Building Through Downturns: Export Slowdown and Construction in China

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Abstract

How do local governments respond to negative labor market shocks? Using variation in Chinese cities' exposure to the mid-2010s export slowdown, this paper shows that cities more exposed to the shock experience large manufacturing employment losses followed by increases in construction employment. This construction response is stronger in cities led by officials with stronger career incentives and in cities experiencing greater labor unrest, and it is accompanied by increased emphasis on employment in government work reports. The results suggest that construction serves as a short-run employment stabilization tool. I further show that one mechanism to create construction projects is through government land sales, which expand real estate development and infrastructure construction. While this strategy mitigates employment losses in the short run, it is associated with higher real estate risks in the longer term.

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1 Introduction

Negative labor market shocks pose a central challenge for governments. Employment losses are economically costly and politically salient, and policy responses to such shocks can shape both short-run employment outcomes and longer-run economic adjustment. A prominent view in the political economy emphasizes that governments sustain economic openness in the age of globalization by compensating adversely affected workers, often through social insurance and redistribution (Rodrik, 1998). Yet governments may rely on policy tools beyond transfers to address employment losses. Understanding how governments respond to adverse labor market shocks, and the policy tools they use to stabilize employment, is therefore a core question.

This paper studies one specific response to negative labor market shocks: the expansion of construction activity. Construction projects, including infrastructure and real estate projects, can generate employment quickly and rely heavily on government control over land, investment, and project approval. Historically, governments have often relied on infrastructure and housing construction to absorb displaced workers during downturns. One example is the establishement of the Public Works Administration in the United States to reduce unemployment during the Great Depression by hiring workers to build public infrastructure. Despite its prominence, systematic evidence on whether and how governments expand construction in response to labor market shocks remains limited.

I examine this question in the context of Chinese city governments. China provides a suitable setting to examine this construction response, as local governments exercise direct control over land allocation and infrastructure provision. This institutional feature allows governments to influence construction activity directly and rapidly, making construction a plausible margin of adjustment in response to local employment shocks. While it is widely believed that Chinese governments rely on construction to address economic challenges,[1] existing discussions are largely descriptive. Empirical evidence linking negative labor market shocks to construction expansion—and tracing the mechanisms and consequences of such responses—remains scarce.

To identify the impact of negative labor market shocks on construction, I exploit the marked slowdown in China's exports in the mid-2010s, during which China's annual export growth rate dropped sharply from 24.7% (between 2001 and 2008) to only 0.8%

[1] As noted by *The New York Times* (August 22, 2023): "Beijing has often addressed economic troubles by boosting spending on infrastructure and real estate."

(between 2013 and 2016).[2] This slowdown was largely driven by the sluggish global trade growth after the 2008 global financial crisis and uneven recovery across China's major trading partners (World Bank, 2020). Because cities differed in their initial export composition across products and destinations, which were recovered differently from the financial crisis, they were exposed to the export slowdown to varying degrees, generating plausibly exogenous variation in local labor demand.

I adopt a shift-share instrumental variable (SSIV) approach to identify the impact of the export slowdown following Campante et al. (2023). The SSIV measures each city's exposure to the export slowdown by combining product-level shifts in the global trade change (excluding China) with each city's initial product mix. The underlying idea is that cities exporting more goods to countries that were hit and did not recover well from the financial crisis experienced more severe export slowdown. Meanwhile, the product-level changes in global trade, which depend on the varying recovery in export destinations, provide a source of exogeneity. To validate the SSIV's exogeneity, I follow Borusyak et al. (2022) and validate that the product-level shocks are as good as randomly assigned, supporting the exogeneity of the SSIV.

I first document the labor market effects of the export slowdown. The slowdown caused an immediate decrease in manufacturing employment, which accounts for 95.11% of the employment decline in all industrial sectors due to the export slowdown. At the same time, cities more exposed to the export slowdown experience an increase in construction employment in the subsequent period.[3] On average, a one-standard-deviation increase in exposure to the export slowdown, equivalent to a $753 reduction in export value per worker, leads to a 0.13 percentage point increase in the share of the working-age population employed in the construction sector. This increase represents approximately 2.27% of the average construction sector size. Notably, construction is the only sector that experienced an employment increase following the export slowdown, offsetting 9.38% of the manufacturing employment loss. This finding highlights the pivotal role of the construction sector in absorbing displaced workers during economic downturns.

Several pieces of evidence indicate that this construction response is closely tied to governments' incentives to stabilize employment and maintain social stability, which has long been a priority in the multi-tasking incentives scheme for Chinese local officials.

[2]The numbers are calculated based on UN Comtrade. Specifically for year 2015 and 2016, China's export growth rate went negative.

[3]All the employment variables are normalized using the city's working age population obtained from the 2010 Census.

