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Educational Responses to Local and Migration Destination Shocks: Evidence from China

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Abstract

Over the last 20 years, China has experienced substantial positive shocks to export-oriented industries—especially following its accession to the World Trade Organization—and these shocks have had major implications for human capital investment. One primary channel through which export expansion can shape choices about human capital accumulation is positive labor-demand shocks, and these shocks can be observed both at potential within-country migration destinations and in the locality of birth. Exploiting cross-county variation in the reduction in export tariff uncertainty post-WTO, both locally and at plausible migration destinations, this analysis finds that youth in China reaching matriculation age post-accession in counties experiencing a larger export shock (either locally or at those destinations) show a lower probability of enrolling in high school. This pattern is observed in a sample including both youth who ultimately migrate and youth who do not migrate. For urban youth, the effects of local shocks are larger than the effects of destination shocks, but the opposite pattern is observed for rural youth.

JEL classification: F14, F16, J24, O15, O18, O19

Keywords: export shock, human capital attainment, China

1. Introduction

In recent decades, the rising tide of globalization has had substantial effects on developing country economies (Goldberg and Pavcnik 2007). Among the most important of these effects has been the contraction of agriculture and the associated shift of productive factors into non-agricultural production, a shift that frequently entails within-country migration to export-oriented urban areas. In addition to a substantial theoretical literature predicting a reallocation of workers from less income-elastic sectors such as agricultural production into more income-elastic sectors (e.g., manufacturing) in response to increased access to export markets (Matsuyama 2009; Herrendorf, Rogerson, and Valentinyi 2014; Matsuyama 2018), this prediction has been substantiated empirically in the context of China and Vietnam (Erten and Leight 2021; McCaig and Pavcnik 2013). There is also evidence of meaningful in-migration into urban areas experiencing positive export-driven shocks in China (Facchini et al. 2019).

Major sectoral shifts in the labor market stimulated by export shocks presumably have substantial implications for human capital investment, and the effects of trade liberalization on education have been

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previously explored in papers focused on Mexico, India, and China (Atkin 2016; Edmonds, Topalova, and Pavcnik 2009; Edmonds, Pavcnik, and Topalova 2010; Li 2018; Lin and Long 2020). However, this literature has generally focused on the effects of local shocks (within a metropolitan-area labor market), and has not systematically analyzed the effects of export shocks at plausible within-country migration destinations.[1] Given that the existing literature suggests that out-migration from rural areas is an important dimension of structural transformation, ignoring the relationship between youth educational decisions and destination shocks may meaningfully underestimate the role of export-oriented shocks in shaping human capital accumulation.

The objective of this paper is to analyze the effects of positive shocks to export-oriented production on educational attainment among Chinese youth, analyzing shocks to both the local economy and the economies of potential domestic migration destinations as predicted by past migration patterns. More specifically, the paper exploits a discontinuity generated by China's WTO accession and the associated reduction in tariff uncertainty in the US market. Prior to WTO accession, China's most favored nation (MFN) status in the United States required annual renewal by Congress, and thus entailed some non-trivial risk; a failure to renew would have implied that Chinese exports were subject to the much higher tariff rates reserved for non-market economies. As of January 1, 2002, this uncertainty was reduced to zero as China became a WTO member, a positive shock that disproportionately benefited industries exposed to high uncertainty ex ante, and regions characterized by a high level of concentration in these industries. The magnitude of pre-accession uncertainty is captured by a measure denoted the normal trade relations (NTR) gap, equal to the average difference between the lower tariffs provided to countries benefiting from NTR status, and the higher tariff imposed on non-NTR nations.

The identification strategy then entails a difference-in-difference, comparing youth who reached the age of 16—the age of matriculation into high school in China—before and after WTO accession, in counties differentially exposed to the reduction in tariff uncertainty. Here, the key variable of interest captures exposure using both the local shock and the shock observed in potential migration destination counties, the latter proxied by counties where local residents have previously migrated. Intuitively, counties that were more exposed to a reduction in tariff uncertainty experienced a larger increase in export-driven manufacturing and associated labor demand post-2002 (Erten and Leight 2021). Our measures capture this increase in labor demand in both the local and the migration destination markets.

This positive shock to labor demand in export-oriented industries may have several effects: Household income may increase if parents access new employment in export-driven industries; higher demand for manufacturing labor, either locally or at migration destinations, may offer adolescents a more attractive outside option vis-a-vis education; and the long-run returns to education may also change, plausibly increasing if export expansion is associated with an increase in the returns to skill (Goldberg and Pavcnik 2007). Utilizing micro-level data on educational attainment reported in the China Household Income Project Surveys in 2007, this analysis identifies the effects of this export-driven shock on enrollment in high school for a sample of youth in both urban and rural China and presents evidence about the relevant channels. Importantly, this is the first paper to analyze the effects of this shock on a full sample of youth including permanent out-migrants, a sample structure that is crucial to accurately estimate the effects of migration destination shocks.

The primary results suggest that youth reaching the point of high-school matriculation post-2002 in counties exposed to higher NTR gaps either locally or at migration destinations show a significant decline in the probability of matriculation: The effect size suggests a one standard deviation increase in the NTR gap in either setting is associated with a decline in this probability of between 2 and 6 percentage

1 A separate literature on "brain drain"—described in considerably greater detail below—has probed the effect of shocks at international migration destinations, but international migration is relatively rare compared to within-country migration.

points. This decline is observed even in specifications controlling for a range of individual covariates, as well as province-year fixed effects, and accordingly does not reflect differential patterns in high-school enrollment comparing across highly industrialized and less industrialized provinces. The analysis also presents evidence that high- and low-NTR-gap counties were previously characterized by largely similar trends in high-school enrollment, with the divergent pattern driven by differential labor demand emerging only post-2002, and demonstrates that our main results are robust to a range of assumptions around violations of the parallel trends assumption (Rambachan and Roth 2023). The evidence of a decrease in high-school enrollment in areas characterized by larger positive shocks to export-driven production is not consistent with a hypothesized positive income effect, assuming that education is a normal good, but rather suggests that the short-term opportunity costs of education in a context of increased labor demand are driving youths' enrollment decisions.

This paper builds on the literature analyzing the effects of trade shocks on human capital accumulation, and expands it by simultaneously analyzing the effects of both local and migration destination shocks. More specifically, this paper contributes to several related strands of work. First, we add to the growing evidence base around the relationship between trade shocks and human capital accumulation. In this literature, Blanchard and Olney (2017) demonstrate using cross-country data that the effect of export growth on education varies based on the skill-intensiveness of the growing sector.[2] Atkin (2016) finds that the growth of export-driven manufacturing in Mexico is associated with a reduction in high-school employment in areas characterized by a more rapid pace of factory openings, a pattern consistent with our findings. In Bangladesh, by contrast, the growth of export-driven garment manufacturing is associated with increased educational attainment for girls (Heath and Mobarak 2015). In India, Edmonds, Topalova, and Pavcnik (2009) and Edmonds, Pavcnik, and Topalova (2010) analyze the inverse case of trade reform—the reduction of protective import tariffs–and find that increased import competition is associated with a decline in school attendance, while Shastry (2012) finds that globalization is associated with a greater growth in school enrollment in districts with a lower cost of learning English. In general, however, these papers do not analyze shocks at potential migration destinations, and often exclude migrants entirely, despite the fact that internal migration rates are as high or higher in these contexts vis-a-vis China (Bell et al. 2015).[3]

In China, previous papers present evidence that reductions in external tariffs (Li 2018; Li et al. 2019) or tariff uncertainty (Liu 2023), increases in exposure to globalization broadly defined (Lin and Long 2020), and the removal of export quotas linked to the Multifiber Agreement (Zhang and Zhou 2023) are associated with differential effects on local educational attainment driven by the skill requirements of local industry. Our empirical strategy builds on this literature, but also entails two important innovations: We use micro-level data that enable us to track all youth from a given household, including out-migrants, and we separately identify the effect of trade liberalization shocks both locally and at migration destinations.

