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JUE insight: Demand for transportation and spatial pattern of economic activity during the pandemic[☆]

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ABSTRACT

Using traffic data from Taiwan for 2020, we quantify how the COVID-19 outbreak affected demand for public and private transportation. Despite there being no governmental restrictions, substantial shifts in travel modes were observed. During the peak of the pandemic in Taiwan within the study period (mid-March 2020), railway ridership declined by 40% to 60%, while highway traffic volume *increased* by 20%. Furthermore, railway ridership was well below pre-pandemic levels, though there were no locally transmitted cases in the eight-month period from mid-April to December. These changes in traffic patterns had implications for spatial patterns of economic activity: retail sales and nighttime luminosity data show that during the pandemic, economic activity shifted away from areas in the vicinity of major railway stations.

1. Introduction

COVID-19 has upended people's lives around the world. Many recent studies have shown that human mobility and use of public transport fell dramatically following the onset of the pandemic (Engle etal., 2020; Fang etal., 2020; Monte, 2020; Cronin and Evans, 2021; Goolsbee and Syverson, 2021; Liu etal., 2020; Xin etal., 2021). However, it is unclear whether the observed changes in mobility and transport mode occurred because of voluntary changes in behaviors or because of enforced measures such as lockdowns and stay-at-home orders. Even without government intervention, rational individuals would still have curtailed their movements or changed the way they traveled in order to reduce their exposure to the virus. Understanding individuals' efforts in the midst of a pandemic, especially in terms of mobility or mode of transportation, has important policy implications. On the one hand, people's travel behavior is highly associated with the spread of COVID-19 (Li and Ma, 2021; Mangrum and Niekamp, 2022; Brinkman and Mangum, 2022). On the other hand, government regulations on travel can and could have resulted in huge economic and welfare costs. This raises questions as to whether these mobility restrictions are necessary or excessive. In addition, changes in human mobility are likely to affect commercial activities around transportation nodes during the pandemic.

This paper studies transportation modes people used during the pandemic, without governmental restrictions, and its implications for spatial distribution of urban activity. In particular, we examine the effect of the COVID-19 outbreak on demand for public and private transportation in Taiwan. The experience of Taiwan during 2020 offers an ideal setting for this study because, except for a few minor regulations,[1] no lockdown policy, stay-at-home order, or restrictions on mobility were imposed. Given this, the response of the general public in terms of mobility can be almost completely attributed to unrestricted choice of the people. We use a difference-in-differences design alongside 2018-2020 traffic administrative data of railway ridership and highway traffic volume to examine whether the utilization of public or private transport during 2020 had changed substantially compared to previous years (2018–2019). We then further investigate how changes in transportation mode affected the spatial pattern of economic activity.

There are three key findings of this research. First, the number of railway passengers decreased immediately following the first COVID-

[1] Several public events were canceled between March 25th and June 7th because the government had announced guidance suggesting that unnecessary public gatherings with more than 100 people indoors or 500 people outdoors should not be held.

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19 case announcement. Moreover, during the period (mid-March 2020) when cases peaked in Taiwan during 2020, railway ridership dropped by more than 60% relative to the same weeks in prior years. As a matter of fact, COVID-induced decline in passenger flow persisted through the whole of 2020, despite Taiwan not having experienced any new local virus cases in the eight-month period from mid-April to the end of 2020. Furthermore, we use Google Trends data on COVID-19-related keywords to construct an index measuring the public perceptions of COVID-19 risk in Taiwan.[2] Our results suggest that, on average, a 10% increase in the index of public perception of COVID-19 risk, equivalent to one additional coronavirus case, reduced the number of daily passengers by 1.6%.

Second, in contrast to public transport, highway traffic flow did not change at the beginning of the COVID-19 outbreak but *had increased* by 20% when the number of new cases in Taiwan reached its peak during 2020. On average, highway traffic volume increased by 1.2% when the index of public perception of COVID-19 risk increased by 10%. Two effects influenced the demand for private transport during the pandemic. On the one hand, people avoided going out due to fear of contracting the coronavirus, so the demand for both public and private transport declined (the fear effect). On the other hand, individuals substituted private for public transportation when they needed to travel (the substitution effect), as the latter was deemed a far riskier mode of travel than the former. Our results indicate that the substitution effect dominated the fear effect.

Finally, changes in transport mode have implications for the spatial pattern of economic activity. Since the pandemic substantially reduced passenger flow at railway stations, it shifted economic activity, measured by retail sales and nighttime luminosity, away from areas close to major railway stations.

This paper contributes to three strands of extant literature. First, it complements the fast-growing body of work on impacts of the COVID-19 pandemic on individual mobility (Argente et al., 2022; Engle et al., 2020; Fang et al., 2020; Goolsbee and Syverson, 2021; Couture et al., 2022; Glaeser et al., 2022). In particular, we provide one of the first pieces of evidence indicating that individuals substituted private for public transport to reduce the risk of exposure to COVID-19. This finding is also related to the "prevalence response" in the literature on economic epidemiology (Ahituv etal., 1996; Gersovitz and Hammer, 2003; Lakdawalla etal., 2006; Bennett etal., 2015). Previous works on this issue have shown that people change their health-related behaviors when faced with an increase in disease risk. Our study contributes to this stream of literature by showing that people adjusted their mode of transport to reduce the risk of contracting an infectious disease. Moreover, our results indicate that people took proactive preventive actions even though the risk was very low.[3]

Second, our results are related to the literature on the relationship between public and private transport (Anderson, 2014; Chen and Whalley, 2012; Parry and Small, 2009; Nelson etal., 2007; Winston and Langer, 2006; Duranton and Turner, 2011). Several studies have shown how the provision of public transport affects traffic congestion (i.e., demand for private transport). This paper provides novel evidence on substitution between public and private transport, using an exogenous epidemic outbreak.

Third, we also contribute to the literature on how risk perception affects spatial patterns of economic activity (Pope, 2008; Abadie and Dermisi, 2008; Manelici, 2017). Previous studies have found that fear of crime (Pope, 2008) or terror attacks (Abadie and Dermisi, 2008; Manelici, 2017) can affect housing prices and shift economic activity away from city centers (i.e., major railway stations). This paper offers new evidence showing that the risk of contracting an infectious disease could affect spatial distribution of economic activity by moving them away from areas close to crowded public places. This result is consistent with the recent evidence on COVID-induced reallocation of activities within and across US cities (Ramani and Bloom, 2021; Rosenthal et al., 2022).

