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

Hyunbae Chun
Sogang University
hchun@sogang.ac.kr

Hailey Hayeon Joo
Sogang University
hjoo@sogang.ac.kr

Jisoo Kang
Sogang University
jskang@sogang.ac.kr

Yoonsoo Lee
Sogang University
ylee@sogang.ac.kr

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Abstract

The widespread of e-commerce has benefited consumers. However, at the same time, it has been blamed for job losses in brick-and-mortar retailers. To quantify the effect of e-commerce on the local labor market, we construct a unique measure of online spending share based on 30 billion transactions of credit cards. Using geographic variation in online spending shares, we examine the causal effect of e-commerce on retail employment at the county level in Korea. We find that the rise in online spending share from 2010 to 2015 decreased the local retail employment by about 3% regardless of counties. Furthermore, job creations from the growth in e-commerce were concentrated in the metropolitan areas and thus such positive effects on employment were not distributed evenly by all locations. Therefore, the diffusion of e-commerce induces restructuring in local labor markets, thereby reshaping retail jobs across locations.

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1. Introduction

Over the past two decades, a rapid growth of e-commerce has improved consumer welfare. The consumers have gained from the reduced search costs (Bakos 1997) and lower price (Brynjolfsson and Smith 2000, Brown and Goolsbee 2002, Cavallo 2017). Furthermore, they have accessed a wider variety of merchants online (variety gains) and saved the travel costs of shopping at brick-and-mortar stores (convenience gains) (Brynjolfsson *et al.* 2003, Einav *et al.* 2017). However, at the same time, there have been more than 40 bankruptcies of the US major retail chains (e.g., Sears in 2018, ToysRus in 2017, and so forth). The e-commerce is regarded as a critical reason of the so-called "Retail Apocalypse" and widely blamed (Economist 2017, New York Times 2017).[1] While there is a growing concern on the negative effect of e-commerce on the offline retail jobs, the evidence so far is mostly anecdotal.

Therefore, in this paper, we quantify the causal effect of e-commerce on the retail employment, by using a unique measure of online spending share. First, we construct detailed measures of online retail spending share (hereafter, "online shares") at the county level, based on more than 30 billion transactions of credit and debit cards in Korea. Using geographic variation in county-level online shares and offline retail employment, we answer the following two questions: (i) how large the impact of e-commerce on local retail employment is, and (ii) how the effects are distributed by geography (e.g., metropolitan vs non-metropolitan).

We find that the rise in online shares from 2010 to 2015 decreases the county-level retail employment by about 172 workers in Korea (about 3% reduction in average retail employment). Our findings on the employment effect of the online expansion are robust to endogeneity issues and various alternative analyses. To address the endogeneity issue, we use the Bartik instruments and conduct falsification tests. Our results were robust when we repeated the analysis with alternative set of IVs or changed model specifications in several different ways.

The negative effect of e-commerce on employment in brick-and-mortar stores is widespread across regions, but job creations in e-commerce are concentrated in metropolitan areas. Together, we find a slight increase in overall retail jobs in metropolitan area but a decrease

[1] The over-expansion of brick-and-mortar shopping malls and change in consumers' spending habits are also considered as main reasons.

in the non-metropolitan area. In other words, while the cost of e-commerce is universal, the benefit is not equally distributed across regions at least in terms of jobs. Therefore, the diffusion of e-commerce induces restructuring in local labor markets, thereby reshaping retail jobs across locations.

More recently, economic literature began to bring out the issues of e-commerce impacts on offline retail sales and employment (Goldmanis *et al.* 2009, Gebhardt 2018, Chava *et al.* 2018). Goldmanis *et al.* (2009) found that the growth of e-commerce reallocates market shares from high to low cost producers. Gebhardt (2018) showed that the 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, the previous studies fail to quantify the causal effect due to lack of an appropriate measure of e-commerce spending with geographic variation.

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. This paper contributes to literature in four ways: (i) construction of a unique measure of online share using credit and debit card transaction data, (ii) quantification of the e-commerce impact on local labor markets, (iii) a broad relation to the studies on the impact of technological progress, and (iv) provision of the evidence regarding insufficient job creation by online retailers.

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

2. Diffusion of E-Commerce

Retail e-commerce sales have grown fast worldwide. For example, the online shares in U.K., China, U.S., and Japan were 24.6%, 10.8%, 7.18%, and 4.75% in 2015, respectively. The online share in Korea reached 14.6% in 2015, which is considerably higher than those in the others, with the exception of U.K. One possible explanation for this is Korea's fastest internet connection that underlies the rapid growth of online marketplaces (e.g., Gmarket and Auction of e-Bay Korea), which reduces consumers' search costs in general (Bakos 1997). The lowered search costs reduce consumers' travel and time costs to find the lowest price online, thus substituting offline for online. Moreover, online shopping malls provide more variety of products to consumers. Another explanation for the rapid growth of e-commerce in Korea is low monetary and time costs of delivery in online shopping. It is well known fact that low shipping costs serve to reduce the fixed disutility costs of online shopping (Goolsbee 2001, Balasubramanian 1998, Forman *et al*. 2009).

[Insert Figure 1 About Here]

Figure 1 describes the changes in county-level online shares between 2010 and 2015. It is worth noting that there exist meaningful differences in online shares portions across counties. Some counties in rural areas (at the lower left on the map) and mountain areas (at the upper right on the map) show relatively high online shares. Counties in these remote areas have a small number of retail stores and bad transportation, and thus the availability of e-commerce itself can incur tremendous convenience gains in terms of travel costs. However, online shares are on average higher in metropolitan areas than in non-metropolitan areas. For example, two largest metropolitan areas (Seoul at the upper left on the map and Busan at the lower right on the map) exhibit high online shares. Counties in metropolitan areas have a large number of retail stores and good transportation, but also have higher opportunity cost for shopping time as well as greater demand for variety of products, which makes online shares in metropolitan areas high. Our finding of high online shares in urban areas is also similar to that of the U.S. (Einav *et al.* 2017).[2]

Between 2010 and 2015, the online shares have increased across all counties. However, the extent to which the online share increased during the sample period varies substantially across locations. Moreover, online share increased faster in metropolitan areas than in non-metropolitan areas. The online shares in metropolitan areas on average increased by 6.5 percentage point (pp) during 2010-2015 (11% at average annual growth rate) while those in non-

[2] Using credit data in the US, Einav *et al.* (2017) found that online penetration was distinctly higher in the Northeast and in the West and Mountain regions than in the South or Midwest.

metropolitan areas did by 3.85 pp (4% at AAGR). A faster increase in online shares in metropolitan areas consistent with the findings of Einav et al. (2017) that consumers in high income and densely populated counties have larger gains from online shopping. Gains from online shopping mainly come from substitution to online merchants. Thus, consumers with high level of consumption, i.e., richer households, have larger gains than poorer households. Richer households appear variety-loving consumers as well.

The diffusion of e-commerce mentioned above would have affected local retail employment. Substitution to online merchants due to convenience of shopping at home could lower offline employment, but online shopping due to the demand for variety might have little impact on brick-and-mortar stores. Therefore, the size of employment effect depends upon not only the growth (diffusion) of online share but also the relative importance between convenience and variety of online shopping. In recent years, as the concerns regarding employment decline in the retail sector began to be realized not only in the U.S. but also in many other countries, various economic researches have been attempted (Pozzi 2013, Chava *et al*. 2018, Brynjolfsson and Smith 2000). However, due to the limitations of data, no empirical analysis has yet been made that uses an accurate measure of online share for the employment effect.

