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Highway havens for hidden horrors: Expressway connections and child trafficking in China

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Abstract

Child trafficking is a deep-seated social issue with enduring consequences that remain concealed or less obvious to the general public. We argue that the intensity of child trafficking increases as an indirect and unintended consequence of improved urban infrastructure, such as the construction of highways that facilitate the expedient transfer of victims between cities. To establish a causal relationship, we analyze data on child abduction and combine it with geo-referenced information on China's highway routes. Using a staggered difference-in-differences approach and a city-to-city analysis, we find that the construction of highways in a city significantly leads to an increase in abducted children. Changes in both demand and supply factors following the highway construction could explain the increase in child trafficking.

JEL classification. H54, K42, O15, O18, R23, J13

Keywords. Child trafficking; Expressways; Highways; Transport infrastructure; Illegal behaviors; China.

1 Introduction

Child trafficking is a grave humanitarian crisis that inflicts significant harm on societies, disrupting social harmony and sustainability while causing immense tragedy. The International Labor Organization's statistics reveal the alarming reality that at least 1.2 million children were trafficked in 2000, predominantly, but not exclusively, in developing nations (Dessy and Pallage, 2006). In China, the process of child trafficking is multifaceted, encompassing abandonment, abduction, illicit trade, and sometimes even governmental corruption (Agbu, 2003); in a narrower sense, it can be equivalent to child abduction or kidnapping (Gao, 2010). Under these circumstances, children are typically abducted by traffickers, subjected to multiple transfers, and eventually, many are illegally adopted by households seeking additional children (Han, 2024).[1] People resort to illegal adoption for various reasons; for example, the formal adoption process involves demanding legal procedures and strict requirements, such as financial stability and a favorable family background. These criteria can be challenging for economically disadvantaged families, leading some to consider illegal alternatives to acquire children.

Child trafficking has significant economic costs. Parents of trafficked children face financial losses from search expenses and disruption to their work, resulting in lost wages and reduced productivity. Additionally, combating child trafficking requires substantial resources for law enforcement, investigations, prosecutions, and victim support services, imposing a significant social cost. Thus, it is crucial to analyze the factors influencing child trafficking, understand the underlying mechanisms, and develop strategies to combat this problem.

Child trafficking networks are well-concealed and complex, widely covering most cities (Wang et al., 2018), and are constructed through transportation networks. Traffickers often choose to transport trafficked children through intercity or interprovincial roads, utilizing private vehicles or public buses to discreetly move them between cities. Unlike planes or trains, which typically involve stringent security checks at airports and train stations, toll stations on highways or other national/provincial roads generally have minimal or no personal identity verification procedures. As a result, traffickers using highways

[1] A proportion of trafficked children are also exploited for labor, begging, or sex slavery (Jiang and Sánchez-Barricarte, 2013).

are less likely to leave identifiable traces, and documentation for children is not required.[2] Conversely, the use of planes or trains presents higher risks and costs: trains often have onboard police, increasing the likelihood of a criminal's arrest, while air travel is relatively costly. Therefore, we hypothesize that increased connectivity to highways allows traffickers to illegally transfer more children across different regions while reducing the operational costs and risks of being caught. However, the impact could be the opposite if increased connectivity lowers son preference and improves the socioeconomic conditions of the region. The impact is theoretically ambiguous, and thus, gaining insight into this question also strengthens the contributions of this paper.

In this paper, we use the occurrence of child abduction as a proxy for child trafficking, as it aligns with China's legal definition of child trafficking and is consistent with relevant literature on the Chinese context (Zhou et al., 2023). Our analysis focuses on the relationship between child abduction and the rapid expansion of expressway networks in China. To test our hypothesis, we collect incidents of trafficking in children aged 0–14 from the Baby Come Back Home (BCBH) website and combine them with georeferenced GIS shapefile data of China's highway routes from the Spatio-Temporal Expressway Database (STED). Constructing a panel dataset spanning the years 1999 to 2014, we incorporate city-level and temporal variations to capture the effects of expressway connectivity on child trafficking. We adopt a staggered difference-in-differences (DID) approach, comparing cities connected by highways with unconnected cities. To address potential endogeneity concerns associated with the non-random placement of highway routes, we further refine our analysis by focusing on targeted cities within the National Trunk Highway System (NTHS). Additionally, we employ a city-to-city analysis and an intercity child movement model, which strengthens the validity of our findings.

Our study reveals a significant and alarming finding: the presence of expressway connections has a profound impact on the prevalence of child trafficking, a grave intercity crime. The baseline results consistently demonstrate a strong positive relationship between the existence of highways and the occurrence of child trafficking in connected cities. The mechanism underlying this relationship can be attributed to changes in both demand and supply markets. The demand market for children (i.e., clients seeking chil-

[2] To pass the identity check on trains or planes, child travelers (under 18 years old) can use either a household registration book or an ID card, if they have one. Infant travelers typically need a birth certificate to prove their identity.

dren) expands as it extends beyond local areas to more distant markets, facilitated by highway networks. The supply market also grows as more vulnerable children enter it, driven by an increase in left-behind children whose parents have migrated for work, spurred by economic growth from expressway development. Additionally, an influx of low-skill migrants, which may lead to higher risks of violence, could also partially explain this outcome.

The implications of these findings are significant, shedding light on the complex interplay between infrastructure development, labor dynamics, rural-urban migration, and the vulnerability of children to exploitation. By identifying the factors exacerbating child trafficking, our research emphasizes the need for targeted interventions, policies, and societal measures to address this issue and safeguard the well-being of children while expanding urban infrastructure for economic growth in China.

The remainder of the paper is organized as follows. Section 2 describes the background and literature review. Section 3 describes our variables of interest and presents the empirical strategy. Section 4 reports the empirical results. Section 5 discusses the mechanisms, and Section 6 concludes.

2 Background and literature review

We introduce the process of child trafficking from three key perspectives: demand, supply, and intermediaries. Each aspect examines different elements of the child trafficking phenomenon, providing a comprehensive understanding of its dynamics.

The incidence of child trafficking is often linked to increased demand for child labor (Edmonds, 2010) and sexual exploitation (Edlund and Korn, 2002; Rafferty, 2013) in various developing countries. However, in China, the main demand for trafficked children may differ, driven by a mix of cultural and economic factors, along with policy and legal loopholes.[3] The Chinese culture values having many children as a

[3] Regarding the punishment for clients who purchase trafficked children, Chinese law imposes more lenient penalties on buyers compared to traffickers. Buying a kidnapped child constitutes a criminal offense, and those found guilty are held criminally liable. According to Paragraph 1 of Article 241 of the Criminal Law, anyone who buys an abducted woman or child may be sentenced to fixed-term imprisonment of up to three years, criminal detention, or surveillance. However, to legally register an abducted child and evade this crime, new parents often collaborate with traffickers to exploit loopholes in China's child adoption regulations. They may falsely claim to have found an abandoned child after purchase or use artificial documentation with the traffickers acting as foster caregivers.

blessing, and thus both boys and girls may be involved in illegal trade for adoption. Boys can be more preferred if gender selection is possible.[4] Due to thousands of years of feudal thinking in China, many families have a strong "son preference," as highlighted in previous literature (Almond et al., 2019). This preference often leads infertile couples or those with only daughters to seek sons through methods such as buying, in order to continue the family lineage. Additionally, land acquisition benefits in certain rural areas are often linked to the number of *male* household members, incentivizing families to acquire boys. Girls, in some circumstances, are selected for purposes such as child marriage or bonded servitude. For instance, in Fujian and Jiangxi, where men engage in high-risk occupations like fishing, families purchase girls to serve as future daughters-in-law and household helpers (Chen et al., 2015).

The supply side of child trafficking pertains to the sources and vulnerabilities of children who are at risk of being abandoned or sold by their biological parents, as well as those who are involuntarily abducted by traffickers. Child abandonment is often highly correlated with extreme poverty, such as the peak of child abandonment during the Great Famine from 1959 to 1961 (Zhou et al., 2023; Dessy et al., 2005). Policy-driven supplies, such as China's former one-child policy (Bao et al., 2023), also play a role. Specifically, stringent penalties, including fines, potential job loss, and limited promotion prospects for exceeding the mandated quota can lead to increased abandonment of girls (Ebenstein, 2010; Howden and Zhou, 2014). Conversely, child abduction is associated with victimization risks in specific regions. These risks refer to the likelihood of individuals becoming victims of various forms of crime, exploitation, or harm within particular geographic areas. Factors influencing these risks include socioeconomic conditions, cultural norms, public security infrastructure, and population dynamics, such as high rates of in- and out-migration; in other words, "traffickers fish in the stream of migration" (Mahmoud and Trebesch, 2010).

The intermediaries involved in child trafficking are the individuals and networks that facilitate the process between the demand and supply sides. Traffickers use various methods to manipulate and exploit children, including deception, coercion, or force, leading them to leave their homes or resorting to outright kidnapping (often targeting places like hospitals, train stations, playgrounds, or during children's commutes to and from school). These activities are generally carried out by smaller, independently

[4] Differing levels of preference have led to a significant disparity in purchase prices, with boys typically commanding prices at least 3–5 times higher than girls.

operating criminal groups. In Appendix B, we detail how trafficking gangs operate, outlining each member's responsibilities and the modes of operation they employ. Once abducted, children are transported or moved to different locations. The high demand and potential for substantial profits, combined with inadequate legal penalties and enforcement, serve as strong incentives for trafficking gangs to engage in these criminal activities (Cai, 2016).

Our study contributes to the literature in two key ways. First, there is a limited body of quantitative research investigating the functioning of trafficking networks both in China and globally. While previous studies have explored direct triggers of child abduction, such as poverty, legislation, law enforcement, and financial incentives, there is a need for greater focus on the deeply ingrained traditional, institutional, and socioeconomic factors driving these phenomena. Existing literature has examined various aspects of child trafficking, including political instability or multiethnic conflicts (Tiefenbrun, 2007), China's birth restriction policy (Bao et al., 2023), patriarchal culture (Wang et al., 2018), and the social acceptance of child labor and child marriage (Kolk and Van Tulder, 2002). Although most of these factors are related to the demand side, only a few studies address the determinants on the supply side, specifically the risk of abduction in hometown regions (Shoji and Tsubota, 2022). Our paper offers a new perspective by examining the role of transportation networks as a key factor linking both the demand and supply sides of child trafficking.

There is also a set of papers focusing on the role of transportation sectors in combating and preventing human trafficking, as traffickers use it to recruit, transport, and control victims (Sokat, 2022b) and to move goods made by forced labor (Sokat, 2022a). Prior research utilizes survey data from transportation personnel, service providers, and trafficking survivors to underscore the perceptions, limitations, and challenges in understanding forced labor (Auguste et al., 2024; Sokat et al., 2024a) . Green et al. (2023) explore this in Africa, while Sokat et al. (2024b) use predictive analytics to study transportation's role internationally. Our paper diverges from the existing literature primarily by distinguishing child trafficking, which involves long-term effects that seriously damage human capital and productivity, from human trafficking. The difference is significant, as child trafficking is more likely driven by the demand for illegal adoption, particularly within Chinese culture, whereas adult trafficking is more often associated with forced labor or sexual exploitation. The characteristics of the victims can also vary considerably, as children trafficked show a higher level of vulnerability due to a lack of autonomy and agency. In addition, our research establishes a causal relationship between transportation improvements and increased trafficking events in situations lacking identity checks, and provides an extensive examination of the underlying mechanisms, complementing conclusions on the role of attention from transportation personnel.

Second, this paper provides novel evidence on the unintended negative consequences of transport infrastructure improvements in developing countries. While the positive impacts on economic development are well-documented—such as increased GDP per capita across sectors (Banerjee et al., 2020), economic growth in poor rural counties (He et al., 2020), stimulation of industrial sorting along with the network, and a more efficient allocation of industries (Ghani et al., 2016)—the negative effects are also significant. For example, transport infrastructure development has not reduced disparities in real income and urbanization across regions (Bosker et al., 2018; Roberts et al., 2012). Instead, it has exacerbated regional inequalities by diminishing economic growth in non-targeted peripheral counties (Faber, 2014), causing hinterland cities to lose manufacturing industries and economic activities (Baum-Snow et al., 2020), and leading to the decentralization of products with low and medium weight-to-value ratios (Baum-Snow et al., 2017). Moreover, the improvement of transport infrastructure may promote economic development at the expense of environmental pollution (He et al., 2020).

