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The Rise of E-Commerce and the Local Wage Structure: Evidence from the Korean Retail Industry*

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The widespread adoption of e-commerce by households has had a significant impact on local brick-and-mortar retailers, changing the wage structure of local service workers. In this study, we examine the effect of e-commerce penetration (EP) among households on the local wage structure during the period 2011–2016. Using the novel measure of county-level EP based on consumers' credit card transactions for online shopping, we find that counties with rapid EP exhibit a broader difference in the local wage growth of skilled and unskilled workers. An increased skill wage gap can be mainly attributed to the wage gains of high-skilled workers, whereas the wages of most unskilled workers show little change. These findings suggest that the skill premium associated with e-commerce diffusion may be concentrated in urban regions where high-skilled workers are in abundance.

JEL Classification: J31, L86, O33, R11, R23
Keywords: E-Commerce, Wage, Skill, Local Labor Market, Credit Card

I. Introduction

Digital technologies have been widely adopted by not only producers but also consumers. In manufacturing, automation and robotics have changed the structure of production, affecting the wages and jobs of workers (Graetz and Michaels, 2018;

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Acemoglu and Restrepo, 2020). The introduction of broadband internet and e-commerce has drastically changed the way firms sell their products (Goldfarb and Tucker, 2019). In addition to these supply-side structural changes, the adoption of digital technologies by households has significantly transformed the structure of consumer demand. The adoption of e-commerce by consumers has changed the shopping mode from physical shopping in stores to online shopping,[1] which has negatively affected local brick-and-mortar stores. Thus, the increased adoption of e-commerce by consumers may have a significant impact on local labor markets.

In most regions, local labor markets rely heavily on location-based service industries; among these, the retail industry provides the most employment. The widespread adoption of e-commerce by consumers has made local retail services and labor markets no longer independent of digital technologies. Unlike manufacturing plants that are densely distributed in specific areas, retail stores serve consumers in every local market, and changes in the consumer demand structure, thereby affecting retailers and their workers' wages. However, to our knowledge, few studies have examined the effect of e-commerce diffusion on workers' wages in the context of the local nature of retail business.

In this study, we investigate the effect of households' e-commerce adoption on local wage structure during the period 2011–2016. The growth of online shopping has increased market competition, spurring the modernization of the retail industry, which, in turn, has changed the wage structure of workers. To understand this trend, we aim to determine the county-level household e-commerce penetration (EP) rate using confidential credit/debit transaction data. Next, we combine the county-level e-commerce measure with local wages by skill type. We define the skill level (high vs. low) for three skill types (education, occupation, and age). In the empirical analysis, we examine (i) whether household e-commerce adoption has an uneven wage effect among workers based on their skill levels and (ii) the implications on the distribution of the skill wage differential across regions.

We find that the effect of household EP on the local wages of retail workers is heterogeneous depending on their skill levels. However, the average wage increase among retail workers is not evident. Across all three skill types—education, occupation, and age—EP has a positive effect on the wages of high-skilled workers relative to those of low-skilled workers. The estimation results indicate that a 1% increase in EP raises the wages of high-education workers by 1.60% relative to those of low-education workers. All three skill types also have independent effects on wage premium. This makes the skill premium significantly high for high-skilled workers classified as high-skilled under two or more out of three skill types.

[1] In addition to saving travel costs, the adoption of online shopping also increases consumer benefits by lowering prices (Brynjolfsson and Smith, 2000; Orlov, 2011) and expanding product variety (Yang, 2013; Dolfen et al., 2017; Quan and Williams, 2018).

Our findings also have implications for the skill premium distribution across regions. Through accounting analysis, we show that the increase in skill premium driven by e-commerce adoption might be concentrated in urban regions where very high-skilled workers are abundant and the speed of e-commerce diffusion is faster. Hence, apart from urban-specific environments that encourage online-friendly firms, as discussed by Forman et al. (2012), the average wage of retail workers might increase faster in urban regions due to the abundance of skilled workers. Lastly, we propose that the differing reactions of retailers by size can be one of the drivers of the heterogeneous wage effect. We find that the positive wage effect is estimated only among firms with more than 100 workers. We also posit that a larger firm size implies a higher wage effect for skilled workers but not for unskilled workers. All our results on the heterogenous wage effects are consistent across various robustness checks: county-level analysis, alternative definitions for skilled workers and EP, and alternative specifications using Bartik-like instrumental variables (BIVs) to address endogeneity concerns.

Our findings contribute to the growing literature on the labor market effects of e-commerce diffusion. Unlike most previous studies focusing on the destruction of offline retail employment (Chava et al., 2018; Gebhardt, 2018), we provide evidence of the effect of e-commerce on the skill wage premium in local labor markets. We also contribute to the literature by improving the measurement of e-commerce diffusion. For example, Chava et al. (2018) use distance from Amazon's fulfillment centers as a proxy for demand for local e-commerce demand. Gebhardt (2018) uses the geographic variation of broadband access in German municipalities to measure the effect of online competition on offline competition. These studies use various proxy variables for e-commerce diffusion because of the lack of a direct measure for e-commerce spending across geographic markets. To overcome this issue, our study provides county-level online spending shares based on credit card transaction data.

Our findings are also related to studies on regional differences in wage and productivity. Most urban studies focus on the agglomeration effect (Glaeser and Mare, 2001; Ciccone, 2002; Combes et al., 2008; D'Costa and Overman, 2014). Firms and workers in urban areas are more productive and highly paid because larger cities and urban areas promote interactions among firms and workers, thereby increasing productivity. Another channel is that stronger competition in urban areas makes more productive firms survive. This selection or sorting process determines firm characteristics, such as larger firm size, in urban areas. Our findings contribute to the literature by providing evidence that the rapid diffusion of new technologies can affect the urban advantage in local service industries, resulting in the widened regional wage differential (Forman et al., 2012). Our findings also suggest the need for place-based policies for low-density areas in response to technological changes.

Finally, our findings are broadly related to the literature on skill-based technological change (SBTC). Most previous SBTC studies focus on the effect of new technologies on the skill wage premium *within* manufacturing firms or industries. Workers who have skills that complement new production technologies become more productive and better paid (Autor et al., 1998; Krusell et al., 2000). Our study provides new SBTC evidence in the context of *local service industries*. In response to the increased competition due to the household adoption of online shopping, local brick-and-mortar stores may focus on improving their distribution efficiency and customer services, thereby affecting the relative demand for skilled workers and their wages. However, not all retail stores may react the same way, depending on their firm characteristics (e.g., store size) and local economic conditions (e.g., skill abundance). Unlike within-firm SBTC in manufacturing, households' technology adoption may affect the demand for skilled workers and their wages through between-firm changes in local labor markets.

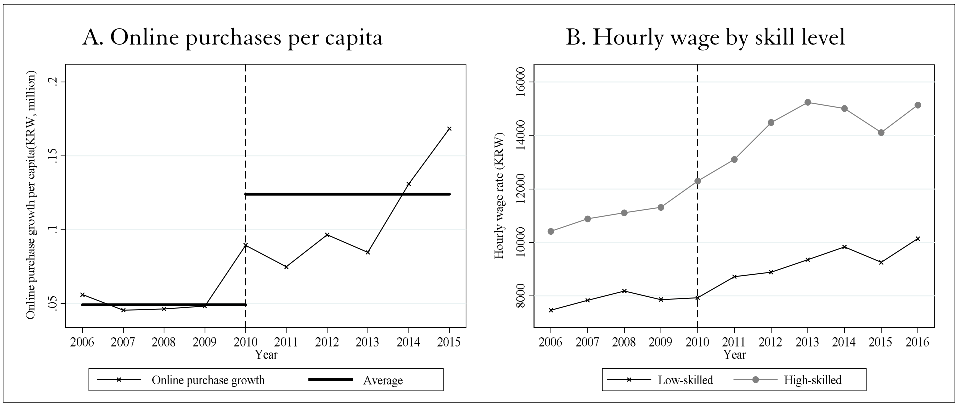
The remainder of this paper is organized as follows: Section 2 briefly reviews the diffusion of e-commerce in South Korea and the wage growth in the retail industry. Section 3 describes our dataset. Section 4 presents our empirical results and findings and discusses theoretical underpinnings. Section 5 presents the robustness checks for the results. Section 6 concludes.