3. Data

3.1 Measuring Online Shares from the Credit Card Data

In this study, we use the credit/debit card transaction data provided from a credit/debit card company (hereafter, "company *X*") to measure the annual online shares by county. From January 1, 2010 to December 31, 2015, approximately 30 billion transactions took place at company *X*. Each transaction has information about the amount and date of the transaction, type of cards (credit or debit), characteristics of merchants and cardholders. To define transactions in the retail trade sector (KISC 47), we use the industry classification of merchants. Among detailed 68 industries of merchants, 19 industries match to the retail trade sector.

To identify whether transactions are made through online, we use the industry classification of merchants. We define online transactions that are made by merchants whose industry classification is e-commerce.[3] In defining online transactions, we also include transactions made by payment gateway (e.g., Inicis, Paypal) that are mainly used by small online merchants.[4] As in Einav *et al*. (2017), e-commerce in our study does not include home shopping (TV or phone orders).[5]

The county-level annual online share (OS_{jt}) is measured by the following equation:

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

where total spending in county j in year t is the sum of both online and offline spending in county j in year t. Online spending in county j in year t is defined as total online shopping expenditures made by company X's credit/debit card holders who live in county j in year t. An online store does not have a physical location and thus consumption does not occur in the area where the online shopping business takes place. That is, online spending is likely determined by the shopping preferences and needs of consumers under local retail environments. Offline spending in county j in year t is defined as total amount of all brick-and-mortar retail stores' transactions located in county j in year t, contracted with company X.

In our analysis, we use transactions of company X to construct a main measure of online spending share. Spending based on transactions of company X is very representative for domestic consumption because company X has been ranked top in market shares during the period of 2010-2015. Its market share has stayed high and stable in both credit and debit card transactions (see Appendix A for more details regarding the representativeness of our data). Moreover, credit cards account for approximately 70% of all payment methods, which is also high and stable in Korea over the sample period. However, our online spending measure might be affected by transactions made by the other card issuers as well as other payment methods (cash, checks and

[3] If a merchant sells products both online and offline, only online transactions are classified as e-commerce.
[4] The payment gateway provides secure connection between merchants' website or browser and the credit card processing company. Although transactions through the payment gateway also include some services, mainly travel services, we cannot identify them. We thus do robustness checks with re-defining the retail sector that includes the travel services.
[5] Home shopping accounts for majority of mail and phone orders in Korea.

etc.). As robustness checks, we also use the online shares with these adjustments. Nonetheless, results are qualitatively the same.

3.2 Employment

For our analysis, we use two employment measures of both the number of workers and FTE jobs. To obtain local retail employment, we mainly exploit the *Census on Establishments* (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 does not inform working hours for employment types. To convert the number of workers into that of full-time equivalent (FTE) jobs, we obtain information of hours worked by employment type from the *Survey on Labor Conditions by Employment Type* (SLCET) from *the Ministry of Employment and Labor*.[6]

To define offline retail trade sector, we exclude nonstore retailers (KSIC 479; e-commerce, mail order, and phone order) from the retail trade sector (KSIC 47). We note that both mail order and phone order (i.e., traditional nonstore retailing) are included in neither 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 (KSIC 4711; department stores, warehouse clubs, and supercenters) because most of large GMS in Korea have both offline and online sales.[7] We thus exclude large GMS in defining offline retail employment. Contrary to the US retail sector, the employment share of large GMS in Korea is very small (approximately 5%). Nearly all retail employment belongs to small and medium-sized retailers (See Appendix E for more details). Nonetheless, the inclusion of large GMS as offline retail generates qualitatively similar results.

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

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

[7] The share of online sales of large GMS is on average approximately 30% in 2010-2015.

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

That is, $\frac{EMP_{jt}}{POP_{jt}}$ is the offline retail employment per 10,000 people. EMP_{jt} is either the number of workers or the number of FTE jobs. The advantage of using this variable is that local employment statuses become comparable across local markets, because heterogeneous employment conditions are considerably controlled by population sizes (Basker 2005, Neumark *et al*. 2008).

3.3 Summary Statistics

Table 1 presents the county-level descriptive statistics for the sample of 197 counties from 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); 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 main dependent variable, i.e., offline retail employment per 10,000 people from CE has a mean of 273, where those of population and offline workers 225,609[8] 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 almost for 40% of total workers in the Korean retail sector.

[Insert Table 1 About Here]

As presented in panel B, the mean of online share is around 24% which is close to its median. The online share is symmetrically distributed around the mean. For control variables, we use the log of per capita property tax, population growth rate, car ownership per capita, share of female population, and average household size. The mean of per capita property tax is 925 thousand KRW; that of population growth rate is 0.248, that of car ownership per capita is 0.395, that of share of female population is 49.945, and that of average household size is 2.384.

[8] The population size of a county in Korea is on average two times larger than that in the US.

4. Impact of E-Commerce Expansion on Employment

4.1 Empirical Model

We evaluate how much the expansion of 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 people. Because e-commerce could affect the local labor market by changing the composition of employment status (i.e., full and part time), we exploit both the number of workers and that of FTE jobs to derive this dependent variable. The main explanatory variable $OS_{j,t-1}$ is the online share in county j in year $t-1$. The annual online share in a county is the annual proportion of the sum of credit/debit card spending at online retail stores made by all who live in the county to that of the corresponding on-and-offline card spending (see Section 3.1 for details). Vector $X_{j,t-1}$ consists of lagged county-level demand 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.

4.2 Main Results

Table 2 presents the estimates of equation (1). Columns (1) and (2) show the results based on the number of workers while columns (3) and (4) display those using the numbers of FTE jobs. Column (1) and (3) contains the online share variable only; we additionally control the county-level control variables in columns (2) and (4). In all columns, we include both county and year fixed effects.

We find that all estimates for the e-commerce impact on the offline retail employment are negative and statistically significant at the 1% level. In column (1), the coefficient of online share is -1.473, which means that a 1 pp increase in online share decreases 1.473 offline retail workers per 10,000 population. In order to convert this into changes in the number of workers in a county, we multiply the estimated coefficient by the average county population in 10K (i.e., 22.56 given in Table 1). Therefore, in a county, a 1 pp increase in online share decreases 33.23 offline retail workers, 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), which implies that a 1 pp increase in online share decreases 35.03 workers (or 0.57% change) at the county level. Thus, the rise in online share during 2010-2015 (4.9 pp) decreases approximately 172 workers in a county, which accounts for approximately 3% reduction of the total offline retail employment.