2. Data and sample

2.1. Data

This sectionbriefly introduces the administrative transportation data used to measure the demand for public transport (i.e., railway ridership) and private transport (i.e., highway traffic volume).

Taiwan Railways (TR) is a 1065-kilometer railway network that services 21 of 22 counties via 241 stations. With annual journeys totaling more than 200 million kilometers, TR provides an extremely important form of transport in Taiwan. We collected daily passenger counts (entries plus exits) for each station from the government's Open Data of Taiwan sharing platform.[4]

In addition to Taiwan Railways, another important transport mode is the national highway system. Currently, the 988.56-kilometer road network consists of nine lines in 20 of 22 counties. In our study, we focus on national highways where a toll is automatically collected by an electronic toll collection (ETC) system. While collecting fees, 327 toll reader devices also record vehicle speed, volume and other data. We collect data on traffic flow in five-minute intervals through each ETC station from the Freeway Bureau database.[5] To maintain consistency with TR data, we aggregate five-minute traffic volume to a daily level. In addition, since we focus on private transport, data on bus and truck traffic are excluded from the sample, i.e., we use only private vehicle data.

2.2. Sample

The sample is at the station-days level. The sample period is the first 24 weeks of 2018, 2019 and 2020.[6] We only use TR stations and ETC stations that can be observed in the first 24 weeks of every year (i.e., a balanced panel). We also exclude TR stations located in Hualien and Taitung counties, where there is no highway. Among all TR stations, 180 satisfy the above criteria. In total, we have a sample size of 90,720 station-days for public transport. Similarly, 324 ETC stations fulfill balanced panel requirements, and we have a sample size of 162,648 station-days for private transport.

3. Empirical strategy and results

Our identification strategy is the differences-in-differences (DID) design. Since the first COVID-19 case in Taiwan was reported on January 21st, 2020 (i.e., the 4th week of 2020), we use 2020 as the treated year and define the 1st to 3rd weeks and 4th to 24th weeks of the year as the pre-outbreak and post-outbreak periods, respectively. To control for seasonal patterns of the demand for public and private transport unrelated to the COVID-19 outbreak, we use 2018–2019 as untreated years, which helps construct the counterfactual trend of transportation patterns in 2020.

[2] We will discuss how to construct this index in Section 3.1 and Online Appendix.

[3] Based on the accumulated number of COVID-19 cases reported as on October 28th, 2020, the incidence of COVID-19 per 1,000,000 population was approximately 23 in Taiwan and 26,960 in the US.

[4] https://data.gov.tw/dataset/8792

[5] https://www.freeway.gov.tw/

[6] Note that the definition of "week in this study follows the World Health Organization (WHO) definition, which always begins on a Sunday and ends on a Saturday, but does not necessarily start from January 1st.

3.1. Effects of the COVID-19 outbreak on demand for public transport

Since the impact of COVID-19 might have evolved over time, we need to trace the full dynamic trajectory of its effects. Therefore, following Chang etal. (2020) and Kleven etal. (2019), we implement a dynamic DID design by estimating the following regression:

$$P_{idt} = \sum_{s\neq-1}^{20} \beta_s \cdot Y_{2020} \times I_s + \lambda_t + \eta_w + \theta_i + X_{idt}\Psi + \epsilon_{idt}. \quad (1)$$

Since we have daily numbers of passengers entering and exiting every TR station, estimation is implemented at the station-day level. P_{idt} represents outcomes of interest, namely, the log of the number of passengers exiting and entering station i on day d in year t. We include year fixed effects (λ_t) to capture the trend in demand for train travel over time. In addition, η_w denotes week of the year fixed effects. This helps to control for seasonal patterns in public transport demand over a year. To control for time-invariant confounding factors at the station level, we also include a full set of station fixed effects θ_i. Finally, X_{idt} is a set of covariates, including day-of-the-week fixed effects, various holiday dummies (e.g., Lunar New Year), daily temperature, daily rainfall, daily gasoline prices, and monthly population.[7]

Y_{2020} is a dummy variable for the treated year, which is set at one for the year 2020, and zero for 2018 and 2019 (untreated years). We denote the week in which the first COVID-19 case was reported with $s = 0$, and then index all weeks relative to that week. The event time s runs from −3 to +20, since observations are from three weeks before the COVID-19 outbreak to 20 weeks after. Therefore, we use I_s, whereby $s = -3, -2, 0, 1, 2 \ldots 19, 20$, to denote the event time dummies. For example, I_1 represents a dummy for the first week following the initial announcement of coronavirus cases. Since we use the week right before the outbreak as a baseline week, we omit the event time dummy at $s = -1$, i.e., the 3rd week of a year is used as the baseline period.

The key variables used for identification in regression (1) are a set of event time dummies I_s interacting with the dummy for the treated year Y_{2020}. Coefficients of interest are β_s, which measures the difference in demand for public transport between week s and the baseline week for 2020, relative to the difference in 2018 and 2019. Therefore, β_s represents the COVID-19-induced change in demand for public transport, if the common trend assumption is valid. That is, in the absence of a COVID-19 outbreak, the time trend in railway ridership is assumed to be similar in both the treated and the untreated years. We examine this assumption by using data from the pre-outbreak period. To account for possible within-group error correlations, we use the multiway clustering approach proposed by Cameron etal. (2012) to calculate the standard errors clustered at both the date and the station levels.

Fig. 1 a shows the results based on the TR data. The vertical axis of the figuredisplays the estimated β_s and the corresponding 95% confidence intervals. Four key insights emerge from the figures. First, estimated coefficients at $s = -3, -2$ in the figuresare small and statistically insignificant, suggesting that trends in number of railway passengers in the treated year (i.e., 2020) and untreated years (i.e., 2018 and 2019) were similar before the COVID-19 outbreak. Therefore, the common trend assumption of our DID design is valid. Second, the TR ridership decreased by 25% within the first four weeks after the first COVID-19 case was announced, although there were only 22 new confirmed cases during this period.