II. E-Commerce and Wages in Retail Industries

The retail industry (e.g., retail stores and restaurants) accounts for the largest proportion of the local economy and jobs. A common misconception is that technological changes are irrelevant to the retail industry. However, in the past decades, rapid technological innovations have significantly transformed the production process of the retail industry (Basker, 2012). The barcode scanning system, point-of-sale system, and supply chain management are typical examples of such innovations. Moreover, the recent advent of e-commerce has induced a fundamental transformation in the retailing business. As consumer demand shifts from offline to online shopping, the power of physical stores in geographic markets has substantially weakened. This, in turn, has induced the organizational and business transformation of offline retailers, involving increasing sales service content and creating an online connection with consumers. The share of the online sales of large chain stores has increased more than two times in the period 2010–2015, reaching approximately 30% in 2015 (Chun et al., 2020).

In Korea, online shopping has steadily grown since 2000, but its growth began accelerating after 2010. Panel A in Figure 1 shows that the growth of average monthly online purchases per capita was about KRW 0.05 million (approximately USD 50) in the period 2006–2010 and KRW 0.12 million (approximately USD 120) in the period 2011–2016. In Korea, large chain stores (e.g., hypermarkets) were a fast-growing retail form before 2010 (Cho et al., 2023), but since then, their

[Figure 1] Growth of E-commerce and Wage Gap by Skill Level

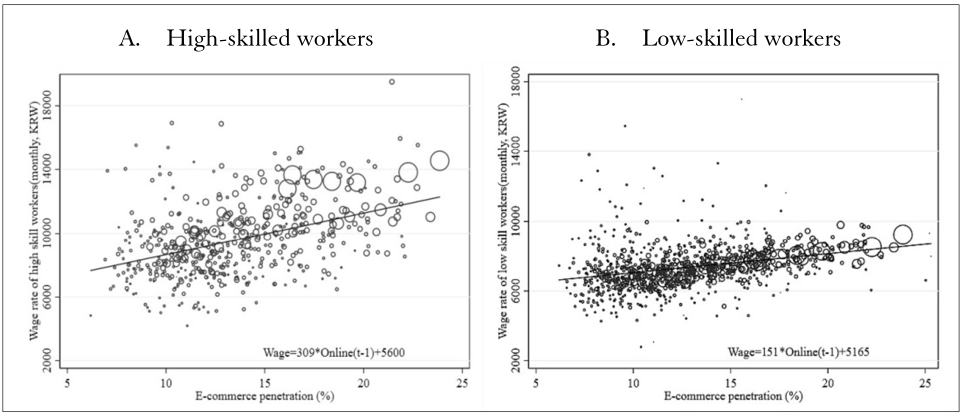


Notes: In Panel A, the average growth of monthly online purchases per capita is obtained from the *Survey on Internet Usage*. The two horizontal lines in Panel A represent the (2006–2010) and (2011–2016) averages of online purchases, respectively. In Panel B, we define high-skilled workers as those with two or more skill factors out of the three skills (education, occupation, and age). The three high-skill factors include university graduate degree (in terms of education), office tasks (in terms of occupation), and young age (25–45). Worker characteristics and hourly wages are obtained from the *Survey on Labor Conditions by Employment Type*.

growth has slowed down. Instead, online retailing has become the fastest-growing retail format. The high share of online shopping in Korea can be attributed to having the world's fastest internet connection, low shipping costs due to the country's relatively small size, and high population density. In particular, low shipping costs are one of the critical factors responsible for the nationwide spread of online sales (Ghezzi et al., 2012) because they enable new online retailers to enter the retail market easily due to the low cost of developing a nationwide transportation and logistics system. Moreover, since 2010, the intensified competition among online retailers and the widespread diffusion of mobile devices accelerated the speed of e-commerce diffusion.

Panel B in Figure 1 shows the wage growth trend of low- and high-skilled workers for the period 2006–2016. We define high-skilled workers as those with more than two of the three conventional high-skill factors. All other workers are defined as low-skilled workers. The three high-skill factors include university graduate degree (in terms of education), office tasks (in terms of occupation), and young age (25–45 years). The wage gap between high- and low-skilled workers was KRW 2,946 and 4,998 in 2006 and 2016, respectively, showing a 69.65% increase in a ten-year period. The gap began to increase around 2010 with the rapid development of e-commerce.

[Figure 2] E-Commerce Diffusion and Retail Wage by Skill Level



Notes: The hourly wages of retail workers are computed using the *Local Area Labor Force Survey*. We deflate the nominal wage using the county-level consumer price index (CPI). The EP rate is defined as the share of online purchases out of the total sales in the retail trade (KSIC 47) or food and beverage service activities (KSIC 56). The size of the marker in the two panels reflects the population size of the regions.

Figure 2 presents the relationship between workers' wages and e-commerce diffusion based on worker skill level. For all 162 counties, we used credit/debit transaction data to measure the EP rate, defined as the share of online purchases out of total expenditure on retail goods and food and beverage service activities.[2] Panels A and B show the scatter plot of the county-level EP and the wage rate for high- and low-skilled workers, respectively. The size of markers in each panel represents the population of each county. Figure 2 shows that the slope of the fitted line of high-skilled workers is approximately two times steeper than that of low-skilled workers. The wages of high-skilled workers are also much more widely dispersed than those of low-skilled ones. This implies that technological changes related to e-commerce diffusion may change the nature of tasks and types of occupations more significantly for high-skilled workers than for unskilled workers. Finally, counties with larger populations are, on average, located on the top right part of the scatter plot. In particular, high-skilled workers in large cities with high EP obtain higher wages, showing a large deviation from the prediction line. By contrast, the wages of low-skilled workers tend to be densely distributed around the fitted line regardless of county size. In summary, as Figure 2 shows, the wages of high-skilled workers are more sensitive to e-commerce diffusion, which can be related to location-specific factors. In other words, the wage effect of e-commerce diffusion is disproportionally felt across regions.

[2] We discuss EP in detail in Section 3.

III. Data and Variables

3.1. E-commerce Penetration

To construct a measure of EP among households, we utilized credit/debit card transaction data provided by a credit card company.[3] The card data included approximately 35 billion transactions, comprising both online and offline purchases, from 2010 to 2015. Each transaction included information on the purchase amount and date, card type (credit/debit), merchant's address and industry classification, and the cardholder's address and socio-demographic characteristics.

In this study, we classified transactions as online purchases if a merchant's industry classification is e-commerce. Offline transactions were defined as all purchases made with merchants with an industry classification of retail trade (KSIC 47; except for non-store retailers) or food and beverage service activities (KSIC 56).[4] To identify county-level online and offline purchases, we determined the location of the transactions. For offline purchases, we used the address of the offline merchant as the transaction location. Unlike offline purchases, the addresses of online merchants do not imply the location of transactions. As such, we used the cardholders' (i.e., consumers') addresses as the transaction locations.

After defining the type (online and offline) and location of the credit/debit card purchases, we constructed the EP variable for county j in year t as follows:

$$EP_{j,t} = \frac{Online\ Purchase_{j,t}}{Online\ Purchase_{j,t} + Offline\ Purchase_{j,t}} \tag{1}$$

This county-level measure of EP represents the extent to which consumers have adopted digital technologies in shopping. The adoption of such digital technologies has led consumer demand to shift from brick-and-mortar stores to online stores, thereby changing the structure of the local retail industry.