[Insert Table 2 About Here]

If e-commerce shifts workers away from part-time to full-time, the number of workers decreases, but the number of FTE jobs decreases little or is unchanged. To address possible changes in employment composition, we use the number of FTE jobs as a dependent variable. In column (3), the coefficient of online share is -1.363, which means that 1.363 FTE jobs disappear per 10,000 population. And, the coefficient in column (4) is -1.410, implying a decrease by 1.410 FTE jobs per 10,000 population with a 1 pp increase in online share. Because columns (3) and (4) use different dependent variables from columns (1) and (2), we cannot directly compare the magnitudes of the coefficients. For comparison, we also convert the estimated coefficients in columns (3) and (4) into the offline retail impact by a 1 pp increase in online share on a change in the number of FTE jobs of a county. Consequently, in a county, a 1 pp increase in online share decreases 30.75 FTE jobs (or 0.54% change) in column (3) and 31.81 FTE jobs (or 0.55% change) in column (4). During the 2010-2015 period, the total FTE job loss is approximately 151 which accounts for 2.9% reduction of total retail FTE jobs in a county. That is, the estimated e-commerce impacts based on FTE jobs are slightly lower than that based on workers, but the difference in the magnitude is small. This implies that decrease in offline employment is not an artifact of changes in employment composition. Furthermore, we run regressions with separate dependent variables of full-time and part-time workers. Results suggest that the diffusion of e-commerce is more likely to affect part-time workers than full-time workers (See Appendix D). But the magnitude of impacts on the two groups are not significantly different. Overall, Table 2 confirms the salient negative impact of e-commerce on local brick-and-mortar workers.[9]

4.3 Employment Shift to Other Sectors

In this subsection, we examine whether the growth of e-commerce has shifted employment from offline retail to other sectors. If employment gains in other sectors outpace employment losses in brick-and-mortar stores in a county, overall county-level employment may not decrease (or rather increase). We examine the sectoral employment shift in terms of both consumer and supplier sides.

First, consumers who save time and money from online shopping may shift their demand toward restaurants, entertainment, aesthetics, and gym. This demand shift may increase employment in restaurants and various services. At the same time, a slowdown in the traffic of shoppers due to the increased online shopping may negatively affect restaurants and other businesses on the street and malls. Thus, the net employment effect depends upon the relative importance of the two effects. Second, the growth of e-commerce may shift employment from store retailing to warehousing and distribution. In fact, online retailers are like wholesale distributors without having stores, but with warehouses (or fulfillment centers). Thus, the growth of e-commerce could add jobs in warehousing. On the other hand, the fading away of brick-and-mortar stores results in substitute of freight transportation for personal transportation (i.e., shopper traffic) in goods delivery, thus expanding jobs in freight transportation but shrinking jobs in passenger transportation (Anderson *et al*. 2003). E-commerce in general is more capital intensive than store retailing so that a shift away from store retailing to nonstore retailing could result in employment losses in warehousing and transportation (i.e., retailing support services).

[Insert Table 3 About Here]

[9] In the industry-level results of equation (1), the negative employment effect is not limited to books and electronics but is widespread across products such as foods and sporting goods (See appendix B).

Table 3 presents results for the effect of e-commerce on sectoral employment shifts. All columns in Table 3 use the same specifications as those in Table 2. In panel A, the e-commerce effects on employment shifts to restaurant and personal service sectors are not evident for all columns of workers and FTE jobs. Since we estimate the net employment shifts, we cannot identify whether consumers' demand shifts are offset by drops in shopper traffic or consumers do not shift their demand toward restaurants and other services. Nonetheless, the employment shifts on the consumer demand side is not found.[10]

Panel B of Table 3 shows that e-commerce has a statistically significant negative effects on employment in the wholesale and commission trade sector. The coefficients in columns (1)-(4) is around -1.559 to -1.721, meaning an employment decline in the wholesale and commission trade sector by 1.559 to 1.721 per 10,000 population with a 1 pp increase in online share. The effect of e-commerce on employment and FTE jobs in transportation and warehousing also exhibit negative. This confirms that employment losses in store retailing support services (e.g., passenger transportation) may outpace employment gains in warehousing and freight transportation to e-commerce. Overall, Table 3 indicates employment losses due to the growth of e-commerce are not offset by employment shifts to other sectors.

4.4 Employment Effect by Location

In this subsection, we examine whether the employment effect of e-commerce is heterogeneous across locations, particularly, metropolitan versus non-metropolitan areas. In our sample, there are 66 counties in metropolitan areas, while non-metropolitan areas consist of 131 counties. Metropolitan areas account for 34% of the total number of counties but do for 48% of the total population because metropolitan areas are on average more densely populated than non-metropolitan ones.

[Insert Table 4 About Here]

[10] Unlike the supply side, it is difficult to determine industries to which consumers' demand shifts. Moreover, the demand shift might not be the same across regions with different socio and demographic characteristics. Further analyses will be added later.

Table 4 presents the estimation results for the employment effects of e-commerce for metropolitan and non-metropolitan areas. All columns of (1)-(4) report negative and statistically significant effects of e-commerce on employment and FTE jobs in both metropolitan and non-metropolitan areas. However, the negative employment effects are larger in non-metropolitan than in metropolitan areas. For example, in column (2), coefficients of online share are 1.413 for metropolitan areas and 1.780 for non-metropolitan areas, respectively. The results imply that a 1pp increase in online share decreases 0.503% in the total offline retail workers of a metropolitan county but 0.661% in those of a non-metropolitan country.

[Insert Figure 2 About Here]

Figure 2 shows the effect of e-commerce growth on changes in total retail employment during 2010-2015. The changes in the total retail employment are decomposed into employment losses in brick-and mortar stores due to e-commerce expansion and employment gains in an e-commerce industry. The figure also compares employment changes between metropolitan and non-metropolitan areas.

Estimates in column (2) of Table 4 are used to calculate employment losses in offline retail. During 2010-2015, brick-and-mortar stores in metropolitan areas lost approximately 21 thousand workers. This estimated change is calculated by the coefficient of metropolitan online share (-1.413) x change in online share in 2010-2015 (6.532 pp) x metropolitan population in 2010 (2,304 in 10K). In the same period, offline retail stores in non-metropolitan areas lost approximately 17 thousand workers, which is similarly calculated by (-1.780) x (3.850 pp) x (2,476 in 10K). Offline retail sector in metropolitan areas has a slightly larger employment loss than does non-metropolitan areas not because of the magnitude of coefficient estimate of online share but because of its fast rise in online share during 2010-2015.

Figure 2 also shows actual employment gains in the e-commerce sector by location. During 2010-2015, metropolitan areas added 22 thousand workers in the e-commerce sector while non-metropolitan did only 10 thousand workers. Unlike job losses in offline retail, employment gains sharply contrast between metropolitan and non-metropolitan areas. In contrast to brick-and-mortar stores, online retailers do not have to be located where their customers are to sell products. Online retailers thus tend to concentrate among a few locations that have favorable business conditions such as abundant human capital of IT staffs and marketing experts (e.g., metropolitan areas). In Korea, online retailers are more concentrated in Seoul that is the largest metropolitan than all the other areas.

Summing employment changes in offline and online retailers, in metropolitan areas, employment losses in offline retail is more than offset by gains in online retail. In contrast, in non-metropolitan areas, employment gains in online retail are too small to offset employment losses in offline retail. In summary, the negative employment effect of e-commerce on offline retail is widespread across regions. However, job creations in e-commerce are concentrated in metropolitan areas. Therefore, the growth of e-commerce results in a widespread employment loss in brick-and-mortar stores, while employment gains in e-commerce sector reshape the location of retail employment away from non-metropolitan toward metropolitan areas.