Within this framework, our paper is related to a growing body of literature examining the unintended consequences of transport infrastructure improvements on crime. For example, Agnew (2020) analyzed data from an annual panel of 562 policing sub-districts in Ireland from 2004 to 2015 and found a 10% increase in burglary rates in the year following the establishment of a motorway connection. Similarly, Baires et al. (2020) observed that the construction of the Northern Transnational Highway led to a notable increase in gang-related crimes such as homicides and extortion. Calamunci and Lonsky (2024) explored this issue using a comprehensive dataset of all US counties from 1960 to 1993, revealing that the introduction of a new highway was associated with a significant 5% increase in the local crime index. Our study adds to this literature by utilizing a unique dataset to investigate interregional illegal behaviors, demonstrating how changes in transportation feasibility and costs are correlated with the incidence of cross-regional crime.

From a broader perspective, weapons, drugs, and humans are the largest trafficking items worldwide

(Di Tommaso et al., 2009), with a growing literature on drug trafficking (Dell, 2015; Dell et al., 2019; Gavrilova et al., 2019; Mejia and Restrepo, 2016). Trafficking of drugs and weapons and human trafficking share similarities in that both involve illegal, often transnational networks, and have significant social, legal, and economic impacts, requiring extensive law enforcement and international cooperation. However, they differ fundamentally in their commodities and trade implications. Human trafficking involves exploitation, violating human rights, and causing profound harm to victims, while drug and weapon trafficking involves inanimate objects, affecting communities through violence and addiction.

Consequently, the ethical, legal, and support frameworks for addressing these issues in various contexts can be distinct. While some actions can reduce incentives across all trafficking types—such as integrating enforcement efforts, implementing preventive measures, and disrupting financial flows—certain policies need to be tailored to specific types of trafficking. For instance, pre- and post-victim support should provide legal, medical, and psychological assistance tailored to each type of trafficking. Specifically for children, this includes teaching basic safety knowledge and establishing communication channels to prevent trafficking.

3 Data and methods

3.1 Road network expansion

Since the completion of the first expressway connecting Shenyang and Dalian in 1984, which ended the absence of highways in mainland China, the growth of highways in China has rapidly progressed. The expansion of China's national expressway network under the National Trunk Highway System (NTHS) took place in several stages. The 7-5 expressway network plan, including seven horizontal and five vertical axes across the country, was approved in 1992 to connect all cities with a registered urban population greater than 500,000 and all provincial capitals with modern highways (Faber, 2014). This plan was largely completed by 2007, 13 years ahead of the original 2020 deadline.

Building upon this progress, the State Council approved another blueprint for highway construction in 2004, known as the 7–9–18 network. This network comprised seven routes originating from Beijing, nine vertical axes, and eighteen horizontal axes, with the goal of expanding the highway network to smaller cities, including those with a registered urban population greater than 200,000.[5] Appendix Fig. A.1 demonstrates the significant growth of expressways in China during these programs. In 1996, highway routes passed through only 62 cities, and the combined length of all lines was below 4,000 kilometers. By the end of 2013, a total of 104,438 kilometers of expressways were constructed, passing through around 300 cities.

As noted, our geo-referenced expressway network is obtained from the STED. This database provides accurate GIS shapefile data on China's highway routes for the years 1998, 2000, 2001, 2003, 2004, 2006, 2007, 2009, 2010, and 2013, facilitating further processing using ArcGIS and has been used for several frequently cited studies of China (Faber, 2014; He et al., 2020). To construct this database, the Australian Consortium for the Asian Spatial Information and Analysis Network (ACASIAN) Data Center digitized dozens of high-resolution road atlases published by China's national and regional road transportation authorities. These atlas sources make it possible to select the network segments open each year for the period examined. Fig. 1 depicts the national expressway network in 1998 and 2013, respectively, demonstrating the rapid expansion of the network during this period.

By projecting the STED database onto a city-level (i.e., prefecture-level) boundary map in 2010, we can identify the year in which cities were connected and examine the differences in criminal activity between connected and unconnected cities before and after the actual construction of highways. It is important to note that we only consider cities as being connected if a highway passes through them with available entrances and exits. Cities where the highway simply passes by without any direct access points are not considered connected in our analysis.[6]

We define cities located on highway routes as the treatment group and those not connected as the control group. To conduct our baseline analysis, we include a lagged term of the explanatory variable to account for the time delay between the construction of highways and its potential impact. Our focus is on the highway construction period from 1998 to 2013, which corresponds with the implementation of both the 7-5 and 7-9-18 plans and the rapid development of the highway network.

[5]Some port cities, tourist cities, and railway hubs are also targeted by this network plan.

[6]Explanatory variables that account for the market size of the connected cities are introduced and used as robustness checks

(a) 1998 Expressways (b) 2013 Expressways

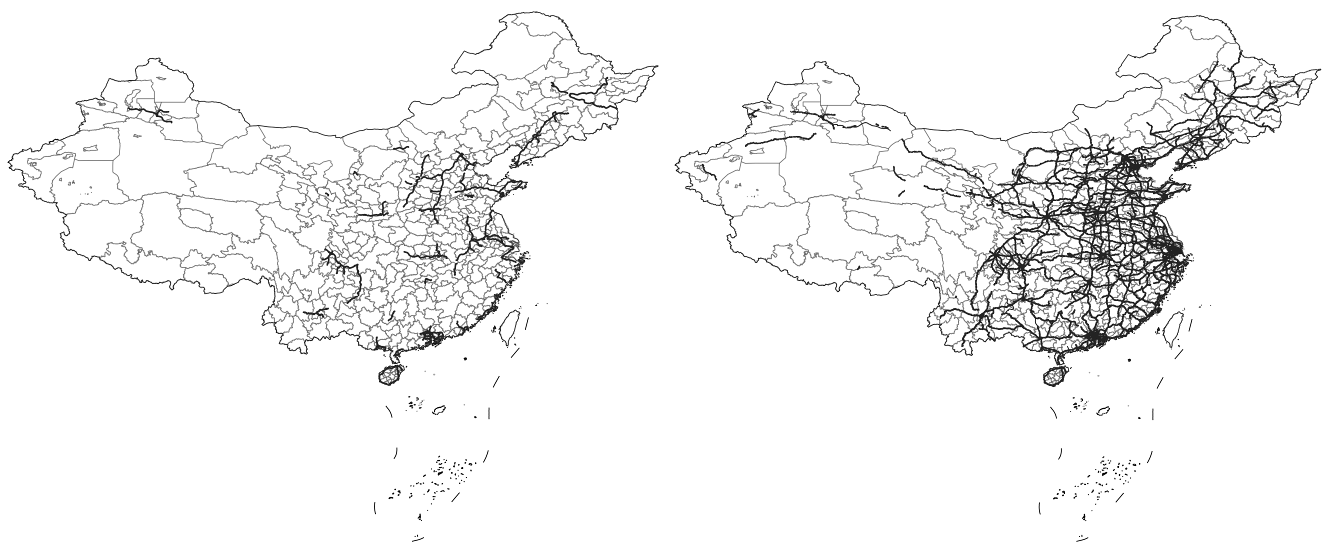

Fig. 1: Highway Network in China (1998 and 2013)

Notes: The figures present the expansion of highway networks between 1998 and 2013. It is important to note that we only consider cities as being connected if a highway passes through them with available entrances and exits. Cities where the highway simply passes by without any direct access points are not considered connected in our analysis.

3.2 Data on abducted children

Due to the confidentiality of official police records in China, data specifically on child trafficking are not accessible. Thus, in our research on trafficked children, we choose to use the available resources.

One prominent resource is the Baby Come Back Home (BCBH) website, an esteemed public welfare tracing platform affiliated with the Baby Come Home Volunteer Association. Serving as the largest public welfare website in China dedicated to providing information on missing persons, it holds the distinction of being an official partner of the Ministry of Public Security in efforts to locate children who went missing. Broadly speaking, there are various reasons for missing children, including illegal adoption, forced labor, sexual exploitation, involvement in drug trades, medical research, and child begging. However, in the context of BCBH and China, most of the cases are related to illegal child adoption. For example, Zhou et al. (2023) also use BCBH to measure various types of illegal adoption, supporting this observation.

The website, accessible at http://www.baobeihuijia.com, allows both families searching for members

in Appendix C.

(family-reported cases) and victims seeking their biological parents (child-reported cases) to submit related information. The information includes details such as name, gender, date of birth, date of disappearance, location of disappearance, and, in the case of child-reported cases, the destination location. This information can be reported online or via a hotline. It is important to note that although the BCBH website was established and made publicly available in 2007, it also allows for the reporting of cases that occurred before this date. Therefore, families or victims can recall and report cases of individuals who went missing in previous years, with no restriction on the reporting time.[7]

The staff of the organization responsible for the website verifies the posts by cross-validating the information with local police authorities to minimize misreporting and ensure the accuracy and credibility of the reported information. Consequently, the substantial influence of the platform and its recognition across China, coupled with the credibility of the information shared, serve to mitigate concerns regarding sample selection bias and enhance the overall quality of the data collected. Once the verification process is complete, the reported cases are officially published on the BCBH platform, where visitors can access and review the information. In Appendix Fig. A.2, we provide examples of both a family-reported abducted child and a child-reported case from the BCBH community. Notably, child-reported cases contain additional information on the destination location, which distinguishes them from family-reported cases.

Each record includes information about the broad nature of the incident, such as abduction and abandonment (including being sold for money and being given to others). We then exclude cases labeled with the keywords "abandoned" or "sold for adoption" to focus solely on instances where children were involuntarily separated from their families. Although the dataset contains cases of "runaway" children, these instances are not included in our analysis for this paper. This exclusion is crucial for addressing selection bias and accurately capturing cases of "child abduction for illegal adoption," which aligns with the narrower definition of child trafficking used in this paper, consistent with (Zhou et al., 2023).

Furthermore, we extract the city name from the address provided in the text for each incident and aggregate the data to city-level units.[8] Additionally, we determine the age at which a child was abducted by calculating the difference between the year of the incident and the child's birth year. To ensure consistency

[7] The website includes cases dating back to as early as 1926.

[8] Given the limitations of incomplete information in many reported cases, conducting city-level analysis is the most feasible disaggregated approach.

in our analysis, we only include children who were younger than 14 at the time of their disappearance.[9] We also exclude cases with missing crucial information, particularly those where the location does not specify a specific city. These restrictions resulted in a final sample comprising 43,991 registered cases of child abduction. Among these, 27,086 cases were reported by families searching for children, while 16,905 cases were reported by victims searching for their families.

It is important to note that each subset of data has its advantages and limitations. The information provided by families searching for children tends to be more reliable and accurate, as younger children may struggle to recall precise details regarding the location and year of their disappearance many years after the incident. Some of these children might receive information from their adoptive households, while others may not have access to such information. Conversely, the dataset of child-reported cases offers valuable insights into both the destination and hometown locations. By considering these distinct subsets, we present the main analysis based on family-reported cases and supplement it with cases reported by children, wherever necessary.[10] Appendix Table A.1 provides detailed information on the characteristics of the victims in both datasets.

We then aggregate the family-reported cases into hometown city-year-level units. To avoid the impact of other concurrent policies confounding our results, we focus on the period between 1999 and 2014 as our main estimation period, aligning it with the lagged expressway data. Table 1 summarizes the descriptive statistics of child abduction cases, along with other important variables relevant to the period of interest in this paper. We can also aggregate the child-reported data by hometown-destination city pair for each year. This significantly increases the number of observations to 1,274,336. However, the mean value decreases substantially because there is not always a positive flow of children from a specific city to a designated destination each year, resulting in many zero-value cells.

The city-level geographic distribution of the cases during 1999–2014 is illustrated in Fig. 2, revealing

[9]In accordance with the definition outlined in China's laws concerning child abduction crimes, individuals under the age of 14 are specifically classified as children. Therefore, our focus remains on cases involving individuals below this age threshold. Notably, the abduction of a citizen over 14 years old does not fall within the scope of child abduction offenses. Instead, if such an act meets the criteria for other criminal offenses as stipulated in the constitution, it will be subject to investigation and prosecution accordingly.

[10]Note that the issue of overlap between the two can be mitigated, as each case is verified by the responsible staff to prevent duplication.