Previous studies have also sought to measure the geographic variation of e-commerce adoption among consumers in various ways. For example, Gebhardt (2018) uses the geographic variation of broadband internet availability, while Chava et al. (2018) employ consumers' distance from Amazon fulfillment centers. Given

[3] The name of the credit card company is confidential. However, the company has a stable and large enough market share to represent nationwide credit card/debit transactions. The transaction data covers all provinces in Korea, except for the Gangwon (mountain area) and Jeju (island) provinces. However, these two provinces account for only 3% of the total population.

[4] We included food and beverage service activities (KSIC 56) because the online purchase of convenience foods and groceries can be considered a substitute for consumers' going to restaurants. We obtained similar results when we narrowly defined offline purchases for only retail trade (KSIC 47; except for non-store retailers).

that consumers' e-commerce adoption can be affected by broadband internet availability and merchandise delivery speed, these proxy variables can measure geographic variations in consumers' e-commerce adoption but not measure the full extent of consumers' actual adoption of e-commerce. In this respect, our EP variable can measure the geographic variations in consumers' e-commerce adoption more accurately than the proxy variables used in previous studies.

3.2. Wages and Skills

To analyze workers' wages based on their skill level, we utilized the *Local Area Labor Force Survey* (LALFS) for the period 2011–2016. The LALFS is a bi-annual cross-sectional survey conducted by *Statistics Korea*. The LALFS provides worker-level information on monthly wage and salary, weekly working hours, gender, age, education, and occupation. The survey also includes workers' (county-level) residence and job locations, enabling us to determine the county-level wage by skill level.[5] To the best of our knowledge, the LALFS is the only survey that provides county-level location information on workers, unlike other Korean labor surveys that provide only province-level location information.

The hourly wage rate is defined as the monthly wage and salary divided by (4.34 × weekly working hours). To calculate the real wage, the nominal wage is deflated by the county-level consumer price index. To investigate the heterogeneous effect of e-commerce diffusion on wage by skill level, we utilized multiple criteria for defining skill types. A single skill type may not be enough to capture the effect of e-commerce on the wage structure of the local service industry. Thus, we considered three skill types: education level, occupation, and age. For each skill type, we further divided the workers into two groups depending on whether they possessed human capital that favors their use of e-commerce technology. In this sense, we classified e-commerce-friendly groups as "high-skilled." Regarding education, a high-skilled worker refers to a worker with a university degree or more. Regarding the occupation skill type, a high-skilled worker refers to a worker whose occupation is neither a salesperson nor an elementary worker. These two occupations in the retail sector mainly involve simple and routine tasks. We defined workers aged 25–45 years as high-skilled workers because workers in this age group are more capable of using Internet technologies and can therefore easily adapt to new tasks or technological environments.[6]

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[5] The LALFS also provides sample weights to calculate the county-level averages of wages.

[6] Given that workers aged 25–45 years account for a significant proportion of retail employees, it would be crude to refer to this group as "high-skilled." However, this paper aims to determine which types of workers benefited from the arrival of e-commerce. We did not seek to determine whether high-skilled workers, as defined by predetermined criteria, benefit from e-commerce.

[Table 1] Employment and Wage by Skill Level, 2011–2016

Skill type	Skill level (share, %)	Wage (unit: KRW)			
		Mean	Std. dev.	P10	P90
Education	High (20.03)	10,171	5,379	4,757	17,518
	Low (79.97)	7,706	3,300	4,563	11,667
Occupation	High (18.32)	11,336	5,323	5,856	18,629
	Low (81.68)	7,491	3,172	4,413	11,521
Age	High (51.36)	9,125	4,311	4,904	14,687
	Low (48.64)	7,368	3,508	4,261	11,432

Notes: All figures are estimated using 37,011 worker-level observations in the *LALFS*.

Table 1 presents the summary statistics of workers by skill level for the three skill types of education, occupation, and age. In a county, the average share of high-education workers in the retail trade sector was 20.03% during the sample period of 2011–2016. The shares of high-skilled workers in terms of occupation and age were 18.32% and 51.36%, respectively. The low share of high-skilled workers in the retail industry indicates that employees in the production process mainly consist of unskilled workers, such as sales workers with a low education level. The average hourly wage rate of high-education workers was KRW 10,171 (approximately USD 10), while that of low-education workers was KRW 7,706 (approximately USD 8). The wage of high-education workers was 31.99% higher than that of low-education workers. The wage differences between high and low skill levels in terms of occupation and age were 51.33% and 23.85%, respectively.

3.3. Control Variables

We utilized a wide set of control variables, such as county population. We also employed control variables that addressed possible differences in the composition of workers across counties. These control variables included the county-level share of male workers and the county-level average age and work experience of workers. Wages are affected not only by worker characteristics but also by employer characteristics. Thus, we utilized employer size as a control variable, which is the only employer-related characteristic included in the LALFS. To control for local labor market conditions, we used the county-level employment rate. Using the *Census of Establishments*, we determined the county-level establishment entry and exit rates, which also affect the local wage structure.

3.4. Summary Statistics

To construct the regression sample dataset, we computed the average real wage rate for each skill group × county × year cell from the LALFS. The eight skill groups consisted of two skill levels (high or low) for each of the three skill types (education, occupation, and age). Table 2 presents the summary statistics of the hourly real wage rate, the EP rate, and the control variables. Both the e-commerce and control variables were lagged by one year. During the sample period of 2011–2016, the average county-level hourly real wage rate was KWR 7,993 (approximately USD 8). The figure is close to the average wage of low-skilled workers, as shown in Table 1. This confirms that the local retail industry mainly employs low-skilled workers. The average EP rate among households was 14%. Although the EP rate increased rapidly during the sample period, it showed a substantial cross-regional variation.

[Table 2] Descriptive Statistics

	Unit	Mean	Std dev.	P10	P90
Panel A. Main variables					
Wage	KRW	7,993	2,055	6,158	10,405
EP rate	[0,1]	0.14	0.04	0.10	0.20
Panel B. Control variables					
Number of entering firms	Log	7.84	1.76	5.39	10.19
Number of exiting firms	Log	7.77	1.78	5.34	10.06
Population	Log	16.68	1.76	14.25	18.96
Retail employment share	[0,1]	0.08	0.02	0.06	0.10
Work experience	Year	3.39	1.54	1.88	5.13
Age of workers	Year	38.23	5.88	32.01	46.31
Share of large-firm workers	[0,1]	0.12	0.12	0.00	0.26
Share of male workers	[0,1]	0.64	0.83	0.42	0.85

Notes: The sample includes 2,190 observations of skill-county-year cells.

IV. Empirical Results

4.1. Empirical Specification

To investigate the effect of e-commerce on the wage gap based on skill level in the local service sector, we utilized the following wage regression equations:

$$\begin{aligned}\log(W_{g,j,t}) = {} & \beta EP_{j,t-1} + \beta_s EP_{j,t-1} H_s + X_{j,t-1}\gamma + Z_{g,j,t-1}\delta + \psi_j + \upsilon_t \\ & + \xi_{g,t} + \phi_{k,t} + \varepsilon_{g,j,t}\end{aligned} \tag{2}$$

where $\log(W_{g,j,t})$ is the log of the average real wage rate of skill group (g) in county j at year t. As discussed, each county has eight skill groups (g)

consisting of two skill levels (high or low) for each of the three skill types (s) (education, occupation, and age). The main explanatory variable $EP_{j,t-1}$ refers to the EP rate of the households in county j at year $(t-1)$. H_s is a dummy variable that equals 1 if each of the three skill types (s) in skill group (g) belongs to the high-skill level. Regarding the wage effect of e-commerce, the coefficient β_s captures the additional wage gains of the high-skill group under each skill type. If e-commerce neither widens nor narrows the wage gap based on skill level, the coefficient β_s is either zero or statistically insignificant.

