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Trade liberalization and wages: Evidence from the closer economic partnership arrangement between mainland China and Hong Kong

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ABSTRACT

This paper studies the impact of tariff cuts on workers' wages in a single labor market by examining the Closer Economic Partnership Arrangement (CEPA) trade liberalization, in which China unilaterally eliminated hundreds of tariffs on Hong Kong's goods in 2004. Utilizing five Hong Kong censuses from 1996 to 2016, we find consistent result that a one-sided tariff concession leads to an increase in the monthly wage of affected workers, averaging between 5.75% and 6.84%. Moreover, we explore the possibility that the effects of exposure to CEPA may be heterogeneous along several dimensions. The workers who benefited the most were more educated, in higher-skilled occupations, Mandarin-speaking, near retirement, or just starting their careers. Surprisingly, we found no increase in employment in the treated industries. We conclude that tariff cuts' wage impact and, hence, their impact on wage inequality, depend on the local labor market composition and structure.

1. Introduction

The conventional wisdom of 20th century economics was that trade liberalization boosts international trade and increases aggregate employment and incomes in affected industries. However, a series of papers have challenged the conventional wisdom (Autor et al., 2013, 2014, 2015, 2016; Acemoglu et al., 2016; Bloom et al., 2016) on liberalization's aggregate labor market impact. One perennial challenge to identifying the impact on labor outcomes is that trade liberalization often involves many simultaneous policy changes, which can be difficult to disentangle. This paper studies trade liberalization's impact on wage levels and inequality by analyzing trade shock in which one party unilaterally eliminated its tariffs.

Specifically, we examine the free trade agreement (FTA) between Mainland China (hereinafter referred to as "the Mainland") and Hong Kong, namely the Closer Economic Partnership Arrangement (hereinafter referred to as "the CEPA"). Because China is the largest manufacturing country in the world and the second largest global economy, its growth has economic externalities on other countries. Bloom et al. (2016) show that trade with China can speed up the rate of innovation and economic growth. However, although the local economy benefits from import competition from China, for example through the increase in aggregate welfare (Caliendo et al., 2019) and skill upgrading (Mion and Zhu, 2013), evidence of a reduction in employment is found. Similarly, Autor et al. (2013, 2015, 2014,

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2016), Acemoglu et al. (2016), Bloom et al. (2016), and Malgouyres (2017) also argue that the rising Chinese import competition leads to a decrease in local employment and earnings. In particular, being a relatively small economy that is adjacent to the Mainland, Hong Kong[1] is also affected by the spillover effects of the growth of the Mainland. In this paper, we examine whether the CEPA, implemented in 2004, raises the incomes of Hong Kong employees working in industries that reap the rewards of this preferential arrangement.

Economists agree that trade liberalization affects incomes. Possible mechanisms underlying these effects include increasing productivity as a result of tariff cuts or quality upgrading (Amiti and Konings, 2007; Verhoogen, 2008; Topalova and Khandelwal, 2011; Yu, 2015) and changes in employment structure or labor reallocation (Revenga, 1997; Davis and Harrigan, 2011; Hasan et al., 2012; Burstein and Vogel, 2017). Most of the existing literature argues that trade liberalization increases wage inequality (Beyer et al., 1999; Xu, 2003; Mehta and Hasan, 2012; Chen et al., 2017; Helpman et al., 2017) as a result of changes in the skill premium. Fewer protections and increased foreign competition have the effect of increasing the skill premium (Attanasio et al., 2004; Galiani and Sanguinetti, 2003; Goldberg and Pavcnik, 2007; Han et al., 2012). Conversely, some studies claim that trade liberalization decreases the wage premium, as demonstrated in Brazil (Gonzaga et al., 2006), Vietnam (McCaig, 2011), India (Kumar and Mishra, 2008), and Indonesia (Amiti and Cameron, 2012). These studies suggest that unskilled workers experience higher wage increases than skilled workers, and thus liberalization decreases wage inequality. A similar mechanism has also been shown to reduce poverty in Indonesia by increasing the incomes of the poorest segment of the population (Kis-Katos and Sparrow, 2015). Regardless of the precise effect, it is evident that trade liberalization changes relative wages in the industries that face tariff cuts (Townsend, 2007).

In accordance with the CEPA clauses, the Mainland has incrementally worked toward zero tariffs on specific imported goods of Hong Kong origin since 2004. Because of its free port status, Hong Kong had already applied zero tariffs to Mainland-origin imported goods before the adoption of the CEPA. Therefore, the CEPA has not directly increased Hong Kong's imports from the Mainland (Zhou, 2019). However, the overall economy of Hong Kong has benefited from this one-sided tariff concession arrangement (Fung and Zhang, 2007). For example, the CEPA has gradually reduced Hong Kong's unemployment rate by 9% per year (Ching et al., 2012), and Hong Kong's real GDP growth rate is 4% higher than it would have been in the absence of the CEPA (Hsiao et al., 2012).

In this paper, we use the adoption of the CEPA as an external shock to examine the benefits of FTAs from the perspective of exporters. Different from the industry-level, firm-level, and region-level data employed in the current literature, we use individual-level data from population censuses in our analysis. In doing so, we capture the heterogeneity between wage of individuals with different industry backgrounds, judged manually by how they are affected by the CEPA. We conclude that the one-sided tariff concession leads to about a 5.75% increase in average wages in the treated industries and has a persistent impact that lasts for about 10 years. Moreover, we find that higher wages after the liberalization of trade can partially be attributed to the ability to speak Mandarin, high-level job skills, and higher education levels. This paper contributes to the existing literature on FTAs by considering heterogeneity between individuals in terms of language skills, age, occupational skill, and educational level. In doing so, we contribute to resolving the debate on the impact of FTAs on wage inequality from the perspective of moderated effects. Moreover, our results are different from those of other individual-level microdata-based research, such as Autor et al. (2014), which finds evidence of the negative impact of import competition of China on the local labor market. As a free trade port dominated by trade with the Mainland, Hong Kong benefits from the volume of the Mainland's international trade. However, there are similarities in industries between China and other large countries such as the United States, and, thus, the growth of China's exports may lead to the reallocation of resources between complementary and substitute industries in the target countries.

The rest of this paper is structured as follows. Section 2 introduces the role of Hong Kong in China's economy and the framework of the CEPA. Section 3 introduces the methods applied in this study and the data obtained. The empirical findings are presented in Section 4, which includes basic estimations and robustness checks. Section 5 provides further analysis of the impact of language skills, age, occupational skill, and educational level on the wages of workers. Finally, Section 6 presents the conclusions.

2. The CEPA and the role of Hong Kong

Since the transfer of sovereignty over Hong Kong to China in 1997, the central government of China and the government of Hong Kong have been devoted to promoting the economic integration of the Mainland and Hong Kong and strengthening the role of Hong Kong as a connection between the Mainland and the rest of the world. The CEPA is a bilateral FTA made by the Mainland and Hong Kong in 2003,[2] intended to strengthen the trade relationship in goods and services and promote investment between the two regions, which would be conducive to accelerating their economic integration and enhancing their long-term economic and trade development. The CEPA covers three broad areas, namely trade in goods, trade in services, and trade and investment facilitation. In terms of the trade in goods, all goods of Hong Kong origin exported to the Mainland enjoy tariff-free treatment, provided that local manufacturers' applications have been approved and the CEPA rules of origin have been agreed upon and met. In terms of the trade in services, Hong Kong service suppliers enjoy preferential treatment when entering into the Mainland market in various service areas. Hong Kong professional bodies and the regulatory authorities on the Mainland have also signed a number of agreements or arrangements on mutual recognition of professional qualifications. In terms of trade and investment facilitation, both sides have agreed to enhance cooperation in various trade and investment facilitation areas to improve the overall business environment. Among these arrangements, trade liberalization was considered the most important, and was the first to be implemented in 2004.

[1] In this paper, "Hong Kong" refers to the Hong Kong Special Administrative Region of China. Under a special "one country, two systems" political arrangement, the Mainland uses a socialist system while Hong Kong retains its capitalist economic and administrative systems.

[2] See https://www.gov.hk/en/business/businessmainland/cepa/ for details of the arrangement.

Because of its unique geographical location and position as an international center of finance and trade, Hong Kong plays an important role in the economic exchange between the Mainland and the rest of the world. In the early stage of China's development, Hong Kong imports supported the economic growth of the Mainland. Even as early as 1980, the trade in merchandise between the two places accounted for 38% of Hong Kong's total international trade and has since increased to more than 50% as of 2012.[3] With the continuous and rapid growth of China's economy, the industries in Hong Kong related to the Mainland market have continued to boom, which has led to rising incomes for employees in those fields.

The CEPA and the first annexes were signed on 29 June 2003 and 29 September 2003, respectively. The annexes and supplements listed the export products and industries that met the requirements of the preferential arrangements. Since 1st January 2004, the Mainland has implemented zero tariffs on imported goods of Hong Kong origin, in stages. Preferential arrangements for the trade in services and trade/investment facilitation were also progressively promoted in subsequent years.[4] The question then arises of whether—considering the booming Mainland market—the CEPA has raised the incomes of Hong Kong employees and employers who work in the industries that benefit from these preferential arrangements.

