured as total online shopping expenditures made by consumers who live in county j in year t.

In estimation, we use an online share measure constructed from the Company's data. This

[5] In Korea, the Company has the largest network for domestic transactions (comparable to the Visa network in the US). Moreover, its market share in Korea is close to (or slightly lower than) that of Mastercard (the second largest network in the US). See Appendix A for the details.

[6] Home shopping accounts for the majority of mail and phone orders in Korea. We find qualitatively similar results once we include home shopping.

[7] We define geographic markets at the county level. However, this definition may not work for a few counties considered as shopping districts; hence, we exclude 12 counties with a large share of consumption by residents living in other counties from our main sample. Nonetheless, our results are qualitatively similar to those from the alternative sample including these 12 counties (See Appendix Table C3 and C4).

measure is practically implementable and consistent with the definition of $Online\ Share_{jt}$. $Online\ Share_{jt}$ requires collection of the county-level information of all online transactions made through all credit card networks and all the offline transactions made by *all* payment methods (cash and credit cards). It is practically impossible to collect such data. However, we can construct online share by substituting both online and offline spending in $Online\ Share_{jt}$ with those measured from the Company's data. This measure is consistent with $Online\ Share_{jt}$, if both the Company's market share and the credit card payment share are high and stable. We found that both the market share of the Company and payment share of credit cards to cash are high and stable (see Appendix A for details).[8]

3.2 Employment

For our analysis, we use two employment measures of both the number of workers and full-time-equivalent (FTE) jobs. To obtain local retail employment, we mainly exploit the CE obtained from Statistics Korea. The advantage of CE is that the number of workers is available at the establishment level. CE provides the number of workers for each type of employment (i.e., full-time, part-time, self-employed, and unpaid family workers), but not the working hours for employment types. To convert the number of workers into that of FTE jobs, we obtain information on hours worked by employment type from the *Survey on Labor Conditions by Employment Type* (SLCET) from the Ministry of Employment and Labor.[9]

To define the offline retail trade sector, we exclude non-store retailers (KSIC 479; e-commerce, mail order, and other non-store retail) from the retail trade sector (KSIC 47). We exclude both mail and phone orders and door-to-door sales (i.e., traditional non-store retailing) in both online and offline employment (and spending) because the location of these merchants' sales cannot be determined at the county-level. We also exclude large general merchandise stores (GMS) that include department stores, warehouse clubs, and supercenters (KSIC 4711).[10] It is because most large GMS in Korea have both offline and online sales, but the employment of offline and online activities cannot be separated.

[8] For the robustness checks of our measurement, we allow the county-level variation in the Company's market share similar to Einav *et al.* (2017). The robustness checks are provided in Section 5.

[9] SLCET provides the working hours for full-time (including self-employed) and part-time (including unpaid household workers) employees.

[10] Including large GMS as offline retail generates qualitatively similar results (see Table C3 and C4). Contrary to the US retail sector, the employment share of large GMS in Korea is insignificant (approximately 5%). Small and medium-sized stores account for nearly all retail employment.

For estimation, we use the population-normalized offline retail employment defined as follows:

$$\frac{Emp_{jt}}{Pop_{jt}} = \frac{\text{Offline retail employment in county } j \text{ in year } t}{\text{Number of population in county } j \text{ in year } t} \times 10,000.$$

That is, $\frac{Emp_{jt}}{Pop_{jt}}$ is the offline retail employment per 10,000 population. The advantage of using this dependent variable is that employment measures become comparable across local markets irrespective of their county size (Basker 2005, Neumark *et al.* 2008).

3.3 Summary Statistics

Table 1 presents the county-level descriptive statistics for the sample of 197 counties between 2011 and 2015. Panel A provides the information of employment (i.e., dependent variable); panel B reports that of e-commerce (i.e., the main explanatory variable); and panel C shows that of control variables. All explanatory variables in panels B and C are lagged by one year. As seen in panel A, the mean of offline retail employment per 10,000 is 273, whereas those of population and offline workers are 225,609 and 5,686, respectively. The mean number of FTE jobs (5,294) is not much different from the number of workers because self-employment accounts for almost 40% of the total workers in the Korean retail sector. As presented in panel B, the mean of online share is approximately 24%, increasing from 23% in 2010 to 28% in 2015. For the control variables, we use the log of per capita property tax, population growth rate, car ownership per capita, share of the female population, and average household size.

[Insert Table 1 About Here]

4 Impact of E-commerce Expansion on Employment

4.1 Empirical Model and Main Results

We examine the extent to which e-commerce affects local retail employment by estimating the following equation.

$$\frac{Emp_{jt}}{Pop_{jt}} = \beta_0 + \beta_1 OS_{j,t-1} + X'_{j,t-1}\gamma + \mu_j + \delta_t + \varepsilon_{jt}, \tag{1}$$

where $\frac{Emp_{jt}}{Pop_{jt}}$ is the offline retail employment per 10,000 population. For the offline retail employment Emp_{jt}, both the number of workers and that of FTE jobs are used. The main explanatory variable $OS_{j,t-1}$ is the online share in county j in year $t-1$ constructed from the credit and debit transactions of the Company. Vector $X_{j,t-1}$ consists of the lagged county-level control variables (e.g., the log of per capita property tax, population growth rate, car ownership per capita, share of female population, and average household size). μ_j is the county fixed effect that captures the time-invariant heterogeneity, δ_t is the year-fixed effect, and ε_{jt} is the county-clustered standard errors.

Table 2 reports the average effect of online shopping expansion on local offline retail employment, estimated from equation (1). In column (1), the coefficient of online share is -1.473, which is negative and statistically significant at the 1% level. This means that a 1 pp increase in online share decreases 1.473 offline retail workers per 10,000 population. To convert this into the change in the number of workers in a county, we multiply the estimated coefficient by the average county population in 10,000 (i.e., 22.56 given in Table 1). Then, this implies that a 1 pp increase in online share decreases 33.23 offline retail workers on average, which is the equivalent of a 0.54% change in the total offline retail workers of a county. Under the model with control variables in column (2), the estimated impact is slightly greater than that in column (1), suggesting that a 1 pp increase in online share decreases 35.03 workers (or 0.57% change) at the county level. Thus, our estimates suggest that the increase in the online share of 4.9 pp between 2010 and 2015 causes approximately 172 offline retail workers to lose jobs in a county, which corresponds to approximately 3% of the total offline retail employment.[11] As Hortacsu and Syverson (2015) highlighted, the diffusion of e-commerce shows no sign of a slowdown, but it may reach saturation within a few decades. Supposing that the online share projected to increase by 15 pp in the next decade, our estimates predict an almost 10% reduction in offline retail employment. In this respect, our finding of the negative effect has an economic significance in the medium or long run.

[Insert Table 2 about here]

One caveat of examining the number of workers is that employment composition may have changed with the diffusion of e-commerce. For example, if e-commerce has shifted workers from full-time to part-time, the number of workers would have been either decreasing little or even

[11] Online spending is not available at the detailed industry level. When we examined the effects of (overall) online spending on employment at the more detailed industry level, we find that the negative employment effect was not limited to books and electronics. The negative effect was widespread across products such as foods and sporting goods.

unchanged, despite a significant negative effect on employment. To address a possible bias due to such a change in employment composition, we exploit the number of FTE jobs for local retail employment.[12] The estimated effects based on FTE jobs are slightly lower than those based on the number of workers, but the difference is relatively small. Specifically, under the full specification in column (4), the estimated coefficient of the online share is -1.410, meaning that 1.410 FTE jobs disappear per 10,000 population. This implies that a 1 pp increase in online share decreases 31.81 FTE jobs in a county (or 0.55% change). Thus, during the 2010–2015 period, the total FTE job loss is approximately 156, which corresponds to about a 2.9% reduction of total retail FTE jobs in a county. Overall, Table 2 confirms the salient finding of the negative impact of e-commerce on local brick-and-mortar employment.[13]

4.2 Employment Effect in Metropolitan versus Non-Metropolitan Areas

In this subsection, we examine whether the employment effect of e-commerce is different between metropolitan and non-metropolitan areas. In general, metropolitan areas are more densely populated than non-metropolitan ones, and offline-retail jobs, which are *local* in their nature, may exhibit different behavior in response. In our sample, metropolitan areas account for 34% of the total number of counties (66 of 131 counties) but 48% of the total population. For this analysis, we estimate the following equation:

$$\frac{Emp_{jt}}{Pop_{jt}} = \beta_M OS_{j,t-1} \times Metro_j + \beta_N OS_{j,t-1} \times NonMetro_j + X'_{j,t-1}\gamma + \mu_j + \delta_t + \varepsilon_{jt}, \qquad (2)$$

where $Metro_j$ is a dummy variable for whether county j is located in metropolitan areas, whereas $NonMetro_j$ is that for whether the county is located in non-metropolitan areas. The other variables and coefficients are the same as those in equation (1).

[Insert Table 3 about here]

[12] We further run regressions with separate-dependent variables of full-time and part-time workers (see Appendix Table E2 for details). The estimated results suggest that the diffusion of e-commerce is more likely to affect part-time workers than full-time workers. However, the magnitude of impacts on the two groups is not significantly different.

[13] In the industry-level results of equation (1), the negative employment effect is not limited to books and electronics, but it is widespread across products such as foods and sporting goods (see Appendix Table E1 for details).

Table 3 presents the estimation results for equation (2). Across all columns, we find the overall negative effects of online shopping expansion on employment in both metropolitan and non-metropolitan counties. In column (2), coefficients of online share are -1.413 and -1.780 for metropolitan and non-metropolitan areas, respectively. The results imply that a 1 pp increase in online share decreases 0.50% in the total offline retail workers of a metropolitan county but 0.66% in those of a non-metropolitan county. The negative employment effect in non-metropolitan areas is only slightly larger than that in metropolitan areas.

4.3 Employment Shift to Other Local Services: Restaurants and Personal Services

In this subsection, we examine whether the growth of e-commerce has shifted employment from offline retail to other local services in the county. As discussed in Section 2.2, time and money saved from online shopping may help consumers shift their demand toward other local services, thereby possibly increasing employment in these service sectors. However, such a positive effect of e-commerce is unlikely to be uniform across local markets. To understand the effect of e-commerce on the local labor market, it is important to examine the extent to which such effects vary across locations.

We consider two local service industries to which those who work in offline retail may switch relatively easily: (A) restaurants and (B) personal services. Here, we define the personal services as services in personal care (e.g., hair shop), sports (e.g., gym), and entertainment (e.g., theater).