Second, our paper adds to a growing literature that analyzes the response of potential migrants' human capital accumulation to economic shocks at international (high-income-country) migration destinations, often described as "brain drain" versus "brain gain." Despite policy debates around the potential for brain drain when highly skilled workers migrate out of low-income countries (Docquier and Marfouk 2006), foundational work using cross-country data has established that the prospect of skilled migration to a higher-income country can lead to positive effects on human capital accumulation in migration source (lower-income) countries (Beine, Docquier, and Rapoport 2001, 2008; Stark, Helmenstein, and Prskawetz 1997; Mountford 1997), and this prediction has been substantiated empirically in a range of contexts.

2 In the United States, an increase in import competition with China leads to an increase in local educational attainment (Greenland and Lopresti 2016), though this effect is slowest to manifest for poorer households (Ferriere, Navarro, and Reyes-Heroles 2018).

3 One recent paper analyzes the effects of shifts in the level of tariffs at migration destinations on educational choices, but uses only aggregate regional data (Cai, Shi, and Xu 2021).

In Nepal, an increase in the returns to education in one potential migration destination (the United Kingdom, or more specifically its armed forces) increased educational attainment (Shrestha 2016), and there is also evidence of increased occupation-specific college enrollment in India in response to positive shocks to the US informational technology sector (Khanna and Morales 2017). In the Philippines, a shift in US visa policy that expanded migration opportunities for Filipino nurses significantly increased nursing enrollment and graduation (Abarcar and Theoharides 2023). In Cape Verde and the Philippines, improved economic conditions (increased labor demand) at migration destinations more broadly increased secondary school enrollment (Batista, Lacuesta, and Vicente 2012; Theoharides 2018; Khanna et al. 2022). Enhanced access to mining employment in South Africa also generated a significant increase in education in the next generation in Malawi (Dinkelman and Mariotti 2016). Finally, in Fiji, a significant increase in skilled out-migration in response to feared discrimination against Indian-origin citizens significantly boosted skill development at home (Chand and Clemens 2023).

However, analysis of the effects of shocks at within-country migration destinations on human capital accumulation in source regions is limited, despite the fact that this is a much more common form of migration. Two previous contributions analyze migration in India: Kochar (2004) demonstrates that rural human capital accumulation responds to regional variation in the urban returns to education, particularly for those with a higher propensity to migrate. Ghose et al. (2021) document that engineering enrollment rises in response to increased exports of informational technology, and this effect is larger when nearby districts (potential sources for migrants) have a larger college-aged population. Given substantial within-country migration rates across much of the developing world (Bell et al. 2015), the effects of economic shocks at potential domestic migration destinations remains an important channel for understanding human capital decision-making.

Finally, our paper connects to the literature on the relationship between the expansion of non-agricultural production in developing countries (separate from any globalization-related shock) and human capital attainment. Evidence from Indonesia suggests manufacturing employment growth in the region modestly increases enrollment for both male and female youth (Federman and Levine 2005). In India, the expansion of call centers (corresponding to more advanced positions in services, rather than manufacturing) is associated with increased enrollment of children in primary school (Oster and Steinberg 2013), and experimental evidence suggests that dissemination of information about outsourcing opportunities similarly leads to increased educational attainment for young women (Jensen 2012). A broader analysis of industrialization in Mexico finds evidence of small positive effects of industrialization on education, larger for domestic-oriented manufacturing vis-a-vis export-oriented manufacturing (Brun, Helper, and Levine 2011).

2. Background and Conceptual Framework

2.1. China's Export Expansion

China's accession to the WTO in 2001 entailed both new trade access benefits for the Chinese economy and a commitment to liberalizing domestic reforms. However, both the benefits and the reforms were largely phased in gradually, and did not result in any discontinuous jumps in 2001: In particular, both China's domestic tariffs and the tariffs imposed by external partners declined incrementally, and primarily in the 1990s.[4]

First, Chinese import tariffs had already been sharply cut prior to 2001 (from a weighted average of over 45 percent in 1992 to approximately 13 percent). WTO accession entailed further cuts, but these

4 Other gradual trade reforms implemented during this period included the loosening of restrictions on direct exporting, eliminated by 2004 (Bai, Krishna, and Ma 2017), and the reduction of requirements for foreign direct investment (Long 2005). This description of the evolution of trade policy in this period draws heavily on Erten and Leight (2021).

shifts were small in magnitude (Bhattasali, Li, and Martin 2004). Similarly, the level of tariffs imposed by the United States and other major trading partners (the European Union, Japan, Korea, and Taiwan) were largely stable in this period. Figure S3.1 in the supplementary online appendix shows the evolution of the average weighted domestic tariff rate and the average weighted NTR rate imposed in the US market. These rates are calculated using industry-level tariffs and the share of each industry in total Chinese imports (for import tariffs) or total Chinese exports (for US tariffs) as reported in 1996. There is no evidence of any dramatic shifts in tariff rates at the point of China's WTO accession.[5]

However, China did experience one discontinuous shock in 2002: a reduction in tariff uncertainty in the US market. Previously, China accessed NTR tariff rates in the United States subject to annual congressional renewals. In the absence of these renewals, Chinese products would have faced much higher tariffs, originally set by the Smoot–Hawley Act in 1930, and designated for non-market economies. This regular approval process generated considerable uncertainty, despite the fact that the tariff imposed on imports did remain low. Using media and government reports, Pierce and Schott (2016) document that firms did not perceive the annual renewal of MFN status as guaranteed, particularly in periods of political tension in the early 1990s. The US Congress passed legislation in October 2000 that granted permanent NTR status to China, effective as of January 1, 2002.

This paper preferentially focuses on analysis of the discontinuous shock induced by the reduction in tariff uncertainty for both conceptual and empirical reasons. Previous evidence suggests the effect of this shock was large in both the United States and China, and larger than the effect of other trade policy fluctuations in this period (Pierce and Schott 2016; Handley and Limão 2017; Erten and Leight 2021). This large effect can also be verified in the subsample of counties examined here: Figure S3.2 in the supplementary online appendix shows the correlation between the estimated long-difference (2001–2011) for county-level exports and county-level GDP, both vis-a-vis the county-level NTR gap. It is evident that this correlation is significant and positive, suggesting that counties characterized by higher NTR gaps show more rapid export-driven growth in the post-WTO period. (By contrast, the corresponding correlation in the pre-WTO period, shown in fig. S3.3, is weakly negative and statistically insignificant, suggesting that the correlation subsequently observed does in fact reflect shocks linked to WTO accession.)

In addition, the data utilized (as described in more detail below) are a cross-sectional survey that allows us to analyze high-school matriculation as observed in a range of cohorts who reach the age of matriculation before and after 2002, exploiting the discontinuous shift in tariff uncertainty and thus labor demand observed at this point. In the absence of a full-scale panel, the analysis generally does not focus on controlling for annual variation in trade policy (e.g., tariff fluctuations), though the results are robust to controlling for variables capturing these additional policy fluctuations.

2.2. Conceptual Framework

Improving access to post-compulsory education has been an important policy goal across the developing world in the last two decades. Compulsory education in China consists of six years of primary and three years of junior secondary (middle-school) education, followed by three years of non-compulsory high school; the transition to high school is via an annual entrance exam. Although China has effectively achieved universal nine-year basic education, the transition rate to high school was modest at 52.9 percent in 2001, the final year prior to the shock of interest in this analysis.[6] The limited attractiveness of post-compulsory education has been attributed to both the substantial tuition fees[7] and the steady enhancement in employment prospects for less educated migrant workers (de Brauw and Giles 2017). Given

5 A similar pattern is evident if this analysis is reproduced for the tariffs imposed in the other four major export markets; graphical evidence is provided in Erten and Leight (2021).

6 Source: China Statistical Yearbook, 2002.

7 According to the China Education Expenditure Yearbooks, tuition fees for high school are 6 to 11 times that of middle school, depending on the high-school type (i.e., academic or vocational).

that meeting the increasing demand for skilled labor is crucial in this period of industrial upgrading in the Chinese economy, it is important to understand the role of factors including trade policy shocks in influencing students' education decisions.