Table 1: Summary statistics of the key variables

	Obs.	Mean	Std. Dev.	Min	Max	Data source
Outcome variables						
Family-reported cases						
#Incidents of child abduction	5,232	1.150	2.660	0	51	
#Abducted boys	5,232	0.701	1.924	0	43	
#Abducted girls	5,232	0.449	1.031	0	13	BCBH
Child-reported cases						
#Incidents of child abduction (hometown-to-destination cities)	1,274,336	0.002	0.068	0	17	
Explanatory variables						
Connected (1=Yes; 0=No)	3,270	0.686	0.464	0	1	STED
Time-variant city-level characteristics						
ln Population	4,317	0.431	0.384	0.003	11.51	
ln Gov spending	4,280	7.237	1.340	2.663	11.51	
ln Infrastructure investment	4,240	8.726	1.281	5.146	12.18	China City
ln Wage	4,315	9.750	0.671	2.283	12.68	Statistical
% of primary industry	4,366	0.046	0.092	0.001	0.844	Yearbook
% of secondary industry	4,353	0.432	0.136	0.045	0.834	
% of tertiary industry	4,396	0.526	0.129	0.099	0.948	

Notes: This table presents the summary statistics, including the number of observations, mean, standard deviation, minimum value, and maximum value. Our main outcome variables are the number of family-reported child abductions, with abducted boys and girls reported separately, as well as child-reported child abductions at the hometown-destination-year level. The data source for abducted children is the BCBH website. Our primary explanatory variable is *Connected*, which indicates whether a city is connected to a highway network. This data is sourced from the STED. The socioeconomic variables are obtained from the China City Statistical Yearbook.

the geographic concentration of our child abduction cases. The top six child abduction outflow locations at the provincial level are Guangdong, Guizhou, Yunnan, Sichuan, Henan, and Guangxi, accounting for 55% of reported cases in the BCBH database, despite comprising only 30% of China's total population. Both the locations of the disappearances and the destinations during this period are medium-sized cities, which, as shown in Section 3.1, were explicitly targeted in the highway construction plan. In particular, these cities closely overlap with those identified in the second stage of the NTHS, which focused on second-tier cities situated in the central and western regions of China.

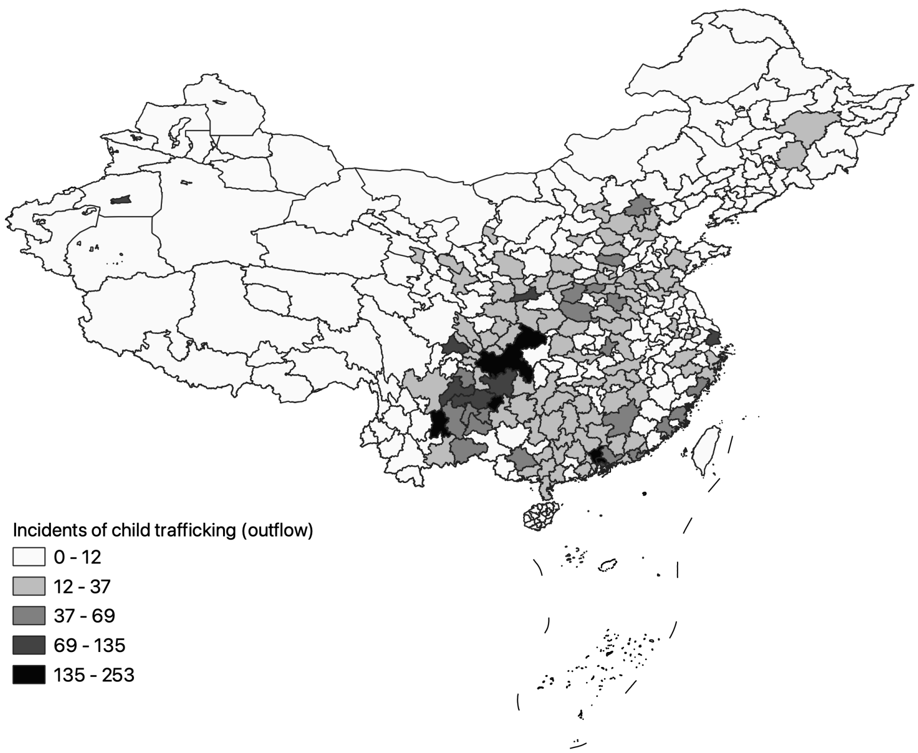

Fig. 2: Distribution of abducted children's hometown cities (1999–2014)

Notes: The figure presents the geographic distribution of the hometown cities of abducted children (i.e., outflow cities) based on family-reported records. The distribution of the destination cities (the cities to which the abducted children were transferred) reported by the children is presented in Appendix Fig. A.3.

3.3 Identification strategy

Taking advantage of the regional and temporal variation in expressway network implementation, we aim to assess the impact of establishing a highway in the hometown city on incidents of child abduction. We employ family-reported data and leverage a staggered difference-in-differences (DID) specification as shown below:

$$\textit{Abduction}_{i,t} = \alpha + \beta \textit{Connected}_{i,t-1} + \lambda_i + \theta_{p,t} + \epsilon_{i,t} \tag{1}$$

where $\textit{Connected}_{i,t-1}$, our main explanatory variable, is a dummy variable that takes a value of one if city i is connected to the highway in year $t-1$, and zero otherwise. $\textit{Abduction}_{i,t}$ represents the yearly statistics, counting the total cases of child abduction in city i during year t. λ_i captures time-invariant characteristics at the city level, while $\theta_{p,t}$ denotes province-by-year fixed effects, which account for macro shocks common to all cities within the same province p in year t. The benchmark model does not include city-level time-varying characteristics to avoid the "bad control" problem. However, we will consider including them as part of our robustness checks (Section 4.1.2). $\epsilon_{i,t}$ is the error term, and robust standard errors are clustered at the city level.

A remaining concern for identification is that, although the decision-making process is determined by the upper-level government, the placement of routes may not be entirely orthogonal to unobservable determinants. Some of these issues can be addressed through the inclusion of city-fixed effects, which account for geographic features, economic endowments, and political and cultural significance. However, time-varying factors, such as local economic and political shocks, can lead to endogeneity issues. Our first attempt to address this non-random route selection is to restrict our study sample to NTHS-targeted cities, as this group of cities exhibits a higher level of homogeneity compared to those that were not included. The selection of these targeted cities was based on criteria outlined in the NTHS planning documents, similar to the approach taken in Faber (2014) and Lin (2017). This analysis enables us to identify the effects driven by the timing of each city's connection to the highways, a timing determined by idiosyncratic factors such as road length, infrastructure construction costs, and engineering challenges.

Moreover, the endogeneity concern is further alleviated by utilizing information from the destination city in child-reported cases and city-pair panel data. The intercity child movement regression model is based on the following specifications:

$$Abduction_{ij,t} = \alpha + \beta Connected_{ij,t-1} + \rho_{ij} + \theta_{i,t} + \theta_{j,t} + \epsilon_{ij,t} \tag{2}$$

where the dependent variable represents the number of children being transferred from hometown city i to destination city j in year t. $Connected_{ij,t-1}$ denotes a dummy variable indicating whether city i and city j are connected by the highway in year $t-1$. This variable equals one only when both cities i and j are connected. The coefficient β captures the increase in the number of abducted children solely due to the intercity connectivity of cities i and j. ρ_{ij} denotes the fixed effects for each hometown-destination pair, which account for all time-invariant characteristics of the pairs, such as spatial distance and cultural differences. $\theta_{i,t}$ and $\theta_{j,t}$ represent time-variant factors and shocks applicable to cities i and j, respectively, including economic shocks, technological shocks (such as Internet penetration rates), and other policy shocks. $\epsilon_{ij,t}$ refers to the error term, and the standard errors are clustered at the hometown-destination pair level. This method is consistent with a rich body of literature in the field of international trade that studies the effect of infrastructure on bilateral trade flows using the gravity model (Anderson and Van Wincoop, 2003, 2004; Baniya et al., 2020; Donaldson, 2018; Duranton et al., 2014; Disdier and Head, 2008).

4 Empirical results

4.1 Baseline results

4.1.1 Staggered DID using hometown cities

Table 2 presents the baseline DID estimates using family-reported records, following Eq. (1). We find that highways are associated with an increase of 0.55 cases of child abduction (46% of the mean of the outcome), as reported in column (1). Restricting our sample to the targeted cities of the NTHS and further including province-year fixed effects do not alter the results, as suggested by columns (2) and (3). Fig. 3 plots the corresponding event-study figure, where coefficients for child abduction on the leads of the treatment dummy are close to zero. This supports the parallel trends assumption: the timing of connection to the expressway network is not correlated with previous trends in child abduction. To address potential issues arising from staggered DID, we further discuss how our estimates are robust to heterogeneous treatment effects across units or over time. More details on heterogeneous treatment effects can be found in Appendix D.

We also considered a specific scenario where a small city lacks a highway connection but is very close to a highway within its neighboring large city, even though this highway is far from the large city's center itself. In this circumstance, our model codes the main independent variable "$Connected_{i,t-1}$" variable as zero for the small city, while for the large city with the distant highway, it is coded as one. However, child transportation may be more convenient and expeditious in the former case. To address this, we further revised the definition of the variable "$Connected_{i,t-1}$" as follows: if a city has a highway within 20 kilometers of its city center, it is coded as one; otherwise, it is coded as zero. The corresponding results, presented in column (4) of Table 2, remain significant.

Moreover, to rigorously estimate the causal impact of infrastructure development, it is useful to examine periods of rapid expansion. Examples include Fernandes et al. (2019) for Internet access in China, Jensen and Oster (2009) for cable television in India, and Heath and Mobarak (2015) for garment factories in Bangladesh. Fig. A.1 indicates that connectivity notably improved between 1998 and 2007, remaining relatively stable since then. Therefore, we restrict our sample to this period as a robustness check, with the results reported in column (5). Our findings confirm the robustness of the results, as they exhibit similar magnitudes to those obtained in our primary model specification.

As a robustness check, we also modify the outcome variable to account for the population of each city, as suggested by columns (1)–(3) of Appendix Table A.2. As reported in column (3), connectivity leads to an additional 0.2 cases per million population, which represents a 65% increase relative to the mean. Furthermore, a general issue with count data is the presence of excess zeros in the response, often referred to as the rare event issue. To address this problem, we exclude the zero cells from our outcome variable; the results remain robust, as shown in columns (4)–(6). While linear models are easy to interpret, they may provide biased estimates and invalid inferences for zero-inflated count data. Therefore, we also consider the left-censoring structure of child abduction measurements by confirming the consistency of the results using a Tobit specification, as illustrated in column (7) of Appendix Table A.2.

To further increase the homogeneity of the hometown cities, we match each connected hometown city with an unconnected hometown city within the same province. This matching process requires each pair of hometown cities to have experienced a similar level of cumulative child abduction between 1960 and 1990. This is because neglecting diverse factors related to historical child abduction, such as the establishment of trafficking networks or cultural aspects of parental care, could lead to a significant underestimation of the true effects. The corresponding results are presented in Panel A of Appendix Table A.3. The results remain robust after including hometown pair fixed effects and varying the clustering level at either the city or province-pair level. The coefficients in columns (1)–(3) show a notable increase, approximately 3 to 4 times larger than those observed in the baseline model without matching. This substantial difference can likely be attributed to the matching procedure, which enhances the comparability between hometown cities with and without highway connections, resulting in a shared support system for initial factors associated with child abduction.[11]

So far, we have focused on the intensive margin, examining the degree of trafficking within observed cases. This focus is due to the high concentration of supply cities and traffickers exploiting existing networks by sourcing children from familiar areas. While the role of highways might be more intensive—facilitating access to greater demand—it is also important to explore the extensive margin, which pertains to the occurrence of trafficking. Our hometown city matching analysis allows us to investigate the extensive margin by changing the outcome variable to a binary indicator of whether trafficking occurs. The results are reported in columns (4)–(6) of Appendix Table A.3 and remain significant.

4.1.2 Confounding factors

Other transportation networks and Internet access. We then perform three additional tests on the baseline results using hometown information from family-reported cases, employing the hometown city-matching method. First, as a placebo test, we use a dummy variable indicating high-speed railway con-

[11] A comprehensive balancing test of our matched hometown cities is presented in Panel B of Appendix Table A.3. The only noticeable difference between these two groups is private investment, which could influence future route selection. However, it is important to note that including this variable does not change our results, as indicated in Table A.5.

Table 2: DID using hometown cities: Equation (1)

	# incidents of child abduction in year t				
	all cities	targeted cities			
	(1)	(2)	(3)	(4) highway within 20 km	(5) year$\leq$ 2007
Connect	0.545***	0.713***	0.563***	0.553***	0.532***
	(0.209)	(0.249)	(0.195)	(0.187)	(0.204)
City FE	✓	✓	✓	✓	✓
Year FE	✓	✓			
Province × year FE			✓	✓	✓
# Obs.	3,270	2,780	2,710	2,710	1,626
# Clusters	327	278	271	271	271
Mean Dep. Var.	1.203	1.286	1.224	1.224	1.603

Notes: The standard errors clustered at the city level are reported in parentheses. *Significant at 10%, ** Significant at 5%, *** Significant at 1%.

nections between 2003 and 2015 as our explanatory variable. This does not yield a similar pattern of results (see columns (1) and (2) of Appendix Table A.4).[12] This is because, despite the lack of identity checks for children on high-speed trains, the checks conducted for adults at the train station significantly increase the likelihood of traffickers being apprehended. Additionally, the presence of train police and numerous staff further heightens the risk of traffickers being caught.