Construction employment rises more in cities led by younger officials, who face stronger career incentives, and in cities experiencing larger increases in labor unrest. Consistent with these patterns, government work reports from such cities place greater emphasis on employment stabilization and job creation. Together, these findings suggest that construction expansion serves as a stabilizer for city governments in response to employment pressure.

Is this construction expansion an employment-driven response or simply a by-product of reactions to broader economic contractions? To distinguish this, I complement the export slowdown analysis with evidence from automation-induced labor demand shocks. Using the standard measure of city-level exposure to industrial robot adoption following Giuntella et al. (2025), I show that cities more exposed to automation experience significant manufacturing loss and they also expand the construction employment in the following period, even though these automation shocks did not decrease the economic growth. The construction response is also higher in cities experiencing larger increases in labor unrest. This auxiliary evidence supports the interpretation that construction expansion reflects employment stabilization rather than a general response to declining economic activity.

I then examine how local governments create the construction jobs. I leverage the institutional feature that local governments in China have autonomy in managing and selling land use rights within their jurisdiction (hereafter using selling land to refer to selling land use rights). Because the state owns all the urban land and local governments are monopolists in land markets, land sales provide a tool to stimulate construction. Specifically, increasing sales of residential and commercial land facilitates real estate projects by developers, while land-sale revenues finance public infrastructure projects. I find that city governments more exposed to the export slowdown have higher land sales revenue, primarily through more sales of residential and commercial land areas. These cities subsequently experience higher real estate investment and expanded infrastructure construction, as reflected in greater bridge construction and higher public housing expenditure.

Finally, this paper examines the potential longer-run consequences of land-financed construction expansion following the export slowdown. I explore this question through the lens of real estate risk. Cities with greater cumulative exposure to the export slowdown and higher land-sale revenues during this period are more likely to experience homeowner protests over presold but unfinished housing projects in subsequent years. Such protests are commonly associated with developers' financial distress and construction delays, suggesting that reliance on residential land sales and real estate development may contribute to vulnerabilities in local housing markets. These findings point to a potential tension between short-run employment stabilization through construction and longer-run risks associated with land-based development strategies.

This paper contributes to the literature on government responses to negative economic shocks, particularly shocks that lead to deteriorating labor market outcomes. Existing works have documented that employment is politically salient (Autor et al., 2020; Choi et al., 2024). In democratic settings, rising unemployment is associated with lower support for incumbents (Fair, 1978; Garz and Martin, 2021), prompting income assistance and employment-friendly policies (Foremny and Riedel, 2014; Margalit, 2011). In authoritarian regimes, employment also plays a critical role in maintaining stability, as job loss and income declines are associated with unrest and conflicts (Bazzi and Blattman, 2014; Campante et al., 2023; Miguel et al., 2004). As a response to instability, governments might increase social and security expenditure, provide unemployment insurance and employment programs (Campante et al., 2023; Blattman and Annan, 2016; Pan, 2020). This paper adds to this literature by documenting how Chinese city governments respond to the export slowdown through construction expansion.

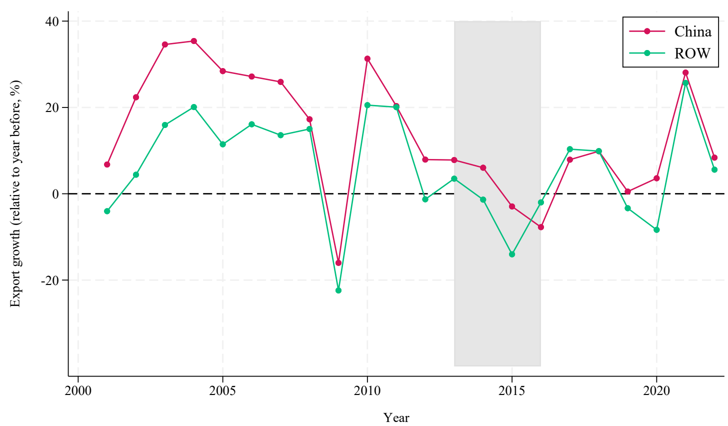
This paper is also related to the literature studying the determinants of land sales by Chinese local governments, which has been related to China's recent real estate challenges (Xiong, 2023). Existing literature emphasizes three main explanations for why local governments in China are inclined to sell more land. First, fiscal pressure, resulting from the tax reform that requires local governments to share tax revenue with the central government, has been argued to increase local governments' incentives to boost land sales revenue, which is an off-budgetary revenue (Han and Kung, 2015). Relatedly, a concurrent work documented that land sales is used to increase revenue in response to negative export shocks (Wang et al., 2025). Second, promotion incentives can encourage local officials to sell more land, as land sales can stimulate real estate development and the urbanization process (Wang et al., 2020; Chen and Kung, 2016). Third, rent-seeking motive associated with land sales revenue has also been documented as a contributing factor for government land sales (Chen and Kung, 2019, 2016). This paper adds to this literature by highlighting a complementary channel: land sales and land-financed construction are associated with local governments' responses to unemployment shocks, enabling the expansion of construction activities that can absorb employment in the short run.