The reduction of tariff uncertainty and the associated export expansion directly affect the post-compulsory schooling decisions of Chinese youth through two major direct channels. The expansion of export-oriented production may alter the skill premium that youth face in the labor market (denoted as direct channel one), and the direction of this effect is unclear. Classic models of trade liberalization such as Stolper–Samuelson generally predict that trade liberalization will raise the relative returns to the more abundant factor (here, unskilled labor). However, the specific sectoral pattern associated with the reduction in the NTR gap—disproportionately high in manufacturing sectors, particularly light manufacturing, relative to primary and extractive sectors such as agriculture and mining—suggests that the benefits of the reduction in trade uncertainty may be higher in sectors requiring more skilled labor and thus may disproportionately accrue to more skilled workers. The correlation between the county-level NTR gap and the level of education in the county workforce (proxied by the percentage of workers who report a high-school education) is in fact highly positive, again suggesting that the benefits of the reduction in tariff uncertainty may be particularly high for highly educated workers.

Though the empirical evidence around the effects of WTO accession on the returns to skill is limited and primarily associational (as summarized in supplementary online appendix S2), it does suggest that the returns to skill in the labor market may be relatively higher in high-NTR-gap counties post-WTO accession. If this is the case, then the direction of this first channel may be positive: Middle-school graduates in counties characterized by a high NTR gap may be more likely to pursue high-school education post-WTO accession given the increased returns to education. However, given considerable uncertainty about the underlying empirical pattern in terms of returns to skill, it is also possible that the broader liberalization effect dominates and the skill premium declines.

Separate from any shift in the longer-term returns to education, the availability of low-skilled positions also immediately raises the short-term opportunity costs of staying in school, incentivizing youth to work directly upon middle-school graduation and forgo secondary school (denoted direct channel two). The sign of the net direct effect on high-school enrollment is thus empirically ambiguous.

In addition to changes in returns and costs of schooling, the reduction in tariff uncertainty may also indirectly affect education through its impact on parental work. First, the increase in labor demand in the labor market either locally or at plausible migration destinations may raise parental wage income. If high-school education is a normal good, the demand for education would be expected to rise (indirect channel one). In addition, a higher level of parental income may render tuition fees more affordable for credit-constrained families, leading to a higher enrollment rate.

Second, an increase in the wage generated by higher labor demand may encourage parents to work for longer hours or induce non-working parents to enter the labor market, reducing the time available for them to invest in their children's educational performance. This shift could also lead to increased demands for youth to care for younger siblings or engage in other household responsibilities; this channel may be particularly salient for girls (Morduch 2000; Dammert 2010; Qureshi 2018). Both effects would reduce high-school enrollment (indirect channel two).

Our empirical analysis will provide evidence around a number of these channels. We focus on first identifying the net effect of the reduction of tariff uncertainty on high-school enrollment. We will provide additional evidence around the effects of local variation in the returns to skill (based on local sectoral composition) to assess direct channel one. To assess the two indirect channels, we will analyze heterogeneity with respect to parental education (correlated with the shift in household income and the associated income effect for education) and with respect to household structure (child gender and sibling composition), allowing us to at least partially assess the plausibility of effects operating through youth time allocation.

3. Data and Descriptives

3.1. Individual-Level Data

The primary data set employed in this study is the 2007 Chinese Household Income Project (CHIP). CHIP households constitute a random sample from the annual household income and expenditure surveys conducted by the National Bureau of Statistics in China (Kong 2010), including 8,000 rural and 5,000 urban households residing in 179 counties in 10 provinces in the eastern, central, and western regions of China.[8] The CHIP survey collected detailed information about demographic characteristics, labor-market performance, and self-reported welfare of individuals and their families.

One unique feature of the CHIP survey is that it collected basic demographic information for all biological and adopted children of heads of sample households and their spouses. The sample of children thus includes not only child household members, but also children who have migrated for education and work purposes, as well as those adult children who have departed the natal household to form their own family. This universal coverage ensures that our empirical analysis is not prone to sample selection biases resulting from migration, family splits, or new household formation.

By contrast, this data structure is not found in other data sets such as the China population census, in which migrated youth cannot be linked to their birth households, rendering it challenging to analyze the effects of both local and migration shocks on human capital. More specifically, youth who have left their hukou households for more than six months (temporary migrants) and those who have changed their hukou residence (permanent migrants) cannot be linked to their birth households in the census. Though the census clearly offers a larger sample, the analysis preferentially uses the CHIP data given the objective of exploring the role of migration in shaping youth educational choices. More details about data sources are provided in supplementary online appendix S1.

The empirical analysis focuses on children born between 1980 and 1991 of the sample households. Cohorts born before 1980 reached the standard age of entry of primary school (6) prior to the passage of China's compulsory schooling law in 1986, and thus may have been less likely to initiate schooling on time, rendering it challenging to estimate the age at which they would make decisions around matriculation to high school. At the same time, cohorts born after 1991 are aged 15 or younger at the point of the survey, and thus may still be in middle school. Any children in the target cohorts that are still in middle school at the point of the survey are dropped from the analysis. We will subsequently demonstrate that our results are robust to alternate birth-year cutoffs.

According to descriptive statistics reported in table 1, the high-school enrollment rate of the resulting sample is 54 percent. The rate is, however, dramatically higher in urban (87 percent) vis-a-vis rural (42 percent) areas. In analyzing urban and rural dynamics, the definition of rural employed is based on the reported hukou (household registration) of the youth's household head at the age of 14, corresponding to the window in which matriculation decisions are made.[9] Importantly, this variable abstracts from any shift in hukou of the youth that may be induced by an educational choice (i.e., the pursuit of occupational high school or tertiary education allows rural individuals to convert to an urban hukou following enrollment). In the sample, 75 percent of youth are from rural families.

3.2. Measurement of Trade Shocks

The primary analysis focuses on the effects of the reduction in NTR uncertainty experienced by China in the US market following its accession to the World Trade Organization. The NTR gap is first defined at the subsector level for each of the 39 subsectors of tradable production reported in Chinese census data,

8 These provinces are Hebei, Shanghai, Jiangsu, Zhejiang, Guangdong, Anhui, Henan, Hubei, Chongqing, and Sichuan.

9 The hukou system categorizes people as assigned to rural or urban residence at birth, according to their parents' status. Households report their hukou status as well as the date of any changes in hukou, allowing us to identify households' status in any given year.

Table 1. Summary Statistics

Variable	Sample		
	mean	Standard dev.	N
Panel A: Human capital measures			
High-school enrollment rate	0.540	(0.498)	9,019
High-school enrollment rate (rural)	0.422	0.494	6,626
High-school enrollment rate (urban)	0.871	0.334	2,216
Panel B: Individual and household characteristics			
Gender (male=1)	0.524	(0.499)	9,473
Ethnic minority	0.012	(0.111)	9,437
Having siblings	0.725	(0.446)	9,473
Birth order	0.161	(0.872)	9,473
Father years of schooling	8.11	(2.88)	9,150
Mother years of schooling	6.51	(3.51)	9,196
Household head with rural household registration (hukou)	0.750	(0.434)	9,463

Source: Authors' calculations from China Household Income Project (CHIP) data.
Note: This table presents summary statistics for the sample.

and calculated as the linear difference between the higher tariff rate that would have applied in the case of revocation of China's NTR status and the lower NTR rate, $\text{NTR\_Gap}_i = \text{Non\_NTR\_Rate}_i - \text{NTR\_Rate}_i$. The NTR gap is weakly positive for all industries. Throughout the empirical analysis, we use the NTR gaps for 1999.[10] The highest NTR gaps are observed for textiles, garments, other manufacturing, medical and pharmaceutical products, and furniture manufacturing, while the lowest NTR gaps are observed for mining products and agricultural output.

The county-level NTR-gap measure is then constructed as the weighted average of subsector gaps, using weights constructed from the baseline composition of tradable employment reported in the 1990 census. The census data allow us to calculate the share of tradable employment by industry in each county c in province p, interacting the NTR gap for subsector i with the subsector's county-specific employment share:

$$\text{NTR\_Gap}_{cp}^{\text{Local}} = \sum_i \text{empshare}_{icp}^{1990} \times \text{NTR\_Gap}_i.$$

In the sample of interest for this analysis, the average NTR gap is 0.199 with a standard deviation of 0.102. Figure S3.4 in the supplementary online appendix shows a histogram of the NTR gap at the county level in the CHIP sample, comprising 179 counties.