Second, it is important to check whether the effect remains significant when we replace highway connectivity with the intensity of all types of roads at the city level. This variable represents the logged total length of roads, including expressways, trunk roads, and rural roads, and is sourced from the Statistical Yearbooks of each city between 1999 and 2014. The majority of China's road network still consists of trunk roads, which differ significantly in quality, speed, and tolls from the newly constructed highways. As shown in columns (3) and (4) of Table A.4, the effects become insignificant, particularly when province-fixed effects are included. This suggests that the significant effect found in the baseline results is primarily

[12]Note that we do not use the same time span from 1999 to 2014 in the main specification because the first high-speed railway train in China was established in 2003.

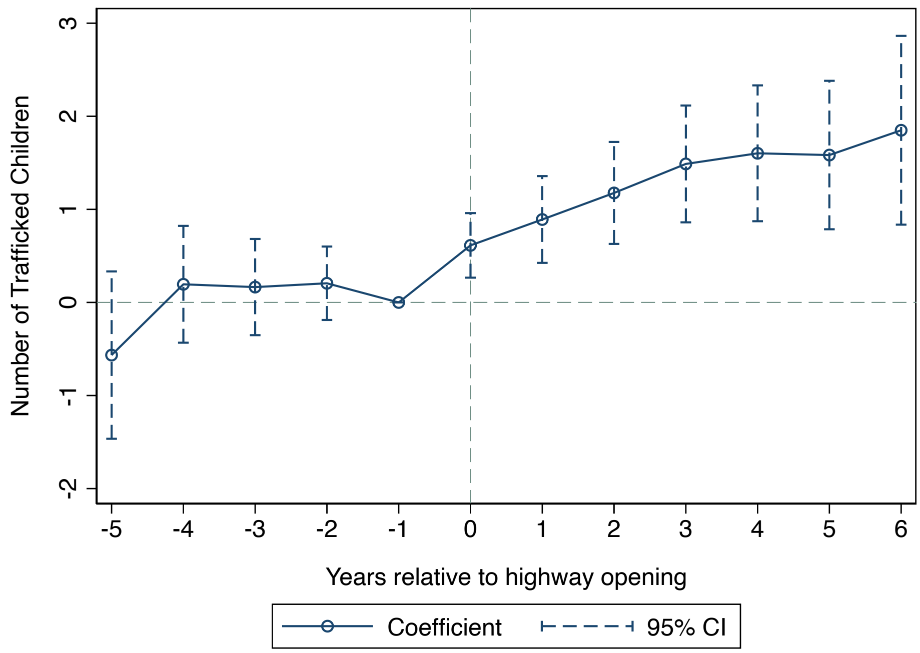

Fig. 3: Staggered event-study regression

Notes: The figure plots the estimates and 95% confidence intervals of the coefficients obtained from a staggered event-study regression as specified in Eq. (1). The y-axis represents the average causal effect, while the horizontal axis denotes the years before or after the connection to the highway network.

driven by connectivity to highway networks rather than an increase in trunk or rural roads.

Third, one may worry that our data on abductions reflect the availability of the Internet rather than highways. Once the Internet became available, people began posting and recording these incidents. As mentioned, records can be posted on the website even if the cases occurred in previous years. To further alleviate this concern, we follow Chen et al. (2020a) to use the city-level coverage of fixed-line telecommunications (broadband Internet/telephone) in 1999, obtained from China's City Statistical Yearbook, to proxy the accessibility of the Internet. We exploit the fact that China's Internet upgrading began in 2000. Specifically, people in cities with higher broadband Internet coverage were more intensively affected and benefited from the Internet upgrading project, making them more likely to rely on the Internet to report abduction cases. We then include an interaction term between Internet coverage and the post-2000 variable in the specification. The results in columns (5) and (6) of Appendix Table A.4 show that the effect of highways is not diminished when we include the proxy for Internet coverage.

Adding time-varying controls. Including time-variant, city-level covariates—such as economic development measured by population density and night-time luminosity, government expenditure, other infrastructure investments, and the employment share across three sectors[13]—in the regressions indicated by Eq. (1) may lead to the problem of "bad controls" since some characteristics are endogenous. However, it is crucial to assess if the conclusions hold when including these variables; otherwise, they may confound the results. For example, changes in child trafficking could be influenced by public spending. If there is a positive correlation between unobservable factors affecting child abduction and public expenditure, as well as between highway connections and public expenditure, then the main coefficient may be upwardly biased. This logic applies to other infrastructure measures as well. In particular, we account for enforcement rates in the hometown cities by creating an interaction term that combines cross-sectional data on the number of police personnel from the 1982 National Population Census with year dummies.

To exclude confounding treatment effects, we re-run the specifications from Table 2 and Appendix Table A.3, including time-variant, city-level characteristics. The results, presented in Appendix Table A.5, show that the estimated coefficients remain highly significant and robust regardless of the explanatory measure used and after including several confounding effects.

Displacement effects. We also would like to know whether building highways leads to a national increase in child trafficking or simply shifts the crime from one location to another. To answer this question, we investigate whether traffickers are more likely to shift from neighboring unconnected cities to cities with highways as their new preferred locations for committing crimes. If this is the case, we would anticipate a decrease in child trafficking incidents in neighboring unconnected cities once a city is connected to a highway. Consequently, we examine whether there is a reduction in trafficked children in an unconnected city when its neighboring city becomes connected to a highway, comparing this scenario to other unconnected cities that lack a nearby highway connection.

Columns (1) and (2) of Appendix Table A.6 present the results illustrating the displacement effect;

[13]The statistics and data sources for these variables are presented in Table 1.

none of the coefficients show statistical significance. This indicates that there is no noticeable decline in child trafficking incidents in unconnected cities when their neighbors have a highway, compared to unconnected cities without neighboring highways. Therefore, based on these findings, we can tentatively conclude that there is no observable shift of crimes from one location to another.

Confounding policies. The laws against human trafficking include the first Criminal Law in 1979, the 1984 Criminal Law, and the 1987 Regulations. During our period of interest, the legal framework surrounding child abduction and trafficking underwent significant changes. Initially, child abduction cases were classified under the broader category of human trafficking, with a maximum fixed-term imprisonment of up to 5 years as prescribed by the Crime Code prior to 1997. However, the 1997 revision introduced a separate classification for child trafficking, imposing harsher punishments of 5 to 10 years in prison, along with fines. Furthermore, in December 2009, the Chinese government ratified the UN Trafficking in Persons Protocol, aligning domestic laws with international standards within 24 months.

We include two dummy variables to represent the periods following the implementation of these laws. The results are reported in column (3) of Table A.6. We find that the revision of the Crime Code significantly decreased the occurrence of child trafficking. However, this did not fully offset the positive effect brought about by highway connections, as being connected still increased the number of abductions by around one case. The 2009 Protocol had no effect on reducing the cases, suggesting that, despite increased awareness, the laws remain lenient for traffickers and are not fully effective in eliminating child abduction.

Other national policies include the modified one-child policy (OCP), implemented in November 2013, which allowed single-child parents to have a second child. As discussed in previous sections, the demand for forced marriage, the sale of children, and the profitable adoption of babies are inexorably linked to the OCP and the resulting shortage of women. However, our data does not include information after 2013, making it unlikely that this policy will confound our results.

The international focus on human trafficking cases may also reduce the number of abductions. An example is the Uyghur Forced Labor Prevention Act, which bans the import of goods or commodities from China produced with forced labor. However, since this act was implemented in 2021, it is unlikely to confound our results. Nevertheless, we excluded samples from Xinjiang province, which has been accused of using forced labor, and found that the results did not change, as reported in column (4) of Table A.6.

4.2 City-to-city analysis

We now move on to a more rigorous analysis using city-to-city comparisons with child-reported data, as outlined in Eq. (2). It is important to acknowledge potential concerns about data quality discrepancies between children searching for their parents. In China, some abducted children, for various reasons, share insights into their life stories as they grow up, actively seeking to reunite with their biological parents through platforms like BCBH. However, many individuals may remain unaware of their trafficking experiences. In this phase of our analysis, we exclusively rely on data from the destination locations to compare outflow cities, providing a more comprehensive perspective on the outcomes. It is crucial to emphasize that these findings complement the baseline regression analysis.

In our analysis, we incorporate time-varying effects of destination and outflow cities in all columns of Table 3. Columns (2) to (6) include the full set of fixed effects, with column (2) starting to include hometown-destination pair fixed effects and columns (3) to (6) restricting the sample to expressway-targeted cities. The results in column (3) suggest that connectivity between two cities leads to a four-fold increase in abducted child flows, and column (4) indicates that these results are robust when limiting the analysis to years in and before 2007. Additionally, in column (5), we show that the results remain consistent when using the incidence per million population in outflow cities as the outcome variable. After the establishment of intercity highways, the incidence of child abduction per million population increased by 3 to 4 times over the outcome mean. These results provide supportive evidence that the results in the benchmark analysis using the outflow cities as study units are likely to be underestimated rather than overestimated. Similarly, our conclusion remains unchanged when estimating the extensive margin instead of the intensive margin of the effect of intercity highways, as shown in column (6).

By comparing child flows between destination and original cities using the intercity child movement model, we establish a stronger causal link between transportation networks and changes in trafficking patterns. This approach is advantageous in controlling for confounding factors that may vary across regions, allowing us to better isolate the causal effect of highway connections on child trafficking while holding constant all other regional characteristics (e.g., Internet improvement and relevant local policies) that might influence trafficking rates. Additionally, we account for changes in son preferences and socioeconomic conditions of the region by including fixed effects on hometown city-year and destination city-year. The results indicate that the sole positive effects of connectivity can be identified using Eq. (2). The findings from both equations are quite similar, leading us to conclude that the positive effects dominate.

While city-to-city analysis offers many advantages, it is not used as a benchmark analysis due to the imprecise nature of child reports and the focus on outflow cities in this paper. Our primary interest lies in understanding why children are more easily abducted in some regions compared to others, rather than the specific destinations to which the children are transferred.

Table 3: City-to-city analysis: Equation (2)

	# incidents of child abduction from city i to j in year t					
	all cities		targeted cities			
				year$\leq$ 2007	per million population	dummy
	(1)	(2)	(3)	(4)	(5)	(6)
Connect	0.0126***	0.0078***	0.0093***	0.0077***	0.0022***	0.0032***
	(0.0014)	(0.0014)	(0.0016)	(0.0016)	(0.0005)	(0.0004)
Hometown city $\times$ year FE	✓	✓	✓	✓	✓	✓
Destination city $\times$ year FE	✓	✓	✓	✓	✓	✓
Hometown-destination pair FE		✓	✓	✓	✓	✓
# Obs.	871,442	871,442	783,354	498,498	744,108	783,354
# Clusters	79,222	79,222	71,214	71,214	71,214	71,214
Mean Dep. Var.	0.0022	0.0022	0.0023	0.0033	0.0006	0.0014

Notes: The standard errors clustered at the hometown-destination pair level are reported in parentheses. *Significant at 10%, ** Significant at 5%, *** Significant at 1%. The outcome variable is the children being transferred from city i to destination city j in year t. The explanatory variable is a dummy variable indicating whether both cities i and j are connected by the highway in year $t-1$.

4.3 Heterogeneity in the effects

Due to the reporting features of the BCBH and the illegal nature of trafficking, information regarding child abduction may suffer from underreporting. While this issue is less severe for child abduction compared to child abandonment—where parents may be unwilling to search for their abandoned child—it still exists. The likelihood of underreporting in child abduction cases could also correlate with variables related to city development, despite the inclusion of city-fixed effects. Therefore, exploring the heterogeneity of these effects, particularly based on city-level characteristics, is crucial for addressing potential underreporting and misreporting issues.

4.3.1 Characteristics of abducted children.

Panel A of Table 4 scrutinizes the heterogeneous effects of road connections on abducted children, differentiated by gender and age groups, using family-reported data. Columns (1) and (2) of Panel A distinguish abducted children according to gender, indicating that highway connectivity positively and statistically significantly affects incidents of child abduction for both boys and girls. Stronger son preferences do not necessarily suggest that there is no increase in abducted girls; girls are more affordable for less wealthy and gender-indifferent households. Additionally, as mentioned, girls can be selected and purchased as future daughters-in-law. Particularly, when the gender ratio becomes increasingly imbalanced due to continuous and various types of gender selection, it becomes difficult for many male offspring to find suitable wives at the time of their marriage.