[Insert Table 4 about here]

The results are reported in Table 4. In columns (1) and (2) of panel A, we find the effects on the employment shifts to the restaurant sector are positive, *on average*, but statistically insignificant. However, when we distinguish metropolitan and non-metropolitan counties in columns (3) and (4), those positive effects are statistically significant in the metropolitan areas. The effects turn to be negative for the non-metropolitan areas, although they are not statistically significant. This finding suggests that the effect of demand shift seems to be confined in the metropolitan areas only. The estimation result is also consistent with the rapid expansion of non-alcoholic beverage places in metropolitan areas from 2010 to 2015 (as discussed in Section 2.2).[14] Although the magnitude

[14] The online appendix provides the results from the additional analysis by dividing the restaurant sector into several

of the coefficients is smaller than that in restaurants, the demand shift effect also seems to be concentrated in metropolitan areas.

4.4 Local Employment Impact of E-Commerce

In the previous sections, we answered the first two of three questions raised in the introduction. First, we found a negative effect of e-commerce on offline retail employment. Second, we found some employment shifts to other local service sectors, the extent to which varies between metropolitan and non-metropolitan areas. To answer the third question regarding the evidence of Retail Job Apocalypse, we combine the employment effects from the first two questions. In summary, we find evidence of Retail Job Apocalypse in non-metropolitan areas, but not in metropolitan ones.

[Insert Figure 2 about here]

Figure 2 presents the estimated job losses and/or gains in (A) the offline retail sector, (B) restaurant and personal service sectors, and (C) total (i.e., A and B combined) in metropolitan and non-metropolitan areas, during the sample period. In total, approximately 5,700 local jobs disappeared in metropolitan areas, whereas approximately 23,500 local jobs were lost in non-metropolitan areas. Previously, we found that retail job losses are common in all areas (approximately 3% on average). Although the magnitude of the impact is substantial, we do not expect a serious problem in the metropolitan areas in which about two-thirds of retail job losses were offset by job gains in other local sectors. However, in non-metropolitan areas, other local jobs were further destroyed (approximately 0.9% of restaurants jobs and personal service jobs combined). Our results provide some prospect of Retail Job Apocalypse in non-metropolitan areas, suggesting spatial disparity in the effects of e-commerce on the labor markets.

[Insert Table 5 about here]

Table 5 provides the details for computing job losses and/or gains by sector described in Figure 2. We estimate the number of job losses and/or gains in location j (metropolitan and non-metropolitan areas) made in sector s (offline retail, restaurant, and personal service sectors) by calculating

detailed industries (see Table E3), based on which the increase in non-alcoholic beverage businesses explains most of the restaurant expansion effect in metropolitan areas.

$$\hat{\beta}_j^s \cdot \Delta OS_j \cdot Pop_j,$$

where $\hat{\beta}_j^s$ is the estimated coefficient of online share in location j in sector s, ΔOS_j is the change in online share from 2010 to 2015 in location j, and Pop_j is the population in 10,000 in the base year of 2010 in location j. For example, in the metropolitan areas, the e-commerce effect in the offline retail sector is estimated by 21,264 job losses ($= -1.413 \times 6.532 \times 2{,}304$). Moreover, the effects in the restaurants and personal service sectors are calculated by 13,619 and 1,896 job gains, respectively, resulting in 15,515 gains in both sectors. Combining these, the number of local jobs that disappeared in the metropolitan areas is 5,749 overall. Similarly, 23,461 local jobs are estimated to be lost in the non-metropolitan areas, confirming our finding that additional job losses in non-metropolitan areas increase the prospect of Retail Job Apocalypse in the non-metropolitan area.

5 Robustness and Discussion

5.1 Robustness Checks

To assess the robustness of our findings, we examine potential endogeneity problems using instrumental variables (IVs) and falsification tests. Then, we address various issues related to the measure of online share, alternative specifications, sample selection, and market definition. A wide range of robustness tests produces qualitatively similar results. That is, our findings regarding the impact of online shopping expansion on employment under these tests remain largely identical to those in the tables presented in the previous section.

Endogeneity: Instrumental Variable

We address the potential endogeneity issue in estimating the effect of e-commerce on local employment. The bias may work in both directions. On the one hand, the negative effect can be underestimated due to a positive correlation between online share and offline retail employment. For example, an unobserved, favorable shock to a location may increase both spending and employment. Moreover, consumers in such areas with high retail employment might face high opportunity costs for shopping time and prefer online shopping. Such high opportunity costs might be attributable to consumers' socio-demographic and economic characteristics or their unobservable preference. On the other hand, the effect can be overestimated if a systematic negative correlation exists. For example, the number of varieties available to local consumers tends to be limited in areas with low retail employment, forcing consumers to shop online for goods not available in neighborhood shops. Such a negative correlation between online shopping and offline retail employment would amplify the negative impact of e-commerce on local employment.

To eliminate the potential endogenous bias in our estimation, we use a Bartik instrument that predicts online shares exogenously by interacting the *initial* value of local consumption share of a good with the online share for each good at the *national* level.[15] This inner product removes county-specific component in the change of online share that might be correlated with unobservable shocks to local employment. The Bartik instrument (IV_{jt}) for the online share in county j in year t is constructed as follows:

$$IV_{jt} = \sum_k z_{jk} g_{kt},$$

where z_{jk} is the consumption share of product k in county j in the base year and g_{kt} is the national-level online share of product k in year t. That is, our Bartik instrument is the inner product of product-location consumption shares and product-specific online shares over time. Goldsmith-Pinkham *et al.* (2020) show that the Bartik-style instrument is equivalent to using local industry (i.e., product) shares as instruments, with the variation in the common industry component of growth only contributing to the instrument relevance. Thus, the validity of instruments requires that the local product consumption shares in the base year should not be correlated with local confounding factors.

The local product consumption share in our instrument is exogenous because we construct the initial local product consumption share in 2010 (z_{jk}) using the inner product of the *predetermined* local age distribution and the national-level product consumption share of the age group. The predetermined local age distribution in 2010 for a county is estimated from the previous decade's population by age group and mortality rate (Maestas *et al.* 2016). The initial local consumption share is constructed as follows:

$$z_{jk} \approx \sum_i a_{ij} c_{ik},$$

where a_{ij} is the predetermined population proportion of age group i (e.g., age 29 and under; age

[15] To take the variation in product-specific online shares caused by improvements in e-commerce technologies, we use the US data rather than the Korean ones (See Table B1 in Appendix B).

30–39; age 40–49; age 50–59; and age 60 years and over) in county j in the base year. c_{ik} is the national-level share of product k's consumption in age group i in the base year. For each age group i, the product k includes seven categories (i.e., electronics, books, clothing, hobbies, cosmetics, food, and furniture) in the *Household Income and Expenditure Survey* (see Appendix B for further details).

[Insert Table 6 About Here]

Table 6 presents the results of the IV estimation. The negative employment effects of online share are stronger than the OLS results in Tables 2 and 3. This finding implies that the impact is likely to be underestimated in the OLS specification, as the positive correlation between local employment and online share dominates the negative bias. Online Appendix C provides the IV estimation results for the restaurants and personal service sectors (see Table C1). Those results are also not qualitatively different from the OLS results.

Endogeneity: Falsification Test

If an increase in online shares coincided with the employment decline in a broad sector, the effects of online shares could be negative even though no such effect exists. Using the falsification test, we investigate whether a negative e-commerce effect on employment similar to that on offline retail is found in the construction sector. The construction sector accounts for the largest portion of the local labor market along with retail, but its market conditions do not move together with retail. Thus, concerns about a systematic local impact beyond sectors can also be solved by providing evidence that there is no significant e-commerce impact on the construction sector. In Table 7, the estimated coefficients in the construction sector are positive and insignificant. The result confirms that our estimates correctly identify the causal effect of e-commerce on local employment.

[Insert Table 7 About Here]

Alternative Measure of Online Share

Our credit card dataset is representative of domestic consumption because the Company has been ranked first in market share from 2010 to 2015 (the details regarding the representativeness of our data are provided in Appendix A1). Nonetheless, our online share measure (i.e., OS_{jt}) may still deviate from the true online share measure based on all transactions from all payment methods including any credit cards and cash (i.e., $Online\ Share_{jt}$ in Section 3.1). As a robustness check, we use an alternative measure of online share by adopting a similar approach introduced by Einav *et al.* (2017).

We construct $\widetilde{OS}_{jt}$ by adjusting OS_{jt} with weights to reflect the spending based on all transactions as follows:

$$\widetilde{OS}_{jt} \equiv \frac{\alpha_j}{\beta_j} OS_{jt},$$

where α_j is the county-level ratio of total spending paid by the Company's credit cards to that paid by all transaction methods (including both credit cards and cash), and β_j is the county-level ratio of online spending paid by the Company's credit cards to that paid by all credit cards.[16] Our adjustment for card-less transactions (α_j) is defined as the ratio of all spending paid by the Company's credit cards in county j to the corresponding county's total retail spending. We estimate each county's total retail spending using the data obtained from Statistics Korea. Our adjustment method is similar to that of Einav *et al.* (2017) who used the county-level ratio of the number of Visa cards to the number of tax filers representing both cardholders and people without cards. Regarding β_j, following Einav *et al.* (2017) who assumed the ratio of the Company's online spending relative to other companies' spending to be the same across counties, we use the ratio of the Company's online spending to the national-level online spending. The details of the adjustment process are given in Appendix A3. Using this alternative online share measure, we reconduct the analysis. The estimated effects are slightly larger than those in Tables 2 and 3, but they are qualitatively the same.

[Insert Table 8 About Here]

Alternative Specification

Three alternative specifications are considered for the main models in equations (1) and (2). First, we use the online and offline spending as separate variables instead of using the online share. This specification has an advantage in evaluating the two effects separately and comparing them. Second, province-specific time trends are added for estimation. Third, the population weights in the base-

[16] We assume online spending only occurs through credit and debit cards as in Einav *et al.* (2017).

year 2010 are used at the county level. The results from these three alternative specifications are qualitatively the same as the benchmark one (see Tables C2, C3, and C4 in Appendix C).

Alternative Sample

We use two alternative samples for estimation. The first alternative sample includes 12 counties that have disproportionately high offline expenditure by non-residents compared with that in other locations. Those counties are one of the largest central business districts in Korea. The second alternative sample excludes counties with a population of 50,000 people or less. The results from both alternative samples are qualitatively the same (see Table C3 and C4 in Appendix C).

Other Robustness Checks

In addition to alternative specifications and samples, we conduct a series of additional robustness checks for various issues that could be raised. First, we alternately measure our main variable, that is, online share, by taking into account spending on home shopping. Second, we extend the definition of metropolitan areas by adding 31 counties located in Gyeonggi Province, which do not belong to the metropolitan areas at the administrative level but are geographically and economically adjacent to Seoul, the largest city in Korea. Finally, we alternatively define offline retail by containing large GMS excluded in our main analysis. The results from these additional robustness checks are also qualitatively the same (see Tables C3 and C4 in Appendix C).