Third, the magnitude of the COVID-induced reduction was most pronounced at the peak of the pandemic in Taiwan during 2020 (i.e., mid-March 2020), with the number of passengers declining by more than 60%. Fourth, although negative effects of the COVID-19 outbreak gradually died away after Taiwan ceased to have any local COVID-19 cases starting from mid-April (i.e., April 12th, 2020), they did not recover to the pre-pandemic baseline.

As a matter of fact, there were no new, locally transmitted cases in Taiwan for 253 consecutive days up to December 23rd, 2020. In Online AppendixA, we extend our sample period to the end of 2020 (i.e., the 48th week after the first case) and find that railway ridership was still 14% to 20% below pre-pandemic levels in December (see Fig.A1). This result is consistent with the survey evidence on the persistence of people's behaviors reflecting the fear of virus infection. For example, according to a survey conducted by the National Taipei University of Nursing and Health Sciences in April,[8] 97.5% of Taiwanese people thought of the coronavirus as a serious disease, and over 90% of the interviewees correctly answered questions regarding how the virus spreads and what prevention measures were in place. Surveys conducted by YouGov (Smith, 2020) show that even at the end of 2020, approximately 60% of respondents said they were avoiding going to crowded public spaces (see Fig.A2). Interestingly, these numbers are comparable to the US, where the pandemic was still ongoing and more severe, implying that people would probably remain fearful of the coronavirus even after community transmission of COVID-19 is eliminated.

So far, we have shown that the use of public transport declined substantially in response to the COVID-19 outbreak. To examine how people's fear of infection affected demand for public transport, we use Google Trends data on search intensity of COVID-19-related keywords. Several medical studies (Ginsberg etal., 2009; McDonnell etal., 2012; Nuti etal., 2014; Ayers etal., 2020) suggest that Google Trends data on disease keywords can be a good proxy for the flu outbreak or fear of a flu pandemic. Following this idea, we sum up the search intensity of keywords "coronavirus" and "confirmed cases" to construct a measure for public perceptions of COVID-19 risk in Taiwan (hereafter, the *COVID-19 Perception Index*). Note that instead of showing the absolute search volume, Google Trends only provides a relative measure for the daily search volume, ranging from 0 to 100, where the numbers represent the search volume relative to the highest one. For example, the value of 100 is the peak popularity of a term, and a value of 50 means it is half as popular. Since we sum up two keywords, the maximum amount of our index is 200. In Online AppendixB, we examine the effect of new COVID-19 cases on the *COVID-19 Perception Index*. Fig.B1 shows that the evolution of new COVID-19 cases in Taiwan and the *COVID-19 Perception Index* have similar patterns. Our results suggest that one new COVID-19 case is associated with a 10% increase in the index. We then use the following regression to examine how the public perception of COVID-19 affects demand for public and private transport:

$$P_{id} = \beta \mathtt{COV\_PI}_d + \eta_w + X_{id}\Psi + \epsilon_{id}. \quad (2)$$

Here, $\mathtt{COV\_PI}_d$ is the log of the *COVID-19 Perception Index* on date d. The other notation is defined in the same way as in Eq. (1).[9] In this specification, we use only 2020 data.

The first three columns of Table 1 display the estimated coefficient of $\mathtt{COV\_PI}_d$ for public transport. Panel A reports our main result, which shows that a 10% increase in the *COVID-19 Perception Index* is associated with a 1.6% decrease in number of daily passengers per TR station (Column (3)). We further conduct a subgroup analysis based on different pandemic periods defined in Online AppendixC: (1) Initial period (i.e., late January to mid-March, 1st to 8th weeks after the first COVID-19 case); (2) Peak period (i.e., mid-March to mid-April, 9th to 14th weeks after the first COVID-19 case); and (3) Recovery period (i.e., mid-April to June, 15th to 20th weeks after the first COVID-19 case). Panels B to D display results for the initial period, the peak period, and the recovery period, respectively. The results suggest that estimates in Panel A are

[7] Table A1 reports summary of statistics of variables used in Sections 3.1 and 3.2.

[8] https://news.sina.com.tw/article/20200509/35111198.html, Date accessed Aug. 10th 2020

[9] Similar to Eq. (1), we also use the multiway clustering approach proposed by Cameron etal. (2012) to calculate the standard errors clustered at both the date and the station levels.