Results in column (1) of the subsample, which includes only abducted boys, address concerns related to the potential misreporting of abandoned children as abducted. This misreporting could occur when parents, who abandoned their children for financial or other reasons, later regret their decision and attempt to reclaim them. Since people are generally less likely to abandon male babies compared to females, focusing on abducted boys helps mitigate this issue.

Columns (3) to (6) suggest that children aged 9–14 are less likely to be abducted in response to improvements in transportation infrastructure. Considering that younger children have less memory and self-awareness, and that it is easier to cultivate relationships between parents and children, the demand for younger children tends to be higher. Therefore, traffickers are more likely to capture and transfer younger children when the availability of trafficking opportunities increases.

Table 4: Heterogeneity in the effects

Panel A: By characteristics of the abducted child

	# incidents of child abduction in year t					
	by gender		by age group			
	(1)	(2)	(3)	(4)	(5)	(6)
	boys	girls	0–1	1–4	4–9	9–14
Connect	0.368**	0.196**	0.010	0.271**	0.252***	0.030
	(0.142)	(0.085)	(0.019)	(0.111)	(0.097)	(0.043)
City FE	✓	✓	✓	✓	✓	✓
Province × year FE	✓	✓	✓	✓	✓	✓
# Obs.	2,710	2,710	2,710	2,710	2,710	2,710
# Clusters	271	271	271	271	271	271

Panel B: By characteristics at the city level

	# incidents of child abduction in year t					
	Economic features				Culture & Institution	
	(1)	(2)	(3)	(4)	(5)	(6)
	large-to-large	large-to-small	small-to-large	small-to-small	arrest rate	social capital
Connect	0.019***	0.001**	0.000	0.013**	1.081***	0.419***
	(0.004)	(0.001)	(0.001)	(0.005)	(0.251)	(0.022)
Connect*High arrest rate					-0.711***	
					(0.238)	
Connect*Social trust						-0.050***
						(0.125)
Hometown-destination pair FE	✓	✓	✓	✓		
Hometown city × year FE	✓	✓	✓	✓		
Destination city × year FE	✓	✓	✓	✓		
City FE					✓	
Province × year FE					✓	
Individual & wave FE						✓
Individual Controls						✓
# Obs.	267,102	178,068	201,267	134,178	2,710	39,412
# Clusters	24,282	16,188	18,297	12,198	271	71,214

Notes: The standard errors clustered at the city level are reported in parentheses. *Significant at 10%, ** Significant at 5%, *** Significant at 1%. In columns (1)–(4) in panel B, we classify the child movement flows into four types: large-to-large, large-to-small, small-to-large, and small-to-small, based on the size of the destination and lost locations; the results are estimated from Eq. (2). In column (7), we use the median value in 1998 as the cutoff to define cities with high and low arrest rates. Then, we interact this variable with the main outcome variable *Connect*. In column (8), we match the abducted children and connection data with a micro-level dataset introduced in the mechanisms section. Social capital is proxied by general trust, which is derived from the question: "In general, do you find most people to be trustworthy?"

4.3.2 Economic features of outflow and inflow cities.

Underreporting can occur due to information obstacles, which may be influenced by household income when families attempt to search for their children through the website. To mitigate this potential issue, we exclude samples from capital cities or first-tier cities, as these areas generally have higher affluence and better access to various platforms, making them more likely to report their own cases.[14] The results after these exclusions are presented in columns (1) and (2) of Table A.7. Additionally, we further divide the samples into areas with lower and higher per capita wages. To determine the cutoff value for high and low wages, we use the mean wage from one year before the start of the panel dataset. The results from these subsamples are shown in columns (3) and (4), confirming that underreporting due to financial restrictions does not significantly affect our findings. Moreover, if one believes that underreporting is more prevalent in underdeveloped and remote regions, then our results are more likely to be underestimated rather than overestimated.

We also use city-to-city analysis (using child-reported data) to conduct a subsample analysis addressing the underreporting issue in a similar manner. The results after excluding capital cities and first-tier cities are presented in columns (5) and (6) of Appendix Table A.7. Similarly, we divide the samples into areas with lower and higher per capita wages, with the findings from these subsets shown in columns (7) and (8) of Table A.7. Interestingly, we observe no significant difference between developed and underdeveloped regions. This implies that the issue of underreporting due to financial constraints appears to be even less pronounced in child-reported data. This phenomenon can be attributed to the widespread availability of the Internet among younger generations in China, which boasts an impressive penetration rate of approximately 96.8% among teenagers. Consequently, this suggests that even in remote and economically disadvantaged areas, the majority of children have access to the Internet.

We also investigate heterogeneity based on the economic characteristics of both hometown and destination cities in the lower panel of Table 4, by utilizing child-reported cases and a specification described by Eq. (2). We categorize each flow of abducted children into four types based on the sizes of the outflow

[14]The list of first-tier cities is obtained from YiMagazine, which classifies city tiers based on a comprehensive evaluation of five indicators: concentration of business resources, urban hubs, urban people's activeness, lifestyle diversity, and future plasticity. There are a total of five tiers.

and inflow cities: large-to-large, large-to-small, small-to-large, and small-to-small (Dong et al., 2020). For instance, a large-to-large movement indicates that the child was transferred from one large city to another. Large and small cities are defined based on their formal economic conditions, with large cities classified as those having a GDP above the median in 1990. This typically includes most cities in the first, second, and third tiers (out of five tiers) in China. The results in columns (1)–(4) of panel B demonstrate that with highway connections, the incidence of large-to-large, large-to-small, and small-to-small movements increased significantly. This reflects the matching process from the demand side, where households in large and developed cities are more likely to purchase children from other large cities, while children from smaller cities are likely to be sold to smaller cities.

4.3.3 Cultural and institutional features of cities.

The cultural and institutional characteristics of *inflow* cities are also particularly important to explore because they determine the demand side of these criminal behaviors. One motive for purchasing a girl is for marriage, where buying a girl from traffickers could serve as a substitute for paying the bride price. Meanwhile, the high bride price discourages the purchase of boys, as households would need to pay a substantial amount when the child grows up and gets married (i.e., the cost of raising a son increases). To investigate this, we analyzed divorce cases from China Judgment Online that mention the bride price. These verdicts specify the amount of bride price given during marriage or engagement, as this amount is typically requested to be returned in the event of a divorce, especially if the marriage has not lasted long. We extracted marriage or engagement years from 65,287 cases, narrowing it down to 44,933 cases with available bride price amounts. Each verdict was assigned a city code, and amounts were winsorized at the 5% and 95% levels to manage outliers.[15] Finally, we calculated the median dowry amount for each city by marriage year, yielding data for 144 cities.

The results presented in columns (1) and (2) of Appendix Table A.8 indicate that cities with higher bride prices experience a greater inflow of girls. The heterogeneity analysis by age group in high bride price regions, shown in columns (3) to (6), reveals that the effects are more pronounced for younger girls compared to older girls, suggesting that the incentive to avoid paying a high bride price in the future is a

[15] The results are consistent with winsorizing at the 1% and 99% levels as well.

more likely explanation. This may also be due to younger children being more vulnerable to trafficking, as older children tend to have greater safety awareness.

Exploring the heterogeneity based on patrilineality in the purchase of boys is also intriguing. One approach is to assess Confucian values within each region by using measurements such as the number of Confucian temples and the density of *jinshi* (i.e., the highest qualification in the imperial examination system; see Chen et al., 2020b). Both metrics are available in the Confucian Culture Database. Confucian temples honor Confucius and reflect a region's adherence to Confucian culture, which emphasizes patriarchy; thus, more temples suggest greater acceptance of patriarchal systems. Similarly, the number of *jinshi* indicates a region's success in Confucian education and its emphasis on patriarchy. We combined these two measurements and created an index using principal component analysis to indicate the level of patrilineality in each region. The results, shown in columns (7) and (8), reveal that cities with stronger Confucian values (above the median value) place greater importance on boys, leading to more boys being abducted into these regions.

An alternative measurement is the selective gender ratio. Columns (9) and (10) of Table A.8 compare the effects of highway connectivity in cities with high and low sex ratios, defined by the ratio of boy births to girl births relative to the median value one year before the panel dataset begins (i.e., in 1998). It is reasonable to infer that cities with stronger patrilineality or higher boy-to-girl ratios among newborns tend to exhibit a stronger preference for boys (Edlund et al., 2013), leading to a higher number of boys being abducted into these regions.

Moreover, the heterogeneity based on the intensity of police intervention and social capital in *hometown* cities is worth exploring, as these are important factors related to underreporting issues. Our sample does not include instances where traffickers attempted to traffic a child but were stopped by parents or neighbors who immediately intervened to rescue the child. This exclusion of unreported cases introduces a downward bias in our results. Regions that were connected to highways earlier are likely to be more developed, with greater social capital and stronger law enforcement.[16] If community mutual aid and police intervention are successful in rescuing children, these cases remain unreported, leading to an underesti-

[16]In areas with high social capital, governments, enterprises, and residents can effectively collaborate to integrate resources, raise funds, and provide technical support, thereby accelerating the construction of expressways. Additionally, higher levels of trust and cooperation in these areas help minimize friction and conflict, promoting the smooth progress of such projects.

mation of the effect of highway connectivity on trafficking.

To illustrate this potential underestimation, we include interaction terms in our analysis: the interaction between connectivity and policing efforts, and the interaction between highway connectivity and social capital levels.[17] Column (5) in Panel B of Table 4 provides evidence from provinces with varying levels of policing efforts, measured by annual arrest rates (where higher arrest rates indicate greater policing efforts). Column (6) captures heterogeneity based on general social trust levels. The coefficients in these two columns indicate a significantly lower impact of highway connections on child abductions in regions with more arrests and higher social capital, supporting our hypothesis on the underestimation.

5 Mechanisms

5.1 Demand factors

The buyer market plays a significant role in child trafficking, as an increase in the number of potential buyers seeking abducted children can lead to a rise in trafficking incidents. Improved highway connectivity can expand the demand market by enabling longer-distance transfers, which otherwise would be limited to local markets. Transporting to distant markets is usually preferred by both clients and traffickers; clients often seek to adopt children from far-away provinces to avoid detection by biological parents and to better integrate the children into their families, while traffickers aim to place children in locations far from their hometowns to reduce the risk of being recognized by parents or apprehended by police.

Without highway connections, long-distance transfers are challenging; however, with improved connectivity, the pool of potential buyers can be expanded beyond the local market due to the emergence of mid-length and long-distance trafficking.[18] To test the hypothesis that trafficking cases are more likely to occur across different provinces (and thus over longer distances) in response to improved transportation

[17]The analysis utilizes the CFPS dataset, a matched individual-level dataset that will be further introduced in the mechanism section. The social capital level is measured by the survey question: "In general, do you think that most people are trustworthy, or is it better to take greater caution when getting along with other people?" We assign a value of one to the former response and zero to the latter.

[18]Traffickers need to use transportation systems to transport children to different locations to be illegally adopted (Anthony, 2018). As noted in the introduction, security and identity checks are strict at train stations and airports in China; thus, cross-regional transfers would more likely be accomplished via bus or private car.

networks, we use two datasets: child-reported data and a subset of successful cases where lost children were reunited with their families. Both datasets document the children's birthplaces and locations where they were found, enabling us to track the movement of abducted children.[19]

Pairing the hometown and destination locations from successful matching cases and self-reported child abductions, we identify the ratio of cross-province movement. Our analysis, as shown in columns (1) and (2) of Table 5, reveals that highways increase the ratio of long-distance travel. Column (1) presents results using the success-matching cases, while column (2) presents results using the child-reported cases.[20] Replacing the ratio with the average distance in kilometers between hometowns and destination places does not alter the conclusion (columns 3 and 4).

A well-constructed expressway can lower the cost of crime by complicating the search for abducted children and making it harder for law enforcement to track down traffickers. This is confirmed in column (5) of Table 5, which shows that the construction of the highway was associated with a decreased likelihood of successfully locating and retrieving abducted children. This is indicated by a reduction in the proportion of successful cases relative to the number of children abducted in the same year and from the same city. The longer transfer distances after the highway construction contributed to this outcome. The results, as reported in column (1) of Appendix Table A.9, suggest that the likelihood of retrieving abducted children is particularly correlated with the distance between hometown and destination locations. Importantly, the size of this negative correlation remains almost unchanged after the connection to the highway networks (columns 2 and 3), indicating that the increased difficulty in finding victims is unlikely to have been influenced by the presence of highways themselves and does not confound our findings.