$X_{j,t-1}$ is the vector of the county-level control variables. $X_{j,t-1}$ includes the log population, log number of entering and exiting establishments, the share of workers employed at firms with more than 100 employees, and employment rate. $Z_{g,j,t-1}$ represents the group of county-level control variables, including average work experience, age, and the ratio of male workers for each skill group in a county. All explanatory variables were lagged by one year. We included a set of fixed effects to control for macro-economic shocks and other possible confounding factors, such as the year fixed effects (v_t), county fixed effects (ψ_j), skill group by year fixed effects $\xi_{g,t}$, and province(k)-specific trend $(\phi_{k,t})$. $\varepsilon_{g,j,t}$ represents the county-clustered errors. The regressions were weighted by the number of workers within each skill-county-year cell. In the estimation, observations (skill-county-year cells) with fewer than three workers were dropped.

4.2. Effects on Local Wage by Skill Level

Main Results

Table 3 presents the estimates of equation (2). The regression results indicate the effect of the EP on the local wage structure by skill level. All regressions included control variables and a set of fixed effects. To examine the heterogeneous wage effects by skill level, columns (1)–(5) included the cross-product of the EP rate and the high-skill dummy variables. The positive coefficients of the high-skill (cross-product) variables represent the wage gains of high-skilled workers relative to their low-skilled counterparts. In column (1), the estimate of the high-education (cross-product) variable is 1.60 and statistically significant at the 1% level. This implies that a 1%p increase in EP raises the wages of high-education workers by 1.60% relative to the wages of low-education workers. In other words, during the sample period 2011–2016, the EP grew by 7%p on average, thereby widening the education wage gap by 11.20% (=1.60×7).

High-skill wage effects are also observed in the other skill types. Columns (2) and (3) show that the coefficient estimates of the high-skill group under the occupation and age skill types are 2.11 and 0.68, respectively. Both coefficients are significant at the 1% level with different magnitudes. The coefficient of office workers (high-

[Table 3] Effects of E-commerce Penetration on Local Wage by Skill Level

	Dependent variable: Log (Real hourly wage)				
	(1)	(2)	(3)	(4)	(5)
E-commerce	0.17	0.15	0.03	-0.07	-0.16
	(0.67)	(0.66)	(0.66)	(0.68)	(0.69)
× High skill (Education)	1.60***			1.32***	
	(0.26)			(0.26)	
× High skill (Occupation)		2.11***		1.86***	
		(0.23)		(0.22)	
× High skill (Age)			0.68***	0.33**	
			(0.15)	(0.16)	
× Middle-skilled					0.73***
					(0.15)
× High-skilled					1.98***
					(0.20)
Adj. R-squared	0.76	0.77	0.76	0.77	0.76
Observations	2,190	2,190	2,190	2,190	2,190

Notes: The dependent variable is the log of the real hourly wage rate. Regressions are weighted by the number of workers within each skill-county-year cell. County, year, skill-year, province-year fixed effects, and control variables are included in all columns. County-clustered standard errors are presented in parentheses. ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

skilled workers in terms of occupation) is slightly larger than that of high-education workers, whereas that of younger workers is smaller than that of the high-skilled group under the education skill type. Column (4) shows that all three skill types have coefficients with statistical significance of similar magnitudes, except for the coefficient for the age skill type. This suggests that the remaining two skill types (i.e., education and occupation) have different magnitudes of skill, thereby widening the skill wage gap in response to an increase in EP. The age factor, however, seems closely related to the other skill types.

The high-skill variable in column (5) is measured by the number of high-skill classifications among the three skill types. Workers are defined as high-skilled if they are classified as high-skilled for two or more skill types and middle-skilled if they are classified as high-skilled for one skill type. The remaining workers are classified as low-skilled workers. The coefficients of the middle- and high-skilled workers are 0.73 and 1.98, respectively, implying that wage gains increase with the skill level of workers. In summary, Table 3 shows that the growth of EP among households widened the wage gap based on skill level in the local retail sector. This increased wage gap associated with e-commerce is observed across all three skill types: education, occupation, and age. Given that most retail workers are low-skilled for each skill type, the findings presented in Table 3 indicate that the widened wage gap can be mainly attributed to the wage increase of high-skilled workers, who make up a small proportion of the overall employment. In the next sub-section, we examine the regional distribution of high-skilled workers and the resultant disproportional wage effect across regions.

Quantifying the Regional Wage Differential

Table 3 shows that the positive wage effect of e-commerce diffusion is concentrated among skilled workers, who account for a relatively small proportion of the whole retail industry. Given that most retail workers are immobile across local labor markets, this disproportional wage effect among workers can lead to heterogeneous wage effects across local labor markets. In other words, many local labor markets that have relatively few high-skilled workers may experience little average wage growth, while the positive wage effect is concentrated only in a few high-skill-abundant regions. Thus, we focused on the heterogeneous wage effect across urban and non-urban areas.

[Table 4] E-commerce and Workers and Wages by Skill Level, 2011 and 2016: Urban versus Non-urban Areas

	Urban		Non-urban	
	2011	2016	2011	2016
A. E-commerce penetration	12.22	19.11	9.48	15.44
B. Worker composition				
Low-skilled	31.25	34.48	39.27	49.13
Middle-skilled	42.41	36.90	47.05	37.47
High-skilled	26.34	28.62	13.68	13.41
C. Worker wage by skill level				
Low-skilled	6,435	7,385	6,230	7,333
Middle-skilled	7,329	8,423	6,793	7,962
High-skilled	10,162	11,440	8,477	9,485
(Average)	7,796	8,928	6,802	7,857

Notes: The figures represent the share of workers by skill level measured by the number of high skills in three skill types for urban and non-urban areas. Workers are defined as high-skilled if they are classified as high-skilled for two or more skill types and middle-skilled for one skill type. Low-skilled workers include the rest. Urban areas consist of seven metropolitan cities and eight cities with a large population in Gyeonggi province; the rest are non-urban areas.

Panel A of Table 4 shows that in 2011, the EP rate in urban areas (12.22%) was higher than that in non-urban areas (9.48%). During the sample period, the EP in urban areas increased by 6.89%, while that in non-urban areas increased by 5.96%. Both the high EP in the initial year and the high growth rate of EP in urban areas imply that retailers in urban areas may experience more pressure to change their way of doing business. The share of high-skilled workers was also larger in urban areas. Panel B shows that the share of high-skilled workers in urban areas increased by 2.28%, that is, from 26.34% in 2011 to 28.62% in 2016. The pattern is quite different from that in non-urban areas, where the share of high-skilled workers decreased by 0.27% despite the low initial level of 13.68% in 2011. The heterogeneous conditions of the two local labor markets shown in Table 4 may have resulted in the differences in the wage effect due to e-commerce diffusion. In other words, the estimated wage effects in Table 3 vary across workers with different skill levels but not across regions. However, the regional differences in skill composition and EP rate may induce heterogeneous wage effects across regions.

The estimated growth effect on the average wage in a certain region and the subsequent regional wage differential across urban and non-urban areas can be expressed as follows:

$$\widehat{\Delta W_r} = \sum_g C_r^g = \sum_g \overline{S}_{gr}\,\widehat{\Delta W_{gr}} = \sum_g \overline{S}_{gr}(\overline{W}_{gr}\hat{\beta}_g \Delta EP_r) \tag{3}$$

$$DF = \widehat{\Delta W_u} - \widehat{\Delta W_n} = (C_u^L - C_n^L) + (C_u^M - C_n^M) + (C_u^H - C_n^H) \tag{4}$$

where r belongs to a set of regions, urban (u) and non-urban (n) areas, and g is the three skill groups of workers (low, L; middle, M; high, H), as in column (5) of Table 3 and Panels B and C of Table 4. In equation (3), $\widehat{\Delta W_r}$ is the estimate for the e-commerce-induced wage growth in 2011–2016, which is the sum of the contribution by worker group g in region $r(C_r^g)$. The contribution of each group is the employment share $(\overline{S}_{gr})$ weighted sum of the average wage effect in group r, $(\widehat{\Delta W_{gr}})$. We calculate $\widehat{\Delta W_{gr}}$ by multiplying $\overline{W}_{gr}, \hat{\beta}_g$, and ΔEP_r. $\overline{W}_{gr}$ is the average wage of worker group g in 2010. ΔEP_r is the percentage point change in the online penetration rate in region r in the period 2010–2015. Lastly, $\hat{\beta}_g$ is the point estimate from column (5) in Table 3. In equation (4), the e-commerce effect on regional wage differential (DF) can be expressed as the sum of the differences in the wage effect (by skill group) in urban and non-urban areas.