The above variable NTR_Gap_{cp} will be employed as a measure of the purely local shock to export production. However, the analysis also uses a second shock designed to capture shocks to the labor market at plausible migration destinations that is constructed as follows. Data on migration from the 2000 census are used to estimate the share of prime age adults in a given county (individuals aged 16–59) who report migrating to (and thus currently residing in) each possible destination county d ($\text{MigDest}_{cp,d}$), relative to the total population of out-migrants from this origin county.[11] We then estimate the weighted average

10 The industry-level NTR-gap data are drawn from Pierce and Schott (2016), who constructed this data using ad valorem equivalent rates. The NTR gap for industry i is the average NTR gap across the four-digit ISIC Revision 3 tariff lines belonging to that industry. The NTR gaps in 1999 are almost identical to those in 2000 or 2001; accordingly, the results are robust to the use of data from other years. The ISIC industry categories were matched to the employment categories reported in Chinese data, and details of this matching are provided in Erten and Leight (2021).

11 In the 2000 census, individuals are identified as migrants if they report residing in the county of residence for more than six months while reporting an official household registration or hukou in a different county; or, residing in a county for

of the NTR gap at all destination counties; there are 2,873 counties represented in the 2000 census, and thus each origin county has 2,872 possible migration destinations:

$$\mathrm{NTR\_Gap}_{cp}^{\mathrm{MigDest}} = \sum_{d=1}^{2872} \mathrm{MigDest}_{cp,d} \times \mathrm{NTR\_Gap}_{d}.$$

Given that migration patterns in rural China are heavily dependent on local networks, a pattern parallel to that observed elsewhere in the developing world (Chen, Jin, and Yue 2011; Mu and de Brauw 2015; Munshi 2003), past migration destinations reported as of 2000 are an informative proxy for plausible migration destinations for youth who are making matriculation and migration decisions in this period. More specifically, if we examine the persistence of migration destinations at the county level over a decade, we find that more than 80 percent of counties report at least one major migration destination that is consistent across this period, and more than 50 percent of counties report at least two consistent destinations.[12] The same census round in 2000 can also be used to roughly quantify the overall salience of migration: The average county in the CHIP data reports 7 percent of its prime-age population having out-migrated, though this probability roughly doubles for the youngest cohorts that are of interest here (14 percent for individuals aged 16–29).

To clarify the overall choice of timing for information linked to the construction of the trade shocks, we preferentially use information drawn from the 1990 census (sectoral weights as well as information about the skill concentration in employment) to minimize endogeneity linked to the rapid advance in global integration observed in the Chinese economy during the 1990s (i.e., prior to WTO accession). Insofar as local economies have already changed rapidly between the 1990 census and the subsequent shock, this may mean that our constructed shock measures are relatively weaker proxies for the realized shock in a particular county post-2002, in which case the results may be biased toward zero; however, we argue that the exclusion restriction (namely, that the initial sectoral and educational composition is uncorrelated with subsequent shifts in outcomes post-2002) is more plausible in using this earlier wave of data.

Importantly, implementing this strategy is not possible in the case of migration weights. Internal migration was relatively low in China prior to 1990, and was not reported in that census wave. The earliest large-scale data source in which migration sources and destinations can be identified is the 2000 census. Accordingly, the analysis uses later data for this variable only; potential endogeneity introduced by this choice is discussed further below , where we also present a robustness check estimated by identifying plausible migration destinations based on geographic proximity, as opposed to past migration destinations.

In additional robustness checks, the specification also includes controls for other trade shocks experienced during this period, including fluctuations in the effective applied tariff rate in the US market (the NTR rate), the domestic tariff rate, and the quotas imposed by the Multifiber Agreement governing the textile industry. For each of these shocks, we construct a county-by-year-level weighted average from the industry-level source data using employment weights from the 1990 census.[13] Data on

less than six months while reporting a hukou in a different county, and reporting living outside of the hukou county for more than six months. The county of residence is thus identified as the migration destination, while the county of hukou is identified as the origin county.

12 Migration destinations are reported in both the 2000 and 2010 census waves. We identify major migration destinations as those counties that are reported as one of the top five destinations for out-migrants (as measured by the number of reported out-migrants) from a given source county in each census round. We can then tabulate how many such destinations as identified in the 2000 census recur as major destinations for the same source county in 2010.

13 Since the industry categories for the export licensing and contract intensity variables are available for SIC categories, these categories are manually matched to the census employment categories. The industry classification for the import tariff data is available in ISIC Revision 3, the same source utilized to construct the NTR-gap variable. Again, details regarding the associated matching are provided in Erten and Leight (2021).

Multifiber Agreement (MFA) quotas are drawn from Khandelwal, Schott, and Wei (2013), and we utilize the same methodology to construct a measure of the degree to which industries' quotas were binding under the MFA by calculating the import-weighted average fill rate. Using data on the universe of county-level shocks, we again construct a migration-augmented shock for each of these variables.

The empirical strategy entails linking the trade data with the individual-level data by the county of parental residence. Compared with youths' current residence, county of parental residence is a better proxy for the location where the youth attended middle school.[14]

4. Empirical Analysis

4.1. Baseline Specification

The primary objective of the empirical analysis is to identify the effect of the reduction in tariff uncertainty driven by WTO accession on the probability of matriculating into high school, for both youth observed to be still living in the county of origin and for youth who have since out-migrated from their county of origin. The dependent variable is a binary variable for high-school matriculation for child i born in household h in county c in province p in year t, Enroll_{ihcpt}. The primary independent variable is an interaction of individual-level treatment intensity defined based on the birth year, $Treat_t$, and the own (birth) county and migration destination gaps.

Treatment intensity measures the proportion of individuals who make decisions about matriculation into high school in 2002 and subsequent years (i.e., following the WTO shock) for each birth cohort. The variation in the age at the decision to attend high school is substantial in China. As shown in fig. S3.5 in the supplementary online appendix, the majority of students graduate from middle school and make decisions about matriculation into high school between the ages of 14 and 16.[15] Therefore, Treat_t is a continuous measure of treatment intensity defined as follows. Youth born in 1985 and prior years (who reach the age of 16 in 2001 and earlier) are defined as $\text{Treat}_t = 0$, or unexposed to the trade shock, as they make decisions about matriculation prior to WTO accession. Youth born in 1988 and subsequent years (who reach the age of 14 in 2002 and subsequent years) are defined as $\text{Treat}_t = 1$, or fully exposed to the trade shock. Youth born in 1986 and 1987 are assigned a continuous variable capturing partial treatment exposure, defined to capture the proportion of a particular birth-year cohort who makes decisions about high-school enrollment prior to the date of the shock; this definition follows Pan (2017).[16] Additional findings presented in the robustness checks will demonstrate that the primary results are robust to the use of alternate binary treatment variables employing different assumptions about treatment of the intermediate cohorts.

As noted above, the NTR gap is time invariant and captures the level of tariff uncertainty faced ex ante in the county of origin and counties identified as plausible migration destinations (regardless of the individual's current county of residence), prior to WTO accession. The primary specification can thus be written

$$\begin{aligned}\text{Enroll}_{ihcpt} = {} & \beta_1 \text{Treat}_t \times \text{NTR\_Gap}_{cp} + \beta_2 \text{Treat}_t \times \text{NTR\_Gap}_{cp}^{\text{MigDest}} \\ & + \kappa_{cp} + \gamma_{pt} + \chi_{ihcpt} + \epsilon_{ihcpt}. \end{aligned} \tag{1}$$

The relationship of interest is estimated conditional on county fixed effects κ_{cp}, province-year fixed effects γ_{pt}, and individual-level controls χ_{ihcpt} (gender, birth order, a binary variable for minority status, a binary

14 We exclude children from households in which the heads themselves are temporary migrants who do not report a hukou (56 children or 0.6 percent of the main sample), because the location in which these children attended middle school cannot be identified.