5.2 Discussion

Throughout the paper, we examine the causal impact of e-commerce on employment change in local brick-and-mortar stores. We find evidence of a significant employment loss in local labor markets, particularly, in non-metropolitan counties. We also find that some lost jobs are offset by new jobs in local restaurants and personal services. In addition, the growth of e-commerce may also create new jobs in online retailers and related business activities, such as warehousing and delivery services. However, the jobs destroyed may not be easily replaced with new jobs in local labor markets if either geography or characteristics of jobs created in e-commerce do not match those destroyed in brick-and-mortar stores. If local labor markets suffer from a mismatch of geography and skills, unemployment may persist. In this subsection, we will examine these issues.

Geography of Jobs in Electronic Shopping and Warehousing

E-commerce has transformed the nature of retail business. Unlike brick-and-mortar stores, online retailers do not have geographic constraints because they do not need to be located where their customers are. As consumers expand online spending, physical stores are replaced by electronic stores that are virtually located. We examine the geographic distribution of employment gains in electronic shopping, warehousing and storage, and delivery service industries between 2010 and 2015 (details are provided in Figure D1 and Table D1 in Appendix D).[17] As expected, employment gains in electronic shopping are mostly concentrated in metropolitan counties, particularly in the Seoul metropolitan area.

Meanwhile, employment gains in warehousing and delivery services are evenly distributed between metropolitan and non-metropolitan counties.[18] However, the employment effect of the expansion of warehouses and distribution centers is relatively small because their expansion involves a considerably fewer number of locations compared with that of big-box chain stores. Houde *et al.* (2017) show that Amazon's rollout of fulfillment centers features far fewer openings than Wal-Mart's store openings because of the tradeoff between delivery cost-saving and tax liabilities and fixed costs of new facilities. For example, Amazon had more than 100 fulfillment centers in the United States as of 2018, but almost half of US states did not have the fulfillment centers. Similarly, fulfillment centers in Korea are also concentrated in a few non-metropolitan counties easily accessible to transportation (highways) and close to large cities. Combining employment gains in electronic shopping, warehousing, and delivery services, we find that the employment gains in metropolitan counties are larger than those in non-metropolitan ones. This finding indicates that new jobs in online retailers and related businesses tend to be concentrated in metropolitan areas and a few non-metropolitan counties near them.

Job Characteristics and Workers' Mobility

Characteristics and skill requirements of jobs created in online retailers may be significantly different from those destroyed in brick-and-mortar stores. A mismatch of skills may lead to hysteresis in unemployment as it may take time for displaced workers to acquire skills for the new jobs. To assess this issue, we compare job characteristics of offline retail, restaurants, and other local services to those of online retail and related industries (details are provided in Table D2 in Appendix D). Jobs in

[17] We note that figures in Table D1 present actual changes in employment, and thus, they cannot be directly comparable with estimated employment effects in Table 5.

[18] Warehousing includes fulfillment centers of e-commerce companies as well as distribution centers of offline retail chains. Thus, the employment change in warehousing can be interpreted as employment changes in online fulfillment center net of those in offline distribution centers.

electronic shopping are predominantly heavy in computer-related occupations and require a higher level of education, which sharply contrasts with skill requirements of brick-and-mortar retail jobs. Meanwhile, jobs in fulfillment centers do not require high education but are physically demanding. Such a difference in skill requirements may hinder reallocation of workers from traditional retailers to online retail and related business.

6 Conclusions

We contribute to the growing literature on the employment effect of e-commerce by providing the first quantitative evidence with the prospect of Retail Job Apocalypse. Using the geographic variation in online spending share constructed from credit card transaction data in Korea, we quantified the effect of e-commerce on the local labor market. We found that the rise in online spending share from 2010 to 2015 decreased the offline retail employment by approximately 3%. Our finding of a negative effect of the diffusion of e-commerce on the physical retail stores implies a prospect of Retail Job Apocalypse in certain local labor markets (i.e., non-metropolitan areas), if not everywhere. Although the offsetting employment growth exists in local retail services, as consumers shift resources saved from online shopping to other local services, such positive effects were confined in metropolitan areas.

Our results are robust to a number of potential issues that can be considered. However, they may not be directly generalized to other countries. As a matter of fact, our study raises important issues to be considered in future research and for designing labor market policy. Retail business is local in nature, and thus, offline retailers are major employers in the local labor markets. However, the diffusion of e-commerce has weakened the local nature of the retail business, transforming the geographic distribution of retail jobs. Some local retail service jobs may be created in the same locale, whereas new jobs related to the service provision of e-commerce need not be located close to the customer. In addition, newly created jobs in online retail and related industries may require different skill mix. Given that characteristics of jobs lost may not be compared with jobs gained, simply counting the number of jobs may not be relevant to assess the true effect of such technological change on the local labor market. Workers' mobility to new jobs, as well as between locations, will be crucial factors in determining the fate of local labor markets when the e-commerce dominates the retail industry. The fast-growing e-commerce is expected to be saturated within the next few decades (Syverson 2015). To implement an appropriate policy to facilitate adjustments in *local* labor markets, further investigation to identify factors driving locational disparity is needed, before it is too late.

References

Acemoglu, D., & Linn, J. (2004), "Market Size in Innovation: Theory and Evidence from the Pharmaceutical Industry," *Quarterly Journal of Economics,* 119(3), 1049–1090.

Acemoglu, D., & Restrepo, P. (2018), "The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment," *American Economic Review,* 119(3), 108(6), 1488–1542.

Acemoglu, D., & Restrepo, P. (2020), "Robots and Jobs: Evidence from US Labor Markets," *Journal of Political Economy,* 128(6), 2188–2244.

Amior, M., & Manning, A. (2018), "The Persistence of Local Joblessness," *American Economic Review,* 108(7), 1942-1970.

Autor, D. H., Dorn, D., & Hanson, G. H. (2013), "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *American Economic Review*, 103(6), 2121-2168.

Bakos, J. Y. (1997), "Reducing Buyer Search Costs: Implications for Electronic Marketplaces," *Management Science*, 43(12), 1676-1692.

Balasubramanian, S. (1998), "Mail versus Mall: A Strategic Analysis of Competition between Direct Marketers and Conventional Retailers," *Marketing Science*, 17(3), 181-195.

Basker, E. (2005), "Job Creation or Destruction? Labor Market Effects of Wal-Mart Expansion," *Review of Economics and Statistics*, 87(1), 174-183.

Basker, E. (2016), "The Evolution of Technology in the Retail Sector," In *Handbook on the Economics of Retailing and Distribution,* Edward Elgar Publishing.

Bloom, N., Draca, M., & Van Reenen, J. (2016), "Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity," *Review of Economic Studies*, 83(1), 87-117.

Bronnenberg, B. J., & Ellickson, P. B. (2015), "Adolescence and the Path to Maturity in Global Retail," *Journal of Economic Perspectives*, 29 (4), 113-134.

Brown, J. R., & Goolsbee, A. (2002), "Does the Internet Make Markets More Competitive? Evidence from the Life Insurance Industry," *Journal of Political Economy*, 110(3), 481-507.

Brynjolfsson, E., Hu, Y., & Smith, M. D. (2003), "Consumer Surplus in the Digital Economy: Estimating the Value of Increased Product Variety at Online Booksellers," *Management Science*, 49(11), 1580-1596.

Brynjolfsson, E., & Smith, M. D. (2000), "Frictionless Commerce? A Comparison of Internet and Conventional Retailers," *Management Science*, 46(4), 563-585.

Cavallo, A. (2017), "Are Online and Offline Prices Similar? Evidence from Large Multi-Channel Retailers," *American Economic Review*, 107(1), 283-303.

Chava, S., Oettl, A., Singh, M., & Zeng, L. (2018), "The Dark Side of Technological Progress? Impact of E-Commerce on Employees at Brick-And-Mortar Retailers," SSRN Working Paper.

Cho, J., Chun, H., & Lee, Y. (2015), "How Does the Entry of Large Discount Stores Increase Retail Employment? Evidence from Korea," *Journal of Comparative Economics*, 43(3), 559-574.

Einav, L., Klenow, P., Klopack, B., Levin, J., Levin, L., & Best, W. (2017), "Assessing the Gains from E-Commerce," Working Paper, Stanford University.

Ellison, G., & Ellison, S. F. (2009), "Search, Obfuscation, and Price Elasticities on the Internet," *Econometrica*, 77(2), 427-452.

Forman, C., Ghose, A., & Goldfarb, A. (2009), "Competition between Local and Electronic Markets: How the Benefit of Buying Online Depends on Where You Live," *Management Science*, 55(1), 47-57.

Foster, L., Haltiwanger, J., & Krizan, C. J. (2006), "Market Selection, Reallocation, and Restructuring in the US Retail Trade Sector in the 1990s," *Review of Economics and Statistics*, 88(4), 748-758.

Gebhardt, G. (2018), "Measuring the Competitive Impact of the Internet: Evidence from a Natural Experiment in Broadband Access," *International Journal of Industrial Organization*, 57, 84-113.

Goldmanis, M., Hortaçsu, A., Syverson, C., & Emre, Ö. (2009), "E-Commerce and the Market Structure of Retail Industries," *Economic Journal*, 120(545), 651-682.

Goldsmith-Pinkham, P., Sorkin, I., & Swift, H. (2020), "Bartik Instruments: What, When, Why, and How," *American Economic Review*, 110(8), 2586-2624.

Goolsbee, A. (2001), "Competition in the Computer Industry: Online Versus Retail," *Journal of Industrial Economics*, 49(4), 487-499.

Greenstone, M., Mas, A., & Nguyen, H. L. (2020), "Do Credit Market Shocks Affect the Real Economy? Quasi-experimental Evidence from the Great Recession and 'Normal' Economic Times," *American Economic Journal: Economic Policy*, 12(1), 200-225.

Haltiwanger, J., Jarmin, R., & Krizan, C. J. (2010), "Mom-and-Pop Meet Big-Box: Complements or Substitutes?" *Journal of Urban Economics*, 67(1), 116-134.

Hortaçsu, A., & Syverson, C. (2015), "The Ongoing Evolution of US Retail: A Format Tug-of-War," *Journal of Economic Perspectives*, 29(4), 89-112.

Houde, J. F., Newberry, P., & Seim, K. (2017), "Economies of Density in E-commerce: A Study of Amazon's Fulfillment Center Network," NBER Working Papers No. 23361.

Maestas, N., Mullen, K. J., & Powell, D. (2016), "The Effect of Population Aging on Economic Growth, the Labor Force and Productivity," NBER Working Papers No. 22452.

Neumark, D., Zhang, J., & Ciccarella, S. (2008), "The Effects of Wal-Mart on Local Labor Markets," *Journal of Urban Economics*, 63(2), 405-430.

Pozzi, A. (2013), "The Effect of Internet Distribution on Brick-And-Mortar Sales," *RAND Journal of Economics*, 44(3), 569-583.