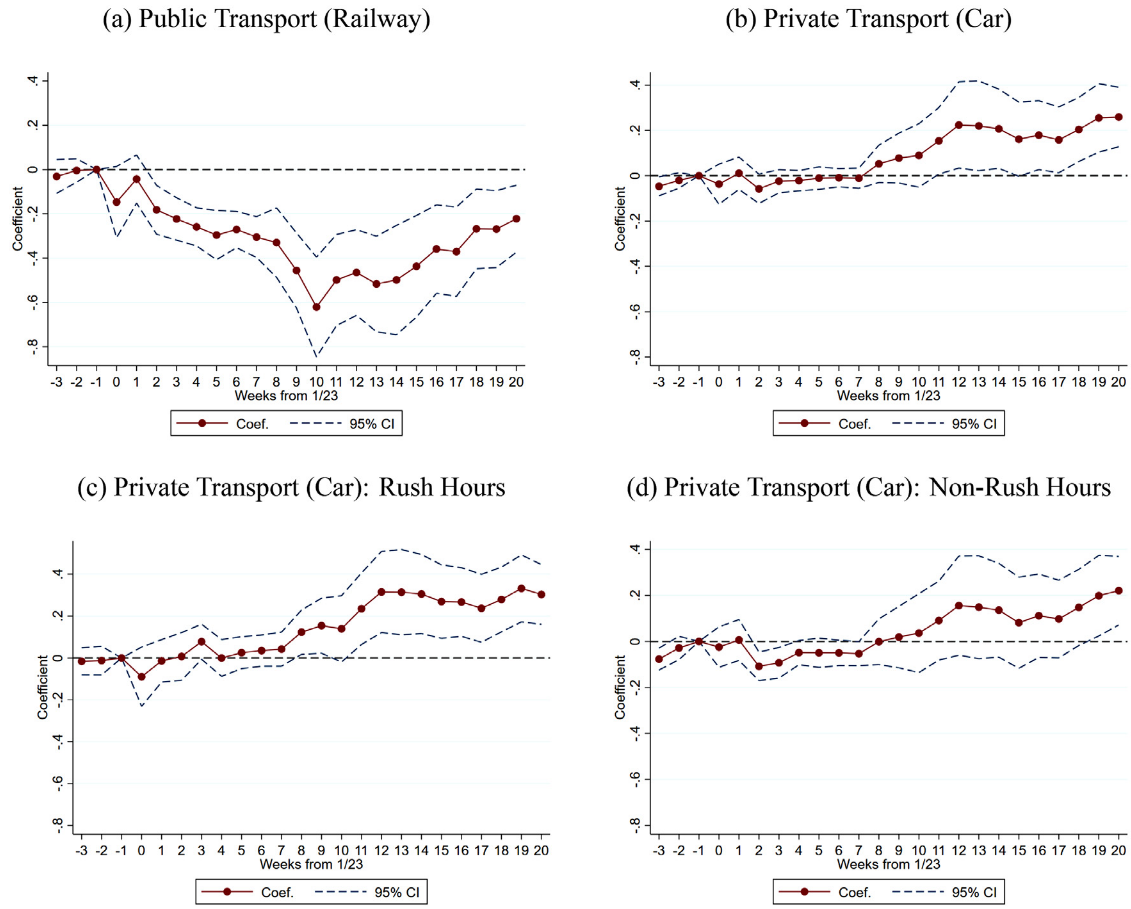

Fig. 1. The effect of the COVID-19 pandemic on transportation patterns. *Notes:* Sample period is the first 24 weeks of 2018-2020. The vertical axis of Fig.1 displays estimated β_s in Eq. (1) and the corresponding 95% confidence level. The horizontal axis denotes weeks from the 4th week of a year. We define rush hours as 7am to 9am and 5pm to 9pm, and other times are defined as non-rush hours.

mainly driven by the peak period when the *COVID-19 Perception Index* reached its peak in 2020 (see Panel C).

3.2. Effects of the COVID-19 outbreak on the demand for private transport

In this section, we use ETC data to measure changes in demand for private transport. To compare it with demand for public transport, we use the log of daily number of cars passing through each ETC station as the outcome of interest, and as the same empirical specification as in Eqs. (1) and (2).

The effect of the COVID-19 outbreak on the use of private transport is ambiguous. On the one hand, businesses could have shut down or shortened their working hours, since the pandemic had negative impacts on economic activity.[10] Companies might also have adopted work-from-home policies to protect their employees from contracting COVID-19. According to an employee survey conducted by the 104 Job Bank, which is the largest human resource company in Taiwan, approximately 16% of employees worked from home during the pandemic in 2020.[11] Moreover, people avoided exposure to the virus by postponing or canceling unnecessary outdoor activities. For all of these reasons, the COVID-19 pandemic reduced demand for both public and private transport. We call this the "fear effect. On the other hand, when people did go out, they adjusted their mode of transport by substituting private for public, as this could help maintain social distancing more easily. Thus, the "substitution effect can reduce demand for public transport but increase demand for private transport.

Fig. 1 b displays the results for private transport. Again, the vertical axis of the figuredisplays the estimated β_s and the corresponding 95% confidence intervals. There are three findings from the dynamic DID estimates. First, the COVID-19 outbreak had little impact on highway traffic volume at the beginning of the COVID-19 outbreak. The effects of COVID-19 on highway traffic turned out to be positive during the peak period of the 2020 pandemic in Taiwan (mid-March 2020). Most likely, at this time, passengers who would have ordinarily taken public transport were so concerned about the risk that they switched to private transport, so the substitution effect dominated the fear effect.

Second, during rush hour, most trips are likely to be work-related and less discretionary. Since large numbers of people travel to work or go home after work during rush hours, the risk of contracting COVID-19 while using public transport is even greater. These facts suggest that the

[10] Unemployment statistics from the Ministry of Labor, released in April 2020, indicate that the number of unemployed workers was 0.48 million, the highest since 2013. In addition, the number of employees working less than 35 hours per week was 0.40 million, higher by 0.21 million from 0.19 million in April 2019.

[11] We obtained this statistic from the following news source: https://www.rti.org.tw/news/view/id/2101392. Several large companies implemented a work-from-home policy in 2020, as reported by newspapers. For example, "Approximately 3,245 employees in several financial firms were told to work from home for two weeks from April 6th (see https://www.taipeitimes.com/News/biz/archives/2020/04/07/2003734109). Taiwan Semiconductor Manufacturing Company (TSMC), having the largest semiconductor foundry in the world, implemented a work-from-home policy for employees not on production lines (see https://www.taiwannews.com.tw/en/news/3903344).

Table 1
Effects of COVID-19 pandemic on the mode of transport.

	Public transport (Railway)			Private transport (Car)		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 2020						
COV_PI	−0.133**	−0.169**	−0.164**	0.103***	0.123***	0.123***
	(0.056)	(0.073)	(0.073)	(0.033)	(0.046)	(0.046)
Observations		30,240			54,108	
Panel B: Initial period						
COV_PI	−0.0649	−0.0873*	−0.0865*	0.0740***	0.0888***	0.0958***
	(0.040)	(0.047)	(0.047)	(0.022)	(0.031)	(0.033)
Observations		13,860			24,948	
Panel C: Peak period						
COV_PI	−0.709***	−0.745***	−0.728***	0.548***	0.579***	0.589***
	(0.235)	(0.247)	(0.242)	(0.182)	(0.188)	(0.188)
Observations		7,560			13,284	
Panel D: Recovery period						
COV_PI	0.001	−0.004	−0.015	0.055*	0.060**	0.070**
	(0.031)	(0.037)	(0.046)	(0.030)	(0.026)	(0.032)
Observations		8,820			15,876	
Basic controls	√	√	√	√	√	√
Holiday FE		√	√		√	√
Gasoline price			√			√