15 This figure draws on data from the China Health and Nutrition Survey, as the CHIP survey employed in this analysis does not provide detailed data about the age of decision-making around high-school matriculation.

16 Based on the numbers in fig. S3.5, $\text{Treat}_{1986} = 0.3646$ and $\text{Treat}_{1987} = 0.7201$.

variable for any siblings, and continuous variables capturing the years of schooling attained by each parent).[17] Standard errors are clustered at the county level, yielding 179 clusters.

The primary results of estimating equation (1) are presented in panel A in table 2. Column (1) reports our preferred, primary specification. In columns (2) and (3), we report two additional specifications including differential trends for manufacturing-intensive counties (in column 2) and both manufacturing-intensive and agricultural-intensive counties (in column 3). Manufacturing- and agriculture-intensive counties are identified as counties characterized by an above-median (local) concentration of employment in the secondary and primary sectors, respectively, in the 1990 census.[18] Column (4) includes control variables for additional trade policy shocks as described above; and column (5) includes more flexible controls for baseline variation in the primary employment share (deciles of primary employment share interacted with cohort fixed effects).

It is clear that the coefficients of interest β_1 and β_2 are consistently negative: Youth who reach the age of matriculation into high school post-2002 in counties exposed to larger NTR gaps ex ante either locally or at plausible migration destinations are significantly less likely to enroll in high school. This effect is estimated for the pooled sample of youth still resident in their origin county as well as those who have migrated, and the magnitudes of the coefficients are fairly stable and larger for the own-county vis-a-vis the migration destination shock. The magnitude conservatively suggests that a one standard deviation increase in the own-county NTR gap (an increase of 0.102) is associated with a decline in the probability of enrollment of 4.1 percentage points, relative to a probability of enrollment for pre-shock cohorts of 49.3 percent. A one standard deviation increase in the migration destination NTR gap (an increase of 0.043) is associated with a decline in the probability of enrollment of (conservatively) 2.1 percentage points, an effect that is about half the size of the own-county effect. However, given the confidence intervals, the hypothesis that the effects are equal cannot be rejected in any specification.[19]

Columns (6) and (7) report separate results for the urban and rural samples (defined using the hukou status of the household head when the target youth was 14 years old), using the simpler specification corresponding to column (1). It is evident that the response for urban youth is primarily driven by a response to local shocks; the coefficient on the destination shock is roughly half the magnitude of the response to the local shock, and statistically insignificant. By contrast, the coefficient estimating the response of rural youth to the local shock is statistically insignificant and around half the magnitude observed for the urban sample, while the response to the migration shock is large and statistically significant. (In both cases, however, the standard errors again do not allow us to reject the hypothesis that the effects of interest are equal comparing across the urban and rural samples.)

Given that the enrollment rate for the untreated birth cohorts (born prior to 1986) is significantly higher in urban areas (85.5 percent) vis-a-vis rural areas (35.6 percent), the proportional effect of the NTR shock—whether locally or at a migration destination—is much larger in rural areas. The implied magnitude suggests that a one standard deviation increase in the NTR gap leads to a decline in enrollment of around 8 percentage points in urban areas, for a proportional decline of 4 percent; in rural areas, the corresponding decline is nearly 20 percent. The educational response to the WTO shock is thus weaker in urban areas, consistent with a general pattern of higher educational attainment, but it is not zero.

17 Although the One Child Policy was strictly enforced for urban households in the sample period, the one-child restriction was relaxed for rural households in 1984, allowing them to have a second child if the first born was a girl; 73 percent of sample children have at least one sibling. If parental schooling data are missing, schooling is coded as zero, and an additional binary variable for missing data is included.

18 The binary variables for manufacturing-intensive and agricultural-intensive counties are not inverses of each other, given that there are also counties heavily concentrated in services (tertiary employment).

19 In both cases, these calculations use the estimated coefficients that are lowest in magnitude, as reported in column (5) of panel A in table 2.

Table 2. Primary Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Main specifications							
	High-school enrollment						
Treatment × NTR gap	−0.803***	−0.761***	−0.662***	−0.761***	−0.400*	−0.634***	−0.345
	(0.111)	(0.136)	(0.164)	(0.139)	(0.218)	(0.223)	(0.475)
Treatment × destination gap	−0.556**	−0.555**	−0.542**	−0.523**	−0.496**	−0.319	−0.664***
	(0.217)	(0.218)	(0.216)	(0.224)	(0.196)	(0.407)	(0.240)
Sample	Pooled	Pooled	Pooled	Pooled	Pooled	Urban	Rural
Observations	8,850	8,850	8,850	8,850	8,850	2,214	6,626
Panel B: Robustness checks							
	High-school enrollment				Birth weight		
Treatment × NTR gap	−0.658***	−0.751***	−1.209***	−0.512***	3.671	–	–
	(0.121)	(0.146)	(0.345)	(0.104)	(4.528)		
Treatment × imputed destination gap	−0.373***	–	–	–	–	–	–
	(0.132)						
Treatment × destination gap	–	−0.611***	−0.517	−0.603**	1.313	–	–
		(0.231)	(0.355)	(0.256)	(8.841)		
Observations	8,850	8,850	8,850	7,134	1,865	–	–

Source: Authors' calculations from China Household Income Project (CHIP) data.

Note: This table presents the results from regressing a binary variable for high-school enrollment on a continuous measure of treatment capturing the relative exposure of different cohorts to post-WTO shocks at the point of matriculation interacted with the county-level local and migration-destination normal trade relations (NTR) gap. In panel A, column (1) includes county and province-year fixed effects and individual controls; column (2) includes differential trends for manufacturing-intensive counties; column (3) includes differential trends for both manufacturing-intensive and agricultural-intensive counties; column (4) includes control variables for additional trade policy shocks; and column (5) includes the interaction of deciles of baseline primary employment share and cohort fixed effects. In panel B, column (1) uses an imputed destination county gap, identifying plausible migration destinations based on the concentration of manufacturing employment and linear distance from the origin county; column (2) includes additional prefecture-level industrial characteristics, interacted with the treatment variable; column (3) restricts the sample to individuals who report at least eight years of education; column (4) adds household fixed effects; and column (5) reports a placebo test using height as the dependent variable. Columns (6) and (7) report the same specification as Column (1) but restricted to the urban and rural samples, respectively. Standard errors are clustered at the county level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Returning to the pooled sample of urban and rural youth, fig. 1 presents event-study plots using a longer pre-period (cohorts born beginning in 1970), graphing the coefficients corresponding to the interaction of birth-year dummy variables and the own county shock (in fig. 1(a)) and the destination county shock (in fig. 1(b)). The estimated coefficients are close to zero and statistically insignificant in the pre-period, consistent with the absence of any meaningful pre-trend, with the observed decline for cohorts born after 1988 who matriculate into high school between 2002 and 2004 (post-WTO).

4.2. Alternate Specifications

Our analysis explored a number of alternate specifications to assess the robustness of these results. First, we consider potential endogeneity in migration destinations. As previously noted, all county-level employment weights used to construct trade shocks are extracted from the 1990 census, with the exception of migration destinations; given the time patterns of migration and data limitations, these are necessarily identified from the 2000 census.[20] Migration patterns in 1990–2000 already reflect a disproportionate flow of migrants to areas experiencing rapid export-driven growth; the most common destinations at the provincial level include, in order, Guangdong, Shanghai, Jiangsu, Zhejiang, and Beijing.[21]

In order to address any potential bias introduced by the endogeneity of migration destinations, we use an alternate strategy to identify plausible destinations as follows: First, we identify the 25 percent of county-level units characterized by the highest (absolute) level of employment in manufacturing in the 2000 census, and consider this set as plausible migration destinations. Each CHIP county is then matched to the three plausible destination counties that are closest in geographic distance (using the linear distance between county centroids). We can construct an imputed destination NTR gap that is equal to the simple mean of NTR gaps across the three imputed destinations, and use this imputed NTR gap in our key specification.