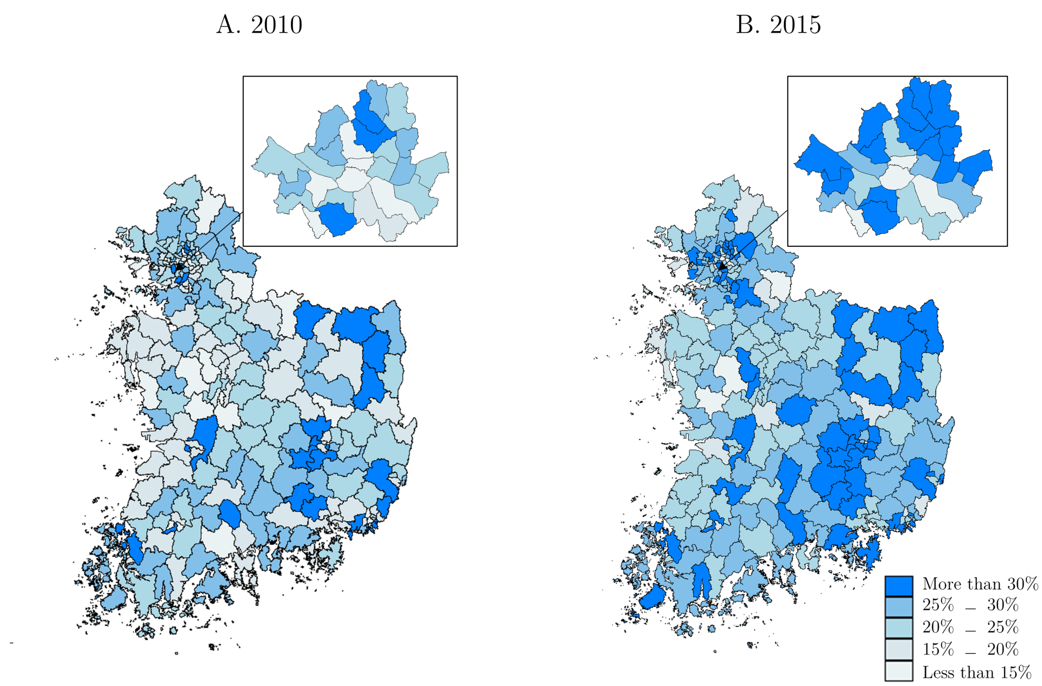
Smith, M. D., & Zentner, A. (2016), "Internet Effects on Retail Markets," In *Handbook on the Economics of Retailing and Distribution*, Edward Elgar Publishing.

Newspapers and Magazines

New York Times, "Is American Retail at a Historic Tipping Point?" April 15, 2017, Retrieved from https://www.nytimes.com/2017/04/15/business/retail-industry.html

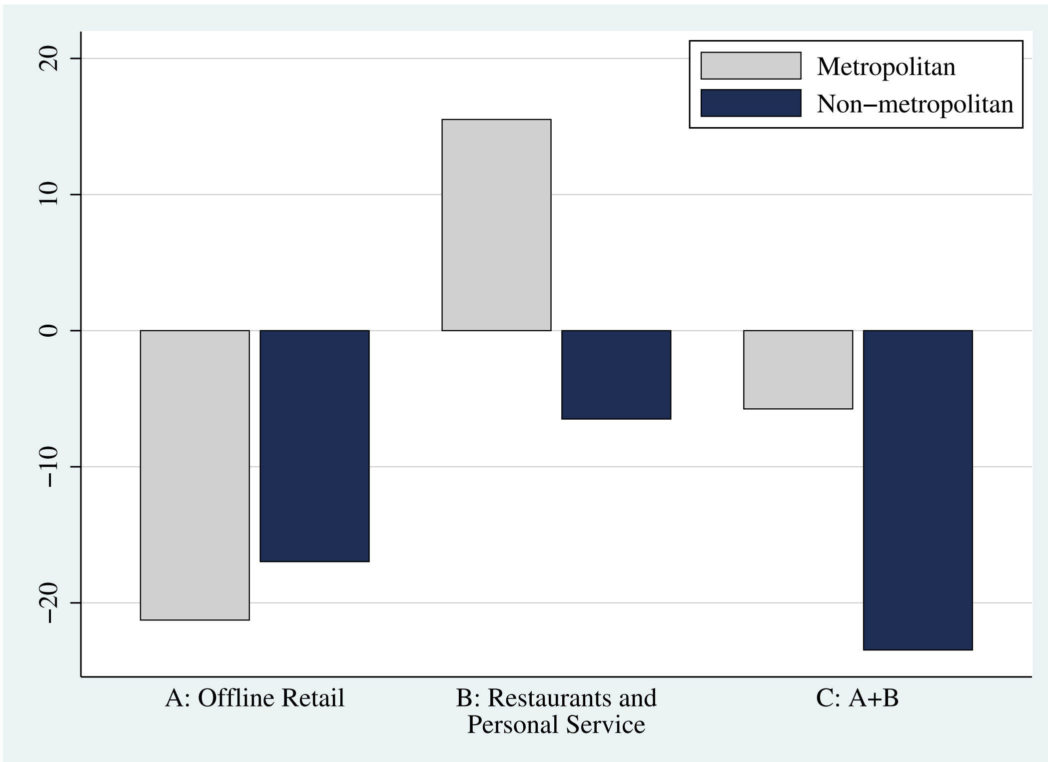
Economist, “The Decline of Established American Retailing Threatens Jobs,” May 13, 2017, Retrieved from https://www.economist.com/briefing/2017/05/13/the-decline-of-established-american-retailing-threatens-jobs

Figure 1: Diffusion of E-Commerce in Korea between 2010 and 2015



Notes: Maps A and B present the county-level online shares in years 2010 and 2015, respectively. The online share of a county is computed by the sum of credit card spending at online retail stores transacted by all credit cardholders of the Company who live in the county divided by that of the corresponding online and offline card spending in that county (see Section 3.1 for details). The zoomed-in section is Seoul.

Figure 2: Local Employment Changes: Metropolitan versus Non-Metropolitan Areas



Notes: Panel A presents the e-commerce effect on local employment changes in the offline retail sector from 2010 to 2015; panel B describes that on the corresponding ones in the restaurants and personal service sectors (including hair shop, gym, and theater but excluding wedding, laundry, and funeral services) during the same period; and panel C depicts the combined effect of panels A and B. The blue bars denote the employment changes in the metropolitan counties, and the red bars indicate those in the non-metropolitan ones. For example, as in Table 5, the metropolitan employment changes in the offline retail sector (e.g., blue bar in panel A) is calculated as the coefficient estimate of metropolitan online share (-1.413) multiplied by the change in online share from 2010 to 2015 (6.532 pp) multiplied by the metropolitan population in 2010 (2,304 in 10,000). The unit of employment change is 1,000 workers. The other effects are calculated similarly.

Table 1: Descriptive Statistics at the County Level

A. Employment: Dependent variables

	Mean	Median	S.D.	P25	P75
Offline retail employment per 10,000 people based on					
Workers	273	257	128	224	295
FTE jobs	255	240	120	209	275
Population	225,609	150,598	214,764	58,375	339,711
Workers	5,686	4,274	5,148	1,615	8,543
FTE jobs	5,294	3,948	4,785	1,513	7,967

B. E-commerce: Main explanatory variable

	Mean	Median	S.D.	P25	P75
Online share (%)					
All	24.124	23.895	6.357	19.751	27.749
Metropolitan counties	24.776	24.557	7.351	19.883	29.078
Non-metropolitan counties	23.795	23.613	5.770	19.724	27.009

C. Control variables

	Mean	Median	S.D.	P25	P75
Per capita property tax (1,000 KRW)	925	877	255	745	1,085
Population growth rate (%)	0.248	-0.213	2.068	-0.810	0.777
Car ownership per capita	0.395	0.400	0.075	0.350	0.440
Share of female population (%)	49.945	49.985	1.056	49.326	50.622
Average household size	2.384	2.370	0.217	2.204	2.564

Notes: The sample consists of 197 counties from 2011 to 2015. Both online shares and control variables in panels B and C are lagged by one year.

Table 2: E-Commerce Effect on Offline Retail Employment

	Dependent Variable: Offline Retail Employment			
	Workers		FTE Jobs	
	(1)	(2)	(3)	(4)
Online share (%)	−1.473***	−1.553***	−1.363***	−1.410***
	(0.470)	(0.502)	(0.439)	(0.467)
Effect of a 1 pp increase in online share on				
Number of offline retail employment	−33.23	−35.03	−30.75	−31.81
% of offline retail employment	−0.54	−0.57	−0.54	−0.55
Control variables	No	Yes	No	Yes
Obs.	985	985	985	985
Adj. R^2	0.249	0.257	0.155	0.164

Notes: The sample consists of 197 counties from 2011 to 2015. The dependent variable is the county-level offline retail employment per 10,000 people. The employment is defined as the number of workers in columns (1) and (2) and the number of FTE jobs in columns (3) and (4). The main explanatory variable online share (%) is computed by the sum of credit card spending at online retail stores transacted by all credit cardholders of the Company who live in the county divided by that of the corresponding online and offline card spending in that county. The control variables include the log of per capita property tax, population growth rate, car ownership per capita, share of female population, and average household size. All explanatory variables are lagged by one year. All regressions include both the county and year-fixed effects. County-clustered standard errors are presented in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 3: Offline Retail Employment: Metropolitan versus Non-Metropolitan

	Dependent Variable: Offline Retail Employment			
	Workers		FTE Jobs	
	(1)	(2)	(3)	(4)
Online share (%) × Metro	−1.341**	−1.413**	−1.291**	−1.327**
	(0.593)	(0.627)	(0.552)	(0.583)
Online share (%) × Non-metro	−1.710***	−1.780***	−1.494***	−1.544***
	(0.450)	(0.494)	(0.399)	(0.435)
Effect of a 1 pp increase in online share on % of offline retail employment				
Metropolitan counties	−0.48	−0.50	−0.49	−0.51
Non-metropolitan counties	−0.64	−0.66	−0.60	−0.62
Control variables	No	Yes	No	Yes
Obs.	985	985	985	985
Adj. R^2	0.248	0.257	0.155	0.164

Notes: The sample consists of 197 counties from 2011 to 2015. The dependent variable is the county-level offline retail employment per 10,000 people. The employment is defined as the number of workers in columns (1) and (2) and the number of FTE jobs in columns (3) and (4). The main explanatory variable online share (%) is computed by the sum of credit card spending at online retail stores transacted by all credit cardholders of the Company who live in the county divided by that of the corresponding online and offline card spending in that county. The variables *metro* and *non-metro* are the dummy for a county located in metropolitan and non-metropolitan areas, respectively. The control variables include the log of per capita property tax, population growth rate, car ownership per capita, share of female population, and average household size. All explanatory variables are lagged by one year. All regressions include both the county- and year-fixed effects. County-clustered standard errors are presented in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4: E-Commerce Effects in the Restaurants and Personal Service Sectors