Note: This table shows the estimated β (i.e. the coefficient on $\texttt{COV\_PI}_d$) in Eq. (2). $\texttt{COV\_PI}_d$ is the log of the *COVID-19 Perception Index* as on d. The sample period in Panel A is the first 24 weeks of 2020. Note that the first confirmed COVID-19 case was announced on January 21st, 2020 (i.e., the fourth week of 2020). Panel B displays results for the initial period: the 1st to 8th weeks after the first COVID-19 case. Panel C displays results for the peak period: the 9th to 14th weeks after the first COVID-19 case. Panel D displays results for the recovery period: 15th to 20th weeks after the first COVID-19 case. *Basic covariates* includes week-of-the-year fixed effect, the day-of-week fixed effect, daily temperature, daily rainfall, and monthly county population. Note that daily temperature, daily rainfall, and monthly population are measured at the county level. Depending on where a TR station is located, we assign the corresponding county-level variables to that observation. *Holiday FE* includes a set of dummies for holidays, and election day, New Year's Eve, New Year, Chinese New Year, Peace Memorial Day, Qing-Ming Festival, Labor Day, and the Dragon Boat Festival. *Gasoline price* includes daily gasoline prices at the national level. In order to account for possible within-group correlations among errors, we use the multiway clustering approach proposed by Cameron etal. (2012) to calculate standard errors clustered at both the date and station levels. Cluster-robust standard errors are reported in parentheses. $^{*}p < 0.1^{**}, p < 0.05^{***}, p < 0.01$

substitution effect could be stronger during rush hours than at non-peak times. Thus, we estimate Eq. (1) and report estimated β_s by rush hour and non-rush hour, in Fig. 1c and d respectively. We define the rush hours as running from 7am to 9am and from 5pm to 9pm, while any other time is defined as "non-rush hour. Fig. 1c suggests that the rush hour traffic volume increased by approximately 25% when the 2020 pandemic in Taiwan was at its peak. In contrast, COVID-19 had little impact on the number of cars on national highways during non-rush hours (see Fig. 1d). Our results imply that people did shift to private vehicles when they had to go out during the pandemic. Third, the highway traffic flow *increased* by 17% to 28% during the period when Taiwan no longer reported any new local COVID-19 cases.

Similar to public transport, we use Eq. (2) to estimate the effect of the public perception of COVID-19 risk on highway traffic. Estimated coefficients of $\texttt{COV\_PI}_d$ for private transport are reported in the last three columns of Table 1. Panel A shows the main result using 2020 ETC data. Our estimates suggest that a 10% increase in the *COVID-19 Perception Index* is associated with a 1.2% *increase* in the daily number of cars (see Column (6)). Combined with estimates in the first three columns of Panel A, our results suggest a strong substitution effect between public and private transport. Again, we conduct a subgroup analysis based on the same definition of the pandemic period as in Section 3.1 (see Panels B to D). Similar to public transport, the results suggest that our main estimate in Panel A is driven by the peak period, when the *COVID-19 Perception Index* rose quickly and attained its highest level in the period studied (see Panel C).

3.3. Impact of depressed public transit ridership on spatial patterns of urban activity

So far, we have shown that the COVID-19 pandemic has induced a substantial decrease in railway ridership. Since most train stations, especially the major ones, are located in downtown areas, we posit that this decline in passenger flow during the pandemic may have negatively affected economic activity in urban areas close to main rail network nodes. In other words, the COVID-19 pandemic could have affected spatial patterns of business activities by shifting them away from areas close to major stations (i.e., city centers).[12]

Inspired by Ramani and Bloom (2021) and Rosenthal et al. (2022), we conduct two analyses to examine the above prediction, namely, between-district and within-district estimations. For the former, we examine whether the pandemic had a larger negative impact on retail sales in districts with major stations (i.e., urban areas) than in others. We use district-by-month-level retail transactional data for 2018 to 2020 and compare retail sales in districts with and without major TR stations, before and after the pandemic.[13] For the latter, we further restrict the sample to districts with major stations and investigate the within-district reallocation of economic activities induced by the pandemic. For within-district estimation, given the difficulty in collecting data on business activities in small areas, following previous studies (Henderson etal., 2011; Chodorow-Reich etal., 2020; Ch etal., 2020), we exploit monthly nighttime lighting data from 2018 to 2020 as the proxy for local economic activity.[14] The high spatial resolution of this nighttime lighting data allows for the comparison of luminosity within a 500-meter radius of a major station with that of 500 to 1000m away from the same station, before and after the pandemic.[15]

[12] Table A2 lists 32 major rail stations, including four special-class stations and 28 first-class stations, in Taiwan and the corresponding location information.

[13] We acquire transactional data of monthly retail sales at the district level from the open data platform offered by the Ministry of Finance (https://data.gov.tw/dataset/36862).

[14] We obtain luminosity data on nighttime lighting from the National Oceanic and Atmospheric Administration (NOAA).

[15] The advantage of this nighttime lighting data is its high spatial resolution (15 arc seconds, $0.5\text{km} \times 0.5\text{km}$) and strong timeliness (monthly data).