The results of this robustness check are reported in column (1) of panel B of table 2, using the simplest specification corresponding to column (1) of panel A. Again, the coefficient on both the own-county and the migration destination gaps are significant and negative; the coefficient on the imputed destination gap is somewhat smaller in magnitude vis-a-vis the corresponding regression in the first panel, suggestive of some bias away from zero in the original specification, but the difference is not statistically significant. This suggests that any potential bias introduced by the endogeneity of migration destinations as observed in the 2000 census is not large.[22]

Columns (2) through (5) then report additional specifications, now using the original migration destination shock. In column (2), the specification includes additional time-invariant prefecture-level characteristics interacted with treatment. The characteristics of interest are constructed from the survey of large-scale industrial firms, a survey of all state-owned enterprises and private firms above a certain sales threshold (Brandt, Van Biesebroeck, and Zhang 2012), and allows us to capture various characteristics of the local industrial sector: the fraction of employment reported in state-owned enterprises, the fraction of

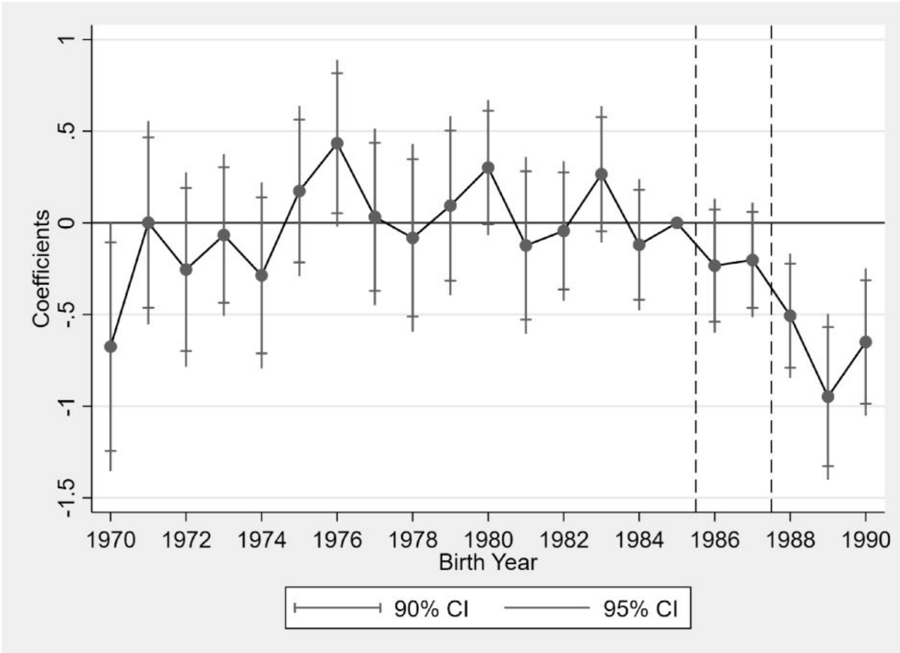
20 The 1990 census does not report migration or migration destinations, and internal migration rates were much lower prior to 1990.

21 We identify these locations as follows: For each origin county in the CHIP data, we identify the top five destination counties, yielding a sample of 875 (non-unique) destinations. We then calculate the provincial composition within those popular migration destinations.

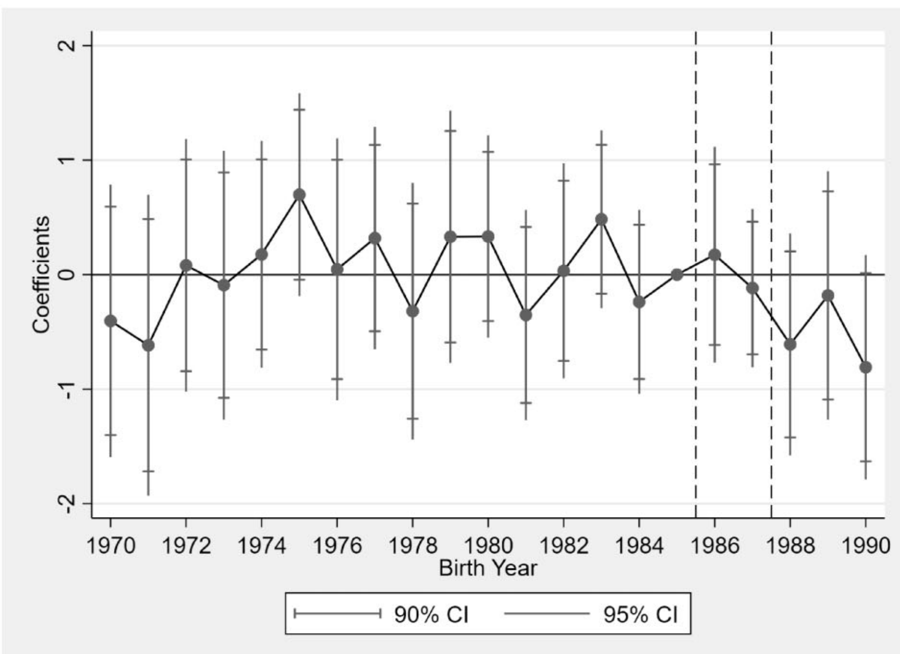
22 It is important to note that the analysis does not estimate any causal effects on the probability of out-migration per se by the target youth, for several reasons. The primary causal argument does not entail any claim that WTO accession necessarily affects the probability of out-migration, but rather that conditional on the ex ante probability of out-migration, the WTO-induced shocks at possible destinations may shift educational choices at migration origins. In addition, the primary source of longitudinal variation exploited (cohorts that reach the age of matriculation before or after WTO accession) has no clear analogue in the case of a migration decision, given that this decision can in principle be made at any time, and thus the research design does not allow us to generate any high-quality evidence around the effects of WTO accession on migration.

Figure 1. Effects of Trade Shock on High-School Enrollment: Event Study Specification.

(a) NTR gap



(b) Destination gap



Source: Authors' analysis based on CHIP data.

Note: The figure shows estimated coefficients and confidence intervals for the effect of the local and destination normal trade relations (NTR) gaps on high-school matriculation for each birth cohort. Cohorts to the rights of the second dashed line are fully treated. Cohorts between the dashed lines are partially treated. The 1985 birth cohort is the omitted group.

foreign capital in large enterprises, the level of exports, value-added per worker, wages per worker, and capital intensity. All variables are measured in the pre-period (more specifically, in the first pre-WTO survey wave, conducted in 1998).[23] This robustness check allows us to assess whether differential trends in the local industrial sector post-WTO could be correlated with shifts in local enrollment rates, but there is no evidence that including these prefecture-level characteristics leads to any meaningful shift in the main estimated coefficients.

In column (3), the main specification now includes household fixed effects; the remaining source of identification in this specification is variation across siblings who reach the age of matriculation before and after WTO accession. In column (4), the sample is restricted to youth who report completion of the mandatory phase of junior high school; around 20 percent of the sample does not report completing it.[24] Both specifications are consistent, though the destination gap index is noisily estimated in column (3).

Finally, column (5) reports a placebo test using birth weight as the dependent variable in equation (1). The potential source of bias assessed here is as follows: If low-NTR-gap counties also experienced a sharp shift in preferences for human capital investment coinciding with the years in which the treated cohorts were born, those cohorts may have been exposed to higher investments in the prenatal period and be characterized (for example) by both higher birth weight and potentially, higher cognitive ability. This could be reflected in a shift in high-school enrollment around 2002 in which those low-NTR-gap counties disproportionately gain in high-school enrollment, consistent with the empirical pattern observed. However, the observed coefficient is of the opposite sign and statistically insignificant.

4.3. Robustness Checks

Assessing robustness of the shift-share instrument. A growing literature in recent years has probed the robustness of Bartik shift-share instruments such as the NTR gap constructed here. Goldsmith-Pinkham, Sorkin, and Swift (2020) present evidence that the validity of these research designs depends crucially on the exogeneity of the estimated shares relative to potential growth in the dependent variable, and recommends identifying control variables measured in the same year as the employment shares (in this case, 1990) and interacting these time-invariant controls with year fixed effects.[25]

Some specifications, including the interaction between time-invariant county characteristics and time trends, were reported in table 2. In panel A of table S3.1 in the supplementary online appendix, we report a series of specifications including more restrictive controls. Column (1) adds interactions between an urban dummy and province-year fixed effects. Column (2) adds interactions between variables capturing deciles of baseline secondary employment shares and cohort fixed effects. In column (3), we construct deciles of the baseline percentage of county population reporting secondary education and interact these binary variables with birth-year fixed effects. In column (4), we construct deciles for the initial employment share in the five industries characterized by the highest NTR gaps, and interact these deciles with birth-year fixed effects. The estimated coefficients remain negative and significant, and of roughly consistent magnitude.