	Dependent Variable: Employment			
	(1)	(2)	(3)	(4)
A. Restaurants				
Online share (%)	0.350	0.307		
	(0.472)	(0.450)		
Online share (%) × Metro			0.860*	0.905**
			(0.473)	(0.441)
Online share (%) × Non-metro			−0.570	−0.662
			(0.469)	(0.489)
Adj. R^2	0.572	0.578	0.578	0.584
B. Personal Services				
Online share (%)	0.090*	0.071		
	(0.047)	(0.050)		
Online share (%) × Metro			0.139**	0.126**
			(0.061)	(0.060)
Online share (%) × Non-metro			0.002	-0.019
			(0.076)	(0.076)
Adj. R^2	0.275	0.293	0.277	0.295
Control variables	No	Yes	No	Yes
Obs.	985	985	985	985

Notes: The sample consists of 197 counties from 2011 to 2015. The dependent variables are the county-level employment per 10,000 people in the restaurant sector for panel A and those in the personal service sector (e.g., including hair shop, gym, and theater but excluding wedding, laundry, funeral services) for panel B. Employment is defined as the number of workers in all columns. The main explanatory variable online share (%) is computed by the sum of credit card spending at online retail stores transacted by all credit cardholders of the Company who live in the county divided by that of the corresponding online and offline card spending in that county. The variables *metro* and *non-metro* are the dummy for a county located in metropolitan and non-metropolitan areas, respectively. The control variables include the log of per capita property tax, population growth rate, car ownership per capita, share of female population, and average household size. All explanatory variables are lagged by one year. All regressions include the county- and year-fixed effects. County-clustered standard errors are presented in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Summary of E-Commerce Effects: Metropolitan versus Non-Metropolitan Areas

	Metropolitan (1)	Non-Metropolitan (2)
E-commerce effect		
Offline retail (A)	−21,264	−16,969
Restaurants and personal service ($B = B_1 + B_2$)	15,515	−6,492
Restaurants (B_1)	13,619	−6,311
Personal service (B_2)	1,896	−181
Total ($A + B$)	−5,749	−23,461
Coefficient estimate of online share ($\hat{\beta}_j^s$)		
Offline retail	−1.413	−1.780
Restaurants	0.905	−0.662
personal service	0.126	−0.019
Change in online share, 2010–2015 (ΔOS_j)	6.532 pp	3.850 pp
Population in 2010 in 10K people (Pop_j)	2,304	2,476

Notes: Column (1) is for metropolitan counties and column (2) is for non-metropolitan ones. The upper panel presents the estimated job losses and/or gains in the offline retail sector between 2010 and 2015 (A); those in the restaurants and personal service sector for the same period (B); and the sum of A and B. The effects A and B are calculated by multiplying three values in the lower panel: (i) the coefficient estimate of online share for the corresponding sector, (ii) change in online share from 2010 to 2015, and (iii) population in 2010 in 10,000 people. For example, the metropolitan employment changes in the offline retail sector (e.g., the blue bar in panel A) is calculated as the coefficient estimate of metropolitan online share (−1.413) multiplied by the change in online share from 2010 to 2015 (6.532 pp) multiplied by the metropolitan population in 2010 (2,304 in 10,000). Employment is measured by the number of workers. The other effects are calculated similarly.

Table 6: IV Estimation

	Dependent Variable: Offline Retail Employment			
	(1)	(2)	(3)	(4)
Online share (%)	−2.542**	−2.735**		
	(1.164)	(1.065)		
Online share (%) × Metro			−2.093**	−2.308**
			(1.037)	(0.970)
Online share (%) × Non-metro			−4.134*	−4.574**
			(2.410)	(2.186)
Control variables	No	Yes	No	Yes
F-statistic in the first stage	65.36	62.83	19.02	28.45
Obs.	985	985	985	985
Adj. R^2	0.043	0.051	0.018	0.015

Notes: The sample consists of 197 counties from 2011 to 2015. The dependent variable is the county-level offline retail employment per 10,000 people. Employment is defined as the number of workers in all columns. The main explanatory variable online share (%) is computed by the sum of credit card spending at online retail stores transacted by all credit cardholders of the Company who live in the county divided by that of the corresponding online and offline card spending in that county. The variables *metro* and *non-metro* are the dummy for a county located in metropolitan and non-metropolitan areas, respectively. The Bartik instrument is used for IV estimation, which exogenously predicts online shares by interacting the predetermined local product consumption shares at the initial period with the national-level online shares by products. The control variables include the log of per capita property tax, population growth rate, car ownership per capita, share of female population, and average household size. All explanatory variables are lagged by one year. All regressions include both the county and year fixed effects. County-clustered standard errors are presented in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Falsification Test

	Dependent Variable: Construction Employment			
	(1)	(2)	(3)	(4)
Online share (%)	0.031	0.540		
	(1.273)	(1.011)		
Online share (%) × Metro			−0.061	0.430
			(1.534)	(1.177)
Online share (%) × Non-metro			0.197	0.717
			(1.598)	(1.500)
Control variables	No	Yes	No	Yes
Obs.	985	985	985	985
Adj. R^2	0.176	0.201	0.175	0.200

Notes: The sample consists of 197 counties from 2011 to 2015. The dependent variable is the county-level construction employment per 10,000 people. Employment is defined as the number of workers in all columns. The main explanatory variable online share (%) is computed by the sum of credit card spending at online retail stores transacted by all credit cardholders of the Company who live in the county divided by that of the corresponding online and offline card spending in that county. The variables *metro* and *non-metro* are the dummy for a county located in metropolitan and non-metropolitan areas, respectively. The control variables include the log of per capita property tax, population growth rate, car ownership per capita, share of female population, and average household size. All explanatory variables are lagged by one year. All regressions include the county and year fixed effects. County-clustered standard errors are presented in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Alternative Online Share

	Dependent Variable: Offline Retail Employment			
	(1)	(2)	(3)	(4)
Alternative online share (%)	−2.185***	−2.284***		
	(0.627)	(0.706)		
Alternative online share (%) × Metro			−1.940***	−2.015***
			(0.694)	(0.773)
Alternative online share (%) × Non-metro			−2.807***	−2.916***
			(0.779)	(0.849)
Control variables	No	Yes	No	Yes
Obs.	985	985	985	985
Adj. R^2	0.250	0.258	0.251	0.259

Notes: The sample consists of 197 counties from 2011 to 2015. The dependent variable is the county-level offline retail employment per 10,000 people. Employment is defined as the number of workers in all columns. The main explanatory variable *alternative* online share is the Company-based online share and then adjusted by its share in total spending made by all payment methods (including both credit cards and cash). The variables *metro* and *non-metro* are the dummy for a county located in metropolitan and non-metropolitan areas, respectively. The control variables include the log of per capita property tax, population growth rate, car ownership per capita, share of female population, and average household size. All explanatory variables are lagged by one year. All regressions include the county and year-fixed effects. County-clustered standard errors are presented in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

ONLINE APPENDIX:
NOT FOR PUBLICATION

Appendix A Credit Card Data

A.1 Data Source and Structure

As explained in Section 3.1, this study uses the Company's credit card data based on more than 30 billion transactions from January 1, 2010, to December 31, 2015. Each transaction in the data contains detailed information about the amount and date of the transaction, the type of card, addresses of both a merchant and a cardholder, industry classification of the merchant, and so on.

For the analysis in this paper, credit card transactions are to be distinguished into offline and online transactions, each of which can be identified by the industry classifications of merchants. More specifically, in our dataset, the card-not-present (CNP) transactions are categorized by detailed industry classifications such as e-commerce, home shopping, and recurring transactions (including phone bills and subscription fee). Using this classification, we can define online spending both in narrow (e-commerce) and broad (e-commerce and home shopping) senses.

The Company chooses a "closed system," that is, not only issues cards directly to the public (like Chase or Citi in the United States) but also handles the card payment network (like Visa or MasterCard). In Korea and Japan, a credit card company typically adopts a closed system (e.g., 99.5% in Korea). However, in the United States, an "open system" is common in which card transactions are cleared through external network companies such as Visa and MasterCard.

Therefore, the company's data used in this study have a great advantage in identifying consumers' location for CNP transactions (e.g., e-commerce). This is because the Company as a card issuer accurately collects the residential address of cardholders who make the CNP transactions.

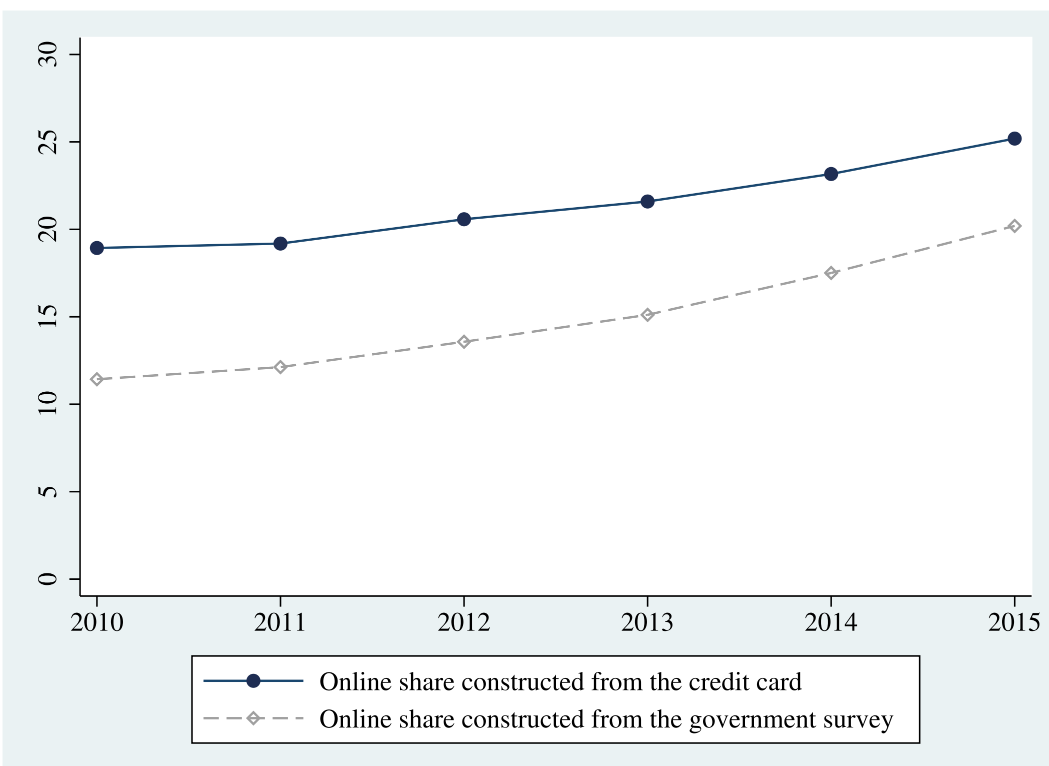
A.2 Online Spending Share

Using the data from the Company has two main advantages: (i) representativeness and (ii) stability over time and across regions. First, the Company has recorded the largest proportion of credit card transactions in Korea. For example, as of December 2017, the Company was ranked first with a market share of 23% based on personal card spending and made a contract with around 21 million cardholders and 2.7 million merchants (i.e., more than 95% of all credit-card affiliated stores). Meanwhile, the second-ranked company had a market share of 13–15% and made contract with 6 to 8 million cardholders. Hence, the data from the Company are highly representative.