3. Estimation strategy

3.1. Identification strategy

The basic method of identification in this paper involved the difference-in-differences (DID) approach, shown below:

$$\ln\left(wage_{i,c,t}\right) = \beta_0 + \beta_1 CEPA_{c,t} + \theta X_{i,t} + \delta_{birth\_year} + \gamma_c + \tau_t + f_e + \vartheta_{c,t} + \varepsilon_{i,c,t} \tag{1}$$

where $i, c,$ and$t$ represent person, industry, and census year, respectively. The outcome is $\ln\left(wage_{i,c,t}\right)$, measured as the monthly wage in a natural logarithm. $CEPA_{c,t}$ is the regressor of interest. Specifically, $CEPA_{c,t} = treat_c \times post_t$, where $treat_c$ equals 1 if industry c benefited from CEPA, and 0 otherwise; $post_t$ is the post-treatment indicator, taking a value of 1 for the 2006, 2011, and 2016 censuses, and 0 otherwise. Table A1 in the Appendix lists the details of the setting of $treat_c$ for different industries.

X_{it} is a vector of the control variables (including *Edu*, *Male*, *Married*, and *Dur7*) that controls for observable individual attributes related to individual wages; δ_{birth_year} is a full set of birth-year dummies to account for life-cycle variation in wages (Autor et al., 2014). γ_c refers to the industry fixed effects, which capture time-invariant unobservable factors at the industry level; τ_t is the time (Census) fixed effects, controlling for the common trend of wage; and f_e is the fixed effects controlling for the highest level of educational qualification achieved.[5] We include treatment-specific or industry-specific linear trends ($\vartheta_{c,t}$) to control for the potential differences in time trends between the treatment and control groups (e.g., Mora and Reggio, 2013; Li et al., 2016). For all models, the standard errors were clustered by industry-by-census level to address the potential heteroscedasticity and serial correlation on the levels of census-by-industry.

3.2. Data

To investigate the effects of trade liberalization on wages in the treated industries, we collected census survey data from five iterations of the Hong Kong Population Census between 1996 and 2016.[6] Based on a broad range of demographic and socio-economic characteristics, we construct the variables listed below for an empirical analysis of the respondents.

- *Wage*: The total amount earned from an individual's main source of employment.
- *Age*: The age of the respondent at the time of the census.
- *Edu*: Educational level, which has been divided into eight categories.[7]
- *Male*: Gender of the respondent, equal to 1 for male.
- *Married*: Marital status, equal to 1 for married respondents, otherwise 0.
- *Dur7*: Duration of residence in Hong Kong, equal to 1 if the total number of years lived in Hong Kong is equal to or higher than seven years, otherwise 0.
- *Mandarin*: Binary variable equal to 1 if the respondent can speak Mandarin, otherwise 0.

[3] Calculated based on data reported by the Census and Statistics Department of the Government of Hong Kong Special Administrative Region (http://www.censtatd.gov.hk/).

[4] The implementation of the CEPA was carried out in several phases, covering four major aspects (i.e. trade in goods, trade in services, investment, and economic/technical cooperation). In January 2004, 273 types of Hong Kong products could be exported to the Mainland with zero tariff, and the tariff-free policy gradually expanded to all products of Hong Kong origin. Details of the CEPA policy can be found on the following website: https://www.tid.gov.hk/english/cepa/index.html.

[5] Field of education is the discipline in which the respondent has attained a qualification. Intuitively, workers with a field of education that is more closely related to the treated industry might change their job if CEPA increases the average wage in the treated industry, which may lead to biases in estimations.

[6] Academic researchers may approach the Hong Kong Census and Statistics department to apply for access to the micro Census data. More information could be found through the following website: https://www.censtatd.gov.hk/service_desk/list/microdata/index.jsp.

[7] The details of educational level are provided in Table A2 in the Appendix.

- *English*: Binary variable equal to 1 if the respondent can speak English, otherwise 0.
- *Chinese*: Binary variable equal to 1 if the respondent's self-identified ethnicity is Chinese, otherwise 0.

We excluded respondents who: (1) were foreign domestic helpers; (2) were aged under 18 or over 65; (3) were full-time or part-time students at the time of the census; (4) were employers; (5) reported a monthly income of less than HK$5000 or more than HK$150,000. Table 1 reports the descriptive statistics of the variables.[8]

Fig. 1 shows a comparison of the log monthly wage trends from 1996 to 2016, suggesting that CEPA-treated industries and control industries displayed a similar changing pattern in log monthly wages prior to 2004. The solid line indicates the average wage of the treated group working in industries that enjoy preferential treatment under the CEPA ($treat_c$ equals 1), and the dashed line indicates the control group (those working in other industries). Initially, the average log monthly wage of the workers in industries that benefit from the CEPA arrangements was lower than that of workers in other industries. However, average log monthly wages in the treatment group increased more rapidly after the CEPA was implemented, thereby narrowing and eventually reversing the wage gap between these two groups of workers. Might the CEPA have contributed to this change? We will address this question in the following section.

4. Empirical findings

4.1. The CEPA and the wage effect

4.1.1. Benchmark results

Table 2 presents estimations of Eq. (1) using various controls. In column (1), we regress *Ln (wage)* on CEPA and a set of fixed effects (i.e., birth year, industry, census, and highest field of education fixed effects), without including other control variables. The estimate of CEPA is 0.0488 and statistically significant at the 1% level. In column (2), we include a full set of control variables. As expected, wages increase with educational level (*Edu*). The estimate of the variable of interest reveals a positive and statistically significant effect of CEPA on log monthly wages. This finding implies that implementation of the CEPA resulted in an increase in the wages of workers in the treated industries by 5.75%. Given that trade liberalization policy may affect the labor supply and demand structures of both groups, the estimated treatment effect should measure the lower bound effect of CEPA on wage in the treatment group. (1) Tariff cuts on goods from a particular industry may lead more workers joining that industry from industries not directly affected by tariff reductions. This second-order, labor supply impact of a tariff cut would then raise worker wages in the unaffected industries and reduce wage increases in the affected industry. (2) Tariff cuts may increase the returns to education or speaking Mandarin, leading to more workers completing college or learning Mandarin, reducing the college and Mandarin language premium in the whole economy.[9] Without these and similar labor supply effects, the measured wage impact of CEPA is expected to be larger.

One concern is that the causal relationship between CEPA and wage may be distorted by the 1997 Asian financial crisis and the 2008 United States' subprime mortgage crisis. In column (3) of Table 2, we repeat the same estimation but restrict our samples to the 2001 and 2006 censuses. The sub-sample results confirm that the CEPA effect is not likely to be affected by the financial crisis. We find that the short-term effect of the CEPA remains positive and statistically significant, and the magnitude, 6.84%, is slightly larger than the long-term average treatment effect identified in column (2). Next, according to the appendix of the CEPA clauses, we divide the treated industries into two areas: 1) trade in goods, and 2) trade in service and investment. Then, we use separate interaction terms to disentangle the effects of the CEPA on these two areas. The results in column (4) reveal that the industries related to goods benefited more (6.95%) from the adoption of the CEPA compared with service and investment industries (4.53%). In the last two columns, we divide our sample into male workers and female workers. The estimated effects of the CEPA for both groups are positive and statistically significant at the 1% level, and the magnitude is much larger in the female group.

4.1.2. Quantile regression

We use the unconditional quantile partial effects (UQPE), proposed by Firpo et al. (2009), to capture the effects of the CEPA on different quantiles of the wage distribution after controlling for, rather than conditional on covariates.[10] In this sense, we can explore the distributional rather than the average treatment effects of the CEPA on wage by analyzing how the CEPA shifts the cumulative distribution of wages.

Fig. 2 shows substantial and statistically significant effects of CEPA on wages of quantiles between the 1st and 40th, increasing slightly above the 50th. This is consistent with our previous findings in the preferred specification in column (2) of Table 2, in which

[8] The cross-tabs of wages by covariate and census are reported in Table A3.

[9] Because age and sex structure are set exogenously, the estimates for these categories are the most credible for estimating the effects of tariff cuts on labor demand. Additionally, the Mandarin premium may increase with supply from network effects.

[10] The commonly used conditional quantile method estimates the impact of the CEPA on the log monthly wages at a specific quantile (e.g., 10th percentile). It quantifies the CEPA effects on those with unusually low wages conditional on their demographic characteristics. (e.g., well-educated graduates with relatively lower wages than counterparts in their educational group). However, we are more interested in the CEPA effects on those with unconditional (in an absolute sense) lower wages after controlling for demographic characteristics. This is what the unconditional quantile partial effects (UQPE) measure. We first estimate the counterfactual cumulative distribution function (CDF) of wages after the CEPA based on recentered influence function (RIF) regression. Subsequently, the unconditional quantile partial effects of CEPA can be derived from the difference between the actual CDF and counterfactual CDF.