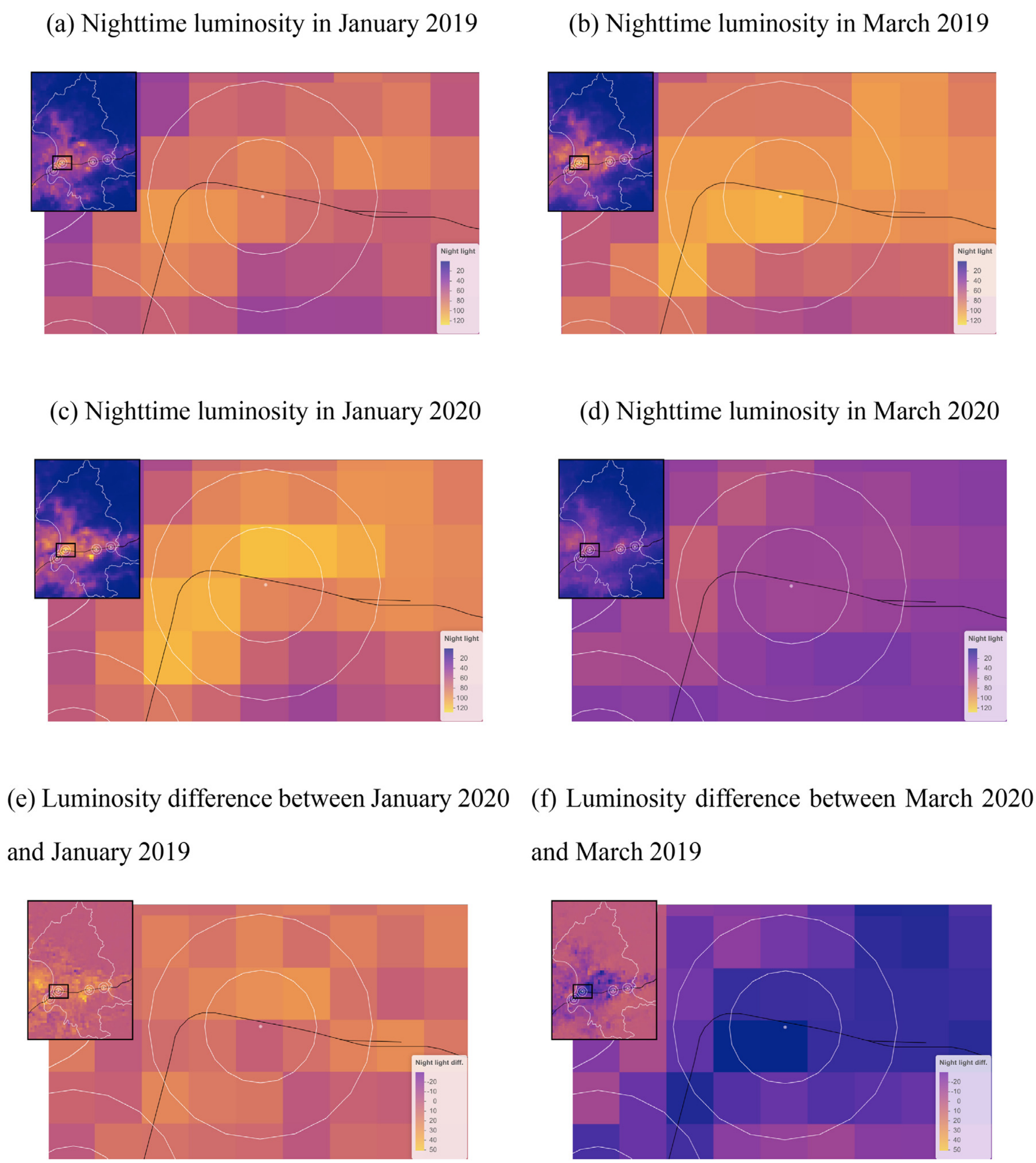

Fig. 2. Nighttime luminosity in the area surrounding Taipei main station. *Notes:* This figuredisplays the geographic distribution of nighttime luminosity around Taipei Main Station. The inner circles (outer circle) represent the areas within a 500-meter (500-to 1000-meter) radius of Taipei Main Station. Fig.2a (2b) and 2c (2d) show nighttime luminosity in the area surrounding Taipei station in January (March) of 2019 and 2020, respectively. Fig.2 (2e) displays the difference in nighttime luminosity between January (March) 2020 and 2019. The nightlight luminosity is measured by radiance values. The unit of radiance value is nano watts per square centimeter per steradian (nW/cm^2/sr). A higher value of radiance means a higher quantity of human-generated light in an area.

Fig. 2 shows the change in nighttime luminosity in areas surrounding Taipei Main Station, the busiest train station in Taiwan, as an example to illustrate how we use the luminosity data. We compare nighttime luminosity around this location in January 2019 (see Fig. 2a) and January 2020 (see Fig. 2c). The inner circles (outer circle) represent areas within a radius of 500m (500 to 1000m) from the railway station. Nighttime luminosity is measured by radiance values.[16] A higher radiance value means a larger quantity of human-generated light in an area. Neither January 2019 nor January 2020 was affected by the COVID-19 pandemic and therefore we use the difference in nighttime luminosity in January as a baseline gap between 2019 and 2020. Fig. 2e indicates that nighttime luminosity was slightly brighter in January 2020 than in January 2019. Fig. 2b and d display similar graphs, using luminosity data in March 2019 and March 2020, respectively. In sharp contrast to Fig. 2e, we find that nighttime luminosity in March 2020 (i.e., the peak of the pandemic in Taiwan during the study period) was much darker than that in March 2019, especially within a 500-meter radius of Taipei Main Station (see Fig. 2f).

In the first instance, we estimate the following difference-in-differences model:

$$E_{jmt} = \gamma Y_{2020} \times Post_m + \lambda_t + \delta_m + \theta_j + X_{jmt}\psi + \varepsilon_{jmt} \tag{3}$$

[16] The radiance value unit is nano watts per square centimeter per steradian (nW/cm^2/sr).

Table 2
Effects of COVID-19 pandemic on spatial patterns of urban activities.

	Retail sales			Nighttime light		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Greater proximity to major TR stations						
$Y_{2020} \times Post$	−153.153***	−173.173***	−145.145***	−174.174***	−202.202***	−167.167***
	(0.013)	(0.013)	(0.013)	(0.030)	(0.036)	(0.030)
Observations		744			744	
Panel B: Less proximity to major TR stations						
$Y_{2020} \times Post$	−120.120***	−127.127***	−118.118***	−142.142***	−175.175***	−135.135***
	(0.007)	(0.008)	(0.007)	(0.025)	(0.036)	(0.025)
Observations		5,100			744	
Panel C: Triple-differences design						
$Y_{2020} \times Post \times Major$	−0317.0317**	−035.035**	−028.028*	−032.032**	−032.032**	−032.032**
	(0.015)	(0.015)	(0.015)	(0.014)	(0.014)	(0.014)
Observations		5,844			1,488	
Basic covariates	√	√	√	√	√	√
District/County variables		√	√		√	√
District FE			√			√