The results in Table 5 show that the regional wage differential can widen as e-commerce penetrates the local labor market. In Table 5, we divided both the left- and right-hand sides of equation (3) by the average wages in urban and non-urban areas in 2011 to convert all figures into contribution rates. Table 5 also shows the estimates when we used the average employment of each worker group as weights to account for the worker composition changes by e-commerce diffusion.

The results in Table 5 show that the low-skilled-abundant regions may experience a lower wage growth rate due to e-commerce diffusion. The benefit of e-commerce diffusion in terms of increases in workers' wages is mostly observed among high-skilled worker groups in urban areas. For low- and middle-skilled workers in urban and non-urban areas, a statistically significant wage effect is not found. The wage effect for high-skilled workers is statistically significant both in urban and non-urban areas. Thus, the e-commerce-driven regional wage differential can be mostly explained by the different wage effects on high-skilled workers. The magnitude of the estimates is slightly larger when we used the average employment share as weights, reflecting the heterogeneous growth pattern in the share of high-skilled workers, as in Table 4. In summary, the results in Table 5 imply that the skill-biasedness of e-commerce technology can lead to a disproportional welfare effect across local labor markets with different skill compositions.

[Table 5] E-Commerce and Wage Growth, 2011–2016: Urban versus Non-urban Areas

			By Skill level		
Region	Share	Total effect	Low	Middle	High
Urban	Base year	5.66	−0.25	1.73	4.18***
		(4.61)	(1.08)	(2.03)	(1.57)
	Average	5.66	−0.30	1.47	4.48***
		(4.63)	(1.28)	(1.73)	(1.68)
Non-urban	Base year	3.38	−0.31	1.71	1.97***
		(4.05)	(1.35)	(2.01)	(0.74)
	Average	2.88	−0.38	1.44	1.83***
		(3.99)	(1.65)	(1.69)	(0.69)
Difference	Base year	2.28***	0.06	0.02	2.21***
(=Urban − Non-urban)		(0.59)	(0.26)	(0.02)	(0.82)
	Average	2.77***	0.09	0.03	2.66***
		(0.68)	(0.37)	(0.04)	(1.00)

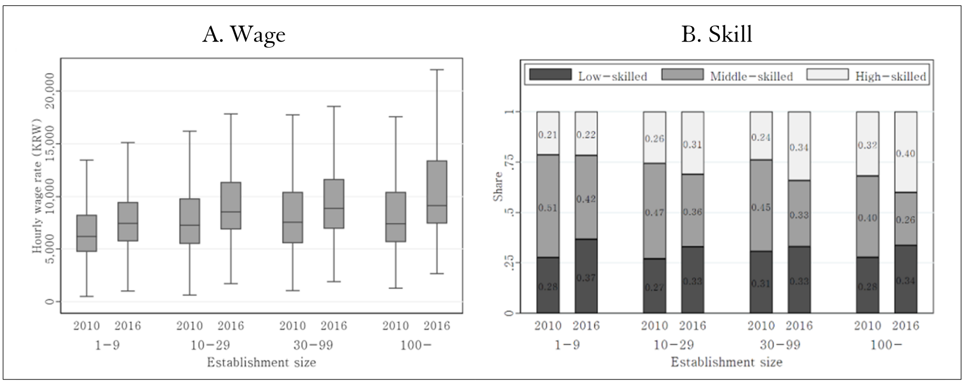
Notes: Each figure shows the contribution rate of skill groups to the wage growth effect induced by e-commerce diffusion. Workers are defined as high-skilled if they are classified as high-skilled for two or more skill types and middle-skilled for one skill type. Low-skilled workers include the rest. Urban areas refer to seven metropolitan cities and eight cities with a large population in Gyeonggi province; the rest are non-urban areas. The employment share of each worker group in a certain region is calculated in two ways: the employment share in 2010 (base year) and the average of the employment share in 2011–2016. ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

4.3. Theoretical Discussion

In this subsection, we discuss theoretical explanations for a possible channel of the skill wage differentials. The rapid diffusion of e-commerce has increased competition among retailers, resulting in the exit of small and less productive firms (Goldmanis et al., 2010; Vitt, 2017; Cambini and Sabatino, 2022). In the United States, Chava et al. (2018) find that small stores are more likely to exit than large stores in e-commerce-affected areas. Consistent with these findings, the *Census on Establishments* registered an increase in the average establishment size in the Korean retail industry from 2.46 to 2.61 workers in the period 2010–2016. This suggests that the restructuring and reallocation process may result in changes in the wage structure due to the rapid diffusion of e-commerce.

To cope with the increased competition from e-commerce, surviving local brick-and-mortar stores may focus on improving their distribution efficiency and customer services. This can increase the relative demand for skilled workers, thereby increasing their wages.[7] However, not all retail stores may respond this way. For example, some retailers have appropriately responded, whereas many other small stores, having failed to do so, have shut down their businesses. This suggests that the skill wage premium may be concentrated among large retailers only. To test this channel, we examine how the skill wage differential driven by e-commerce is related to establishment size.

[Figure 3] Wage and Skill Distribution by Establishment Size



Notes: In Panel A, box plots represent the wage distribution by establishment size in 2010 and 2016. The horizontal line in a box indicates the median wage. The upper and lower hinges indicate the 75th and 25th percentile values. The upper (lower) whisker is defined as the 3rd (1st) quartile plus (minus) 1.5×IQR (interquartile range). In panel B, high-skilled workers refer to those with two or more skill factors out of the three skills; middle-skilled workers, with one skill factor; and low-skilled workers, with no skill factor.

Figure 3 shows a change in wage distribution and skill composition according to establishment size. In panel A, the largest wage dispersion occurs in establishments with 100 or more workers. Such a large wage dispersion in these establishments is mainly attributable to high-wage workers rather than low-wage workers. The lower adjacent values and P25 values are similar across all establishment sizes, while the upper adjacent values and P75 values are significantly high in establishments with

[7] The rise of e-commerce startups that use web-based technologies may have a higher demand for skilled workers than brick-and-mortar stores (Mandel, 2017; Behl, 2019). This can increase the wage of skilled workers in the retail sector, also potentially affecting the skill wage premium in brick-and-mortar stores.

100 or more workers, particularly in 2016. Panel B presents the change in skill composition by establishment size between 2010 and 2016. The increase in the share of high-skilled workers becomes prominent as the establishment size grows. On the contrary, micro-sized firms (1–9 workers) exhibit a very minor increase in their share of high-skilled workers.