5. Robustness Checks

To assess the robustness of our findings, we examine potential endogeneity problems, and then address various issues related to alternative uses of variables (e.g., online share, instrument, and dependent variable), sample selection, and market definition. A wide range of robustness tests produces qualitatively similar results: that is, our findings regarding the impact of e-commerce on employment under these tests remain largely identical to that in the tables presented in the previous section.

5.1 Endogeneity

In this subsection, we discuss potential endogeneity biases in estimating the impact of e-commerce on local employment. On one hand, a positive correlation between online share and offline retail employment can underestimate the impact. For instance, local markets with high-speed Internet access promote online shopping (Bakos 1997). Such favorable market conditions can attract a new business and eventually create more jobs. Furthermore, the consumers in those markets face a high opportunity cost for shopping time and/or receive a wide variety of products, which also works as a factor of underestimation. On the other hand, a systematic negative correlation is also likely to exist and thus the impact can be overestimated. In general, the availability of specialty stores gets lower in a market with low employment, which can amplify the negative impact of e-commerce on local employment.

Therefore, in order to eliminate the potential bias in our estimation, we first use a Bartik instrument and then conduct a falsification test. First, our Bartik instrument is constructed based on (i) the differences in the proportions across the *initial* age distributions for consuming several retail products in a given county and (ii) those in online penetration rates for the products (see Appendix C for details). Second, for the falsification test, we investigate the effect of online share on employment in the construction sector. The concerns about a systematic local impact beyond sectors can be also solved, by providing evidence that there is no significant impact in other uncorrelated sector.

[Insert Table 5 About Here]

Table 5 shows the results of the Bartik instrument in panel A and those of the falsification tests in panel B. In panel A, the negative employment effects of online share are more strongly estimated compared with the OLS results in Table 2. This finding implies that the impact is likely underestimated in the OLS specification, due to the positive correlation between local employment and online share. Also, as seen in panel B, the estimated coefficients in the construction sector are positive and insignificant. That is, an endogeneity regardless of sectors is not observed.

5.2 Other Robustness

In this subsection, we conduct additional analyses to check the robustness. Specifically, we deal with alternative choices of online share, Bartik instrument, dependent variable, sample, and market definition. The results are provided in Table 6. For direct comparison, our main results in Table 2 are included in panel A as a benchmark.

[Insert Table 6 About Here]

In panel B of Table 6, we use alternative measures of online shares for the purpose of reflecting cash transactions with the province-level data from the *Bank of Korea*: The numerator and denominator are adjusted by the shares of company X in online and total expenditures, respectively. As mentioned earlier, due to the exclusion of cash transactions, online share constructed from the credit card is higher in all periods than that from the government survey. Although online shares from the two datasets show very similar time trend, the estimates can be biased if the share of payment varies significantly across regions and periods. The impacts are larger in all columns, but the statistical significance remains the same.

In panel C, we alternatively construct the Bartik instruments using online shares by product in a European country instead of US. We use the data from *Statistics Norway*, because it provides the online sales data by detailed product category. The results are qualitatively the same. In panel D, we test alternative measures of dependent variables. We use working age population for normalizing employment instead of total population in a county. Again, the results are qualitatively similar to the benchmark results.

In panel E, we restrictively use the sample. We run the same regressions for counties with populations of more than 50,000 people, and the results are very similar to the benchmark. In panel F, we use a different market definition, i.e., the commuting zones instead of counties. The magnitudes of estimates are lower, but the statistical conclusions are the same as the benchmark results. To sum, our results are quite robust across several tests.

6. Conclusions

In this paper, we quantified the effect of e-commerce on the local labor market, using a unique measure of online spending share based on 30 billion transactions of credit/debit cards. We found that the rise in online spending share from 2010 to 2015 decreased the local retail employment by about 3% regardless of counties (about 172 workers per county in Korea).

Our findings on the employment effect of the online expansion were robust. To assess the robustness of our findings, we examined potential endogeneity problems, and then addressed various issues related to alternative uses of variables, sample selection, and market definition. A wide range of robustness tests produced qualitatively similar results: that is, our findings regarding the impact of e-commerce on employment under these tests remained largely identical.

Furthermore, we found the negative employment effect of e-commerce on birck-and-mortar stores is widespread across regions. However, job creations in e-commerce were confined in metropolitan areas. More specifically, in metropolitan areas, job losses in offline stores were more than offset by new jobs in e-commerce. But in non-metropolitan areas, the number of jobs created in e-commerce falls far short of compensating for the job losses. Therefore, the diffusion of e-commerce induced restructuring in local labor markets, thereby reshaping retail jobs across locations.

References

Anderson, W.P., Chatterjee. L, and Lakshmanan T.R. 2003. "E-Commerce, Transportation, and Economic Geography." *Growth and Change* 34(4): pp. 415–432.

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

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

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

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

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

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

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

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

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

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

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

Fan, J., Tang, L., Zhu, W., and Zou, B. 2018. "The Alibaba Effect: Spatial Consumption Inequality and the Welfare Gains from E-Commerce," *Journal of International Economics* 114: pp. 203–220.

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

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

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

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

Jo, Y.J., Matsumura, M., and Weinstein, D.E. 2019. "The Impact of E-Commerce on Prices and Welfare?" Working Paper. Columbia University.

Mandel, M. (2017) "How E-Commerce Is Raising Pay And Creating Jobs Around The Country" *Forbes*. Retrieved from https://www.forbes.com/sites/realspin/2017/04/03/how-e-commerce-is-raising-pay-and-creating-jobs-around-the-country/#5367d21e6dff

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

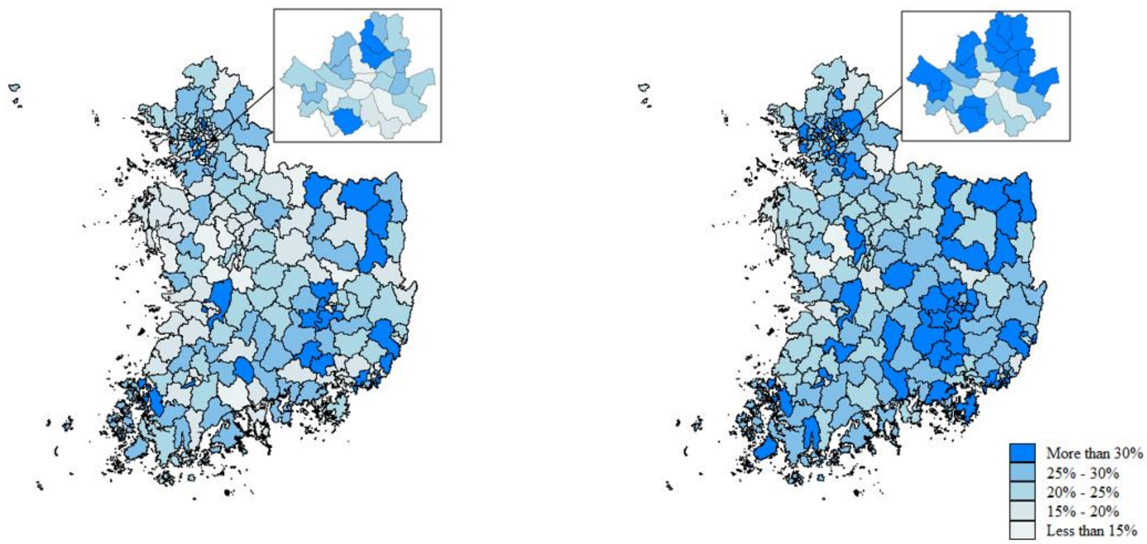
Pozzi, A. 2013. "The Effect of Internet Distribution on Brick-And-Mortar Sales." *The RAND Journal of Economics* 44(3): pp. 569-583.