We can also identify whether pre-trends in high-school enrollment are correlated with other covariates reported in 1990 that are themselves correlated with employment shares: particularly, total county population, the primary-/secondary-school enrollment rate (the ratio of the number of students to the total youth population ages 5 to 15), the unemployment rate (the ratio of the number of individuals actively

23 These variables are constructed at the prefecture level because there are no county-level indicators in the survey.

24 This is broadly consistent with existing literature suggesting around 80 percent of rural youth did not complete compulsory education in the period around 2000 (Xiao, Li, and Zhao 2017).

25 We preferentially use the framework of Goldsmith-Pinkham, Sorkin, and Swift (2020) rather than Borusyak, Hull, and Jaravel (2022) given that the latter relies on a large number of shocks, or in our case, assuming that the number of NTR-gap shocks at the subsector level approaches infinity. Our analysis utilizes data from 39 subsectors, and thus this assumption is arguably not appropriate. In addition, given that the analysis uses subsector shares from 1990 considerably prior to the shock of interest, we argue that exogeneity of the employment shares is plausible.

searching for work to the total labor force), and the fertility rate (average children per woman for women aged 15–64). Each of these variables is highly correlated with employment shares: On average, a higher share in non-agricultural employment is observed for larger counties, characterized by lower fertility and higher school enrollment.

Following the recommended methodology in Goldsmith-Pinkham, Sorkin, and Swift (2020), we use data from earlier cohorts observed in the CHIP survey to calculate the average matriculation rate for cohorts born in 1980 and 1985 and construct a short-difference for matriculation rates for these pre-WTO cohorts (the 1985 cohort would reach the age of matriculation by 2001, at latest). The results reported in panel B of table S3.1 in the supplementary online appendix suggest that none of the cited variables are significantly correlated with this county-level difference conditional on provincial fixed effects, consistent with the hypothesis that these omitted variables are not a meaningful source of bias.

Alternate definitions of treatment and sample. We can also explore the robustness of our findings to several alternate definitions of treatment. In panel A of table S3.2, we replicate the primary results (panel A of table 2) constructing the NTR gap using employment data as reported in the 2000 census. The use of 2000 employment weights may increase precision, by using employment data more proximate to the shock; however, it introduces bias associated with strategic industrialization by counties seeking to expand manufacturing in anticipation of WTO accession. There is ultimately no meaningful difference comparing across the estimates constructed with 1990 and 2000 data weights.

In panel B of the same table, we report alternate specifications that employ different assumptions about treatment status by year, in all cases reporting the analogue of the simplest specification analyzed in the main results (column (1) of panel A of table 2). Column (1) uses a simpler, binary measure of treatment exposure; cohorts born in 1986 and 1987, identified in our main specification as subject to intermediate exposure to the NTR shock, are excluded from the analysis. Columns (2) and (3) report additional robustness checks that allow us to construct bounds: We define a variable deemed "binary high treatment", equal to 1 if the youth was born in 1987 or 1986 (intuitively, assuming that these intermediate cohorts were fully treated); we then define a second variable deemed "binary low treatment" that makes the opposite assumption, equal to 0 if the youth was born in 1986 and 1986. All three specifications show that both the local and destination NTR gap lead to a significant decline in enrollment.

We also explore the robustness of the primary results to broadening the birth-year cutoff used to identify the sample. The primary sample includes birth cohorts born between 1980 and 1991, inclusive; we expand this window first by two years (1979—1992) and then by four years (1978—1993). The results remain consistent, as reported in table S3.3 in the supplementary online appendix.

Assessing robustness to differential trends. We can also demonstrate that our results are robust to controlling for existing pre-trends, building on recent methods developed by Rambachan and Roth (2023). First, we re-estimate the relationship of interest in a county-year panel framework, rather than the individual-level regression that constitutes our primary specification, in order to generate a more standard difference-in-difference. While we observe each individual only once and thus cannot construct an individual-level panel, we can link each individual to a county–birth-year cell and collapse to a county-year panel. We then estimate the following specification at the county level, employing for conciseness a single NTR gap that is the weighted average of the home-county (destination) shock, weighted by the share of non-migrants (migrants).[26] Each county-year cell is weighted relative to its number of observations, and the NTR gap is interacted with the same continuous measure of treatment used in equation (1).

26 More specifically, this measure is constructed as follows, where NonMig_{cp} is the share of non-migrants in this population, and AllMig_{cp} is the population share of out-migrants (to all possible destinations):

$$\text{NTR\_Gap}_{cp}^{\text{Full}} = \text{NonMig}_{cp} \times \text{NTR\_Gap}_{cp} + \text{AllMig}_{cp} \times \text{NTR\_Gap}_{cp}^{\text{MigDest}}.$$

The variables χ_{cpt} are individual-level covariates collapsed to a county-year mean:

$$M_{cpt} = \beta \text{Treat}_t \times \text{NTR\_Gap}_{cp}^{\text{Full}} + \mu_t + \phi_{cp} + \chi_{cpt} + \epsilon_{icp}. \tag{2}$$

We verify that the primary coefficient β remains comparable to that estimated in the individual-level specification ($\beta = -0.779$, $p < 0.001$), and generate a county-level event study plot, fig. S3.6 in the supplementary online appendix, to visually inspect pre-trends at the county level.

Second, we use the methodology estimated in Rambachan and Roth (2023) to evaluate the sensitivity of this estimate, reporting fixed-length confidence intervals (FLCIs) that are robust to a violation of the parallel trends process that is either linear (notated as $M = 0$) or characterized by non-linearities parameterized by positive M (defined as a differential trend whose slope changes by no more than M in consecutive periods). We focus on the dynamic treatment effect estimated for the cohort born in 1991, the final treatment year observed in this analysis, as compared to the cohort born in 1985, corresponding to the final purely untreated pre-WTO cohort (matriculating into high school at latest in 2001). We then report the FLCIs in a sensitivity plot, fig. S3.7 in the supplementary online appendix: Figure S3.7(a) shows the 95 percent confidence intervals, and fig. S3.7(b) shows the 90 percent confidence intervals. It is evident that the confidence intervals are consistently negative and statistically significant, and generally robust to even a non-linear differential trend. Thus even if, for example, the probability of matriculation was already decreasing in treated counties by an additional 0.015 percentage points per year vis-a-vis control counties (relative to a pre-treatment mean of 49 percent), the estimated treatment effect could still be identified.[27]

4.4. Mechanisms

The primary results suggest that for a sample of youth including both migrants and non-migrants, the rise in the short-term opportunity costs of education given the increase in local- and migration-destination non-agricultural labor demand dominates any shift in the returns to education or any potential positive income effect induced by the same shock. To further probe the hypothesized mechanisms, we first analyze heterogeneity with respect to the implied skill premium in the relevant labor market—whether local or at plausible migration destinations—affected by the export shock. As noted in the conceptual framework (direct channel one), the effect of a reduction in tariff uncertainty on the skill premium is ambiguous, on average. However, in areas where export-oriented industries are more likely to demand skilled labor, this implies a relative increase in the skill premium as export-oriented production expands, vis-a-vis areas where export-oriented industries are more likely to demand unskilled labor.

In order to analyze this channel, we calculate the industry-level share of employees reporting high school or higher education in the 1990 census as a proxy for skill intensity, and calculate the weighted average of skill intensity for the manufacturing sector in each county. We use this to construct a measure of average skill intensity for the local labor market and the average destination labor market in each county, and denote each county as characterized by a high-skilled versus low-skilled labor market at home, and a high-skilled versus low-skilled labor market at migration destinations. We then re-estimate the primary specification, equation (1), for youth in counties facing a high-skill vis-a-vis a low-skill shock in the home county, as well as in destination counties.