[Table 6] Effects of E-commerce on Local Wage by Skill Level and Establishment Size

	Dependent Variable: Log (Real hourly wage)		
	(1)	(2)	(3)
E-commerce	−0.54	−0.65	−0.29
	(0.69)	(0.71)	(0.68)
× (Establishment size: 10–29)	−0.27	−0.28	−0.34*
	(0.19)	(0.19)	(0.20)
× (Establishment size: 30–99)	0.24	0.22	0.08
	(0.23)	(0.22)	(0.22)
× (Establishment size: 100+)	0.75***	0.71***	−0.17
	(0.10)	(0.11)	(0.14)
× High-skilled		1.14***	−0.10
		(0.16)	(0.67)
× (Establishment size: 10–29) × High-skill			0.04
			(0.20)
× (Establishment size: 30–99) × High-skill			0.57**
			(0.23)
× (Establishment size: 100+) × High-skill			1.14***
			(0.11)
Adj. R-squared	0.72	0.73	0.74
Observations	2,365	2,365	2,365

Notes: The dependent variable is the log of the real hourly wage rate. High-skill is the dummy variable that indicates workers who are classified as high-skilled for two or more skill types. Regressions are weighted by the number of workers within each skill-county-year cell. County, year, skill-year, province-year fixed effects, and control variables are included in all columns. County-clustered standard errors are presented in parentheses. ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

Using workplace size information in the LALFS, we ran regressions to examine whether the skill wage differential due to the diffusion of e-commerce varies depending on establishment size. Column (1) of Table 6 shows that the diffusion of e-commerce has a positive wage effect only for workers at large establishments. This wage effect on large establishments does not disappear even though the high-skilled dummy is included in column (2). Column (3) shows that the skill wage premium is observed in medium-sized and large establishments, but not in small establishments. Table 6 indicates that the skill wage differential driven by the diffusion of e-commerce is mainly concentrated in larger retailers. This finding suggests that larger retailers have more actively responded to the increased competition driven by e-commerce than smaller ones. Overall, the findings in Table 6 suggest that the increased skill wage differential can be closely related to offline retailers' strategic responses to the expansion of online retailers.

V. Robustness

We performed a wide set of robustness checks and addressed potential endogeneity problems using instrumental variables. We present in this section the county-level regression results to confirm that the wage effect can vary across regions. We also performed various robustness checks for our baseline results: (i) earnings as a dependent variable to check the hour effect, (ii) full samples without trimming the observations, (iii) an alternative measure for EP, and (iv) detailed definitions of skill levels. These robustness tests all produced qualitatively similar results.

5.1. Endogeneity

Although we included various control variables and a set of fixed effects, there may have been unobservable confounding factors. To address possible endogeneity problems, we constructed the following instrumental variable:

$$EP_{j,t}^{BIV} = \sum_{p} z_{j,p} g_{p,t} \quad \text{where} \quad z_{j,p} = \sum_{a} s_{a,j} c_{p,a} \tag{5}$$

where $z_{j,p}$ is the consumption share of product p in county j at time 0 and $g_{p,t}$ is the nationwide online consumption share of product p at time t. The instrument can capture the exogenous variation of $EP_{j,t}$ because neither the product–location share in the initial year nor the nationwide product share is related to time-varying and location-specific confounding factors. In contrast to the (typical) Bartik instrument, which is formed by the interaction between local product shares and the national product growth rate, our instrument uses the national product share rather than the growth rate. Goldsmith-Pinkham et al. (2020) define a BIV that uses the inner product structure of the endogenous variable to construct an instrument. Following the definition of Goldsmith-Pinkham et al. (2020), we also name our instrumental variable a Bartik-like instrument.

We utilized seven product types (i.e., electronics, books, clothing, hobbies, cosmetics, food, and furniture) for our analysis. As Goldsmith-Pinkham et al. (2020) state, an endogeneity issue in the Bartik instrument arises from the initial share. Thus, we estimated the product–location shares using the inner product of the nationwide product–age share $(c_{p,a})$ and the age–location shares $(s_{a,j})$.[8] We estimated the nationwide product–age share using the 2010 *Household Income and Expenditure Survey* from Statistics Korea. We also measured the age–location shares using the 2010 *Population and Housing Census*. We utilized five age categories (e.g., under 30 years, 30–39 years, 40–49 years, 50–59 years, and 60 and older).

Following Goldsmith-Pinkham et al. (2020), we checked whether the BIV was valid. More specifically, we checked whether the product consumption share of each county $(z_{j,p})$ was uncorrelated with the growth of retail workers' wages. We intended that both cross-sectional and time-series variations would be derived from different sources, $z_{j,p}$ and $g_{p,t}$, respectively. In this sense, $z_{j,p}$ should be uncorrelated with the change in our dependent variable in the second stage. All figures in Table A in the Appendix are statistically insignificant, indicating the validity of our instrumental variable.

In the 2SLS estimation, we utilized our BIV, $EP^{BIV}_{j,t-1}$, as an instrument for the endogeneous variable, EP rate $(EP_{j,t-1})$. In our baseline regression model, equation (2), the endogenous variable of $EP_{j,t-1}$ also interacted with binary skill variables (H_s). In the case of non-linearly transformed endogenous variables, $EP^{BIV}_{j,t-1}H_s$ need not be a good instrument for $EP_{j,t-1}H_s$. Following the suggestions of Angrist and Pischke (2008) and Wooldridge (2010), we also used $\widehat{EP}_{j,t-1}H_s$ as an instrument for $EP_{j,t-1}H_s$, where $\widehat{EP}_{j,t-1}$ is the fitted value of $EP_{j,t-1}$ from the first-stage regression. For the endogenous variables, $EP_{j,t-1}$ and $(EP_{j,t-1}H_s)$, a set of instruments— $EP^{BIV}_{j,t-1}$, $EP^{BIV}_{j,t-1}R_K$, and $\widehat{EP}_{j,t-1}H_s$ —was used in the 2SLS estimation, where R_K indicates the ten province dummies for a more efficient model fit.[9]

Table 7 reports the 2SLS estimates of the effect of e-commerce on wages based on skill level, which is comparable to the results in Table 3. The results for both the weak instrument test and the overidentifying restrictions test confirm the relevance and validity of our BIVs. In all columns, the EP rate that estimates the wage effect on the baseline (low-skilled) workers is statistically insignificant, while the high-skill interaction variables of all three skill types are positive and statistically significant. The magnitudes of the skill interaction variables are not significantly different from those in Table 3. Overall, the 2SLS estimation generates the same qualitative results as those in Table 3.

[8] Chun et al. (2020) provide details on how to construct BIVs.

[9] Refer to Appendix Table B for the first-stage estimation results.

[Table 7] Robustness Checks: 2SLS Estimates

	Dependent Variable: Log (Real hourly wage)				
	(1)	(2)	(3)	(4)	(5)
E-commerce	0.09	0.09	0.07	−0.25	−0.31
	(0.58)	(0.63)	(0.62)	(0.61)	(0.60)
× High skill (Education)	1.68***			1.46***	
	(0.21)			(0.20)	
× High skill (Occupation)		2.02***		1.79***	
		(0.19)		(0.19)	
× High skill (Age)			0.62***	0.29**	
			(0.12)	(0.13)	
× Middle-skilled					0.79***
					(0.15)
× High-skilled					1.91***
					(0.17)
Weak IV *F*-stat	64.08	64.11	64.06	56.49	56.50
Hansen *J*-stat	11.09	12.30	11.93	11.43	10.84
(*p*-value)	(0.60)	(0.50)	(0.53)	(0.57)	(0.62)
Number of IVs	12	12	12	14	13
Adj. R-squared	0.83	0.83	0.82	0.83	0.83
Observations	2,190	2,190	2,190	2,190	2,190

Notes: The dependent variable is the log real hourly wage rate. 2SLS estimation uses Bartik-like instruments that are formed by the interaction between county-level product shares and the nationwide online consumption shares of the corresponding product. Regressions are weighted by the number of workers within each skill-county-year cell. County, year, skill-year, province-year fixed effects, and control variables are included in all columns. Weak IV *F*-stat indicates the joint Cragg–Donald Weak IV *F*-statistics for multiple endogenous variables. County-clustered standard errors are presented in parentheses. ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

5.2. County-level Analysis

Next, we examined whether the skill wage premium in local labor markets is associated with e-commerce diffusion. In Section 4.3, we showed that e-commerce diffusion may result in disproportional wage growth between urban and non-urban areas. Here, we exploited the *county-level* variation of the average wage to confirm our previous results.