Meanwhile, some may argue that longer distances should lead to a higher probability of police detection during transportation. While this risk does increase with distance, the features of highways may actually mitigate it. This is because highways typically have fewer stops, intersections, and traffic signals compared to urban or local roads. This continuous flow of traffic provides fewer opportunities for law

[19] We do not include the subset of successful cases in the city-to-city analysis to prevent duplication with child-reported cases, as some posts may not have been withdrawn online after reunions.

[20] The number of observations in column (1) is significantly smaller in this analysis because we have focused exclusively on the subset of success cases, which is inherently smaller than the total number of cases. Specifically, we have included only city-year samples where there is a non-zero value for the outcome variable.

enforcement to intercept vehicles, especially if the driver maintains a constant, legal speed. It is important to note that if the police detected the abduction and arrested the traffickers during transportation, those attempts would not appear in our data. Therefore, we can only use counterfactuals as the outcome variable. We find that reported cases decreased as distance increased, but the interaction term has the opposite sign and is highly significant, indicating that highways largely mitigated the risk on long-distance trips (columns 4 and 5 of Table A.9), leading to many successful trafficking attempts.

Table 5: Mechanisms: Demand factors

	cross-province transfer		dist. to the destination		success cases over total cases
	success data	child-reported data	success data	child-reported data	
	(1)	(2)	(3)	(4)	(5)
Connect	0.275***	0.070***	1.761***	2.054***	-0.069**
	(0.061)	(0.021)	(0.366)	(0.215)	(0.034)
City FE	✓	✓	✓	✓	✓
Province × year FE	✓	✓	✓	✓	✓
# Obs.	375	3,194	375	3,194	1,659
# Clusters	158	277	158	277	259

Notes: The standard errors clustered at the city-pair level are reported in parentheses. *Significant at 10%, ** Significant at 5%, *** Significant at 1%. We pair the hometown and destination places obtained from the success-matching cases (columns 1, 3, and 5) and the child-reported abduction (columns 2 and 4).

5.2 Supply factors

On the supply side, the ease with which traffickers can exploit at-risk children is crucial, particularly in the context of the hometown environment. Increased out-migration and in-migration, especially among the low-skilled population following highway connectivity, are key supply-side channels.

On the one hand, the establishment of highways can lead to improved economic growth, increased employment opportunities, and higher real wages along the highways (Asher and Novosad, 2020). As transport infrastructure improves, the opportunity cost for parents to care for their children independently rises, prompting more parents to migrate for work. This results in an increase in left-behind children, often cared for by grandparents or relatives (Jiang and Sánchez-Barricarte, 2013). In the worst cases, some children must take care of themselves, performing tasks such as walking to school or home alone. Deprived of parental care, these children are at increased risk of being trafficked for various reasons (EU, 2015, 2019; EUCPN, 2020), thereby increasing the probability of successful trafficking. On the other hand, improved highway connectivity boosts immigration, increasing the likelihood of violent delinquency (Bianchi et al., 2012; Spenkuch, 2014). Low-skill populations are particularly affected due to reduced movement costs and the cross-regional transfer of labor-intensive sectors (Baum-Snow et al., 2017; Ma and Tang, 2024; Qin, 2017; Kong et al., 2021). The in-migration of low-skilled workers can destabilize communities, creating an environment where traffickers more easily operate. These workers often reside in temporary or informal housing with limited community support, resulting in a lack of social ties. This creates the areas of anonymity that traffickers can exploit to victimize vulnerable children.

We test these two channels, and Table 6 presents the results. We first use the China Family Panel Studies (CFPS) data with the survey years of 2010, 2012, and 2014 to empirically test the increased opportunity cost for child care and the decreased actual time the parents spent with their children.[21] We restrict the sample to rural households and run a specification with the household fixed effects. Column (1) shows that expressway connections increase the likelihood of out-migration for a job. The increased income from working, equivalent to a decreased opportunity of accompanying children, would lead to a decreased probability of children living with their parents, being accompanied by and taken care of by parents other than other relatives, or becoming left-behind children (columns 2–4).

Then, we test whether the inflow of low-skill migrants could be an alternative explanation. Using county-level data from the National Population Census for 2000, 2005, 2010, and 2015, we define an immigrant as someone living in a county different from their *hukou* county at the time of the survey.[22] We first use the ratio of low-skill and high-skill migrants over total immigrants as outcome variables and confirm that most migrants drawn by highway connectivity are low-skilled rather than high-skilled (columns 5–6).[23] However, to determine the extent to which the low-skill immigrant channel is valid,

[21]The CFPS was launched by the Institute of Social Science Survey of Peking University, has five waves (2010, 2012, 2014, 2016, and 2018), and is still ongoing. Its sample covers 25 provinces, representing 95% of China's total population (Xie, 2012).

[22]The *hukou* system in China is an administrative system that governs Chinese citizens' migration based on their birthplace.

[23]We define low-skilled immigrants as those who have only a junior high school degree or below, and high-skilled immigrants

we need to include the ratio of low-skilled migrants to total immigrants as a control and re-estimate the baseline models. Column (7) in Table 6 presents the results. Compared to the main findings (e.g., column (3) in Table 2), the coefficient decreases from 0.563 to 0.539. This suggests that while low-skill migrants do play a role, their influence is limited. This finding aligns with current literature indicating that the negative impact of immigrants on crime may be minor (Ajzenman et al., 2023; Nunziata, 2015; Spenkuch, 2014).

Table 6: Mechanisms: Supply factors

	Out-migration				In-migration		
	out-migrate for work (1)	live with parents (2)	left-behind children (3)	taken care by parents (4)	low-skill migrants (5)	high-skill migrants (6)	baseline result (7)
Connect	0.084***	-0.066***	0.036**	-0.123***	0.018***	-0.020***	0.539***
	(0.025)	(0.019)	(0.016)	(0.019)	(0.004)	(0.005)	(0.188)
Low-skill Migrants							1.328
							(1.695)
Household FE	✓	✓	✓	✓			
Survey year FE	✓	✓	✓	✓			
City FE					✓	✓	✓
Province × year FE					✓	✓	✓
# Obs.	5,792	5,737	9,991	9,988	2,710	2,710	2,710
# Clusters	93	93	93	93	271	271	271

Notes: The standard errors clustered at the city level are reported in parentheses. *Significant at 10%, ** Significant at 5%, *** Significant at 1%. The analysis in columns (1)–(4) is at the household level, in columns (5)–(7) is at the city level.

6 Conclusion

This study provides compelling evidence of the relationship between the expansion of expressway networks and the prevalence of child trafficking in China. Our findings indicate that enhanced highway connectivity facilitates the transportation of trafficked children, thereby increasing the unexpected incidence of this grave crime. The results reveal that highways not only expand the demand side of the trafficking market by connecting distant regions but also contribute to industrial transformations and migration patterns that elevate the risks of child trafficking.

as those with a college degree or above.

Our findings have several policy implications. First, our results suggest that improved highway connectivity increases employment opportunities, prompting higher out-migration of rural parents for better jobs, thereby decreasing parental supervision and increasing children's vulnerability to trafficking. Given that young victims are unable to protect themselves, this highlights the differences between human trafficking and other types, as well as between human trafficking and child trafficking. Therefore, it is crucial to support childcare in rural areas to counteract the reduced parental supervision. Policymakers should consider establishing community childcare centers and creating local employment opportunities to minimize parental migration and enhance child protection.

Second, our finding identifies the importance of enhancing surveillance on highways and transportation hubs. Policymakers who want to minimize the negative impacts of transport infrastructure improvements may want to deploy targeted monitoring technologies,[24] such as automated license plate recognition systems and selective use of CCTV in high-risk areas, including provincial borders, cities at critical nodes of the transportation network, medium-sized cities, and cities with high concentrations of lower-skilled immigrants. Additionally, integrating data from various surveillance systems into a central database for real-time analysis and response can improve monitoring efficiency without excessive costs.

In conclusion, while highway connectivity is vital for economic growth, it poses significant risks for child trafficking. Addressing these risks requires a comprehensive approach involving not only legal measures and enforcement but also targeted surveillance, community support, and local employment creation. By implementing these measures, policymakers can mitigate the negative impacts of transport infrastructure improvements, safeguard the well-being of children across China, and provide strong support for the China Action Plan Against Human Trafficking.

[24] In 2016, the Ministry of Public Security of China launched an emergency release platform for searching abducted children. Monitoring technologies can be integrated with this platform and combined with mobile terminals.

Declarations

Declaration of Generative AI and AI-assisted technologies in the writing process: During the preparation of this work the authors did not use any Generative AI to produce the work and take full responsibility for the content of the publication.

Conflict of Interest: The authors have no conflicts of interest to declare that are relevant to the content of this article.

Availability of replication files: Data and code are available upon request.

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Appendix A: Figures

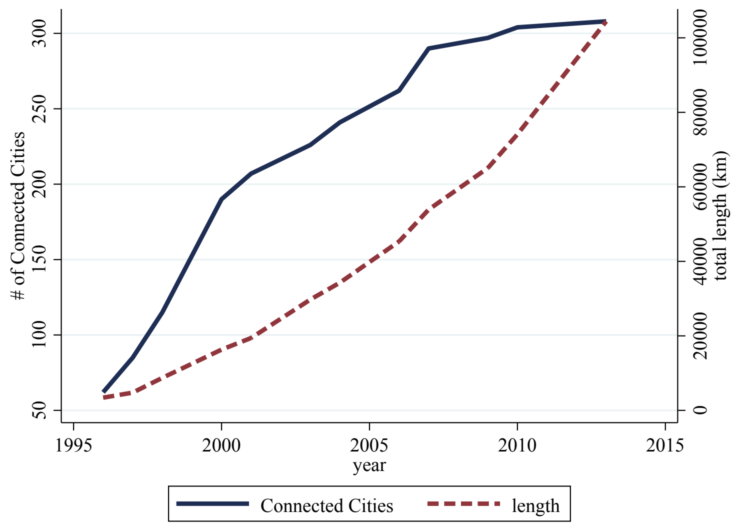


Fig. A.1: Highway construction in China

Notes: The figure shows the changes in the number of cities with highways passing by and total expressway length from 1996 to 2013.

(a) Family-reported case

寻亲类别：	家寻宝贝	**Type: Families Looking for Children**
失踪类型：	被拐	**Missing Type: Abduction**
寻亲编号：	688384	**Child ID: 688384**
姓名：	[redacted]	**Child Name**
性别：	男	**Child Gender: Male**
出生日期：	1971-10-16	**Child Birth Date: 16th Oct, 1971**
失踪时身高：	100CM	**Height of Child When Lost: 100cm**
失踪时间：	1974-07-26	**Child Lost Date: 26 July, 1974**
失踪地点：	江苏省,宿迁市,沭阳县,李恒乡胡圩村大野场组	**Lost Location: Dayechang Group, Huxu Village, Liheng Township, Shuyang County, Suqian City, Jiangsu Province**

(b) Child-reported case

寻亲类别：	宝贝寻家	**Type: Abducted Child Looking for Parents**
失踪类型：	被拐	**Missing Type: Abduction**
寻亲编号：	687819	**Child ID: 687819**
姓名：	[redacted]	**Child Name**
性别：	女	**Child Gender: Female**
出生日期：	1995-11-27	**Child Birth Date: 27th Nov, 1995**
失踪时身高：	60CM	**Height of Child When Lost: 60cm**
失踪时间：	2000-01-12	**Child Lost Date: 12th Jan, 2000**
失踪地点：	北京市,市辖区,石景山区,undefined	**Child Lost Location: Shijingshan District, Beijing**
失踪人所在地：	河南省,南阳市,社旗县,undefined	**Child Destination Location: Sheqi County, Nanyang City, Henan Province**

Fig. A.2: Example of abducted cases reported in the BCBH website

Notes: The upper panel presents an example of a family-reported abducted child, while the lower panel presents an example of a child-reported case in the BCBH community. The most apparent difference is that only child-reported cases have information on destination locations.