Table 1
Summary statistics.

	1996		2001		2006		2011		2016	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Ln(wage)	9.338	0.583	9.468	0.629	9.440	0.637	9.588	0.659	9.803	0.644
Edu	3.988	1.595	4.171	1.693	4.418	1.751	4.673	1.836	4.890	1.859
Male	0.623	0.485	0.585	0.493	0.569	0.495	0.544	0.498	0.531	0.499
Age	36.11	10.51	37.71	10.53	39.10	10.57	40.77	11.19	42.08	11.77
Birth year	1959.9	10.51	1963.3	10.53	1966.9	10.57	1970.2	11.19	1973.9	11.77
Married	0.611	0.488	0.616	0.486	0.602	0.489	0.604	0.489	0.605	0.489
Dur7	0.950	0.218	0.952	0.214	0.963	0.188	0.965	0.185	0.956	0.206
Occupational Skill	0.282	0.450	0.316	0.465	0.330	0.470	0.378	0.485	0.401	0.490
Mandarin	0.336	0.472	0.422	0.494	0.464	0.499	0.543	0.498	0.549	0.498
English	0.484	0.500	0.530	0.499	0.537	0.499	0.539	0.498	0.569	0.495
Chinese	0.957	0.204	0.972	0.166	0.976	0.154	0.972	0.164	0.964	0.187
Observations	107,191		112,218		114,483		127,614		132,673	

Notes: The table shows descriptive statistics for each census.

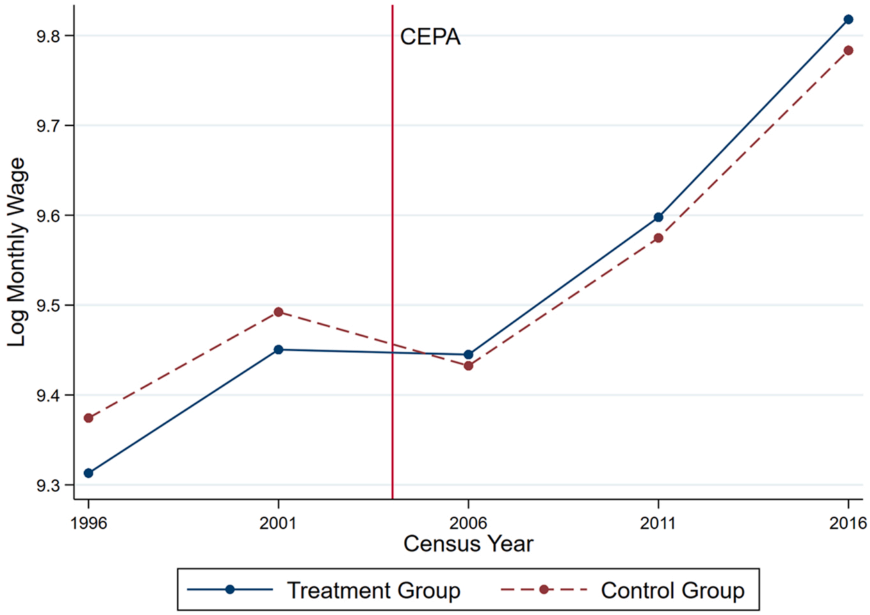

Fig. 1. Log monthly wage trend comparison 1996–2016. Notes: Trends of the average monthly wage (in logarithm) are plotted for the control group and the treatment group. The vertical red line indicates the implementation of CEPA in 2004.

Table 2
Main results.

	Dependent Variable: *Ln (Wage)*					
	(1) All	(2) All	(3) Census 2001 & 2006	(4) All	(5) Male	(6) Female
CEPA	0.0488***	0.0575***	0.0684***		0.0401**	0.0785***
	(0.016)	(0.016)	(0.015)		(0.015)	(0.022)
CEPA(Goods)				0.0695***		
				(0.013)		
CEPA(Services & Investments)				0.0453*		
				(0.024)		
Edu		0.2051***	0.1964***	0.2051***	0.1863***	0.2252***
		(0.008)	(0.012)	(0.008)	(0.008)	(0.009)
Male		0.1592***	0.1675***	0.1592***		
		(0.010)	(0.017)	(0.010)		
Married		0.1386***	0.1064***	0.1386***	0.1994***	0.0710***
		(0.005)	(0.004)	(0.005)	(0.007)	(0.006)
Dur7		0.0300	0.0737**	0.0299	-0.0617**	0.0924***
		(0.022)	(0.031)	(0.022)	(0.026)	(0.016)
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Census fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Field fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Birth fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.41	0.49	0.46	0.49	0.49	0.50
Observations	594,456	594,456	226,807	594,456	337,601	256,855

Notes: The table shows the impact of CEPA on log monthly wage based on Eq. (1). CEPA is the DID interaction term between *treat* and *post*. *Treat* equals 1 for individuals in CEPA-affected industries. *Post* equals 1 for the census after 2004. CEPA(Goods) is the interaction between CEPA and dummy variables equal to 1 for industries related to goods. CEPA (Services & Investments) is the interaction between CEPA and dummy variables equal to 1 for industries related to service and investment. The individual control variables include *Edu*, *Male*, *Married*, and *Dur7*. Robust standard errors, clustered by the industry-by-census level, are reported in parentheses; ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

the average treatment effect of CEPA on log monthly wage is 0.058. We find that individuals with wages at the upper quantiles benefit more from the CEPA, which provides us with evidence that the CEPA may bring about unequal wage gains. We further scrutinize the heterogeneous effects of the CEPA on wages in the following sections.

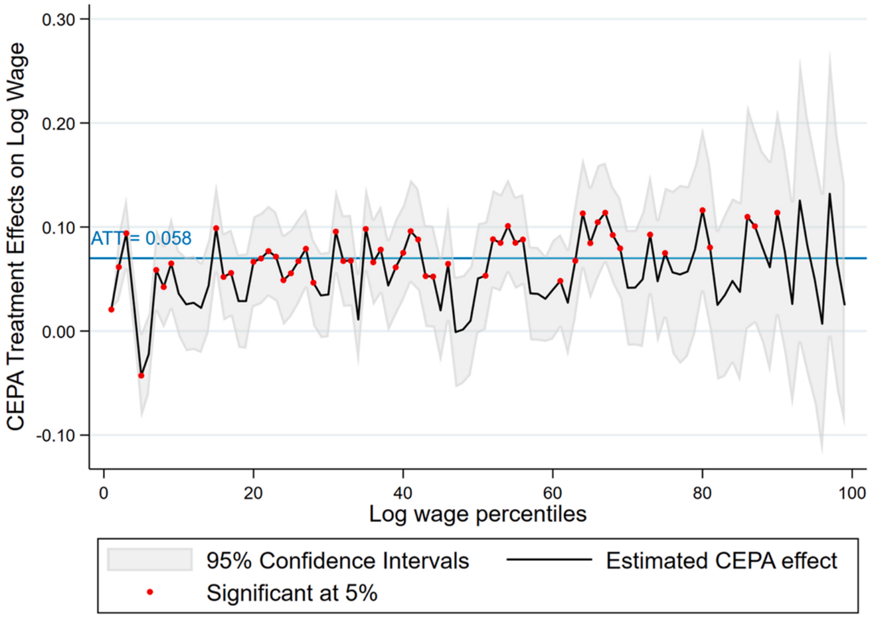

Fig. 2. The impact of CEPA on different percentiles of the wage distribution. Notes: The estimated impact of CEPA on the natural logarithm of a specific percentile of the monthly wage distribution is shown. Red dots represent estimates significant at the 5% levels after clustering the standard errors at the industry-by-census level. The dark area denotes the 95% confidence intervals of the estimated CEPA effects for wages on different percentiles. The blue line represents the average treatment effects of CEPA on the log monthly wages (reported in column [2] of Table 2).

4.2. Robustness checks

The above results show that the effects of the CEPA on wages are robust to the inclusion of different controls and sample periods. Next, we provide a set of robustness checks on the identification.

4.2.1. The individual visit scheme

If some other economic stimulus policies were implemented during the same period, the estimated treatment effect might be confounded and biased. In 2003, the tourism industry and overall economy of Hong Kong were adversely affected by the outbreak of severe acute respiratory syndrome. To stimulate the local economy, the Individual Visit Scheme (IVS) was launched on 28 July 2003, which allowed residents from Mainland China to visit Hong Kong on an individual basis instead of using business visas or joining group tours. According to the Hong Kong Tourism Board,[11] the number of visitors from Mainland China surged from 8.46 million in 2003–42.8 million in 2016, as shown in Fig. 3. The explosion of tourists under the IVS boosted Hong Kong's tourism industry and may have increased the wages of employees in related industries. To eliminate this effect, we exclude the samples of employees who worked in the restaurant, hotel, and retail industries. The results are reported in Table 3. The coefficient of the CEPA is still positive and significant at the 1% level.