Note: Panel A and Panel B show the estimated γ (i.e. the coefficient on $Y_{2020} \times Post$) in Eq. (3). Panel C shows the estimated γ_1 (i.e. the coefficient on $Y_{2020} \times Post \times Major$) in Eq. (4). Columns (1) to (3) show the results for between-townships analysis on retail sales. Columns (4) to (6) show the results for within-townships analysis on nighttime lights. *Basic covariates* for Panels A and B refers to year fixed effect and month fixed effect. *Basic covariates* for Panel C include a dummy variable for major stations $Major$, interaction terms $Y_{2020} \times Major_j$ and $Post_m \times Major_j$, and year-by-month fixed effects. *District/County variables* include average temperatures, average rainfall, number of households, population size, average housing price, and number of real estate transactions. Note that average temperatures and average rainfall are measured at the county-by-month level. Number of households, population size, average housing price, and number of real estate transactions are measured at the district-by-year level. The real estate data were from administrative data on all house transactions in Taiwan provided by the Ministry of Interior (https://lvr.land.moi.gov.tw/). *District FE* includes a district fixed effect. In order to account for possible within-group correlations of the errors, we use the multiway clustering approach proposed by Cameron etal. (2012) to calculate the standard errors clustered at both the year-month and township level. Cluster-robust standard errors are reported in parentheses. $^{*}p < 0.1^{**}, p < 0.05^{***}, p < 0.01$

E_{jmt} represents the log of either retail sales or luminosity in district j in month m of year t.[17] Y_{2020} is a dummy variable for the treated year, denoted by one if an observation is in 2020, and zero otherwise. $Post_m$ is a binary variable that takes the value one if an observation corresponds to the months between February and August (i.e., the post-outbreak period), and zero if the sample is observed in January (i.e., the pre-outbreak period). The year fixed effect λ_t controls for the general trend in local economic activity over time. The month-of-the-year fixed effect δ_m controls the seasonal patterns over a year. District fixed effects θ_j control for any time-invariant confounding factors at the district level. Finally, X_{jmt} refers to a set of covariates, including average temperature, average rainfall, number of households, population size, average house price, and number of real estate transactions. The key variable is the interaction term $Y_{2020} \times Post_m$. Coefficient γ measures the difference in local economic activity (i.e., retail sales or nighttime lighting), before and after the COVID-19 outbreak in 2020, relative to the difference in the corresponding periods in 2018 and 2019. To identify the pandemic-induced reallocation of economic activity, we estimate Eq. (3) separately and compare the estimates of γ. For the between-districts analysis of retail sales, we estimate Eq. (3) by using districts with and without a major TR station. For the within-districts analysis of nighttime lights, we estimate the model using areas within 500m of major stations and those within 500 to 1000m away from the same station.

Estimates are reported in Table 2. Columns (1) to (3) show that during the pandemic, districts with major TR stations experienced a 14.5% decline in retail sales (see Panel A), while districts without major stations saw only an 11.8% decline (see Panel B). Using the luminosity data (nighttime lighting), we go one step further and examine the effects of COVID-19 on economic activities in areas surrounding major TR stations. Columns (4) to (6) suggest that nighttime luminosity within 500m of a major TR station (see Panel A, indicating a 16.7% decrease) experienced larger declines than areas slightly farther away (see Panel B, a 13.5% decrease).

To summarize our findings, we consider the following triple-differences estimation.

$$E_{jmt} = \gamma_0 Major_j + \gamma_1 Y_{2020} \times Post_m \times Major_j + \gamma_2 Y_{2020} \times Major_j + \gamma_3 Post_m \times Major_j + \lambda_t \times \delta_m + \theta_j + X_{jmt}\psi + \varepsilon_{jmt} \quad (4)$$

In this specification, we add a dummy variable $Major$, indicating districts with major TR stations (between-districts estimation) or areas within 500m of a major TR station (within-districts estimation). Therefore, we can control for the specific time trend and seasonality in areas close to major stations by including interaction terms $Y_{2020} \times Major_j$ and $Post_m \times Major_j$. In addition, this empirical setting allows us to flexibly control for the time trend in economic conditions common in each district by including year-by-month fixed effects $\lambda_t \times \delta_m$. The key variable in the triple-differences design is $Y_{2020} \times Post_m \times Major_j$, which can capture the differential effect of the COVID-19 pandemic on economic outcomes in regions close to or far away from major TR stations.

Estimates in Panel C of Table 2 show that retail sales in districts with major TR stations fell almost 2.8 percentage points relative to changes in other districts during the pandemic (see columns (1) to (3)). When using only districts with major rail nodes, we find that luminosity of nighttime lighting in areas surrounding major TR stations saw losses of approximately 3.2 percentage points compared to changes in areas slightly farther away from the same major nodes after the COVID-19 outbreak (see Columns (4) to (6)). There was extensive media coverage showing that hotels, theaters, and shopping malls, which are usually around public transit nodes, were either closed or had shortened their business hours during the pandemic.[18] These stories are consistent with

[17] Table A3 of the Online Appendixprovides summary statistics for these outcome variables.

[18] For example, Eslite Mall at Taipei Rail Station closed one hour earlier (from 10:30pm to 9:30pm), since passenger flow decreased significantly during the pandemic (see https://udn.com/news/story/7934/4430775). Taipei

our findings related to the decline in nighttime luminosity in areas close to rail stations. Moreover, our result is consistent with the evidence provided by Rosenthal et al. (2022), whose results suggest that commercial rent premiums for properties close to rapid transit stations declined after the COVID-19 outbreak.

To investigate the full dynamic trajectory of COVID-19s effects, we replace a dummy variable indicating the post-outbreak period $Post_m$ in Eq. (4) with event time dummies $PostMonth_m$, where $m = 1, 2, 3, 4, 5, 6, 7, 8$. Note that we use January, the month just before the virus outbreak, as the baseline month and omit the event time dummy at $m = 1$ (i.e., January). We estimate the following regression:

$$E_{jmt} = \gamma_0 Major_j + \sum_m \alpha_m Y_{2020} \times Major_j \times PostMonth_m + \gamma_2 Y_{2020} \times Major_j + \gamma_3 Post_m \times Major_j + \lambda_t \times \delta_m + \theta_j + X_{jmt}\psi + \varepsilon_{jmt} \quad (5)$$

The key coefficients α_m measure the difference between economic outcomes for districts with and without major stations (area surrounding or slightly farther away from major nodes) in a given month, relative to the difference in the baseline month. Fig. 3 plots the estimated α_m for effects on retail sales and nighttime luminosity, respectively. Fig. 3a suggests that compared to districts without major stations, those with major nodes experienced a relative fall in retail sales of approximately 2 to 6 percentage points, which was most pronounced in mid-March, the pandemic's peak in Taiwan during 2020. Moreover, the retail sales gap gradually closed, but the point estimates did not return to pre-pandemic levels. This finding is consistent with evolution of the COVID-induced decline in TR ridership shown in Fig. 1a. A similar pattern can also be found in the within-district estimation, using nighttime luminosity as an outcome (see Fig. 3b).