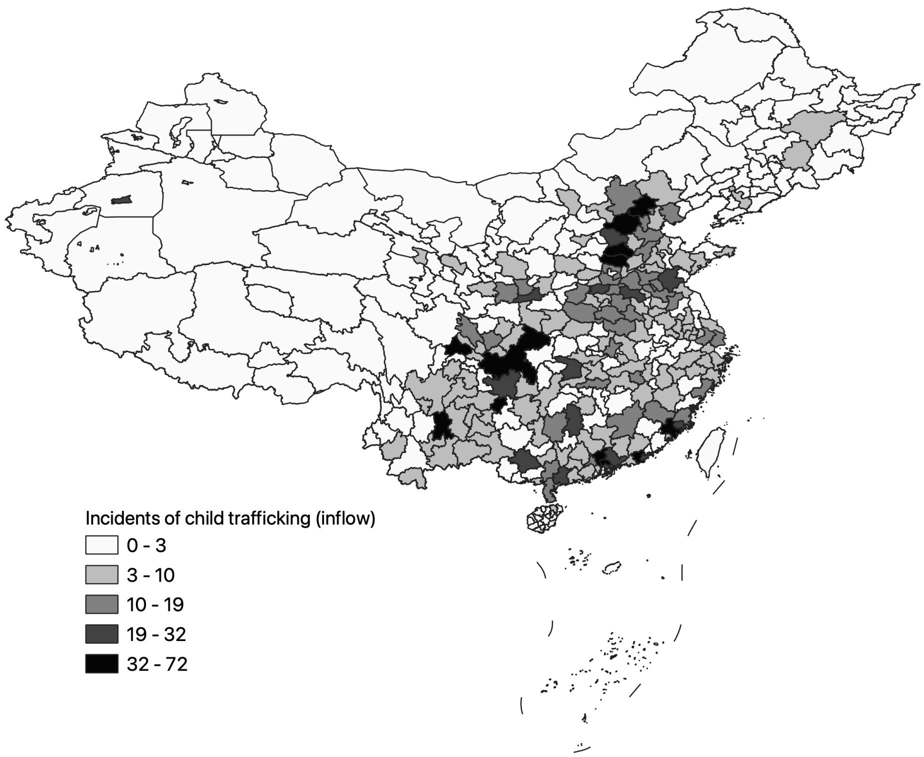


Fig. A.3: Distribution of abducted children's destination cities (1999–2014)

Notes: The figure displays the geographic distribution of destination cities (cities to which the abducted children were transferred) of the abducted children, obtained from the child-reported records. The destination location is available in the BCBH only if the information is reported by the victims (children would report where they live now in self-reported records), and a small subset of success cases of families who find their lost children (although the number is rather small). The distribution of the outflow cities reported by their family are shown in Fig. 2.

Appendix A: Tables

Table A.1: Summary statistics of the cases

	Obs.	Mean	Std. Dev.	Min	Max
Family-reported cases					
Type					
Abduction	33,348	0.812	0.391	0	1
Abandonment	33,348	0.188	0.391	0	1
Age when being abducted	27,086	4.219	3.392	0	14
Gender (1=Boy, 0=Girl)	27,086	0.591	0.492	0	1
Child-reported cases					
Type					
Abduction	28,932	0.584	0.493	0	1
Abandonment	28,932	0.416	0.493	0	1
Age when being abducted	16,905	2.087	2.600	0	14
Gender (1=Boy, 0=Girl)	16,905	0.511	0.500	0	1
Age when sending the post	16,905	34.31	13.68	8	80

Notes: This table presents the summary statistics (number of observations, mean, standard deviation, minimum value, and maximum value). This table reports the statistics of the important features of the cases and victims from the BCBH website. Our benchmark analysis focuses only on abduction.

Table A.2: Alternative models and outcome variables

Models	OLS						Tobit
Dep. Var.	# incidents per million population			# incidents (non-zero cells)			# incidents
Sample	all cities	targeted cities		all cities	targeted cities		targeted cities
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Connect	0.255***	0.242**	0.213***	1.462***	1.583***	1.291***	0.563***
	(0.098)	(0.097)	(0.079)	(0.436)	(0.470)	(0.379)	(0.186)
City FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓		✓	✓		
Province × year FE			✓			✓	✓
# Obs.	2,690	2,648	2,583	1,431	1,305	1,227	2,780
# Clusters	285	278	271	265	237	227	-
Mean Dep. Var.	0.327	0.327	0.326	2.720	2.715	2.644	1.286

Notes: The standard errors clustered at the city level are reported in parentheses. *Significant at 10%, ** Significant at 5%, *** Significant at 1%. In columns (1)–(3), we use the full sample. In columns (4)–(8), we run alternative models, such as by excluding zero cells in columns (4)–(6) and by running Tobit regression in column (7).

Table A.3: Baseline results: Homogenous hometown cities

Panel A: Hometown city-pair+DID						
	Cities with similar past child trafficking					
	# incidents of child abduction			dummy of child abduction		
	all cities	targeted cities		all cities	targeted cities	
	(1)	(2)	(3)	(4)	(5)	(6)
Connect	1.942**	2.044**	1.457***	0.095***	0.078***	0.075**
	(0.255)	(0.283)	(0.192)	(0.023)	(0.025)	(0.029)
City FE	✓	✓	✓	✓	✓	✓
Hometown-pair FE	✓	✓	✓	✓	✓	✓
Year FE	✓			✓		
Province × year FE		✓	✓		✓	✓
# Obs.	5660	5310	5310	5660	5310	5310
# Clusters: province-pair	284	284	284	284	284	284
Mean Dep. Var.	1.945	1.996	1.996	0.522	0.531	0.531
Panel B: Balancing tests: difference within hometown pair in 1998						
	Luminosity	Population	Wage	Investment	Industry Employment	Service
	(1)	(2)	(3)	(4)	(5)	(6)
Difference within pair	0.073	0.002	0.076	0.337*	0.013	0.003
	(0.051)	(0.021)	(0.053)	(0.180)	(0.012)	(0.009)

Notes: In Panel A, the standard errors clustered at the province-pair are reported in parentheses; using robust standard errors clustered at the city level does not alter the results. In Panel B, robust standard errors clustered at the province level are reported in parentheses. *Significant at 10%, ** Significant at 5%, *** Significant at 1%. In Panel A, we apply the DID estimators to within-province hometown pairs that exhibited similar levels of cumulative child trafficking between 1960 and 1990. To ensure comparability, we use cross-sectional data from 1998 to test whether the main socio-demographic characteristics were balanced within each pair. The results of this balance test are presented in Panel B.

Table A.4: Additional tests

	# incidents of child abduction in year t					
	High-speed rail		Length of all roads		Internet access	
	(1)	(2)	(3)	(4)	(5)	(6)
High-speed rail	0.272	-0.011				
	(0.305)	(0.132)				
Increase in length			0.965	-0.079		
			(0.861)	(0.203)		
Connect					2.156**	1.451***
					(0.953)	(0.529)
Internet Access					✓	✓
City FE	✓	✓	✓	✓	✓	✓
Hometown-pair FE	✓	✓	✓	✓	✓	✓
Year FE	✓		✓		✓	
Province × year FE		✓		✓		✓
# Obs.	5,830	5,830	7,434	7,434	4,870	4,870
# Clusters	254	254	255	255	211	211
Mean Dep. Var.	1.189	1.189	1.771	1.771	2.093	2.093

Notes: The standard errors clustered at the city level are reported in parentheses. *Significant at 10%, ** Significant at 5%, *** Significant at 1%. We restrict the sample to targeted cities and use a similar level of past cumulative child trafficking between 1960 and 1990 to construct the hometown pairs.

Table A.5: Adding in Time-varying Controls

	# incidents of child abduction in year t				
	all cities	targeted cities			
					+Matching
	(1)	(2)	(3)	(4)	(5)
Connect	0.706***	0.725***	0.608***	0.710***	1.203***
	(0.239)	(0.242)	(0.192)	(0.262)	(0.439)
City FE	✓	✓	✓	✓	✓
Hometown-pair FE					✓
Year FE	✓	✓			
Province × year FE			✓	✓	✓
Time-variant covariates	✓	✓	✓	✓	✓
City-level police number × year FE				✓	✓
# Obs.	2,510	2,472	2,409	2,150	4,820
# Clusters	285	278	271	215	255
Mean Dep. Var.	1.279	1.295	1.241	1.215	2.065

Notes: The standard errors clustered at the city level are reported in parentheses. *Significant at 10%, ** Significant at 5%, *** Significant at 1%. Time-variant city-level covariates include city economic development measured by logged population density and logged average income, logged government spending, logged infrastructure investment, and the share of employees across three sectors. All variables are displayed in a lagged term covering the period between 1998 and 2013. We use a similar level of past accumulative child trafficking between 1960 and 1990 to construct the hometown pairs in column (5).

Table A.6: Displacement effect and national laws

	# incident of child trafficking			
	Displacement effect		National Law	
				Excluding Xinjiang
	(1)	(2)	(3)	(4)
Neighbor city connect	0.059	-0.149		
	(0.261)	(0.314)		
Connect			5.130***	0.721***
			(1.951)	(0.249)
Crime Law revision $\times$ Connect			-4.478***	
			(1.740)	
UN Protocol $\times$ Connect			-0.169	
			(0.703)	
City FE	✓	✓	✓	✓
Province $\times$ year FE		✓	✓	✓
Excluding Xinjiang				✓
# Obs.	336	288	3,848	2,770

Notes: In columns (1) and (2), the sample includes 39 cities that remain unconnected. *Neighbor city connect* equals one if any of their neighboring cities have been connected to highways. Column (3) contains the 95–13 extended sample, while column (4) contains the baseline sample but exclude Xinjiang. The standard errors clustered at the city-pair level are reported in parentheses. *Significant at 10%, ** Significant at 5%, *** Significant at 1%.

Table A.7: Subsample of involving cities to address under-reporting

	# incidents of child abduction in year t							
	DID using hometown cities				City-to-city analysis			
Subsample	without capital	without first tier	developed	non-developed	without capital	without first tier	developed	non-developed
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Connect	0.429***	0.335**	1.298***	0.617**	0.0064***	0.0060***	0.0095***	0.0095***
	(0.160)	(0.140)	(0.456)	(0.285)	(0.0014)	(0.0012)	(0.0025)	(0.0020)
City FE	✓	✓	✓	✓				
Hometown-pair FE	✓	✓	✓	✓				
Province × year FE	✓	✓	✓	✓				
Hometown-destination pair FE					✓	✓	✓	✓
Hometown city × year FE					✓	✓	✓	✓
Destination city × year FE					✓	✓	✓	✓
# Obs.	2,351	2,301	778	1,767	692,120	663,806	371,228	412,126
# Clusters	242	237	97	168	62920	60346	33748	37466
Mean Dep. Var.	1.117	1.027	1.663	1.310	0.0019	0.0017	0.0025	0.0021

Notes: The standard errors clustered at the city level are reported in parentheses. *Significant at 10%, ** Significant at 5%, *** Significant at 1%. We exclude the sample of capital cities or first-tier cities in columns (1) & (5) and (2) & (6), respectively. Additionally, we further divide the samples into areas with lower wages per capita and areas with higher average income in columns (3)–(4) and (7)–(8). To determine the cutoff value for high and low wages per capita, we use the mean wage from one year before the start of the panel dataset.

Table A.8: Heterogeneous effects based on the inflow cities

	# incidents of abduction of girls in year t						# incidents of abduction of boys in year t			
	By bride price		By age group of girls in high bride price regions				Confucian value		Gender ratio	
	High	Low	0-1	1-4	4-9	9-14	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Connect	0.777**	-0.093	0.566***	0.088	0.113**	0.009	0.611***	0.157	0.537***	0.324*
	(0.312)	(0.174)	(0.239)	(0.063)	(0.055)	(0.017)	(0.197)	(0.147)	(0.168)	(0.173)
City FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Province × year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1,644	1,620	1,644	1,644	1,644	1,644	1,812	1,416	1,752	1,440
R-squared	0.619	0.569	0.595	0.366	0.367	0.298	0.576	0.532	0.572	0.532

Notes: The standard errors clustered at the city level are reported in parentheses. *Significant at 10%, ** Significant at 5%, *** Significant at 1%. Columns (1)–(2) examine the heterogeneity of girls based on bride price, while columns (3)–(6) explore this heterogeneity further by age in high bride price regions. Columns (7)–(8) investigate heterogeneity based on Confucian values, and columns (9)–(10) analyze heterogeneity in the gender ratio in 1998.

Table A.9: Likelihood of retrieving abducted children and potential police detection

	Proportion of success cases			# Reported abducted	
	(1)	(2)	(3)	(4)	(5)
Dist. to destination	-0.025***		-0.022***		-0.151***
	(0.006)		(0.007)		(0.037)
Diff provinces		-0.150***		-1.956***	
		(0.052)		(0.231)	
Dist. to destination × Connect			-0.005		0.211***
			(0.005)		(0.047)
Diff provinces × Connect		-0.057		0.399**	
		(0.043)		(0.178)	
City FE	✓	✓	✓	✓	✓
Province × year FE	✓	✓	✓	✓	✓
# Obs.	743	743	743	3,194	3,194
# Clusters	182	182	182	277	277

Notes: The standard errors clustered at the city-pair level are reported in parentheses. *Significant at 10%, ** Significant at 5%, *** Significant at 1%. We pair the hometown and destination places obtained from the success-matching cases in columns (1)–(3) and from child-reported data in columns (4) and (5).