4.2.2. Placebo test: randomly generated treatment status

Next, we employ a placebo test to check the extent to which the estimates are driven by any omitted variables (see La Ferrara et al., 2012; Li et al., 2016). We apply the falsification specification by randomly assigning the treated industries and policy time. First, among the 27 industries in total, 13 are put into the treatment group at random. Second, the year of CEPA adoption is randomly selected from between 1997 and 2015. Finally, we run the placebo regression using the same specifications as in column (2) in Table 2. Fig. 4 illustrates the cumulative distribution density of the estimated coefficients of the "false" $CEPA_{c,t}$ from 500 simulations. Each dot shows the estimated coefficient from a separate placebo regression. The estimated coefficients of the "false" $CEPA_{c,t}$ exhibit a normal distribution with a mean of zero, and mostly below the benchmark estimate of the CEPA (the vertical red line with the reference value of 0.058, reported in column [2] of Table 2). Thus, the placebo test provides further evidence for the validity of our main findings.

4.2.3. Treatment and industry-specific time trends

The primary identification assumption is that we would have observed the same average changes in log monthly wages in industries not exposed to the CEPA after accounting for covariates. The last challenge to the identification is that industry and census fixed effects might not fully capture all unobserved variations over the past 20 years. For example, some of the treated industries may provide more

[11] Please refer to Hong Kong Annual Digest of Statistics, Various Issues.

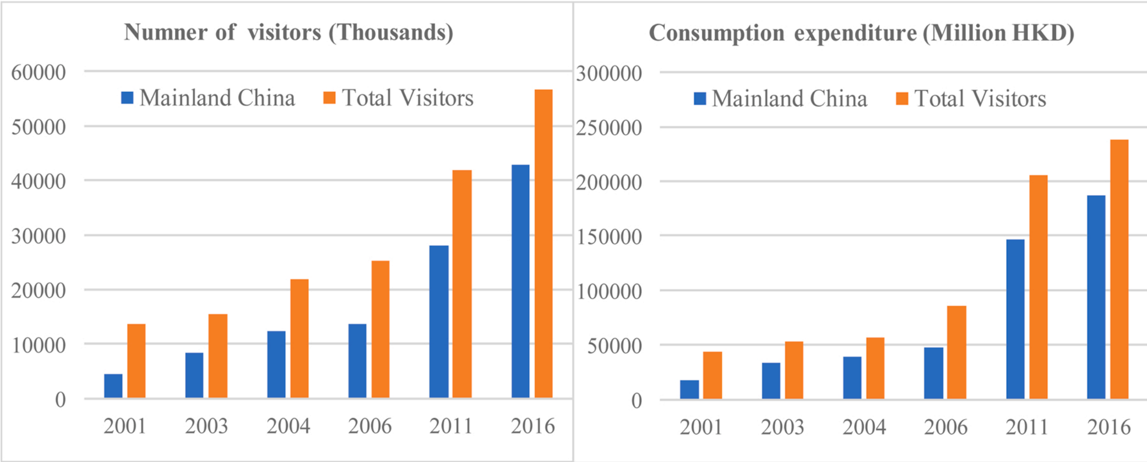

Fig. 3. Number of visitors and consumption expenditure under IVS.

jobs or offer higher wages after the tariff deduction. Meanwhile, workers may flow into the treated industries if they are offered higher wages. These changes in the workforce and wage structure may lead to different trends in each industry. To address this concern, we add linear treatment-specific and industry-specific time trend in columns (1) and (2) of Table 4, respectively, to account for unobserved industry-specific confounding factors that could bias the main results (e.g., Li et al., 2016; Mora and Reggio, 2013). The estimated CEPA effects are even larger than the benchmark results shown in column (2) of Table 2.

4.3. Dynamic study and common trend

Finally, we conduct a dynamic study to explore the prolonged effects of the CEPA and verify the common trend hypothesis. Specifically, we estimate Eq. (1) by substituting the CEPA with a set of interaction terms between treatment assignments and census dummies. We consider a 15-year window, spanning from 3 years (census 2001) before the adoption of the CEPA until 12 years after (census 2006, 2011, 2016).

$$\ln\left(wage_{i,c,t}\right) = \beta_0 + \beta_1^{Pre} CEPA_{c,2001} + \beta_1^{Post1} CEPA_{c,2006} + \beta_1^{Post2} CEPA_{c,2011} + \beta_1^{Post3} CEPA_{c,2016} + \theta X_{i,t} + \gamma_c + \tau_t + f_e + \vartheta_{c,t} + \varepsilon_{i,c,t} \tag{2}$$

In Eq. (2), $CEPA_{c,year}$ equals 1[12] for industry c that benefited from the CEPA and the observation i belongs to *year*; otherwise, 0. Thus, β_1^{Post1}, β_1^{Post2}, and β_1^{Post3} measure the dynamics of the CEPA effect from 2006 to 2016, while β_1^{Pre1} denotes whether the samples meet the common trend requirement before the shock. We exclude the benchmark year 1996 to avoid multicollinearity. The results are presented in Table 5. In column (1), we focus on the dynamic treatment effect of CEPA after 2004 and only include β_1^{Post1}, β_1^{Post2}, and β_1^{Post3} based on Eq. (2). The results reveal that the adoption of the CEPA policy has persistent effects on wages: around a 4.77–6.30% increase in log monthly wages for industries exposed to CEPA after 2004. In column (2), we additionally include the term $CEPA_{c,2001}$ to verify the common trend hypothesis. Fig. 5 shows the coefficient on $CEPA_{c,2001}$ is insignificantly different from zero, suggesting the absence of pre-trends in changes in the log monthly wages before the adoption of the CEPA. The estimated CEPA effects last for about 10 years after CEPA implementation, and then level off slightly. Nevertheless, these results confirm that the average wages of the treated and controlled industries began to diverge after the adoption of the CEPA.

5. Heterogeneity analysis

Our results so far indicate a positive and robust effect of the CEPA policy on wages in Hong Kong. In this section, we explore which types of workers may have benefited more from the trade liberalization policy. We start by examining whether speaking Mandarin offers a higher wage premium. We then explore the extent to which the CEPA effect differs based on the dimensions of age, occupational skill, education level, and employment structure.

5.1. Language skills

We first explore the possibility that the effects of exposure to CEPA are heterogeneous along the dimension of language skill. Cantonese and English are the most used languages in Hong Kong. Although Mandarin and Cantonese share the same base alphabet, they differ greatly in terms of pronunciation. Mandarin is the official language of the Mainland, while Cantonese is widely used in Hong

[12] See Table A1 in Appendix.

Table 3
Robustness check: Excluding the influence of IVS.

	Dependent Variable: *Ln (Wage)*	
	(1) All except restaurant/hotel	(2) All except restaurant/hotel/retail
CEPA	0.0625*** (0.017)	0.0600*** (0.018)
Individual Controls	Yes	Yes
Industry fixed effect	Yes	Yes
Census fixed effect	Yes	Yes
Field fixed effect	Yes	Yes
Birth Year fixed effect	Yes	Yes
Adjusted R^2	0.49	0.49
Observations	543,258	492,924

Notes: The table shows the impact of CEPA on log monthly wage based on Eq. (1) after excluding industries potentially influenced by IVS. CEPA is the DID interaction term between *treat* and *post*. *Treat* equals to 1 for individuals in CEPA affected industries. *Post* equals to 1 for the census after 2004. The Individual control variables include *Edu*, *Male*, *Married* and *Dur7*. Robust standard errors, clustered by the industry-by-census level, are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

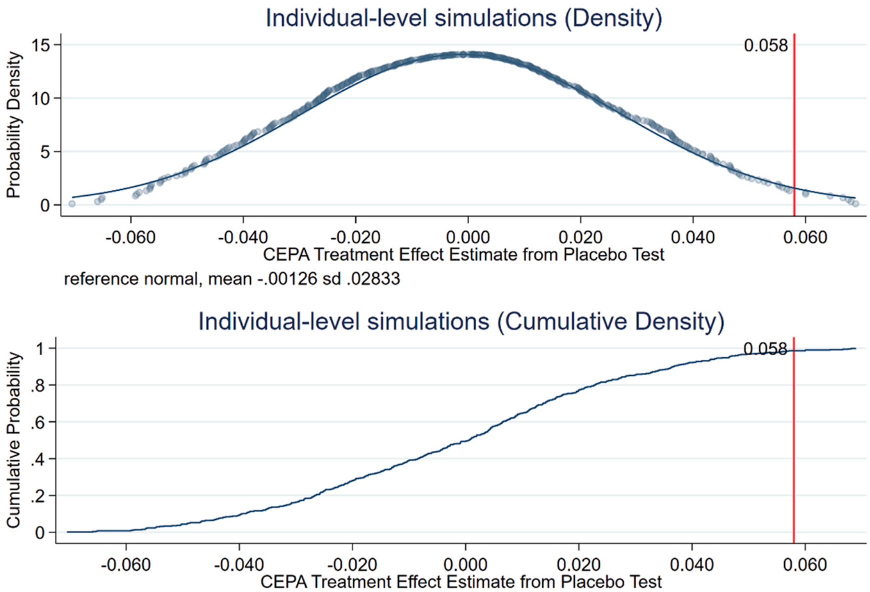

Fig. 4. Distribution of the estimated coefficients of the falsification test. Notes: The figure plots the cumulative distribution density of the estimated coefficients from 500 simulations using false treated industries and false time of CEPA. The vertical red line indicates the estimate of column 2 in Table 2.