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

The Economist. 2018. "Superstar Cities Have a Big Advantage in Attracting High-Paying Jobs." Retrieved from https://www.economist.com/finance-and-economics/2018/11/15/superstar-cities-have-a-big-advantage-in-attracting-high-paying-jobs

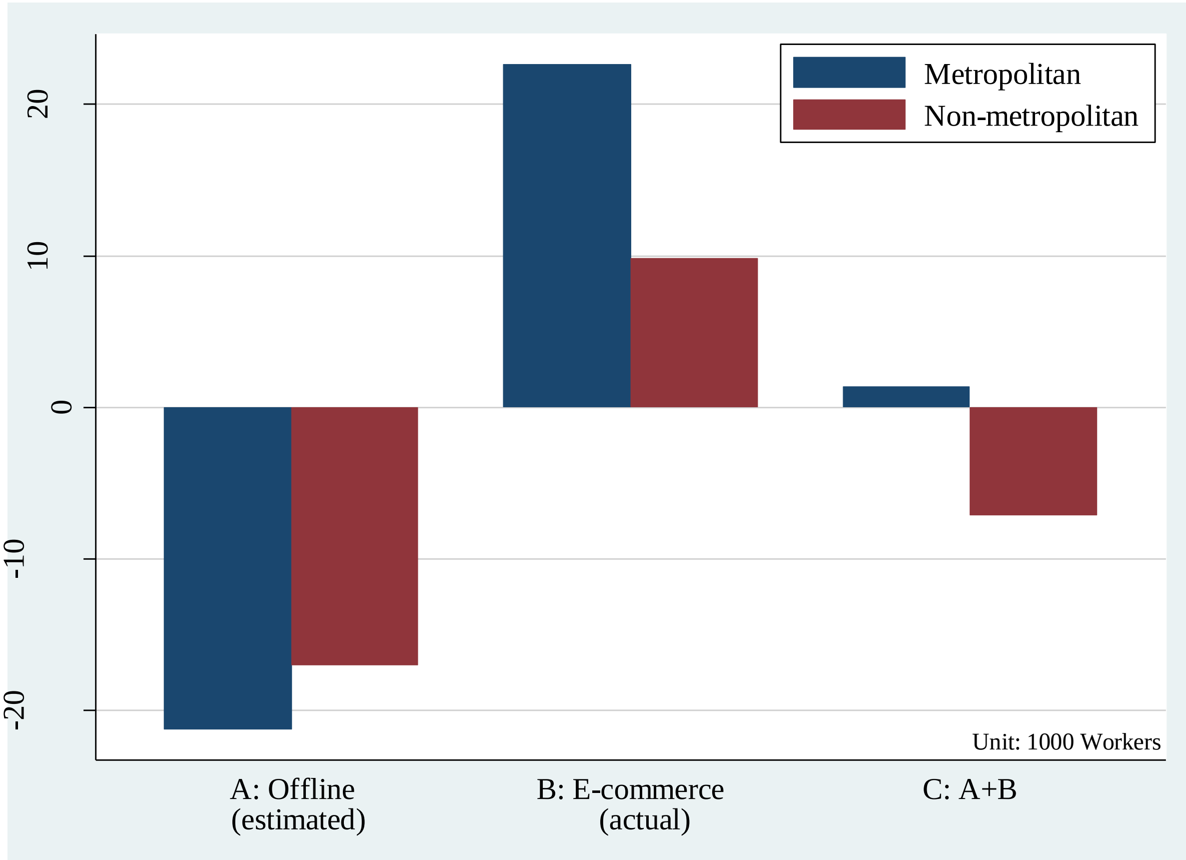
Figure 1. Diffusion of E-Commerce by County, 2010–2015

A. 2010 B. 2015



Notes: The maps in diagrams A and B describe the county-level online shares in years 2010 and 2015, respectively. The online share in a county is the ratio of the sum of credit and debit card spending at online retailers made by all who live in the county to that of the corresponding on-and-offline card spending (see Section 3.1 for details). The zoomed-in section is Seoul.

Figure 2. Heterogeneous Effect of E-Commerce on Retail Employment, 2010-2015



Notes: The bar graph describes the effects of e-commerce on retail employment changes in metropolitan areas and non-metropolitan areas from 2010 to 2015. The category Offline (actual) indicates the estimated effect of e-commerce on change in offline retail employment. The category E-commerce (actual) indicates the actual change in e-commerce retail employment. The category A+B indicates the sum of both offline and e-commerce employment changes.

Table 1. County-level Descriptive Statistics

A. Employment: Dependent variables

Variable	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

Variable	Mean	Median	S.D.	P25	P75
Online share (%)	24.124	23.895	6.357	19.751	27.749

C. Control variables

Variable	Mean	Median	S.D.	P25	P75
Per capita property tax (1,000 KRW)	925	877	255	745	1085
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 share and control variables in panels B and C are lagged by one year.

Table 2. Effects of E-Commerce on Offline Retail Employment

	Dependent Variable: Employment per 10K People			
	Workers		FTE Jobs	
Variable	(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				
the 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
County and year fixed effects	Yes	Yes	Yes	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. Employment is defined as the number of workers in columns (1) and (2) and as the number of FTE jobs in columns (3) and (4). 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. *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table 3. Effects of E-Commerce on Sectoral Shift in Employment

		Dependent Variable: Employment per 10K People			
		Workers		FTE Jobs	
		(1)	(2)	(3)	(4)
A. Consumer Side					
Restaurants	Coeff.	-0.077	-0.007	-0.119	0.014
	SE	(0.581)	(0.481)	(0.464)	(0.393)
	Adj. R^2	0.527	0.529	0.245	0.258
Personal services	Coeff.	-0.102	-0.138	-0.188*	-0.187
	SE	(0.123)	(0.133)	(0.106)	(0.115)
	Adj. R^2	0.245	0.250	0.082	0.087
B. Supplier Side					
Wholesale and commission trade	Coeff.	-1.721**	-1.706*	-1.592**	-1.559*
	SE	(0.799)	(0.968)	(0.759)	(0.920)
	Adj. R^2	0.530	0.540	0.521	0.531
Transportation and Warehousing	Coeff.	-0.703*	-0.376	-0.704*	-0.384
	SE	(0.422)	(0.439)	(0.394)	(0.408)
	Adj. R^2	0.074	0.077	0.072	0.077
Control variables		No	Yes	No	Yes
County and year fixed effects		Yes	Yes	Yes	Yes
Obs.		985	985	985	985

Notes: The sample consists of 197 counties from 2011 to 2015. The dependent variable is the county-level employment per 10,000 people for each of four sectors. Employment is defined as the number of workers in columns (1) and (2) and as the number of FTE jobs in columns (3) and (4). 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. *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table 4. Heterogeneous Effects of E-Commerce on Offline Retail Employment