Second, the Company's shares in both total retail and online sales have been stable from 2010 to 2015. We checked the shares of retail spending transacted through the Company to the total spending made by all payment methods, except for spending on items whose online transactions are to be prohibited under Korea's current laws (e.g., medicines, new cars, and gas).[A1] To obtain retail spending made by all payment methods, we use the Service Industry Survey (SIS) from Statistics Korea and the National Accounts from Bank of Korea. Due to the data confidentiality agreement with the Company, we cannot report the accurate numbers of the shares, but the shares are fairly stable during the sample period. The stable shares are attributed to both the stable market shares of the Company and the stable payment shares of the credit cards during the sample period.

Figure A1 presents the online shares constructed from the Company's data and those constructed from the SIS data. Online shares based on the Company data are higher than those based on the SIS data mainly because the total retail spending in the SIS data includes transactions made by not only credit cards but also cash. Nonetheless, both graphs show similar time-series trends. Lastly, the Company's shares in the total retail sales are distributed fairly evenly across regions (detailed figures cannot be released due to data confidentiality). Moreover, the Company's regional

Figure A1: Trends in Online Shares, 2010–2015



[A1] The online share in 2015, shown in Figure A1, is higher than the official figure of 11.7% we reported in Section 1 because total spending used in the official one includes spending on medicines, new cars, gas, and so on.

shares are also stable over the sample period.

A.3 Adjustment Process for Online Share

As briefly described in Section 5.1, we construct an alternative measure of online share ($\widetilde{OS}_{jt}$) by adjusting OS_{jt} with weights, to address a potential bias issue due to the exclusion of cash transactions in the Company's data. Specifically, the weights are based on the local shares of the Company in online and offline spending in all transaction methods and thus computed using the data from Statistics Korea and from the Company data. The adjustment process is based on the following equation:

$$\widetilde{OS}_{jt} \equiv \frac{\alpha_j}{\beta_j} OS_{jt},$$

where α_j is the county-level ratio of total spending paid by the Company's credit cards to that paid by all transaction methods (including both credit cards and cash). β_j is the county-level ratio of online spending paid by the Company's credit cards to that paid by all credit cards.

The above equation assumes the following two relationships:

$$\text{Online spending in county } j = \frac{1}{\beta_j} \times \text{Online spending via the Company in county } j$$
$$\text{Offline spending in county } j = \frac{1}{\gamma_j} \times \text{Offline spending via the Company in county } j,$$

where γ_j is the county-level ratio of offline spending paid by the Company's credit cards to that made by all payment methods. Then, using the fact that total spending is the sum of online and offline spending, α_j is indirectly derived as follows:

$$\begin{aligned}\text{Total spending in county } j =& \frac{1}{\alpha_j} \times \text{Total spending via the Company in county } j \\ =& \frac{1}{\beta_j} \times \text{Online spending via the Company in county } j \\ &+ \frac{1}{\gamma_j} \times \text{Offline spending via the Company in county } j.\end{aligned}$$

The adjustment factor of γ_j is obtained from the county-level sales data in the offline retail sector provided by the 2010 *Economic Census* from Statistics Korea. It is not possible to compute β_j

because online spending data by all credit cards are available only at the national level. Thus, we alternatively use the national-level ratio of online spending measured by the Company's data to that measured by the official data from Statistics Korea. However, the Company's market share is substantial and stable across regions, although certain proportions in online spending are attributable by other credit cards. Therefore, it is reasonable to assume that β_j is constant across all counties, as Einav *et al.* (2017) presumed that the Visa's share in online spending is 100% across all counties.

Appendix B Instrumental Variables

This study uses a Bartik instrument to eliminate the potential endogenous bias in the estimation, as explained in Section 5.1. The Bartik instrument and its variants have been widely adopted in various fields of economics (Acemoglu and Linn 2004, Amior and Manning 2018, Greenstone *et al.* 2020). In line with the literature (e.g., Goldsmith-Pinkham *et al.* 2020), our Bartik instrument is formed by interacting the initial value of local consumption share of each good with the national-level online share of the corresponding good in the year of interest; the construction process is as follows.

First, our main explanatory variable, online share in county j in year t can be decomposed into

$$OS_{jt} = \sum_k z_{jkt} g_{jkt} \quad \text{where} \quad \sum_k z_{jkt} = 1,$$

where z_{jkt} is the consumption share of product k in county j in year t and g_{jkt} is the online share of product k in county j in year t. Then, g_{jkt} can be divided into

$$g_{jkt} = g_{kt} + g_{jt} + \widetilde{g_{jkt}},$$

where g_{kt} is the national-level online share of product k in year t, g_{jt} is the online share in county j in year t, and $\widetilde{g_{jkt}}$ is the idiosyncratic error term. To eliminate county-based components in a change in OS_{jt}, we estimate it using the product-specific local consumption shares in the base year of 2010 (i.e., z_{jk}) and product-specific online shares at the national level in the year of interest (i.e., g_{kt}) as follows:

$$OS_{jt} \approx \sum_k z_{jk} g_{kt} \quad \text{where} \quad \sum_k z_{jk} = 1$$

To take exogenous variations in g_{kt} mainly caused by product-specific technology improvements in online retailing (e.g., the differences across product categories in consumer search costs, inventory management, and technological development in delivery), we exploit the US data rather than the Korean ones (Autor *et al.* 2013, Bloom *et al.* 2016, Acemoglu and Restrepo 2020). Table B1 presents the annual product-specific online shares in the United States.

Moreover, to make the local product consumption share exogenous, we construct z_{jk} as the inner product of the *predetermined* local age distribution and the national-level product consumption

Table B1: US Product-Specific Online Shares (%)

	Year					
	2010	2011	2012	2013	2014	2015
Electronics and appliances	23.30	26.35	27.96	29.65	31.77	34.60
Books, magazines, and stationery	30.81	36.33	41.06	43.52	45.51	48.28
Clothing	10.38	11.63	13.17	15.10	16.98	18.57
Hobbies	19.67	21.67	23.41	25.97	27.97	30.27
Cosmetics	3.35	3.50	4.25	5.04	5.35	5.77
Fresh food	0.69	0.77	0.94	0.98	1.13	1.29
Furniture and household supplies	8.05	9.22	10.26	11.36	12.76	14.81

Source: Annual Retail Trade Survey, Census Bureau (https://www.census.gov/data/tables/2016/econ/arts/annual-report.html).

share of the age group:

$$z_{jk} \approx \sum_k a_{ij} c_{ik},$$

where a_{ij} is the predetermined population proportion of age group i (e.g., age 29 and under; age 30–39; age 40–49; age 50–59; and age 60 years and over) in county j in the base year of 2010 and c_{ik} is the national-level share of product k's consumption in age group i (including seven product categories such as electronics, books, clothing, hobbies, cosmetics, food, and furniture) in the base year. Table B2 shows the product-specific consumption shares by the age group (i.e., c_{ik}), which are calculated from the *2010 Household Income and Expenditure Survey* from Statistics Korea.

Notably, the predetermined age distribution in a county (i.e., a_{ij}) would be correlated with disturbing factors that affect the offline retail employment. For example, a high consumption share in durable goods such as furniture is likely a consequence of large population inflows from other areas, which would be positively correlated with retail employment. Moreover, a high consumption

Table B2: Product-Specific Consumption Shares by Age Group (%)

	Under 30	30–39	40–49	50–59	Over 60
Electronics	6.31	6.51	6.49	6.02	4.42
Books	5.42	3.94	1.93	1.05	0.94
Clothing	21.46	22.10	20.16	17.49	11.68
Hobbies	7.79	6.89	6.45	6.18	5.65
Cosmetics	5.43	5.69	5.77	4.88	3.44
Food	41.70	42.16	45.13	50.79	62.13
Furniture	11.88	12.72	14.07	13.60	11.74

Source: *2010 Household Income and Expenditure Survey* from Statistics Korea.

Table B3: National Survival Rates by Age Group

Age group in 2010	National survival rates between 2000 and 2010
15–29	0.992
30–39	0.989
40–49	0.980
50–59	0.966
Over 60	0.796

Note: The national survival rate for each age group is computed using the *2000* and *2010 Population Census* from Statistics Korea.

share in food is likely associated with a high proportion of the elderly population, which would be negatively correlated with retail employment. Hence, in this study, we exploit predictable variations that were only predetermined by both the prior age distribution at the county level and the age-specific survival rate at the national level.

Table B4: First Stage Regressions for Tables 6 and C1

	Dependent Variable:					
	Online Share (%)		Online Share × Metro		Online Share × Non-metro	
	(1)	(2)	(3)	(4)	(5)	(6)
Bartik instrument	15.51***	18.41***				
	(1.919)	(2.324)				
Bartik instrument × Metro			3.128	6.519***	9.997***	10.17***
			(2.153)	(1.870)	(1.755)	(1.669)
Bartik instrument × Non-metro			1.826	5.213***	10.95***	11.21***
			(2.322)	(1.965)	(1.803)	(1.705)
Log of per capita property tax		6.996		8.075*		−0.603
		(4.814)		(4.707)		(1.065)
Population growth rate		0.252***		0.181*		0.0611*
		(0.0951)		(0.0973)		(0.0348)
Car ownership per capita		−2.496		4.555**		−6.317
		(4.778)		(1.845)		(3.976)
Share of female population		1.765***		1.390*		0.231
		(0.571)		(0.762)		(0.585)
Average household size		−6.005		0.481		−5.007*
		(6.875)		(7.198)		(2.929)
County and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
F-Statistic for instruments	65.36	62.83	19.02	28.45	19.02	28.45
Obs.	985	985	985	985	985	985
Adj. R^2	0.440	0.504	0.430	0.510	0.403	0.419

Notes: The sample consists of 197 counties from 2011 to 2015. The dependent variables are online share (%) in columns (1) and (2), its interaction term with the dummy for the metropolitan area in columns (3) and (4), and that with the dummy for the non-metropolitan one in columns (5) and (6). County-clustered standard errors are presented in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Following the method proposed by Maestas *et al.* (2016), we estimate the number of people in age group i in county j in 2010 ($n_{ij,2010}$) as follows:

$$n_{ij,2010} \approx n_{ij,2000} \times \frac{n_{i,2010}}{n_{i,2000}},$$

where $n_{ij,2000}$ is the number of population of age group i in county j in 2000 and $\frac{n_{i,2010}}{n_{i,2000}}$ is the *national-level* survival rate of age group i over the period 2000–2010. Precisely, for example, the age group of 30–39 years in 2010 can correspond to that of 20–29 years in 2000. Thus, the survival rate for the age group of 30–39 years in 2010 is computed by the population aged 30–39 years in the *2010 Population Census* divided by that aged 20–29 years in the 2000 Census. In the same way, the survival rates for the other age groups can be calculated (see Table B3).