Kong and other areas of southern China (i.e., Guangdong Province and Macau). In the 1996 census, one year before the regime change took place, only 33.56% of Hong Kong citizens stated that they could speak Mandarin.[13] This percentage increased steadily to reach 54.92% in 2016, in large part owing to the Mandarin promotion program carried out by the Hong Kong government after the regime change in 1997 (Zheng and Zhou, 2021). In the context of the booming business opportunities in connection to the Mainland, speaking Mandarin facilitates communication and increases work efficiency in the treated industries, and hence Mandarin speakers may earn higher wages. We test this hypothesis by including the interaction between the Mandarin spoken dummy value and CEPA in Eq. (3):

$$\ln\left(wage_{i,c,t}\right) = \beta_0 + \beta_1 Mandarin_{i,t}{*}CEPA_{c,t} + \beta_2 CEPA_{c,t} + \beta_3 Mandarin_{i,t}{*}treat_c + \beta_4 Mandarin_{i,t}{*}post_t + \beta_5 Mandarin_{i,t} + \theta X_{i,t} + \delta_{birth\_year} + \gamma_c + \tau_t + \vartheta_{c,t} + \varepsilon_{i,c,t} \tag{3}$$

where $Mandarin_{i,t}$ equals 1 if either the language usually spoken at home or other languages spoken is "Putonghua", and 0 otherwise. We use the integration term between language and CEPA (*Mandarin***CEPA*) to test the moderated effect of language skill on wages in

[13] See Table A4 in the Appendix.

Table 4
Treatment-specific and industry-specific time trends.

	Dependent Variable: *Ln (Wage)*	
	(1) Treatment-specific time trends	(2) Industry-specific time trends
CEPA	0.0746**	0.0789***
	(0.029)	(0.023)
Individual Controls	Yes	Yes
Industry fixed effect	Yes	Yes
Census fixed effect	Yes	Yes
Field fixed effect	Yes	Yes
Birth Year fixed effect	Yes	Yes
Adjusted R^2	0.49	0.49
Observations	594,456	594,456

Notes: The table shows the impact of CEPA on log monthly wage based on Eq. (1). CEPA is the DID interaction term between *treat* and *post*. *Treat* equals 1 for individuals in CEPA-affected industries. *Post* equals 1 for the census after 2004. We include treatment-specific and industry-specific linear time trends in columns (1) and (2), respectively, to control for the potential differences in paths between the treatment and control groups. The Individual control variables include *Edu*, *Male*, *Married*, and *Dur7*. Robust standard errors, clustered by the industry-by-census level, are reported in parentheses; ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

the treated industries. Different from basic regressions, the sample is restricted to Chinese respondents according to their self-identified ethnicity.[14]

The results are reported in Panel A of Table 6. The estimate of the interaction term between *CEPA* and *Mandarin* in column (1) is positive and statistically significant at the 5% level, which implies that respondents in the treated industries earned 2.62% more after 2004 if they spoke Mandarin. One concern is that Mandarin speakers might benefit from the network effects. The CEPA policy might be associated with increased migration of Mainland Chinese people to Hong Kong, which accounts for the increased return to speaking Mandarin. To address these concerns, we control for the percentage of Mandarin speakers in the area where the respondent lived (i.e., Local Mandarin-speaking Fraction [%]). The results in column (2) show that the coefficient on the interaction term between *CEPA* and *Mandarin* remains highly positive and statistically significant after adjusting for the network effects. The other concern is about the anticipation effect, given that the Mandarin-learning trend might begin before the adoption of CEPA. To alleviate this concern, we conduct a dynamic analysis of Mandarin's impact by including an interaction term $Mandarin_{i,t}*Treat_c*census_{2001}$ ($census_{2001}$ is a dummy variable for census 2001). We find no evidence of the moderated effect of Mandarin-speaking skills in census 2001 in column (3). The results still reveal a substantial positive and significant moderated effect of Mandarin-speaking skills on CEPA treatment effects. However, the moderated effects of English-speaking skills on CEPA treatment effects in Panel B of Table 6 are never significant.

5.2. Age effect

Next, we analyze other dimensions of heterogeneity, including age, occupational skills, and education level. First, in Table 7, we split the sample into four groups according to the ages of the respondents at the time of the census. The results reveal an interesting pattern of the CEPA wage effects. The age-specific mean monthly wages are also presented, suggesting an inverted U-shaped age-wages profile. The highest wages are achieved for the 41–50 years age group and the lowest for the 18–30 years age group. The wage effect of CEPA on the youngest group was 5.83% (column [1]), decreasing to 3.26% (column [2]) for those aged 31–40 years, and increasing again to 4.80% (column [3]) and 8.52% (column [4]) for those aged 41–50 and 51–65 years. Thus, the workers benefitting the most are those who are just starting their careers or are near retirement, both of which are the lowest-paid periods of one's entire lifetime.

5.3. Occupational skill effect

We explore the heterogeneous effects of CEPA on the log monthly wages of workers with different occupational skill levels. We split the sample into low or high groups according to the respondents' occupational levels and report the results in columns (1) and (2) In Table 8. Specifically, the highly occupational skill group includes managers, administrators, professionals, and associate professionals,

[14] Because there is no information about ethnicity in the 1996 census, we judge by whether the place of birth is Hong Kong, the Mainland, Macao, or Taiwan.

Table 5
Dynamic study and common trend.

	Dependent Variable: *Ln (Wage)*	
	(1)	(2)
post1	0.0630***	0.0620**
	(0.019)	(0.024)
post2	0.0627***	0.0617**
	(0.019)	(0.024)
post3	0.0477**	0.0466*
	(0.024)	(0.028)
pre		-0.0020
		(0.026)
Individual Controls	Yes	Yes
Industry fixed effect	Yes	Yes
Census fixed effect	Yes	Yes
Field fixed effect	Yes	Yes
Birth Year fixed effect	Yes	Yes
Adjusted R^2	0.49	0.49
Observations	594,456	594,456

Notes: The table shows the impact of CEPA on log monthly wage based on Eq. (2). *pre, post1, post2,* and *post3* measure the dynamic CEPA effects in the 2001, 2006, 2011, and 2016 censuses, respectively. The DID dynamic term for benchmark census 1996 is dropped to avoid multicollinearity. The individual control variables include *Edu, Male, Married*, and *Dur7*. Robust standard errors, clustered by the industry-by-census level, are reported in parentheses; * ** , * *, and * denote significance at 1%, 5%, and 10%, respectively.

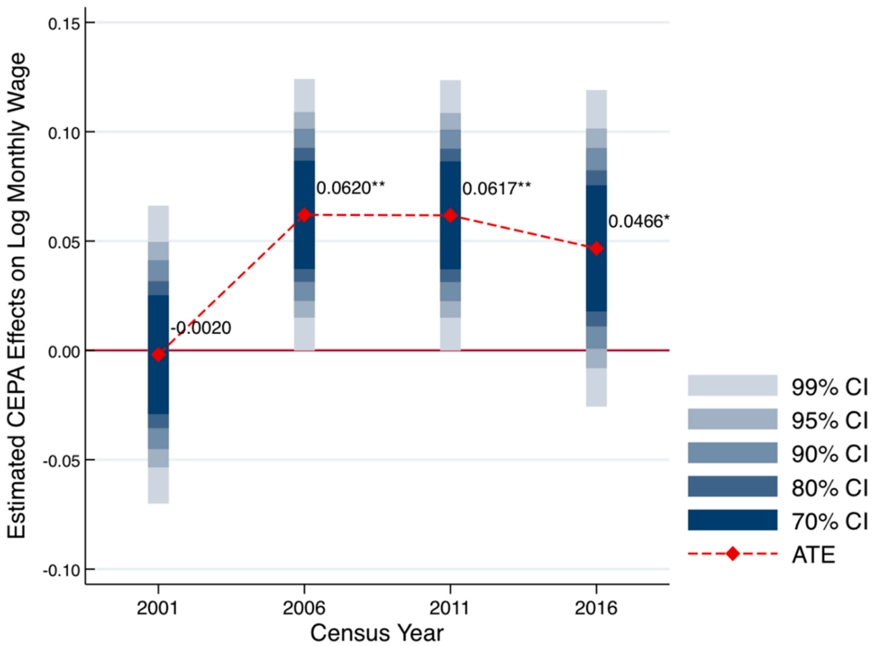

Fig. 5. Dynamic effects. Notes: This figure displays the estimated coefficients β_1^{Pre}, β_1^{Post1}, β_1^{Post2}, and β_1^{Post3} in Eq. (2) and confidence intervals at different significant levels.

while the other remaining occupations are assigned to the low-skilled worker group.[15] The effect of CEPA on the low-skilled (column [1]) and the highly skilled worker group (column [2]) is 2.72% and 7.73%, respectively, showing that workers with higher occupational skills benefited most. This finding indicates a significant skill premium in those industries exposed to CEPA and complements

[15] I.e., clerks, service workers, and workers in sales, skilled agricultural and fishery workers, craft and related workers, plant and machine operators and assemblers, and elementary occupations.