For this purpose, we regressed the county-level average wage rate on EP rate:

$$\log(W_{jt}) = \gamma_1 EP_{j,t-1} + \gamma_2 EP_{j,t-1} Urban_j + X_{j,t-1}\gamma + \psi_j + \upsilon_t + \varepsilon_{gjt} \tag{6}$$

where the dependent variable is the log of the average real hourly wage rate in county j at year t. The main explanatory variable is the same as the baseline specification, i.e., the EP. Our parameter of interest is γ_2, which shows us the additional wage effect in urban areas $(Urban_j)$. $Urban_j$ is equal to 1, if a county j belongs to an urban area; otherwise, it is 0. We present our regression results using another dummy variable that has a value of 1 for regions with a smaller proportion of the older population (aged more than 60 years) in 2010 to confirm that the wage effect is prominent in regions where more of the households have adopted e-commerce. $X_{j,t-1}$ is the vector of county-level control variables also used in equation (2). v_t and ψ_j indicate the year and county fixed effects, respectively. All observations are weighted by the number of retail workers in each county in the prior year.

[Table 8] County-level E-commerce Effect and Heterogeneity

	Dependent variable: Log (County-level wage)		
	(1)	(2)	(3)
E-commerce	1.15***		
	(0.46)		
× Urban areas		0.98**	
		(0.47)	
× Non-urban areas		0.48	
		(0.62)	
× Cities with old population share (< p50)			1.04***
			(0.47)
× Cities with old population share (≥ p50)			0.38
			(0.56)
Adj. R-squared	0.76	0.76	0.76
Observations	787	787	787

Notes: The dependent variable is the log of the average real wage in each county. Regressions are weighted by the number of workers within each county. County- and year-fixed effects and control variables are included in all columns. Urban areas refer to seven metropolitan cities and eight cities with large populations in Gyeonggi province; the rest are non-urban areas. The old population share is calculated using the figures in the base year 2010. County-clustered standard errors are presented in parentheses. ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

Table 8 presents the estimates from equation (6). The results in column (1) show that a 1% increase in EP rates causes the average hourly wage rate to increase by 1.15% annually. The results in columns (2) and (3) indicate that this wage increase is mainly limited to urban areas and/or cities populated with young people. Columns (2) and (3) represent the total wage effect in two different areas, $(\gamma_1+\gamma_2)$ and γ_1, and show that statistical significance is found only in urban areas and cities with younger people. In column (2), the wage effect is larger by 0.50% for urban areas, which is quite similar to the annualized effects on the regional wage differential in column (1) in Table 5: 0.46% (=2.28/5) and 0.55% (=2.77/5).[10] These results are consistent with the baseline wage effect based on skill level in Table 3, where the wage effect based on the cross-regional variation across skill groups is partially included. The results in column (3) seem qualitatively the same as those in Column (2). This implies that young consumers in urban areas adopt e-commerce more, which may lead to the structural transformation of local retail stores. The results in Table 8 support the finding that e-commerce diffusion generates an unequal skill wage premium across regions.[11]

5.3. Further Robustness Checks

We conducted several robustness checks to confirm that our main findings remain consistent when we change our empirical specifications in various ways. For this purpose, we (i) changed the dependent variable to monthly earnings, which we obtained by multiplying working hours with our baseline dependent variable, i.e., hourly wages, (ii) utilized full samples without trimming cells with a small number

[Table 9] Further Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)	
		Additional effect for high skill					Adj. R-squared
	Base	Edu.	Occ.	Age	Middle	High	[Observations]
A. Effect on	0.32	1.26***	1.04***	0.39*			0.76
earnings	(0.72)	(0.35)	(0.24)	(0.22)			[2,190]
	0.19				0.91***	1.38***	0.76
	(0.73)				(0.19)	(0.25)	[2,190]
B. Full sample	−0.48	1.34***	1.73***	0.48***			0.64
	(0.58)	(0.23)	(0.25)	(0.18)			[4,050]
	−0.45				0.64***	2.24***	0.64
	(0.60)				(0.21)	(0.20)	[4,050]
C. Alternative	−0.07	1.57***	2.19***	0.39***			0.77
measure of EP	(0.76)	(0.31)	(0.27)	(0.18)			[2,190]
	−0.16				0.85***	2.31***	0.76
	(0.76)				(0.19)	(0.23)	[2,190]

Notes: The dependent variable in Panel A is the log of earnings. In the rest of the table, the log of the monthly wage rate is the dependent variable. The figures in columns (2) to (6) are the estimates for the additional wage effect of high skill in each skill type. All estimates are calculated using a cell–panel data set weighted by the number of workers within each cell. All control variables and dummies for fixed effect are the same as in equation (2). County-clustered standard errors are presented in parentheses. ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

[10] To obtain the annualized effects on regional wage differentials, all the figures in Table 5 are divided by 5.

[11] Table C in the Appendix presents the 2SLS estimation results for county-level wage effect.

of observations, (iii) used an alternative measure that includes non-retail consumption in total consumption in estimating the EP rate, and (iv) used more detailed skill types. In all our regressions, we found our conclusions to be consistent. The results of the robustness checks are presented in Table 9.

Effect on Earnings

Institutional factors, such as minimum wage, can cause wage rates to increase without any corresponding structural changes in the retail industry. In this case, workers' earnings will not be affected since firms shorten their working hours to restrict increases in the total labor cost. Such institutional and nationwide trends are captured in our baseline specification by the year-fixed effects and the region- and worker-group-specific trends. Given the concern that uncontrolled factors still exist, we replaced our dependent variable with a log of monthly earnings (= wage rate × working hours). The results in Panel A show very similar patterns to our baseline findings.

Full Sample

In our baseline models, we excluded cells that had less than three workers at least once over the sample period. Consequently, some remote or isolated counties with a small number of workers were excluded. The results in Panel B show that including these samples does not result in a noticeable difference in our main findings.

Alternative Measure of EP

The key mechanism behind retail modernization is the increase in the share of online consumption relative to the rest. In Section 3, we assumed that online spending substitutes for offline consumption in the retail and restaurant industries. However, the increase in online shopping can also cause a change in spending on other types of local services. Thus, we used the total offline spending on all kinds of goods and services as "offline purchases" in equation (1). The results in Panel C show the same qualitative results as our baseline results.

Detailed Definition of High-Skilled Workers

Defining high-skilled workers using one specific threshold can cause misunderstanding of the compounding effects and may result in misleading conclusions. Thus, we classified workers in detail into high- and low-skill workers to check whether our previous findings remain valid. We classified workers into four education groups: middle school or less, high school, college, and university graduates. We also classified them into four occupation groups: routine physical, sales, technology and craft, and office. We classified workers into four age groups: 30 and younger, 30–39 years, 40–49 years, and 50 years and older. Overall, our findings for the skill wage premium remained qualitatively similar when we utilize the detailed skill types, as seen in Table D in Appendix.

VI. Conclusion

New technologies do not favor all types of workers, thereby creating winners and losers in the labor market. Households' e-commerce adoption decreases the competitiveness of local brick-and-mortar stores and worsens conditions for low-skilled workers. By contrast, the relative wages of high-skilled workers in response to e-commerce-induced structural changes in the retail sector may increase. Our empirical results suggest that only high-skilled workers benefit from e-commerce diffusion, while the wages of low-skilled workers show no significant change. Moreover, the urban concentration of high-skilled workers leads to a faster increase in the average wage of workers in urban areas than that of workers in non-urban areas. Thus, the diffusion of e-commerce leads not only to a rise in the skill wage premium but also to the regional wage differential in the local retail industry. Households' e-commerce adoption occurs everywhere, i.e., in all local labor markets, which has widened the differences in regional wage growth, unlike the skill wage premium in the manufacturing sector.

This study focuses on the effect of e-commerce on the labor market but does not identify the detailed channel of the wage effect, i.e., within or between firms. An increase in the skill wage premium can arise within or across stores. Some retail stores may upgrade their distribution processes and improve customer services, thereby increasing the demand for skilled workers and their wages. This increased skill premium can be attributed to new market entrants with new technologies that replace offline retail stores. New datasets that can identify the underlying channel of the increased skill premium may become available, inviting further research.