	Dependent Variable: Employment per 10K People			
	Workers		FTE Jobs	
	(1)	(2)	(3)	(4)
Online share (%) × Metropolitan	-1.341**	-1.413**	-1.291**	-1.327**
	(0.593)	(0.627)	(0.552)	(0.583)
Online share (%) × Non-Metropolitan	-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	-0.477	-0.503	-0.491	-0.505
Non-Metropolitan Counties	-0.635	-0.661	-0.596	-0.616
Control variables	No	Yes	No	Yes
County and year fixed effects	Yes	Yes	Yes	Yes
Obs.	985	985	985	985

Notes: The sample consists of 197 counties from 2011 to 2015. The dependent variable is the county-level employment per 10,000 people. Employment is defined as the number of workers in columns (1) and (2) and as the number of FTE jobs in columns (3) and (4). 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. *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table 5. Robustness Checks for Endogeneity: IV Estimation and Falsification Test

A. Instrumental Variable Estimation

	Dependent Variable: Employment per 10K People			
	Employment		FTE jobs	
	(1)	(2)	(3)	(4)
Online share (%)	-2.542**	-2.735**	-2.012**	-2.303**
	(1.164)	(1.065)	(1.003)	(0.912)
F-statistic in the first-stage	65.36	62.83	65.36	62.83
Control variables	No	Yes	No	Yes
County and year fixed effects	Yes	Yes	Yes	Yes
Obs.	985	985	985	985

B. Falsification Test: Construction Employment

	Dependent Variable: Employment per 10K People			
	Employment		FTE jobs	
	(1)	(2)	(3)	(4)
Online share (%)	0.031	0.540	-0.400	0.097
	(1.273)	(1.011)	(1.192)	(0.890)
Control variables	No	Yes	No	Yes
County and year fixed effects	Yes	Yes	Yes	Yes
Obs.	985	985	985	985
Adj. R^2	0.176	0.201	0.123	0.164

Notes: The sample consists of 197 counties from 2011 to 2015. The dependent variables in Panel A and B are the county-level offline retail and construction employment per 10,000 people, respectively. Employment is defined as the number of workers in columns (1) and (2) and as the number of FTE jobs in columns (3) and (4). Panel A reports results using the Bartik instrument formed by interacting the county-level product share in the initial year of 2010 and the US product-level online share in 2010-2014. For weak instrument test, Panel A reports *F*-statistics robust to cluster standard errors. 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. *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table 6. Other Robustness Checks

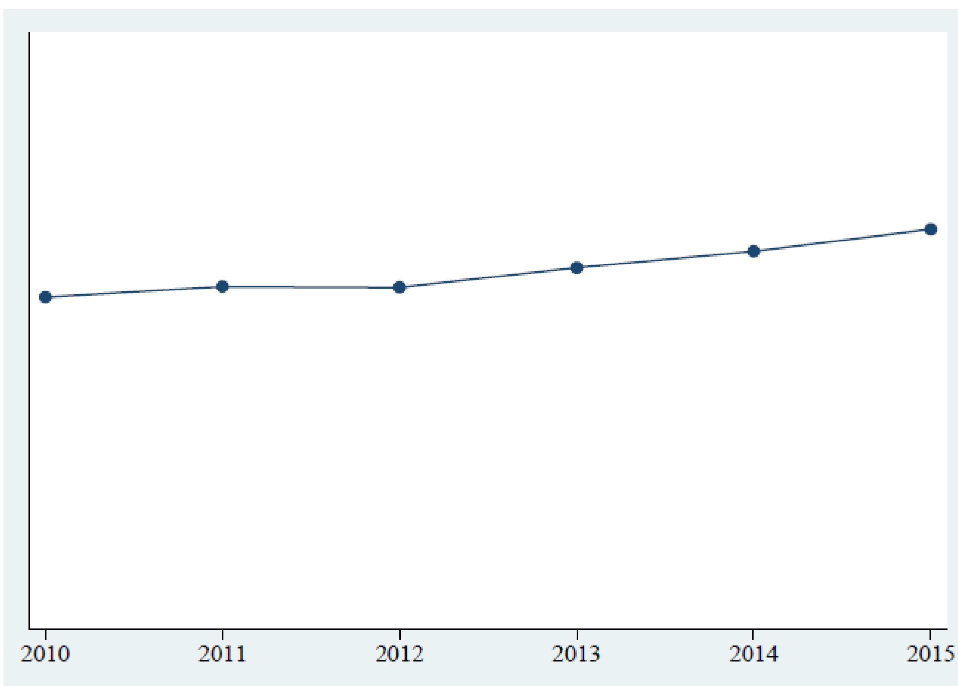
		Dependent Variable: Employment per 10K People			
		Employment		FTE jobs	
		(1)	(2)	(3)	(4)
A. Benchmark results in Table 2	Coeff.	-1.473***	-1.553***	-1.363***	-1.410***
	SE	(0.470)	(0.502)	(0.439)	(0.467)
	Adj. R^2	0.249	0.257	0.155	0.164
	Obs.	985	985	985	985
B. Alternative online share	Coeff.	-2.092***	-2.184***	-1.885***	-1.961***
(*adjusted to reflect cash transaction*)	SE	(0.633)	(0.693)	(0.595)	(0.647)
	Adj. R^2	0.249	0.256	0.154	0.163
	Obs.	985	985	985	985
C. Alternative Bartik measure	Coeff.	-2.860**	-3.041***	-2.287**	-2.576***
(*using the Norway data*)	SE	(1.204)	(1.112)	(1.035)	(0.952)
	F-stat	60.70	56.14	60.70	56.14
	Obs.	985	985	985	985
D. Alternative dependent variables	Coeff.	-2.570***	-2.804***	-2.318***	-2.490***
(*using working age population*)	SE	(0.696)	(0.730)	(0.650)	(0.682)
	Adj. R^2	0.280	0.291	0.194	0.204
	Obs.	985	985	985	985
E. Restricted Sample	Coeff.	-1.652***	-1.566**	-1.569***	-1.461**
(*counties with at least 50,000 people*)	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. Alternative market definition	Coeff.	-0.999**		-0.942**	
(*commuting zones*)	SE	(0.442)		(0.404)	
	Adj. R^2	0.337		0.205	
	Obs.	610		610	
Control variables		No	Yes	No	Yes
County and year fixed effects		Yes	Yes	Yes	Yes

Notes: Panel A reports our main results in Table 2 as a benchmark. Panel B uses alternative measures of online shares adjusted to reflect cash transactions using the province-level data from the *Bank of Korea*. Panel C uses alternative Bartik instruments computed based on the online shares in Norway. For the weak-instrument test, Panel C reports *F*-statistics robust to cluster standard errors. Panel D uses working age population (aged 15 to 64) to calculate the ratio of retail employment to population. Panel E uses a restricted sample which includes the counties with at least 50,000 population. Panel F defines commuting zones as local markets. 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. *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Appendix A. Credit/Debit Card Data