Table 6
Language Skill.

	Dependent Variable: *Ln (Wage)*		
	(1)	(2)	(3)
Panel A. Mandarin-speaking:			
CEPA * Mandarin	0.0268**	0.0273**	0.0333***
	(0.012)	(0.012)	(0.012)
CEPA	0.0431**	0.0436**	0.0437**
	(0.018)	(0.018)	(0.018)
Mandarin * Treat	0.0243**	0.0239**	0.0180**
	(0.009)	(0.009)	(0.009)
Mandarin * Post	-0.0075	-0.0053	-0.0055
	(0.009)	(0.009)	(0.009)
Mandarin	0.0168**	0.0134*	0.0136*
	(0.008)	(0.008)	(0.007)
Local Mandarin-speaking Fraction (%)		0.4763***	0.4767***
		(0.044)	(0.044)
Treat * Mandarin * Census2001			0.0104
			(0.012)
Adjusted R^2	0.49	0.49	0.49
Observations	575,474	575,474	575,474
Panel B. English-speaking:			
CEPA * English	0.0331	0.0346	0.0549
	(0.037)	(0.037)	(0.035)
CEPA	0.0426*	0.0423*	0.0427*
	(0.023)	(0.023)	(0.022)
English * Treat	0.0113	0.0099	-0.0104
	(0.030)	(0.030)	(0.027)
English * Post	-0.0003	0.0009	0.0007
	(0.026)	(0.026)	(0.026)
English	0.1517***	0.1442***	0.1445***
	(0.022)	(0.022)	(0.022)
Local English-speaking Fraction (%)		0.4818***	0.4823***
		(0.031)	(0.031)
Treat * English * Census2001			0.0385
			(0.032)
Adjusted R^2	0.50	0.51	0.51
Observations	575,474	575,474	575,474
Individual Controls	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes
Census fixed effect	Yes	Yes	Yes
Field fixed effect	Yes	Yes	Yes
Birth Year fixed effect	Yes	Yes	Yes

Notes: The table shows the heterogeneous impact of CEPA on log monthly wage based on Eq. (1) across individuals with different language skills. CEPA is the DID interaction term between *treat* and *post*. *Treat* equals 1 for individuals in CEPA-affected industries. *Post* equals 1 for the census after 2004. Local Mandarin-speaking Fraction (%) in Panel A is the fraction of Mandarin speakers in the area in which the individual lives. Local English-speaking Fraction (%) in Panel B is the fraction of English speakers in the area in which the individual lives. The individual control variables include *Edu*, *Male*, *Married*, and *Dur7*. Robust standard errors, clustered by the industry-by-census level, are reported in parentheses; ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

previous research on developing economies by revealing an increase in the post-trade liberalization skill premium (e.g., Chen et al., 2017; Goldberg and Pavcnik, 2007; Robbins and Gindling, 1999); further, these results support the conjecture of Notowidigdo (2020) that high-skilled workers are exposed to more structural shocks than low-skilled workers in the US.

5.4. Educational effect

In Table 9, we investigate the heterogeneity of the CEPA effect in terms of education level. Specifically, education level is divided into four categories according to the highest level of education attained by a respondent, i.e., low education, less education, median education, and high education.[16] Table 9 provides evidence that the positive effects of CEPA on wages are more pronounced for more-educated than for less-educated workers in exposed industries. This finding suggests unequal gains from the CEPA in log monthly wages for workers with different education levels.

[16] The details of the educational classifications are as follows. Low education = no schooling or primary school education (Grades 1–6) or Secondary 1–3 (Grades 7–9); less education = Secondary 4–7 (Grades 10–12) and trade school-level courses; median education = College degree/ Diploma/Certificate courses; high education = bachelor's degree and above.

Table 7
Age Effects.

	Dependent Variable: *Ln (Wage)*			
	(1)	(2)	(3)	(4)
	Age 18–30	Age 31–40	Age 41–50	Age 51–65
CEPA	0.0580***	0.0316*	0.0478***	0.0804***
	(0.017)	(0.017)	(0.015)	(0.026)
Individual Controls	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
Census fixed effect	Yes	Yes	Yes	Yes
Field fixed effect	Yes	Yes	Yes	Yes
Birth Year fixed effect	Yes	Yes	Yes	Yes
Average Monthly Wage	13,288.32	20,052.53	20,323.54	17,695.67
Adjusted R^2	0.46	0.49	0.53	0.50
Observations	153,975	171,668	157,094	111,719

Notes: The table shows the heterogeneous impact of CEPA on log monthly wage based on Eq. (1) across individuals in different age cohorts. CEPA is the DID interaction term between *treat* and *post*. *Treat* equals 1 for individuals in CEPA-affected industries. *Post* equals 1 for the census after 2004. The individual control variables include *Edu*, *Male*, *Married*, and *Dur7*. Robust standard errors, clustered by the industry-by-census level, are reported in parentheses; ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Table 8
Occupational Skill Effects.

	Dependent Variable: *Ln (Wage)*	
	(1) Low occupational skill	(2) High occupational skill
CEPA	0.0272*	0.0773***
	(0.016)	(0.014)
Individual Controls	Yes	Yes
Industry fixed effect	Yes	Yes
Census fixed effect	Yes	Yes
Field fixed effect	Yes	Yes
Birth Year fixed effect	Yes	Yes
Average Monthly Wage	11,508.57	30,123.71
Adjusted R^2	0.30	0.40
Observations	389,196	204,983

Notes: The table shows the heterogeneous impact of CEPA on log monthly wage based on Eq. (1) across individuals with different occupational skill levels. CEPA is the DID interaction term between *treat* and *post*. *Treat* equals 1 for individuals in CEPA-affected industries. *Post* equals 1 for the census after 2004. The individual control variables include *Edu*, *Male*, *Married*, and *Dur7*. Robust standard errors, clustered by the industry-by-census level, are reported in parentheses; ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Table 9
Educational Effects.

	Dependent Variable: *Ln (Wage)*			
	(1) Low education	(2) Less education	(3) Median education	(4) High education
CEPA	0.0236	0.0366	0.1019***	0.1153***
	(0.015)	(0.024)	(0.026)	(0.019)
Individual Controls	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
Census fixed effect	Yes	Yes	Yes	Yes
Field fixed effect	Yes	Yes	Yes	Yes
Birth Year fixed effect	Yes	Yes	Yes	Yes
Average Monthly Wage	10,610.27	14,617.01	21,242.40	33,721.71
Adjusted R^2	0.24	0.25	0.34	0.35
Observations	188,230	230,655	50,573	124,998

Notes: The table shows the heterogeneous impact of CEPA on log monthly wage based on Eq. (1) across individuals with different education levels. CEPA is the DID interaction term between *treat* and *post*. *Treat* equals 1 for individuals in CEPA-affected industries. *Post* equals 1 for the census after 2004. The individual control variables include *Edu*, *Male*, *Married*, and *Dur7*. Robust standard errors, clustered by the industry-by-census level, are reported in parentheses; ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

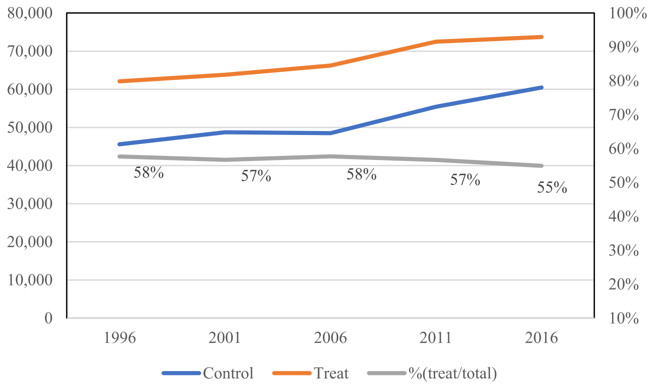

Fig. 6. Number of employees in control and treatment industries: 1996–2016.

Table 10
The Impact of CEPA on Employment.

	(1) No. of persons engaged (log)	(2) No. of vacancies (log)
CEPA	-0.0331	-0.1686
	(0.078)	(0.103)
Industry fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Month fixed effect	Yes	Yes
Adjusted R^2	0.99	0.96
Observations	1218	1134

Notes: The table shows the impact of CEPA on employment. CEPA is the DID interaction term between *treat* and *post*. *Treat* equals 1 for individuals in CEPA-affected industries. *Post* equals 1 for the census after 2004. Robust standard errors, clustered by the industry-by-census level, are reported in parentheses; ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

5.5. Trade liberalization and employment

In this section, we use aggregate industry-level data[17] to investigate whether CEPA promotes employment opportunities in industries that benefit from preferential arrangements. This helps distinguish between aggregate demand and aggregate supply effects of trade liberalization. If the tariff reduction simply increased aggregate demand in Hong Kong, we expect to find greater employment in the affected industries. In the case of tariffs being a supply-side shock (by allowing successful exporters to scale and potentially consolidate), we could find either increased employment or unemployment in the affected industries. As Fig. 6 shows, the numbers of employees of control and affected industries exhibit similar trends over time. Next, we analyze the impact of CEPA on employment and job vacancy outcomes, and present the results in Table 10. We find no evidence that CEPA affects employment and job vacancy.