To sum up, our results clearly indicate that the pandemic could have induced movement of economic activity away from areas around major rail stations. Our finding is consistent with results found in recent studies using US data (Ramani and Bloom, 2021; Rosenthal et al., 2022), which suggests that COVID-19 reduced the value of living in city centers and led to reallocation of activities within or across cities. Given the low risk of contracting COVID-19 and the no-lockdown policy implemented in Taiwan, we believe our estimates could serve as a "lower bound for economic impacts of the decline in public transit ridership in other countries.

4. Conclusion

Exploiting Taiwans unique experience and high-quality administrative data, we provide evidence that though there were no enforced restrictions on mobility during the pandemic, strong self-imposed restrictions existed. Specifically, our results indicate that the COVID-19 outbreak reduced the number of passengers taking a train journey by 40% to 60% at the peak of the pandemic in 2020. In contrast, highway traffic increased by 20% during the same period. This suggests that in the face of a pandemic, individuals not only curtailed mobility but also adjusted the mode of transport in order to reduce the risk of infection.

Moreover, data of retail sales and nighttime luminosity show that this shift in transport modes is not only related to patterns of population mobility but also results in movement of economic activity away from areas around major rail stations. Since we also find that the decline in public transit ridership can persist even after a pandemic, our findings point towards some fruitful directions for future research. For example, it would be interesting to examine whether the pandemic would have a long-term or permanent impact on people's mobility decisions or transport modes. In addition, future studies could investigate how this change affects spatial patterns of economic activity in a post-pandemic period.

An interesting question is why people reacted so strongly and persistently to the pandemic in Taiwan, even though the risk was so low. Although we do not have direct evidence for this hypothesis, we speculate that the painful experience of SARS, which ravaged Taiwan (as well as China, Singapore, Hong Kong, Vietnam, South Korea and Canada) during 2002–2003, might have played a role in giving individuals in these areas a strong incentive to practice social distancing.[19] However, since only a few regions experienced the SARS outbreak, this lesson might be difficult to carry over to other countries.

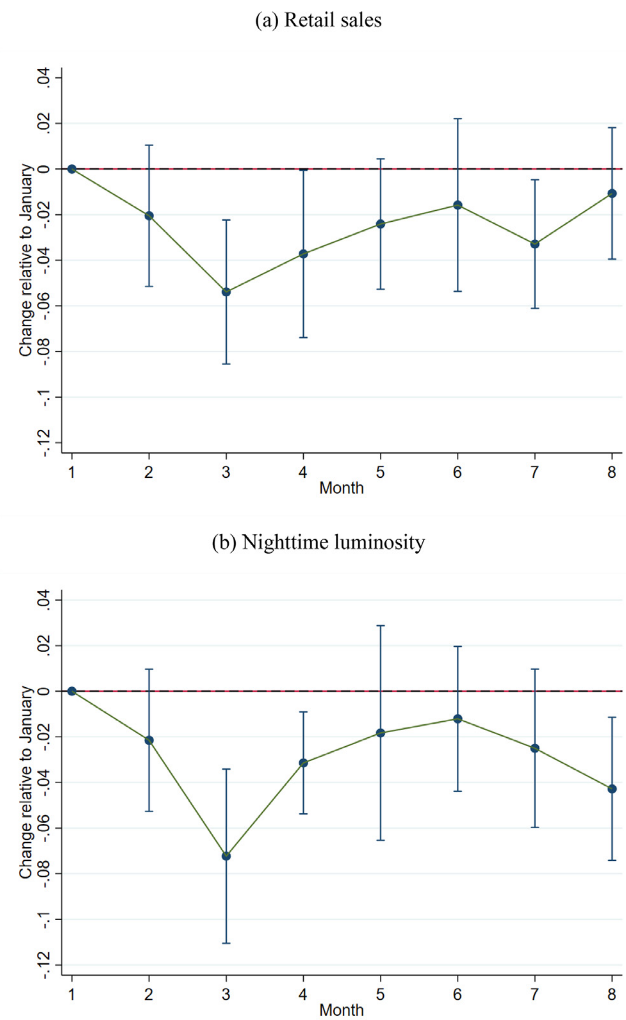

Fig. 3. Dynamic effects of COVID-19 pandemic on spatial patterns of economic activities. *Notes:* This figuredisplays the coefficients α_m, which are the measure of difference in economic outcomes in a given month between the districts with and without major stations (areas surrounding and slightly farther away from major nodes) relative to the difference in the baseline month, in Eq. (4). The baseline month is January. Fig.3a shows the estimated α_m for retail sales. Fig.3b shows the estimated α_m for nighttime luminosity.

101 also shut down two hours earlier from April 2020 (see https://www.taipeitimes.com/News/biz/archives/2020/04/01/2003733744?fbclid=IwAR1zxqb14B4LA7v8tQmAnEn0IMUFH3gja_YiIb1hmnmjclQyjfTXsUfc7cQ). Another example is a five-star hotel close to Taichung station that decided not to open due to the pandemic (see https://news.ltn.com.tw/news/life/paper/1365882), and two theaters around Changhua rail station that closed after the COVID-19 outbreak (see https://www.taipeitimes.com/News/taiwan/archives/2020/04/27/2003735378?fbclid=IwAR0rHdJ6pgXAag1ue_AZx_R9Vg51WyJ4c6M7Y1qE0Pdv0ParQd58awA1QLI)

[19] As of September 2021, these countries have relatively low COVID-19 incidence rates. For example, the total cases per 1,000,000 population is 40,380 in Canada but 121,520 in the US. Note that among these countries, Canada has the highest COVID incidence rate.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jue.2022.103426.

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