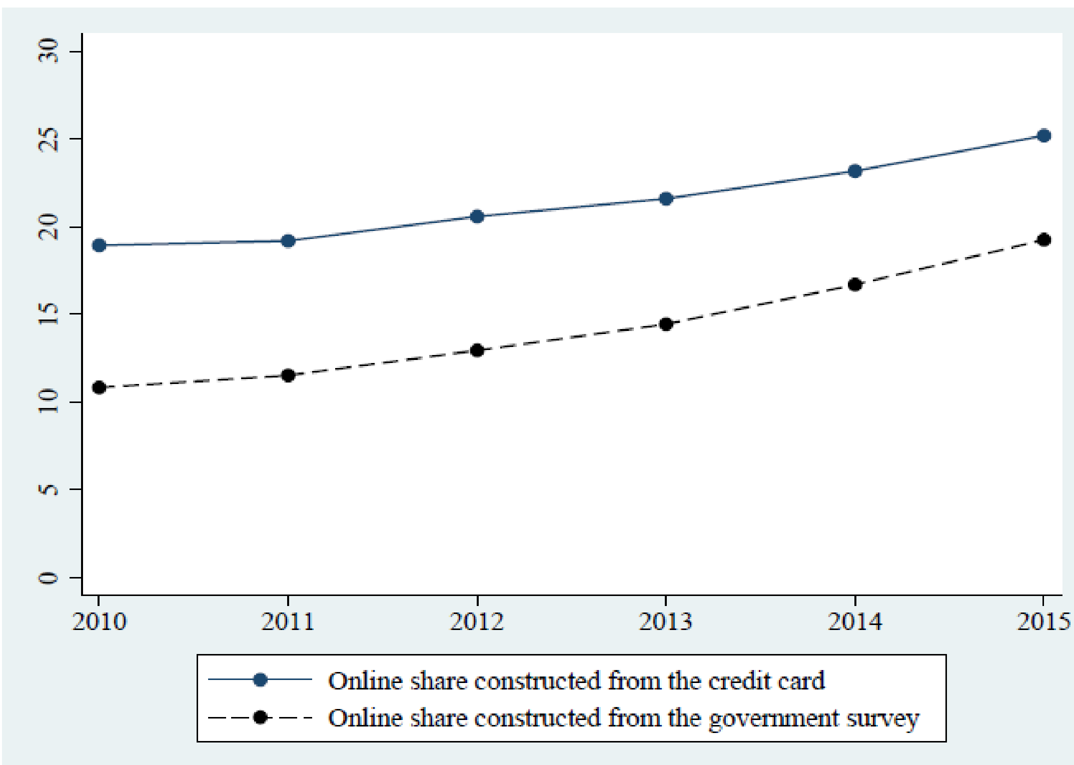
There are two main advantages of using the data from company *X*: (i) representativeness and (ii) stability over time and across regions. First, among all credit and debit card transactions, the largest portion has been occupied by those via company *X*. As of December 2017, a total of 22 firms belonged to the payment card industry (PCI), out of which 8 were the credit and debit card companies, 11 the banks, and 3 the subsidiaries of retail companies. Company *X* was top ranked with a market share of 23% on the basis of personal cards and contracted with around 12 million consumers and 2.7 million affiliated stores that cover more than 95% of all credit card affiliated stores, while the second-placed company had a market share of 13-15% and was contracted with 6-8 million consumers. Therefore, the data from company *X* is highly representative.

Figure A1. Company *X*'s Share of Total Retail Sales, 2010–2015



Second, company *X*'s shares in both total retail sales and online sales have been stable during the period of 2010-2015. Figure A1 displays the proportions of retail spending by company *X* to the total by all payment methods, excluding the expenditure on retail products that cannot be transacted at online stores under the Korea's current laws (e.g., medicines, new cars, gas, and so on). For spending by all payment methods, we use the data of Service Industry Survey (SIS) from *Statistics Korea*. Due to data confidentiality, we cannot report the accurate numbers of proportions, but the gap between the highest and the lowest rates in the figure is not greater than 2%. The stable share is due to not only stable market shares of company X and but also the stable payment share of credit/debit card during the sample period. Figure A2 presents the online shares based on company *X*'s data and those as based on SIS. Both show similar time-series trends, based on which the stability of the shares over time can be ensured. Lastly, company *X*'s shares in the total retail sales are distributed fairly equally across regions (Detailed figures cannot be released due to confidentiality). Moreover, the company *X*'s regional shares are also stable over the sample period.

Figure A2. Trends in Online Shares, 2010–2015



Appendix B. Industry-Level Results

Table B1 summarizes the industry-level results of equation (1), based on eight primary industry categories in the retail sector: (i) music, videos, books, and stationery, (ii) office equipment, (iii) food (grains, fruit, and vegetables), (iv) electronics and appliances, (v) household supplies, (vi) sporting goods and photographic equipment, (vii) clothing and accessories, and (viii) general merchandise. Each column in Table B1 is based on the same specification used in the corresponding one in Table 2.

[Insert Table B1 About Here]

As shown in Table B1, the diffusion of e-commerce decreases local offline employment in not only the industries of standardized retail products but also those of non-standardized ones. More specifically, the offline retail effects of e-commerce are substantial in the industries trading the following products: (i) music, videos, books, and stationery, (ii) office equipment, (iii) food (grains, fruit, and vegetables), (iv) electronics and appliances, (v) household supplies, and (vi) sporting goods and photographic equipment. On the other hand, neither the retailers of clothing and accessories nor supermarkets show a significant impact. The implications are that the offline retail employment is less influenced, if online shopping is less substitutable with offline shopping. For example, in case of the products for which physical shopping experience is required or preferred for purchasing (e.g., clothing), online shopping is less likely to replace offline shopping. Also, supermarkets (selling groceries or miscellaneous goods) are located in proximity to consumers, and therefore, their geographical advantages tend to make online shopping less substitutable with offline shopping.

Table B1. Selected Retail Industries

		Dependent Variable: Employment per 10K People			
		Workers		FTE Jobs	
		(1)	(2)	(3)	(4)
Music, Videos, Books, Magazines, Stationery	Coef.	-0.040**	-0.029*	-0.038**	-0.028*
	S.E.	(0.019)	(0.016)	(0.018)	(0.015)
	Adj. R^2	0.289	0.297	0.366	0.376
Office Equipment	Coef.	-0.013**	-0.011**	-0.014**	-0.011**
	S.E.	(0.006)	(0.005)	(0.006)	(0.005)
	Adj. R^2	0.033	0.067	0.039	0.078
Food: Grains, Fruit, and Vegetables	Coef.	-0.490***	-0.444***	-0.420***	-0.375***
	S.E.	(0.148)	(0.133)	(0.127)	(0.114)
	Adj. R^2	0.143	0.169	0.125	0.153
Electronics and Appliances	Coef.	-0.081**	-0.075**	-0.081**	-0.073**
	S.E.	(0.034)	(0.035)	(0.033)	(0.034)
	Adj. R^2	0.271	0.275	0.294	0.298
Household Supplies	Coef.	-0.165***	-0.170***	-0.148***	-0.147***
	S.E.	(0.059)	(0.063)	(0.054)	(0.056)
	Adj. R^2	0.022	0.026	0.060	0.063
Sporting Goods and Photographic Equipment	Coef.	-0.019*	-0.019	-0.018*	-0.018
	S.E.	(0.011)	(0.014)	(0.010)	(0.013)
	Adj. R^2	0.082	0.098	0.060	0.078
Clothing and accessories	Coef.	-0.563	-0.703	-0.559	-0.684
	S.E.	(0.434)	(0.489)	(0.407)	(0.458)
	Adj. R^2	0.063	0.085	0.057	0.079
Supermarket	Coef.	-0.095	-0.038	-0.075	-0.022
	S.E.	(0.088)	(0.072)	(0.087)	(0.069)
	Adj. R^2	0.082	0.106	0.086	0.109
Control		No	Yes	No	Yes
County and year fixed effects		Yes	Yes	Yes	Yes
Observations		985	985	985	985

Appendix C. Instrumental Variables

In this section, we explain the Bartik instrument exploited in our IV estimation. Bartik instrument uses the inner product structures of the endogenous variable (Goldsmith-Pinkham *et al.* 2017). This instrument and its variants have been widely adopted across many fields in economics (Acemoglu and Linn 2004, Greenstone *et al*. 2015, Amior and Manning 2018).