This evidence is difficult to reconcile with the demand-side framework, where cutting tariffs boosts aggregate demand and affects job creation. However, the results are more consistent with the supply-side framework where CEPA facilitates productivity or boosts firm expansion. This finding is in line with previous literature showing that tariff cuts have positive effects on firms' productivity (Amiti and Konings, 2007; Verhoogen, 2008; Topalova and Khandelwal, 2011). Meanwhile, trade liberalization will encourage firms in the affected industries to upgrade export quality, which increases firms' revenue and employee's wage (Bas and Strauss-Kahn, 2015). Besides, skill premium resulting from CEPA could be rationalized if CEPA increases firms' incentives to create jobs for skilled workers to achieve "quality upgrading". Overall, this finding could be explained by employment adjustment on the production-side driven by tariff cuts.

6. Implications for changes in wage inequality

In this section, we discuss the impact of trade liberalization on wage inequality. To quantify the equalizing impact of CEPA, we calculate the Gini coefficients, the 90th/10th and 75th/25th inter-quantile differences in the counterfactual cumulative distribution functions (CDF) of wages based on recentered influence function (RIF) regression. This RIF approach enables measurement of wage inequality at the individual level. The descriptive summary for the individual-level inequality index is presented in Table A5 in the Appendix. Subsequently, we examine the distributional effect of CEPA in a DID setting. Overall, we find no evidence that trade liberalization leads to changes in wage inequality, as shown in Table A6.

[17] We are not able to identify the previous industry of the unemployed respondents because there is no such question in the Hong Kong population census. The responses in each census were randomly selected and not traceable.

We further decompose wage inequality into components driven by observable characteristics (i.e., occupational skills, education level, language skills, gender, and age) to quantify CEPA's impact on the wage structure and evaluate how CEPA contributes to shifts in between- and within-group wage inequality. Between-group inequality captures wage disparities between workers with different characteristics, while within-group inequality reflects the wage differentials among workers with identical attributes. We find that CEPA significantly increases between-group wage inequality along the dimensions of the occupational skills and education levels, as shown in panels A and D of Table A7 in the Appendix. This skill premium could be attributed to skill-biased growth in productivity and compositional adjustment within the labor markets resulting from supply-side changes. However, whether this skill premium is translated to an increase in wage inequality also depends on the changes in within-group inequality. We find evidence that CEPA simultaneously reduces the within-group inequality among (i) workers in skilled occupations, (ii) those with a college degree or higher, and (iii) those aged between 31 and 40 years, as shown in panels A, D, and E of Table A7, respectively. Therefore, a reduction in within-group wage inequality may partly offset the skill premium, explaining why there are no significant changes in overall wage inequality after the CEPA.

7. Conclusion

In this paper, we investigate the impact of trade liberalization on log monthly wages through the quasi-natural experiment of CEPA based on individual-level Hong Kong population census data from 1996 to 2016. We exploit the policy background to determine which industries were exposed to a round of unilateral Chinese tariff cuts in 2004. We find that trade liberalization produces significant and persistent increases in wages for workers in industries that benefit from the preferential arrangements, while it exerts virtually no influence on the aggerate employment in CEPA-affected industries. Our main findings remain robust and not driven by simultaneous policy shocks like IVS and industry-specified unobservable differences. Besides, the placebo test provides further evidence for the validity of our identification strategies. In heterogeneous analysis, we find that trade liberalization has raised the wages of most Hong Kong workers, but the workers who have benefited most are: (i) better educated, (ii) in higher-skilled occupations, (iii) Mandarin speakers, (iv) nearing retirement, or (vi) just starting their careers. Overall, our evidence is consistent with the structural-shock argument that tariff reductions provide pronounced benefits to higher-skilled workers (Notowidigdo, 2020).

In addition, we find that tariff cuts' wage impact and hence their impact on wage inequality depend on the local labor market composition and structure. On the one hand, our results show that highly skilled and/or educated workers, most of whom belong to the high-income group, benefited more from the adoption of the CEPA. On the other hand, the typical low-income groups that have experienced above-average wage increases from the CEPA are the young and those near retirement. These sources of downward pressure on wage inequality may moderate the upward pressure on wage inequality from CEPA's skill-biased wage gains. After decomposing the CEPA effects on wage inequality by occupational skills/education, we find an increase in between-group inequality but a reduction in within-group inequality. This explains the lack of evidence on the CEPA's impacts on overall wage inequality but structural changes in inequality within demographic groups. These results could be a useful first step to better understanding the ambiguous effects of trade liberalization on income inequality. Finally, we add to the literature on "China Shock" by analyzing trade liberalization between Mainland China and Hong Kong SAR, a free trade port relying heavily on trade with the Mainland. We provide evidence on how the labor market in Hong Kong responds to trade liberalization and the associated distributional consequences.

Author Statement

We acknowledge that:

*The information reported in the paper is accurate according to our best knowledge.

*The paper is entirely original work conducted by us without copying or plagiarism issues.

*The paper has not been and will not be submitted simultaneously to other journals.

*The authors of the paper cited reported publications' work and proper acknowledgment of the work of others has been given.

*All of the authors of the paper have participated in certain substantive aspects of this study, and they are acknowledged or listed as contributors.

*The work does not involve any hazards, such as the use of animal or human subjects' issue.

*There is no financial or other substantive conflict of interest that might be construed to influence the results or interpretation of our manuscript.

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Appendix

(See here Table A1-A7).

Table A1
Description, treatment status, and distribution of industries.

Code	Description	Treatment	Observations	Frequency (%)
310	Food, Beverage Industries and Tobacco Manufactures	1	4066	0.69
321	Manufacturing of Wearing Apparel, Leather Products, Footwear and Textiles Goods	1	15,836	2.69
330	Manufacturing of Wood and Cork Products, Furniture and Fixtures	1	688	0.12
340	Manufacturing of Paper and Paper Products, Printing, Publishing and Allied Industries	1	9619	1.64
350	Manufacturing of Chemicals and Chemical Products, Products of Petroleum and Coal, Rubber Products and Plastic Products	1	5454	0.93
370	Manufacturing of Basic Metal Industries	1	1017	0.17
381	Manufacturing of Machinery, Equipment, Apparatus, Parts and Components, Transport Equipment, Professional & Scientific, Measuring & Controlling Equipment and Photographic & Optical Goods	1	19,366	3.29
390	Manufacturing Industries, N.E.C	0	3560	0.61
410	Electricity, Gas and Water Electricity	0	3418	0.58
510	New Construction Works, Pre-erection Works at Building and Construction Sites, Site Investigation works	0	7197	1.22
520	New Construction Works - Architectural and Civil Engineering Works at Building and Construction Sites and Miscellaneous New Construction Works	0	10,650	1.81
530	Specialized construction activities include: 530 (HSIC V1.1): Decoration, Repair and Maintenance; 540 (HSIC V1.1): Special Trades - Erection and General Finishing; 550 (HSIC V1.1): Special Trades - Electrical and Mechanical Fitting; 560 (HSIC V1.1): Special Trades - Gas and Water Fitting; 590 (HSIC V1.1): Special Trades - Miscellaneous	0	31,417	5.34
610	Wholesale	1	10,366	1.76
620	Retail	1	49,980	8.50
630	Import/Export	1	52,378	8.91
640	Restaurants	0	41,769	7.11
650	Hotels and Boarding Houses	0	8302	1.41
710	Includes: 710 (HSIC V1.1): Transport and Supporting Services; 720(HSIC V1.1): Storage	1	59,551	10.13
730	Communications	0	11,158	1.90
810	Banking, Finance and Investment Companies, Stock, Commodity and Bullion Brokers, Exchanges and Services	1	33,539	5.71
820	Insurance	0	6352	1.08
830	Real Estate, Rental of Machinery and Equipment, Legal Services, Accounting, Auditing and Bookkeeping Services, Architectural, Surveying, Engineering and Technical Services, Advertising and Related Services, Data Processing and Tabulating Services and Miscellaneous Business Services	1	74,672	12.70
910	Public Administration	0	28,417	4.83
920	Sanitary and Similar Services	0	8185	1.39
930	Education Services, Research and Scientific Institutes, Medical, Dental, Other Health and Veterinary Services, Welfare Institutions, Business, Professional and Labor Associations, Religious Organizations and Miscellaneous Social and Related Community Services	0	64,571	10.98
941	Motion Pictures and Other Entertainment Services, Libraries, Museums, Gardens and Cultural Services, Miscellaneous Amusement and Recreational Services	0	12,066	2.05
950	Repair Services, Laundry, Dry Cleaning and Garment Services, Domestic Services and Miscellaneous Personal Services	0	14,279	2.43

Notes: We define a new set of industry codes based on HSIC (V1.1) and crosswalk all samples from the 1996–2016 censuses.