Appendix

[Table A] Relationship between Product Shares and Changes in Dependent Variable

	Dependent variable: County-level wage growth						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Electronics and appliances	−3.74						
	(4.99)						
Books, magazines, and stationery		−3.78					
		(5.52)					
Clothing			−0.88				
			(1.17)				
Hobbies				−6.60			
				(9.40)			
Cosmetics					−3.39		
					(4.43)		
Fresh food						0.43	
						(0.58)	
Furniture and household supplies							−3.51
							(4.67)
Adj. R-squared	−0.002	−0.001	−0.002	−0.001	−0.002	−0.002	−0.004
Observations	135	135	135	135	135	135	135

Notes: The dependent variable is the annualized growth rate of retail wages in each county. The independent variable is the consumption share of products in each county. Standard errors in cross-sectional regressions are presented in parentheses. ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

[Table B1] First-Stage Regression Results

Panel A. Column (1) in Table 7	Dependent variable:	
	EP	EP × High skill (Education)
	(1)	(2)
Bartik-like instrument	7.523*	−0.141
	(3.861)	(0.333)
Fitted EP × High skill (Education)	−0.002	0.998***
	(0.003)	(0.002)
Panel B. Column (2) in Table 7	EP	EP × High skill (Occupation)
	(1)	(2)
Bartik-like instrument	7.522*	−0.106
	(3.862)	(0.472)
Fitted EP × High skill (Occupation)	−0.002	0.999***
	(0.002)	(0.002)
Panel C. Column (3) in Table 7	EP	EP × High skill (Age)
	(1)	(2)
Bartik-like instrument	7.535*	−0.492
	(3.860)	(1.952)
Fitted EP × High skill (Age)	−0.004	0.998***
	(0.003)	(0.002)

Panel D. Column (4) in Table 7	EP	EP × High skill (Education)	EP × High skill (Occupation)	EP × High skill (Age)
	(1)	(2)	(3)	(4)
Bartik-like instrument	7.534*	−0.143	−0.106	−0.492
	(3.862)	(0.333)	(0.472)	(1.952)
Fitted EP × High skill (Education)	−0.002	0.998***	−0.002**	−0.001
	(0.003)	(0.002)	(0.001)	(0.002)
Fitted EP × High skill (Occupation)	−0.001	−0.001	0.999***	0.000
	(0.002)	(0.002)	(0.002)	(0.001)
Fitted EP × High skill (Age)	−0.001	0.000	0.000	0.998***
	(0.002)	(0.002)	(0.001)	(0.002)

Panel E. Column (5) in Table 7	EP	EP × Middle skill	EP × High skill
	(1)	(2)	(3)
Bartik-like instrument	7.537*	−0.513	−0.132
	(3.861)	(1.693)	(0.494)
Fitted EP × Middle skill	−0.005	0.998***	0.000
	(0.003)	(0.002)	(0.001)
Fitted EP × High skill	−0.004	-0.001	0.999***
	(0.004)	(0.001)	(0.002)

Notes: The dependent variables are the endogenous variables in columns (1)–(5) of Table 7, i.e., the EP rate and its interaction term with skill dummies. The coefficient estimates of the cross-product of the Bartik-like instrument and 11 province dummies are not reported. Regressions are weighted by the number of workers within each skill-county-year cell. County, year, skill-year, and province-year fixed effects are used. Control variables are the same as those in the 2nd-stage regressions. The number of observations is 2,190. County-clustered standard errors are presented in parentheses. ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

[Table B2] Regression Results for Generating the Fitted Value of EP

	Dependent variable: E-commerce penetration rate	
	(1)	(2)
Bartik instrument	13.50***	7.39**
	(5.45)	(3.41)
× City of Pusan		0.30***
		(0.03)
× City of Daegu		1.42***
		(0.02)
× City of Incheon		−0.10***
		(0.02)
× City of Gwangju		0.45***
		(0.03)
× City of Daejeon		0.19***
		(0.03)
× City of Ulsan		0.07***
		(0.02)
× Gyunggi-province		−0.05
		(0.06)
× Chungcheong-province		−0.02
		(0.04)
× Jeolla-province		0.17
		(0.11)
× Gyeongsang-province		0.11
		(0.07)
Control Variables		Yes

Notes: The dependent variable is the e-commerce penetration rate in each county. Regressions are weighted by the number of workers within each skill–county–year cell. County, year, skill–year, and province–year fixed effects are used. Control variables are the same as those in the second-stage regressions. The number of observations is 2,190. Standard errors are presented in parentheses. ***, **, * are significant at the 1%, 5%, 10% levels, respectively.

[Table C] County-level E-commerce Effect and Heterogeneity: 2SLS Estimates

	Dependent Variable: Log (County-level wage)		
	(1)	(2)	(3)
E-commerce	1.94***		
	(0.36)		
× Urban areas		0.95**	
		(0.44)	
× Non-urban areas		0.24	
		(0.52)	
× Counties with old population share (< p50)			1.44***
			(0.46)
× Counties with old population share (≥ p50)			0.91
			(0.72)
Weak IV *F*-stat	94.33	45.11	59.25
Hansen *J*-stat	12.21	8.86	11.14
(*p*-value)	(0.27)	(0.45)	(0.27)
Adj. R-squared	0.71	0.71	0.72
Observations	787	787	787

Notes: The dependent variable is the log of real wages in each county. Regressions are weighted by the number of workers within each county. County-, year-fixed effects, and control variables are included in all columns. The share of the old population is calculated using the figures from 2010. County-clustered standard errors are presented in parentheses. ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

[Table D] Robustness Checks: Detailed Skill Types

	Dependent variable: Log(Real hourly wage)				
	(1)	(2)	(3)	(4)	Adj. R-squared
Skill type	Baseline	Additional effect by skill specification			[Observations]
A. Education		High school	College	Bachelor	
	−0.27	0.16	0.61*	1.92***	0.66
	(0.68)	(0.30)	(0.34)	(0.33)	[5,806]
B. Occupation		Sales	Tech & crafts	Office	
	−0.68	0.44**	−0.16	3.02***	0.66
	(0.66)	(0.25)	(0.46)	(0.33)	[5,457]
C. Age		Aged 30-39	Aged 40-49	Aged over 50	
	−0.41	0.67**	−0.05	−0.74***	0.65
	(0.60)	(0.27)	(0.26)	(0.25)	[4,243]

Notes: The dependent variable is the log of the real hourly wage rate in each worker group. Regressions are weighted by the number of workers within each skill-county-year cell. County, year, skill–year, province–year fixed effects, and control variables are included in all columns. County-clustered standard errors are presented in parentheses. ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

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온라인 쇼핑 확산이 지역 임금구조에 미치는 효과: 소매업을 중심으로*

신 동 한 · **전 현 배*****

초 록 소비자의 온라인 쇼핑 이용 확대는 오프라인 상점뿐만 아니라 업체 종사자의 임금에도 영향을 미친다. 본 연구는 2011−2016년 기간 온라인 쇼핑 확산이 소매업의 지역 임금구조에 미친 영향을 살펴본다. 소비자의 신용카드 거래 자료에 기반한 지역별 온라인 쇼핑 침투율을 이용한 분석 결과는 온라인 쇼핑 침투율이 빠르게 증가한 지역에서 고숙련 근로자와 저숙련 근로자 사이의 임금 격차가 확대되었음을 보여준다. 저숙련 근로자의 임금은 거의 변동하지 않고 고숙련 근로자의 임금 상승을 통해 임금 격차가 확대되었다. 본 연구의 결과는 전자상거래로 인한 숙련 임금 프리미엄의 증가는 고숙련자가 많은 도시 지역과 그렇지 않은 비도시 지역 간의 임금 격차 확대로 이어질 수 있음을 시사한다.

핵심 주제어: 전자상거래, 임금, 숙련, 지역노동시장, 신용카드
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