Appendix B: Allocation of responsibilities and modes in child trafficking activities

Child trafficking is described as the "recruitment, transportation, transfer, harboring or receipt" of a child for exploitative purposes, as outlined in the United Nations Palermo Protocol. This definition has been widely accepted by the U.K. and many other nations globally.[25] However, the interpretation of child trafficking can differ between countries. In China, for example, it is often linked to illegal adoption, where parents may pay a price for the child. The relatively low cost of participating in this criminal market and widespread demand have made such offenses more prevalent.

The child trafficking market in China is dominated by numerous competing gangs rather than a single monopolistic syndicate, as there is no central organization controlling the trafficking network across the country. According to the Ministry of Public Security of the Communist Party of China, from 2009 to 2013, public security agencies dismantled over 11,000 child trafficking gangs and rescued more than 54,000 trafficked children.

Traffickers typically form small to medium-sized groups with a clear division of labor. The typical roles within these groups are as follows:

- Recruiters/Kidnappers: These individuals identify and contact potential victims in locations such as schools and playgrounds. If deception fails, they resort to coercion or outright abduction using threats or physical force. Once the child is taken, recruiters quickly hand them over to other gang members who facilitate their movement to another location.

- Transporters: After a child is trafficked, transporters are responsible for moving them from the site of abduction to the point of sale or intended destination.

- Sellers: Members designated as sellers oversee the transaction of trafficked children to potential buyers. They use various channels and methods to secure financial gains from these transactions.

[25] See source at https://www.ecpat.org.uk/faqs/what-is-child-trafficking.

- Organizers and Planners: Often at the core of the gang, these individuals orchestrate and strategize the entire trafficking operation. They design detailed plans and strategies to enhance efficiency, minimize risks, and ensure successful outcomes throughout the operation.

Trafficking gangs in China often operate across specific regions without remaining fixed in a single city. These groups are more active in certain areas, moving between locations to evade law enforcement and capitalize on regional demand. This mobility allows traffickers to exploit different areas based on varying demands for trafficked children, making it difficult for authorities to track and dismantle these networks effectively. The following two cases illustrate the mobile nature of human trafficking:

- Case 1: On June 12, 2024, the Intermediate People's Court of Nanchong City, Sichuan Province, delivered its verdict on the child abduction and trafficking case involving Wang Haowen and others. Wang Haowen, the principal culprit, was sentenced to death for multiple crimes. Evidence revealed that Wang began engaging in child abduction and trafficking in October 2001. In 2006, he was sentenced to a fixed-term prison sentence for child abduction. However, after his release, he continued his criminal activities until June 2014, committing 14 crimes across various locations over more than ten years. In total, 14 children were abducted and trafficked in these and previous crimes.

- Case 2: On November 28, 2023, the high-profile child abduction and trafficking case involving Yu Huaying underwent its second hearing at the Guizhou Provincial Higher People's Court. According to the prosecution, between 1993 and 1996, Yu Huaying and his accomplice, Gong Xianliang, traveled extensively across Guizhou Province, Chongqing City, and other locations. They rented houses and familiarized themselves with local environments to search for suitable children for trafficking. Through these methods, they committed eight crimes, abducting 11 children, including Hualan and Hua Bai, and transporting them to Handan City, Hebei Province. They then found buyers through an intermediary, trading the children for profit.

Appendix C: Alternative measurement

We also follow Donaldson & Hornbeck (2016) and use market access measures as an alternative explanatory variable for robustness checks. The market access of a city is not only decided by its connectivity to other cities but also by the market size of the cities to which it is connected. We adopt city-year level market access (MA) as our alternative regressor, which takes the following form:

$MA_{i,t} = \sum_{j}^{j\neq i} T_{ij,t}^{-\theta} * pop_{j,t}$

where j stands for the destination city, t represents the periods, and $pop_{j,t}$ is the population size in destination city j in year t. The highway network is translated into travel costs, measured by a power decay function. In this function, θ is the power decay parameter estimated based on Jing & Liao (2022) and determines how *MA* power decays with travel time along with the expressway network.[26] $T_{ij,t}$ approximates the travel time in minutes across the expressway network to targeted city j. To calculate the travel time in minutes, we assume the highway has a conventional speed of 100 km/h. The *MA* variable, thus, is intuitively interpreted as the travel cost weighted by the population at destination city j.

By considering transportation costs, market access, however, takes into account both enhanced connections between cities and the expanded demand in interconnected markets. Market access encompasses the concepts of accessibility and scale, reflecting both the degree of integration of a location and the population size of accessible markets. This approach provides a more nuanced measurement of how geographical location influences market interactions and trade patterns. We use three *MA* measures. The first takes into account the connectivity to all cities throughout China, the second considers only the connectivity to cities within the same province, and the last considers the connectivity to the port cities. The value can be zero if the city has not been connected by the highways.

Appendix Table C.1 presents the results. Columns (1) and (4) use the first *MA* measure, columns (2) and (5) employ the *MA* measure within a province, while columns (3) and (6) take into account the *MA* to the connected port cities. The results are consistent, indicating that a 1% increase in the *MA* is associated with an additional 0.03–0.07 cases, regardless of the measure used. Using *MA* measures offers a distinct advantage, as it incorporates both the quantity and size of cities that can be reached following the highway's

[26] The power-decay parameter is also known as trade elasticity developed from the gravity model of trade (Burger et al., 2009; Coşar & Demir, 2009).

construction. This approach provides a more nuanced and comprehensive assessment compared to a binary measure, allowing for a broader range of variations to be considered.

Table C.1: Market Access approach

	# incidents of child abduction in year t					
	DID			Hometown city-pair+DID		
	(1) overall	(2) within province	(3) port	(4) overall	(5) within province	(6) port
ln Market access	0.026***	0.028***	0.029***	0.066***	0.069***	0.070***
	(0.009)	(0.009)	(0.010)	(0.025)	(0.025)	(0.025)
City FE	✓	✓	✓	✓	✓	✓
Province × year FE	✓	✓	✓	✓	✓	✓
Hometown-pair FE				✓	✓	✓
# Obs.	2,710	2,710	2,710	5,310	5,310	5,310
# Clusters	271	271	271	255	255	255
Mean Dep. Var.	1.224	1.224	1.224	1.996	1.996	1.996

Notes: The sample in this table includes only targeted cities of the NTHS. We use a similar level of past accumulative child trafficking between 1960 and 1990 to construct the hometown pairs in columns (4)–(6). The standard errors clustered at the city level are reported in parentheses. *Significant at 10%, ** Significant at 5%, *** Significant at 1%.

Appendix D: More details on heterogeneous treatment effects

The traditional DID method uses earlier treated observations as the comparison group for later treated observations, assuming a stable treatment effect. However, if the treatment effect increases over time, the traditional DID method may incorporate part of the increasing effect as the year-fixed effect, leading to an underestimation of the treatment effect, and vice versa. The estimates from the two-way fixed effects DID model are variance-weighted average treatment effects on the treated sample, using several 2×2 DID methods. Each method compares treated and control groups in different configurations: earlier vs. later treated, later vs. earlier treated, treated vs. never-treated, and already vs. later treated.

When already-treated groups are used as comparison units, time-varying changes in their treatment effects are subtracted from the changes of later-treated units. While this cautions against summarizing time-varying effects with a single coefficient, it does not indicate a design failure. If the treatment effect for treated cities stabilized by 1998, it does not cause bias. To avoid econometric concerns about the existence of already-treated cities, we restricted their number by extending the data on the highways of each city for the years 1995–1997 from the List of Expressways in China. In 1995, only a limited number of cities were linked to the highway. Notably, all our findings, whether derived from two distinct equations or utilizing either the count measure or the number of flows over the population, remain consistent and robust. This consistency is maintained even when we omit the cities that were already connected in the previously treated groups, as indicated by the results in Appendix Table D.1.[27]

We then use this extended panel data to explore the Goodman-Bacon (2021) DID decomposition to illustrate the source of variation and examine potential heterogeneity in the treatment effect.[28] Appendix Fig. D.1 plots each 2×2 DID against its weight and the average effect for the abovementioned comparisons. Around 37% of the variation is found to be from different treatment timing, and the rest from comparisons to cities whose connection dummy is unchanged during the sample period. When already-treated and never-treated units serve as controls, the effects are both highly positive (2.201 and 0.475), in addition to

[27] We do not use the data before 1998 in the benchmark analysis because we do not have the geo-referenced maps of highways for years before that. However, using the extended panel data does not alter the conclusions of this paper.

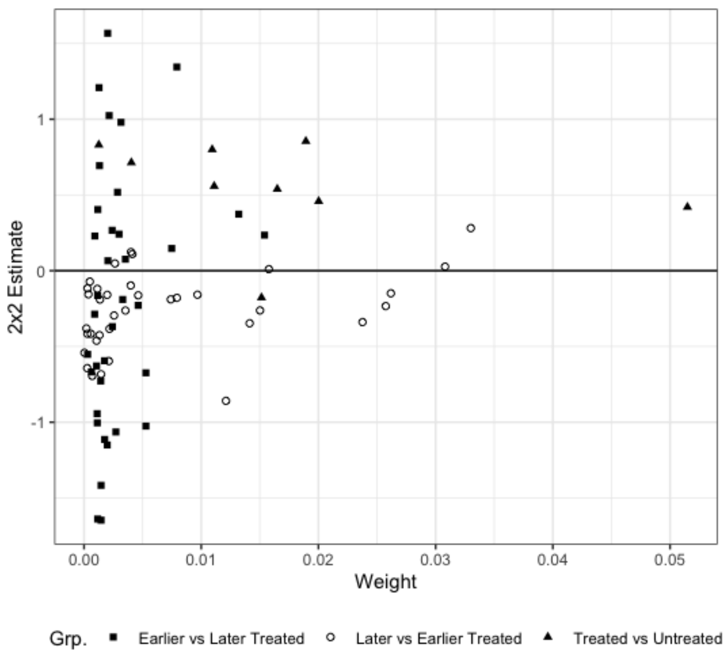
[28] Please note that the Goodman-Bacon (2021) method is actually a diagnosis method and can only tell the severity of problems in the DID setting that we used, and thus it cannot apply to the main estimate.

the comparison of earlier- to later-connected cities (0.057). Moreover, the comparison of later- to earlier-connected cities—the group that may bias our estimate, is negative (-0.158), on average. Thus, using the decomposition theorem to subtract the late-to-early components that lead to potential bias from the weighted average may be appropriate and lead to an even larger positive coefficient.

Table D.1: Excluding the cities in the already-treated groups

	# incidents of child abduction in year t					
	DID using hometown cities			City-to-city analysis		
Sample	All cities	targeted cities		All cities	targeted cities	
Form of outcome		count	population		count	population
	(1)	(2)	(3)	(4)	(5)	(6)
Connect	0.819***	0.466***	0.210**	0.0034***	0.0043***	0.0010**
	(0.240)	(0.157)	(0.081)	(0.0012)	(0.0014)	(0.0004)
City FE	✓	✓	✓			
Hometown pair	✓	✓	✓			
Province × year FE	✓	✓	✓			
Hometown-destination pair FE				✓	✓	✓
Hometown city × year FE				✓	✓	✓
Destination city × year FE				✓	✓	✓
# Obs.	4,543	4,158	3,957	850,630	762,542	723,516
# Clusters	266	253	253	77330	69322	69322
Mean Dep. Var.	1.709	1.747	0.449	0.0016	0.0017	0.0004

Notes: The standard errors clustered at the city level are reported in parentheses. *Significant at 10%, ** Significant at 5%, *** Significant at 1%. In columns (1)–(3), we apply the DID estimators to within-province hometown pairs that share a similar level of past accumulative child trafficking between 1960 and 1990.



Group	Avg. est.	Weight
Earlier vs Later Treated	0.057	0.110
Later vs Always Treated	2.202	0.479
Later vs Earlier Treated	-0.158	0.262
Treated vs Untreated	0.475	0.150

Fig. D.1: DID decomposition for highway connection and child abduction

Notes: The estimate of two-way fixed effects equals the average estimated values multiplying the variance weights, as indicated in the table. The figure displays the 2x2 DID components from Goodman-Bacon (2021)'s decomposition theorem against their weight. The open circles are later treatment vs. earlier control terms. The closed squares are earlier treatment vs. later control terms. The closed triangles are the treated vs. untreated terms.

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