Table A2
Educational attainment of respondents.

Edu	Description	Frequency	Percentage
1	No schooling/Pre-primary	6868	1.2
2	Primary school	70,791	11.9
3	Secondary school	110,571	18.6
4	High school	192,734	32.4
5	Craft-level courses/Project Yi Jin	37,921	6.4
6	Diploma/ Certificate courses /College degree	50,573	8.5
7	Bachelor's degree	96,413	16.2
8	Postgraduate courses	28,585	4.8
	Total	594,456	100

Note: The education level of workers was based on the highest level of education completed in school or other educational institutions. The details of the educational classifications are as follows. Low education = no schooling or primary school education (Grades 1–6) or Secondary 1–3 (Grades 7–9); less education = Secondary 4–7 (Grades 10–12) and trade school-level courses; median education = College degree/Diploma/Certificate courses; high education = Bachelor's degree and above.

Table A3
Descriptive statistics for monthly wages.

	Census					
	1996 Before CEPA	2001	2006 After CEPA	**2011**	**2016**	**Total**
Groups by age (in years)						
18–30 (n = 153,975)	11588.33	12749.33	11441.87	14052.76	17252.79	13288.32
31–40 (n = 171,668)	16015.79	19183.69	18433.90	21456.74	25702.19	20052.53
41–50 (n = 157,094)	15799.76	17932.31	18228.51	21564.83	26415.01	20323.54
51–65 (n = 111,719)	12738.53	15109.00	15159.86	17322.67	21579.60	17695.67
Groups by education level						
Low (n = 188,230)	9485.86	10315.57	10102.23	10421.14	13112.75	10610.27
Less (n = 230,655)	12946.65	14390.99	13736.32	14592.15	17492.47	14617.01
Medium (n = 50,573)	21170.75	22586.40	19051.64	20117.19	22960.05	21242.40
High (n = 124,998)	29567.37	33304.35	29216.20	34283.67	37482.76	33721.71
Gender						
Female (n = 256,855)	12760.31	14829.30	14809.72	17467.66	21001.24	16592.14
Male (n = 337,601)	14954.35	17634.16	17092.36	20029.29	24606.48	18946.40
Occupational Skill						
Unskilled (n = 389,196)	10020.58	11019.24	10711.71	11472.17	14227.80	11508.57
Skilled (n = 204,983)	24560.93	28253.10	27059.82	31037.00	35881.65	30123.71
Mandarin-speaking						
No (n = 315,829)	13364.30	15097.47	15002.04	17054.67	21450.55	16251.90
Yes (n = 278,627)	15638.11	18353.95	17387.14	20381.35	24118.83	19830.36
Total (n = 594,456)	14126.63	16471.16	16108.36	18860.76	22915.91	17929.16

Table A4
Descriptive Statistics for Mandarin-speaking Percentage.

	Census					
	1996 **Before CEPA**	**2001**	**2006** **After CEPA**	**2011**	**2016**	**Total**
Groups by age (in years)						
18–30 (n = 153,975)	31.03	40.79	51.15	65.83	65.71	49.60
31–40 (n = 171,668)	35.23	44.93	46.97	57.70	58.94	48.41
41–50 (n = 157,094)	35.81	41.87	44.42	49.92	52.81	45.72
51–65 (n = 111,719)	31.38	39.19	41.61	44.32	45.59	42.35
Groups by education level						
Low (n = 188,230)	24.12	29.90	33.22	37.72	41.76	32.86
Less (n = 230,655)	36.77	45.90	49.65	54.55	54.83	48.33
Medium (n = 50,573)	44.39	55.04	56.31	64.97	58.76	57.64
High (n = 124,998)	46.83	55.29	56.52	68.33	64.82	60.91
Gender						
Female (n = 256,855)	36.41	45.53	50.01	58.14	57.67	50.75
Male (n = 337,601)	31.78	39.82	43.64	51.06	52.49	43.92
Occupational Skill						
Unskilled (n = 389,196)	29.52	36.72	41.47	48.12	50.43	41.36
Skilled (n = 204,983)	43.84	53.97	56.36	64.47	61.61	57.37
Total (n = 594,179)	33.56	42.18	46.39	54.29	54.92	46.88

Table A5
Descriptive Statistics for Wage Inequality at Individual Level.

	1996		2001		2006		2011		2016	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Log 90/10 ratio	1.40	1.64	1.58	1.89	1.66	1.56	1.67	1.73	1.78	1.97
Log 75/25 ratio	0.66	0.96	0.80	1.04	0.81	0.99	0.85	1.07	0.83	1.18
Gini coefficient	0.034	0.027	0.037	0.031	0.039	0.025	0.038	0.027	0.038	0.031
Observations	107362		112248		114559		127614		132673	

Notes: Log 90/10 ratio and Log 75/25 ratio are derived from recentered influence functions (RIF) for inter-quantile difference (90 10) and RIF for inter-quantile difference (75 25), respectively.

Table A6
CEPA Treatment Effects on Wage Inequality.

	Dependent variable: Wage Inequality		
	(1) RIF for Inter-quantile difference (90 10)	(2) RIF for Inter-quantile difference (75 25)	(3) Gini coefficient
CEPA	0.0736	0.0188	0.0005
	(0.061)	(0.040)	(0.001)
Individual Controls	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes
Census fixed effect	Yes	Yes	Yes
Field fixed effect	Yes	Yes	Yes
Birth Year fixed effect	Yes	Yes	Yes
Adjusted R^2	0.19	0.18	0.21
Observations	594,456	594,456	594,456

Notes: The table shows the impact of CEPA on wage inequality based on Eq. (1). CEPA is the DID interaction term between *treat* and *post*. *Treat* equals 1 for individuals in CEPA-affected industries. *Post* equals 1 for the census after 2004. Robust standard errors, clustered by the interaction between industry and census year, are reported in parentheses; ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Table A7
Decomposing the Impact of CEPA on Wage Inequality to Between- and Within-Groups.

Panel A. Decomposition by Occupational Skills:							
				Occupational Skills			
	Total	Between Groups	Within Groups	Unskilled		Skilled	
CEPA	0.0030	0.0063*	-0.0033	0.0032		-0.0146**	
	(0.007)	(0.004)	(0.004)	(0.003)		(0.007)	
	Total	Between Groups	Within Groups	No		Yes	
Panel B. Decomposition by Mandarin-speaking Ability:							
				Mandarin-speaking ability			
	Total	Between Groups	Within Groups	No		Yes	
CEPA	0.0031	0.0015	0.0016	-0.0003		0.0006	
	(0.007)	(0.001)	(0.007)	(0.0o09)		(0.008)	
Panel C. Decomposition by Gender:							
				Gender			
	Total	Between Groups	Within Groups	Female		Male	
CEPA	0.0031	0.0022	0.0009	0.0019		-0.0011	
	(0.007)	(0.001)	(0.007)	(0.008)		(0.007)	
Panel D. Decomposition by Education Level:							
				Education Level			
	Total	Between Groups	Within Groups	Low	Less	Median	High
CEPA	0.0031	0.0099***	-0.0068	0.0005	-0.0060	-0.0264***	-0.0164**
	(0.007)	(0.004)	(0.005)	(0.006)	(0.007)	(0.008)	(0.008)
Panel E. Decomposition by Age:							
				Age			
	Total	Between Groups	Within Groups	18–30	31–40	41–50	51–65
CEPA	0.0031	0.0022	0.0009	-0.0105	-0.0131*	0.0021	-0.0025
	(0.007)	(0.002)	(0.006)	(0.006)	(0.008)	(0.008)	(0.013)

Notes: This table shows the impact of CEPA on wage inequality as measured by the Theil index. All decompositions control for industry and year fixed effects. In panel A, we split the sample into two mutually exclusive groups: (a) Unskilled, and (b) Skilled. In panel B, we split the sample into two mutually exclusive groups: (a) Mandarin-speaking, and (b) Not Mandarin-speaking. In panel C, we split the sample into two mutually exclusive groups: (a) Female, and (b) Male. In panel D, we split the sample into four mutually exclusive groups: (a) Low educational attainment ($Edu = 1, 2, 3$), (b) Less Educational attainment ($Edu = 4, 5$), (c) Median Educational attainment (edu = 6), and (d) High Educational attainment ($Edu = 7,8$). In panel E we split the sample into four mutually exclusive groups by age of respondents. The Theil index is established for workers in 18 districts, 27 industries, and over 5 years. The number of observations in each inequality decomposition is 2271 (we exclude clusters of fewer than 10 workers). In the second and third columns, we estimate the CEPA effect on inequality between and within the different groups, respectively. These two columns add up to the first column. Finally, we estimate the impact of CEPA on inequality separately within each group. Standard errors are adjusted for district-by-census level clustering and appear in parentheses; ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

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