Finally, Table B4 provides the first-stage regression results for Tables 6. Table B5 provides the IV estimation results using alternative Bartik instruments, which is based on the national-level online shares in Norway instead of those in the United States.

Table B5: IV Estimation with Alternative Bartik Instruments

	Dependent Variable: Offline Retail Employment			
	(1)	(2)	(3)	(4)
Online share (%)	−2.860**	−3.041***		
	(1.204)	(1.112)		
Online share (%) × Metro			−2.444**	−2.693**
			(1.121)	(1.056)
Online share (%) × Non-metro			−4.758**	−5.093**
			(2.358)	(2.130)
Control variables	No	Yes	No	Yes
F-statistic in the first stage	60.70	56.14	16.82	24.79
Obs.	985	985	985	985
Adj. R^2	0.032	0.040	−0.007	−0.009

Notes: The sample consists of 197 counties from 2011 to 2015. The dependent variable is the county-level offline retail employment per 10,000 people. Employment is defined as the number of workers in all columns. The main explanatory variable online share (%) is computed by the sum of credit card spending at online retail stores transacted by all credit cardholders of the Company who live in the county divided by that of the corresponding online and offline card spending in that county. The variables *metro* and *non-metro* are the dummies for a county located in metropolitan and non-metropolitan areas, respectively. The Bartik instrument is used for IV estimation, which exogenously predicts online shares by interacting the local product consumption shares at the initial period with the national-level online shares by products in Norway. The control variables include the log of per capita property tax, population growth rate, car ownership per capita, share of female population, and the average household size. All explanatory variables are lagged by one year. All regressions include both the county- and year-fixed effects. County-clustered standard errors are presented in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Appendix C Other Robustness Checks

Table C1: IV Estimation: Restaurants and Personal Service Sectors

	Dependent Variable: Employment			
	(1)	(2)	(3)	(4)
A. Restaurants				
Online share (%)	1.915*	1.866*		
	(1.148)	(0.970)		
Online share (%) × Metro			2.485**	2.423***
			(1.070)	(0.895)
Online share (%) × Non-metro			−0.105	−0.530
			(0.469)	(0.489)
B. Personal Services				
Online share (%)	0.927***	0.707***		
	(0.178)	(0.145)		
Online share (%) × Metro			0.972***	0.777***
			(0.169)	(0.137)
Online share (%) × Non-metro			0.769**	0.403
			(0.380)	(0.337)
Control variables	No	Yes	No	Yes
F-statistic in the first stage	65.36	62.83	19.02	28.45
Obs.	985	985	985	985

Notes: The sample consists of 197 counties from 2011 to 2015. The dependent variables are the county-level employment per 10,000 people in the restaurant sector for panel A and those in the personal service sector (e.g., including hair shop, gym and theater but excluding wedding, laundry, funeral services) for panel B. The employment is defined as the number of workers in all columns. The main explanatory variable online share (%) is computed by the sum of credit card spending at online retail stores transacted by all credit cardholders of the Company who live in the county divided by that of the corresponding online and offline card spending in that county. The variables *metro* and *non-metro* are the dummies for a county located in metropolitan and non-metropolitan areas, respectively. The Bartik instrument is used for IV estimation, which exogenously predicts online shares by interacting the predetermined local product consumption shares at the initial period with the national-level online shares by products. The control variables include the log of per capita property tax, population growth rate, car ownership per capita, share of female population, and the average household size. All explanatory variables are lagged by one year. All regressions include both the county- and year-fixed effects. County-clustered standard errors are presented in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table C2: Elasticity Estimates

	Dependent Variable: Log of Employment			
	(1)	(2)	(3)	(4)
Log of online spending	−0.063***	−0.066***		
	(0.008)	(0.011)		
Log of offline spending	0.075	0.074		
	(0.050)	(0.045)		
Log of online spending × Metro			−0.056***	−0.060***
			(0.012)	(0.016)
Log of online spending × Non-metro			−0.095***	−0.104***
			(0.034)	(0.033)
Log of offline spending × Metro			0.040	0.044
			(0.094)	(0.085)
Log of offline spending × Non-metro			0.113***	0.106***
			(0.029)	(0.030)
Control variables	No	Yes	No	Yes
Obs.	985	985	985	985
Adj. R^2	0.319	0.336	0.322	0.339

Notes: The sample consists of 197 counties from 2011 to 2015. The dependent variable is the log of county-level offline retail employment per 10,000 people. Employment is defined as the number of workers in all columns. The main explanatory variables are online and offline spending. Online spending is the sum of credit card spending at online retail stores transacted by all credit cardholders of the Company who live in the county; and offline spending is that of the corresponding offline card spending in that county. The variables *metro* and *non-metro* are the dummies for a county located in metropolitan and non-metropolitan areas, respectively. The control variables include the log of per capita property tax, population growth rate, car ownership per capita, share of female population, and the average household size. All explanatory variables are lagged by one year. All regressions include both the county- and year-fixed effects. County-clustered standard errors are presented in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table C3: Other Robustness Checks

		Dependent Variable: Offline Retail Employment			
		Workers		FTE Jobs	
		(1)	(2)	(3)	(4)
A. Benchmark	Coeff.	−1.473***	−1.553***	−1.363***	−1.410***
	SE	(0.470)	(0.502)	(0.439)	(0.467)
	Adj. R^2	0.249	0.257	0.155	0.164
	Obs.	985	985	985	985
B. Alternative specification: Including province-specific trends	Coeff.	−1.478***	−1.399***	−1.359**	−1.273***
	SE	(0.556)	(0.513)	(0.523)	(0.479)
	Adj. R^2	0.278	0.284	0.186	0.194
	Obs.	985	985	985	985
C. Weighted regression using the county population in the base year of 2010	Coeff.	−1.230***	−1.140**	−1.190***	−1.065**
	SE	(0.391)	(0.459)	(0.361)	(0.420)
	Adj. R^2	0.342	0.351	0.198	0.209
	Obs.	985	985	985	985
D. Alternative sample: Including twelve shopping districts excluded in the main sample	Coeff.	−1.539***	−1.629***	−1.400***	−1.449***
	SE	(0.479)	(0.481)	(0.441)	(0.444)
	Adj. R^2	0.249	0.257	0.155	0.164
	Obs.	1,045	1,045	1,045	1,045
E. Alternative sample: Counties with a population of 50,000 or more	Coeff.	−1.652***	-1.566**	−1.569***	−1.461**
	SE	(0.501)	(0.615)	(0.470)	(0.577)
	Adj. R^2	0.326	0.336	0.197	0.208
	Obs.	795	795	795	795
F. Including home shopping into online spending	Coeff.	−1.244***	−1.327***	−1.162***	−1.214***
	SE	(0.428)	(0.453)	(0.399)	(0.423)
	Adj. R^2	0.247	0.256	0.154	0.163
	Obs.	985	985	985	985
G. Including large GMS into offline retail	Coeff.	−1.393***	−1.428***	−1.271***	−1.273***
	SE	(0.471)	(0.492)	(0.438)	(0.455)
	Adj. R^2	0.266	0.275	0.180	0.193
	Obs.	985	985	985	985
Control variables		No	Yes	No	Yes

Notes: The sample consists of 197 counties from 2011 to 2015, except panel D (i.e., 209 counties) and panel E (159 counties). The dependent variable is the county-level offline retail employment per 10,000 people. Employment is defined as the number of workers in columns (1) and (2) and that of FTE jobs in columns (3) and (4), respectively. The main explanatory variable online share is computed by the sum of credit card spending at online retail stores transacted by all credit cardholders of the Company who live in the county divided by that of the corresponding online and offline card spending in that county. The control variables include the log of per capita property tax, population growth rate, car ownership per capita, share of female population, and average household size. All explanatory variables are lagged by one year. All regressions include both the county and year-fixed effects. County-clustered standard errors are presented in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table C4: Other Robustness Checks: Metropolitan versus Non-Metropolitan Areas

		Dependent Variable: Offline Retail Employment			
		(1)		(2)	
	Variables	OS × Metro	OS × Non-metro	OS × Metro	OS × Non-metro
A. Benchmark	Coeff.	−1.341**	−1.710***	−1.413**	−1.780***
	SE	(0.593)	(0.450)	(0.627)	(0.494)
	Adj. R^2	0.248		0.257	
	Obs.	985		985	
B. Alternative specification: Including province-specific trends	Coeff.	−1.492	−1.467***	−1.393	−1.403***
	SE	(1.124)	(0.347)	(1.030)	(0.350)
	Adj. R^2	0.277		0.283	
	Obs.	985		985	
C. Weighted regression using the county population in the base year of 2010	Coeff.	−1.188***	−1.345***	−1.013*	−1.431***
	SE	(0.433)	(0.478)	(0.517)	(0.522)
	Adj. R^2	0.341		0.351	
	Obs.	985		985	
D. Alternative sample: Including twelve shopping districts excluded in the main sample	Coeff.	−1.282**	−1.954***	−1.408**	−1.948***
	SE	(0.598)	(0.574)	(0.580)	(0.597)
	Adj. R^2	0.224		0.228	
	Obs.	1,045		1,045	
E. Alternative sample: Counties with a population of 50,000 or more	Coeff.	−1.594***	−1.804***	−1.428*	−1.892***
	SE	(0.569)	(0.510)	(0.726)	(0.545)
	Adj. R^2	0.326		0.336	
	Obs.	795		795	
F. Including home shopping into online spending	Coeff.	−1.094*	−1.509***	−1.153*	−1.604***
	SE	(0.565)	(0.394)	(0.600)	(0.435)
	Adj. R^2	0.247		0.256	
	Obs.	985		985	
G. Alternative definition for metropolitan areas	Coeff.	−1.473***	−1.471***	−1.526***	−1.627***
	SE	(0.543)	(0.428)	(0.578)	(0.507)
	Adj. R^2	0.248		0.256	
	Obs.	985		985	
H. Including large GMS into offline retail	Coeff.	−1.231**	−1.684***	−1.238**	−1.735***
	SE	(0.591)	(0.454)	(0.614)	(0.497)
	Adj. R^2	0.266		0.276	
	Obs.	985		985	
Control variables		No		Yes	