In panel A of table 3, columns (1) and (2) report the results for high-skill home counties versus low-skill home counties: The response to the own-county shock is significantly lower in high-skill counties, where a one standard deviation increase in the NTR gap is associated with an only 8 percentage-point decline in the probability of matriculation, vis-a-vis 17 percentage points in low-skill counties. (There is no differential response to the migration destination shock comparing across these two subsamples, though the migration shock coefficient is noisily estimated in the first column.) Columns (3) and (4) report the results for

27 This is roughly similar to the magnitude of the differential trends assessed in the empirical applications discussed in Rambachan and Roth (2023).

Table 3. Mechanisms

	(1)	(2)	(3)	(4)	(5)	(6)
	High-school enrollment					
Panel A: Heterogeneity by locality and parental characteristics						
Treatment × NTR gap	−1.317***	−0.723***	−0.935***	−0.526*	−0.782***	−0.286
	(0.233)	(0.134)	(0.123)	(0.280)	(0.157)	(0.288)
Treatment × destination	−0.323	−0.546*	−0.659***	0.139	−0.670**	−0.116
Gap	(0.343)	(0.316)	(0.232)	(0.533)	(0.267)	(0.457)
Sample	Low-skill (own)	High-skill (own)	Low-skill (dest.)	High-skill (dest.)	Low-educ. parents	High educ. parents
Cross-spec. tests (local shock)	–	0.023	–	0.161	–	0.099
Cross-spec. tests (dest. shock)	–	0.623	–	0.15	–	0.262
Observations	5,417	3,433	7,154	1,696	7,535	1,148
Panel B: Heterogeneity by individual characteristics						
Treatment × NTR gap	−0.849***	−0.811***	−0.480**	−0.968***	−0.998*	−0.997*
	(0.158)	(0.171)	(0.195)	(0.328)	(0.534)	(0.530)
Treatment × dest.	−0.381	−0.749**	−0.841**	−0.486*	−1.025**	−0.162
Gap	(0.300)	(0.361)	(0.403)	(0.277)	(0.433)	(0.416)
Sample	Female	Male	No sibling	Any sibling	First born	Non-firstborn
Cross-spec. tests (own-county shock)	–	0.859	–	0.185	–	0.998
Cross-spec. tests (dest. shock)	–	0.425	–	0.424	–	0.111
Observations	4,186	4,664	2,396	6,454	2,754	3,700

Source: Authors' calculations from China Household Income Project (CHIP) data.
Note: Both panels present results from regressing a binary variable for high-school enrollment on a continuous measure of treatment interacted with the county-level local and migration-destination normal trade relations (NTR) gap. The sample is restricted as specified in each column, and the cross-specification tests report tests of equality of the coefficients estimated across complementary subsamples. All columns include county and province-year fixed effects and individual controls. Standard errors are clustered at the county level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

high-skill destination counties versus low-skill destination counties, and we observe the same pattern: The response to the destination county shock is close to zero for youth linked to destination counties with high skill levels, while the response to the own-county shock is roughly consistent. (However, the wider confidence intervals for the estimated coefficients on the migration shock render it impossible to reject the hypothesis that the effects are equal comparing across these two subsamples.) These findings suggest that while the higher short-term opportunity costs of education seem to dominate educational choices, the first hypothesized direct channel (in which variation in the skill premium simultaneously affects educational choices) is also operational.

Second, we evaluate the first indirect channel described: An expansion in labor demand generates a positive income effect for parents, increasing demand for education. Assessing heterogeneity in the household-level income effect requires some assumptions around the characteristics of adult workers (parents) who may experience a larger increase in income post-WTO accession. As is discussed in the conceptual framework and at some length in supplementary online appendix S2, the available evidence suggests it is generally more educated parents who will experience a larger increase in income in high-NTR-gap counties, and thus the income effect should be larger for youth in these households. We thus explore heterogeneity in households where at least one parent does not report a high-school education, vis-a-vis households where both parents report a high-school education.

These results are reported in columns (5) and (6) in panel A of table 3, and suggest that the effect of the NTR shock on high-school enrollment in households in which both parents report a high-school education is in fact not significantly different from zero (column 6). The adverse effect on enrollment is entirely observed in households in which at least one parent is characterized by a lower skill level (column 5).[28] This pattern suggests that the first hypothesized indirect channel is also operational: The income effect following WTO accession is larger in households with more educated parents, and given that education is a normal good, this results in an attenuation of the main decline in enrollment toward zero.

Third, consider the second indirect channel: a shift in household time allocation by parents into paid work in response to an expansion of labor demand that leads to a decline in youth educational performance because of reduced parental supervision, or youth substitution into household domestic responsibilities. This hypothesis is challenging to assess directly, but descriptive evidence suggests it is unlikely. Patterns of heterogeneous effects with respect to both child and family characteristics reported in panel B of table 3 suggest there is little evidence of heterogeneity with respect to gender, sibship size, or birth order, while in general first-born and female children would be expected to be more burdened by childcare responsibilities if parents are more engaged in work. Data directly reported by households also suggest that care-taking by siblings is rare.

5. Conclusion

This paper presents new evidence about the effect of positive export shocks both locally and at plausible migration destinations on human capital attainment in China. Comparing youth who reached the age of high-school matriculation before and after China's accession to the WTO in counties more or less exposed to reduced tariff uncertainty, we find evidence that youth reaching matriculation age in counties characterized by positive export shocks show a lower probability of enrolling in high school.

These findings are consistent with several prior papers that have analyzed the effect of trade access shocks (tariff cuts or WTO accession), and have found a decline in enrollment rates (Liu 2023; Li et al. 2019; Lin and Long 2020).[29] However, this analysis generally finds larger effects on educational attainment, reflecting two key differences in our empirical strategy that we argue render our estimates more credible. First, the sample includes all youth born into a household, even those who are permanent out-migrants; since youth who exit education and enter the labor market are disproportionately likely to migrate, excluding these youth will systematically underestimate the effect of trade shocks. Second, we analyze the response to both local shocks and shocks at migration destinations.

This evidence suggests that examining the response to local shocks only may significantly underestimate the effect of export-driven growth on human capital accumulation, particularly in rural areas.[30] More specifically, our findings suggest that the effect of shocks at migration destinations comprises about 40 percent of the full shock effect for a pooled sample on average. For rural youth, however, the effect of

28 The difference between these two sets of coefficients is somewhat noisily estimated given the smaller sample of households where both parents, particularly the mother, has a high-school education; but the difference between the coefficients on own-county skill is close to significant at the 10 percent level.

29 One additional paper, Li (2018), separately analyzed the effect of shocks in high-skill and low-skill sectors, but did not analyze the aggregate effect.

30 Li (2018) uses census data from 2005 and finds that shocks to high-skill industries raise education, while our findings suggest these shocks still reduce education, but by a smaller margin vis-a-vis shocks to low-skill industries; this difference presumably reflects the analysis's exclusion of youth who have permanently departed their birth household. Liu (2023) uses the same census data as Li (2018) but finds the effect of shocks in high-skill industries is positive and insignificant; again, this is plausibly an underestimate of the effect of the trade shock on educational attainment. Lin and Long (2020) find that the effect for urban youth is insignificant, unlike our findings, but uses a very different region-level shock, and also excludes youth who have exited their birth households.

shocks at migration destinations accounts for the majority (around two-thirds) of the overall effect on the probability of matriculation, while for urban youth the pattern is roughly inverted (local shocks account for around two-thirds of the overall effect). Thus, especially for a rural or a primarily rural sample in a context characterized by rapid structural transformation (a description that would characterize much of East and Southeast Asia), failing to incorporate the effects of migration destination shocks into a model of the effects of trade shocks on human capital accumulation would neglect the dominant channel through which those shocks affect matriculation decisions. In a context characterized by more limited structural transformation and/or internal migration, by contrast, focusing on the effects of local shocks may be sufficient.

Data Availability Statement

The CHIP data is publicly available from ICPSR. Replication code is available upon request from the authors.

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