Online share in county j in year t can be decomposed into:

$$OS_{jt} = \sum_{k} z_{jkt} g_{jkt} \,,$$

where z_{jkt} is the share of county j's consumption in product category k in year t and g_{jkt} is the online share of product category k in county j in year t. Then, g_{jkt} is broken down into:

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

where g_{kt} is the category-period component, g_{jt} is the location-period component, and $\widetilde{g_{jkt}}$ is the idiosyncratic product-location-period component. Therefore, we eliminate all location-specific components and estimate OS_{jt} only using the variations unrelated with counties (i.e., g_{kt}) as follows:

$$OS_{jt} \approx \sum_{k} z_{jk0} g_{kt} \quad \text{where} \quad \sum_{k} z_{jk0} = 1.$$

In fact, it is ideal to take the variations caused by exogenous improvement in product-specific online retailing technology (e.g., the differences of products in search costs, inventory managements, technology development of delivery and on on). In that sense, we exploit the product-specific online shares in U.S. rather than those in Korea, to further exclude the country-specific factors in the rates (David *et al.* 2013, Draca and Van Reenen 2015, Acemoglu and Restroepo 2018). The online shares in U.S. are presented in Table C1.

Table C1. Online Share (%) by Product in U.S.

	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

We fix z_{jkt} as z_{jk0} (i.e., the initial value). By definition, $\sum_k z_{jk0}$ is the sum of the share of county j's consumption in product category k in the initial year, and thus has a value of 1. However, because z_{jk0} is unknown, we utilize the variation in consumption ratio by item determined by the initial age distribution of county j:

$$z_{jk0} = \sum_a S_{aj0} C_{ak0} \approx \sum_a P_{aj0} C_{ak0} \,,$$

where S_{aj0} is the share of age group a's consumption in county j's total consumption in the initial year, C_{ak0} is the share of product k's consumption in age group a in the initial year, and P_{aj0} is the share of age group a in county j's population in the initial year. Table C2 shows the product consumption share by age (i.e., C_{ak0}), using 2010 Household Income and Expenditure Survey from *Statistics Korea*.

Table C2. Product Consumption Share by Age

	Under 30	30-39	40-49	50-59	Over 60
Electronics and appliances	6.31%	6.51%	6.49%	6.02%	4.42%
Books, magazines, and stationery	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%
Fresh food	41.70%	42.16%	45.13%	50.79%	62.13%
Furniture and household supplies	11.88%	12.72%	14.07%	13.60%	11.74%

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

However, the initial age distribution in county *j* may still have a correlation with disturbance factors that affect the offline retail employment. For example, a high proportion in durable goods consumption such as household appliances can be determined by a large number of population inflows from other areas, which is positively correlated with retail employment. And, a high proportion in food consumption is likely associated with a high proportion of elderly population, which is negatively correlated with retail employment. Hence, in this study, we make use of the predictable variation predetermined by the prior age distribution. Following the method proposed by Maestas *et al*. (2016), we estimate the age distribution in 2010 from the 2000 Population Census. Finally, Table C3 provides the first stage regression results for Tables 2.

Table C3. First Stage Regression for Tables 2

	(1)	(2)
Bartik index	15.51***	18.41***
	(1.919)	(2.324)
Log of per capita property tax		6.996
		(4.814)
Population growth rate		0.252***
		(0.0951)
Car ownership per person		-2.496
		(4.778)
Share of female population		1.765***
		(0.571)
Number of persons per household		-6.005
		(6.875)
County and year fixed effects	Yes	Yes
Obs.	985	985
Adj. R^2	0.440	0.504

Notes: The sample consists of 197 counties from 2011 to 2015. The dependent variable is county-level online share (%). *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table C4. IV Estimation Results for Regional Analyses

	Dependent Variable: Employment per 10K People			
	Workers		FTE jobs	
	(1)	(2)	(3)	(4)
Online share (%) × Metropolitan	-2.093**	-2.308**	-1.707*	-1.987**
	(1.037)	(0.970)	(0.902)	(0.839)
Online share (%) × Non-metropolitan	-4.134*	-4.574**	-3.093	-3.666**
	(2.410)	(2.186)	(1.992)	(1.802)
F-statistic in the first stage	19.02	28.45	19.02	28.45
Control variables	No	Yes	No	Yes
County and year fixed effects	Yes	Yes	Yes	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 retail employment per 10,000 people. Employment is defined as the number of workers in columns (1) and (2) and as the number of FTE jobs in columns (3) and (4). For weak instrument test, *F*-statistics robust to cluster standard errors are reported. 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. *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Appendix D. Additional Robustness Checks

Table D1. Elasticity Estimates

	Dependent Variable: Employment per 10K People			
	Workers		FTE Jobs	
	(1)	(2)	(3)	(4)
Log of online spending	-0.063***	-0.066***	-0.047***	-0.048***
	(0.008)	(0.011)	(0.007)	(0.011)
Log of offline spending	0.075	0.074	0.081*	0.077*
	(0.050)	(0.045)	(0.047)	(0.041)
Control variables	No	Yes	No	Yes
County and year fixed effects	Yes	Yes	Yes	Yes
Obs.	985	985	985	985
Adj. R^2	0.319	0.336	0.227	0.257

Note: 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 columns (1) and (2) and as the number of FTE jobs in columns (3) and (4). 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. *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table D2. Effects on Full-Time and Part-Time Workers

	Dependent Variable: Employment per 10K People			
	Full-Time workers		Part-Time workers	
Variable	(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				
the 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
County and year fixed effects	Yes	Yes	Yes	Yes
Obs.	985	985	985	985
Adj. R^2	0.420	0.424	0.027	0.039

Note: 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 full-time workers in columns (1) and (2) and as the number of part-time workers in columns (3) and (4). 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. *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Appendix E. Additional Tables

Table E1. Retail Employment in Korea, 2010-2015 (Unit: 10K)

	Year						Growth rate
	2010	2011	2012	2013	2014	2015	
Retail trade	135.9	140.4	145.9	150	153.1	158.1	3.3%
General merchandise	36.1	37.9	39.4	41.2	42	44.1	4.4%
Large general merchandise	7.8	7.8	7.8	8.8	8.9	9.4	4.1%
Non-large general merchandise	28.3	30.1	31.6	32.4	33.1	34.7	4.5%
Specialized retailers	96.3	98.7	102.3	104.1	105.4	107.3	2.3%
Non-store retailers	3.5	3.8	4.2	4.7	5.7	6.7	18.1%
E-commerce	2.8	3.2	3.6	4.2	5.1	6.1	23.6%
Mail order	0.7	0.6	0.6	0.5	0.5	0.6	-2.8%

Notes: Mail order includes mail order, phone order, and TV home shopping. The growth rates are calculated as annual averages computed over 2010-2015.