Notes: The sample consists of 197 counties from 2011 to 2015, except panel D (i.e., 209 counties) and panel E (159 counties). The dependent variable is the county-level offline retail employment per 10,000 people. Employment is defined as the number of workers in all columns. The main explanatory variable online share (OS, %) is computed by the sum of credit card spending at online retail stores transacted by all credit cardholders of the Company who live in the county divided by that of the corresponding online and offline card spending in that county. The variables *metro* and *non-metro* are the dummies for a county located in metropolitan and non-metropolitan areas, respectively. The control variables include the log of per capita property tax, population growth rate, car ownership per capita, share of female population, and average household size. All explanatory variables are lagged by one year. All regressions include both the county and year-fixed effects. County-clustered standard errors are presented in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Appendix D Employment in E-Commerce, Warehousing and Delivery Services

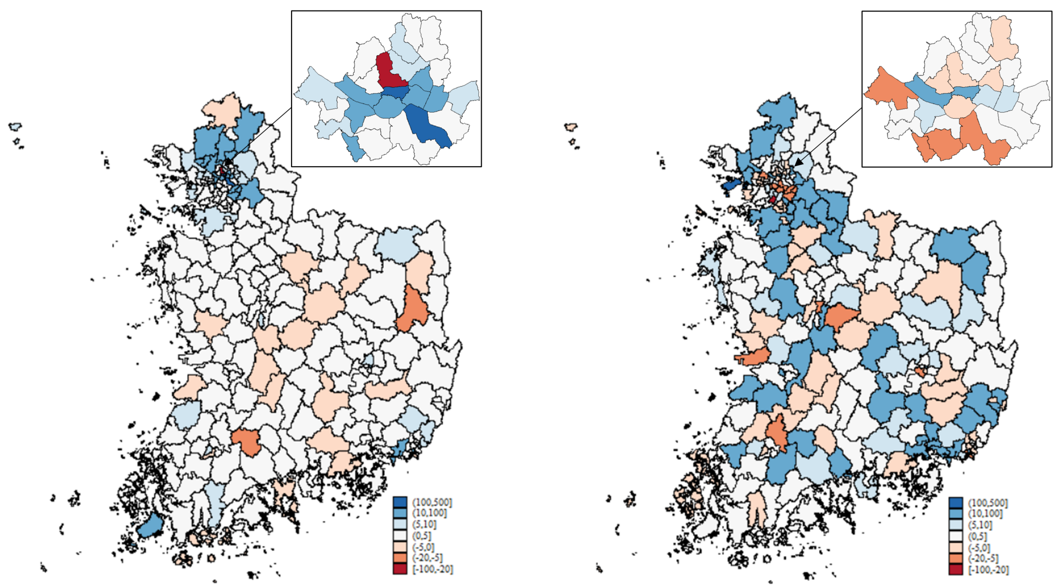
Table D1: Employment Changes in E-commerce and Warehousing and Delivery Services between 2010 and 2015: Metropolitan versus Non-Metropolitan Areas

	Metropolitan			Non-metropolitan		
	2010	2015	*Change*	2010	2015	*Change*
E-commerce	9.7	19.5	*9.8*	2.4	6.1	*3.7*
Warehousing and Delivery Services	10.9	14.1	*3.2*	19.5	23.7	*4.2*
Warehousing and Storage	4.8	6.1	*1.3*	13.1	15.3	*2.2*
Delivery Services	6.1	8.0	*1.9*	6.4	8.4	*2.0*
Total	20.6	33.6	*13.0*	21.9	29.8	*7.9*

Notes: Table D1 presents the increasing trends in employment per 10,000 people in e-commerce itself between 2010 and 2015 and those in employment in two closely related sectors such as warehousing and delivery service sectors.

Figure D1: Graphical Distribution of Employment Changes between 2010 and 2015

A. E-commerce B. Warehousing and Delivery Service



Notes: Map A presents the county-level employment changes in e-commerce per 10,000 people from 2010 to 2015. Map B shows those in the warehousing and delivery service sector per 10,000 people during the same period. The zoomed-in section is Seoul.

Table D2: Demographic Composition by Sector (%)

Sector	Male	Female	Young	Old	Middle school	High School	College & above
Offline retail	45.6	54.4	42.9	57.10	12.94	48.03	39.03
Restaurants	33.4	66.6	30.59	69.41	25.32	51.09	25.39
Personal service	24.3	75.7	49.90	50.10	16.44	54.38	28.98
E-commerce	51.3	48.7	40.36	59.64	18.32	44.36	37.32
Warehousing and storage	78.5	21.5	54.99	45.01	6.03	48.03	45.95
Delivery service	83.4	16.6	45.47	54.53	10.72	57.23	32.04

Notes: Young people are those who are aged between 15 and 50 years, and old people are those who are aged 50 years and above.

Sources: Census on Establishments, 2010; *Population and Housing Census*, 2010.

Appendix E Heterogeneous Effects

Table E1: Selected Retail Industries

		Dependent Variable: Offline Employment			
		Workers		FTE Jobs	
		(1)	(2)	(3)	(4)
Music, videos, books, magazines,	Coeff.	−0.040**	−0.029*	−0.038**	−0.028*
and stationery	SE	(0.019)	(0.016)	(0.018)	(0.015)
	Adj. R^2	0.289	0.297	0.366	0.376
Office equipment	Coeff.	−0.013**	−0.011**	−0.014**	−0.011**
	SE	(0.006)	(0.005)	(0.006)	(0.005)
	Adj. R^2	0.033	0.067	0.039	0.078
Food: Grains, fruits, and vegetables	Coeff.	−0.490***	−0.444***	−0.420***	−0.375***
	SE	(0.148)	(0.133)	(0.127)	(0.114)
	Adj. R^2	0.143	0.169	0.125	0.153
Electronics and appliances	Coeff.	−0.081**	−0.075**	−0.081**	−0.073**
	SE	(0.034)	(0.035)	(0.033)	(0.034)
	Adj. R^2	0.271	0.275	0.294	0.298
Household supplies	Coeff.	−0.165***	−0.170***	−0.148***	−0.147***
	SE	(0.059)	(0.063)	(0.054)	(0.056)
	Adj. R^2	0.022	0.026	0.060	0.063
Sporting goods and photographic	Coeff.	−0.019*	−0.019	−0.018*	−0.018
equipment	SE	(0.011)	(0.014)	(0.010)	(0.013)
	Adj. R^2	0.082	0.098	0.060	0.078
Clothing and accessories	Coeff.	−0.563	−0.703	−0.559	−0.684
	SE	(0.434)	(0.489)	(0.407)	(0.458)
	Adj. R^2	0.063	0.085	0.057	0.079
Supermarket	Coeff.	−0.095	−0.038	−0.075	−0.022
	SE	(0.088)	(0.072)	(0.087)	(0.069)
	Adj. R^2	0.082	0.106	0.086	0.109
Control variables		No	Yes	No	Yes
Obs.		985	985	985	985

Notes: The sample consists of 197 counties from 2011 to 2015. The dependent variable is the county-level offline employment per 10,000 people in each selected retail industry. Employment is defined as the number of workers in columns (1) and (2) and that of FTE jobs in columns (3) and (4). The main explanatory variable online share (%) is computed by the sum of credit card spending at online retail stores transacted by all credit cardholders of the Company who live in the county divided by that of the corresponding online and offline card spending in that county. The control variables include the log of per capita property tax, population growth rate, car ownership per capita, share of female population, and average household size. All explanatory variables are lagged by one year. All regressions include both the county- and year-fixed effects. County-clustered standard errors are presented in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table E2: E-Commerce Effects on Full-Time and Part-Time Workers

	Dependent Variable: Offline Retail Employment			
	Full-time Workers		Part-Time Workers	
	(1)	(2)	(3)	(4)
Online share (%)	−1.176***	−1.183***	−0.297*	−0.370**
	(0.352)	(0.393)	(0.168)	(0.156)
Effect of a 1 pp increase in online share on				
Number of offline retail employment	−26.53	−26.69	−6.700	−8.347
% of offline retail employment	−0.612	−0.616	−0.365	−0.455
Control variables	No	Yes	No	Yes
Obs.	985	985	985	985
Adj. R^2	0.420	0.424	0.027	0.039

Notes: The sample consists of 197 counties from 2011 to 2015. The dependent variable is the county-level offline employment per 10,000 people. Employment is defined as the number of full-time workers in columns (1) and (2) and the number of part-time workers in columns (3) and (4). The main explanatory variable online share (%) is computed by the sum of credit card spending at online retail stores transacted by all credit cardholders of the Company who live in the county divided by that of the corresponding online and offline card spending in that county. The control variables include the log of per capita property tax, population growth rate, car ownership per capita, share of female population, and average household size. All explanatory variables are lagged by one year. All regressions include both the county- and year-fixed effects. County-clustered standard errors are presented in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table E3: Detailed Industries in the Restaurants Sector

	Dependent Variable: Employment			
	(1)	(2)	(3)	(4)
A. Full-Service Restaurants				
Online share (%)	−0.151	−0.011		
	(0.450)	(0.382)		
Online share (%) × Metro			0.052	0.266
			(0.503)	(0.403)
Online share (%) × Non-metro			−0.517	−0.460
			(0.396)	(0.378)
Adj. R^2	0.434	0.464	0.436	0.467
B. Limited-Service Restaurants				
Online share (%)	0.107	0.020		
	(0.110)	(0.110)		
Online share (%) × Metro			0.244**	0.159
			(0.120)	(0.119)
Online share (%) × Non-metro			−0.140	−0.205
			(0.149)	(0.156)
Adj. R^2	0.361	0.376	0.368	0.382
C. Snack and Non-alcoholic Beverage Bars				
Online share (%)	0.394***	0.297**		
	(0.122)	(0.117)		
Online share (%) × Metro			0.564***	0.479***
			(0.156)	(0.141)
Online share (%) × Non-metro			0.087	0.002
			(0.180)	(0.167)
Adj. R^2	0.523	0.569	0.531	0.577
Control variables	No	Yes	No	Yes
Obs.	985	985	985	985

Notes: The sample consists of 197 counties from 2011 to 2015. The dependent variables in panels A, B, and C are the county-level employment per 10,000 people in the full-service restaurants, limited-service restaurants, and snack and non-alcoholic beverage bar industries, respectively. Employment is defined as the number of workers in all columns. The main explanatory variable online share (%) is computed by the sum of credit card spending at online retail stores transacted by all credit cardholders of the Company who live in the county divided by that of the corresponding online and offline card spending in that county. The variables *metro* and *non-metro* are the dummies for a county located in metropolitan and non-metropolitan areas, respectively. The control variables include the log of per capita property tax, population growth rate, car ownership per capita, share of female population, and average household size. All explanatory variables are lagged by one year. All regressions include both the county and year-fixed effects. County-clustered standard errors are presented in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.