The rest of the paper is organized as follows. Section 2 introduces the data and measures. Section 3 describes the empirical design. Section 4 reports the result and discusses the interpretation. Section 5 explores the strategy governments use and the potential consequences. Section 6 concludes.

2 Data

Sample This study focuses on the prefectural level city as the unit of analysis, which is the administrative level below the province and above the county in China's administrative hierarchy. My sample includes 281 cities, for which data on city characteristics are available. I exclude Beijing, Tianjin, Shanghai, and Chongqing from the sample as they are provincial level cities. Overall, the sample consists of almost all prefectural cities across China except cities in Tibet.

Figure 1. China's export growth (2001-2021)



Note: This figure plots the export growth rate of China and the average of the rest of the world. Data are obtained from *UN Comtrade*.

For the time period, I focus on years 2013 to 2016 for the following reasons. First, as shown in Figure 1, despite the 2008 financial crisis, China (and the global economy) experienced a rebound in export growth in 2010. The consistent decline in export growth occurred between 2013 and 2016, with growth turning negative in 2015 and 2016, which supports the 2013 to 2016 as the export slowdown period (marked as a gray region in the figure). Secondly, I exclude years prior to 2012 to avoid potential confounding effects from the extraordinary stimulus program known as the "4 trillion yuan stimulus". Announced in 2008, this stimulus package aimed to stimulate the slumped export-driven economy in the wake of the financial crisis by boosting investment in infrastructure and social welfare. Moreover, this stimulus was largely financed by local governments, with government land sales revenue being an important finance source. As a result, the stimulus period could potentially confound both export slowdown exposure and construction related measures. Finally, the years after 2017 are excluded to avoid the potential confounding effects of the US-China trade war.

Export Slowdown. The measure of export slowdown is obtained from Campante et al. (2023), with the original data comes from China's General Administration of Customs. The database covers the universe of China's exporters and importers. It provides information on the trading firm's location, trade values at the Harmonized System (HS) six-digit product level, and trade partners. My sample includes 4596 HS6 products. The exposure to export slowdown is measured using the annual change in the city's exporting values per worker, with more negative value indicating more severe exposure to the export slowdown:

$$\Delta Export_{ct} = \sum_{k} \sum_{f \in c} \frac{\Delta X_{fckt}}{L_{c,2010}} \tag{1}$$

where f denotes firm, c city, k product, and t year. X_{fckt} is the export values of firm f in product k at year t. $\Delta X_{fckt} = X_{fckt} - X_{fck,t-1}$, is the annual change of firm f's export values. $L_{c,2010}$ is the working-age population (ages 15-64) of the city c in the year 2010, which is obtained from the 2010 Census.

Construction Employment. The city-by-sector-level employment data are obtained from City Statistics Yearbooks, which provide employment data in sectors of manufacturing, construction, mining, energy and utility, and all the various services sectors. The main dependent variable is defined as:

$$\Delta Construction\ Employment_{c,t+1} = \frac{\Delta N_{c,t+1}}{L_{c,2010}} \tag{2}$$

where $N_{c,t+1}$ is the number of construction employment in city c at time $t+1$. $\Delta N_{c,t+1} = N_{c,t+1} - N_{c,t}$ is the annual change of city c's construction employment. $L_{c,2010}$ is the working-age population (ages 15-64) of the city c in the year 2010, which is obtained from the 2010 Census.[4] The interpretation of $\Delta Construction\ Employment_{c,t+1}$ is the change in the share of construction employment in the working-age population.

For other sectors, I construct the employment share measure similar to Equation 2. Specifically, the change in the share of employment in sector i in the working-age

[4]The working-age population is only available during the Census years.

population is defined as:

$$\Delta Sector\ i's\ Employment_{i,c,t+1} = \frac{\Delta N_{i,c,t+1}}{L_{c,2010}} \tag{3}$$

where $N_{i,c,t+1}$ is the number of sector i's employment in city c at time $t+1$. $\Delta N_{i,c,t+1} = N_{i,c,t+1} - N_{i,c,t}$ is the annual change of city c's employment in sector i.

Land Sales. Data on land sales come from the website of the Land Transaction Monitoring System (http://www.landchina.com/), which provides records of land transactions from the year 2000 till now. For each land transaction, the Ministry of Land and Resources records the transaction date, location of the land parcel (address and postal code), size, total payment, land usage (e.g., residential, commercial, and industrial), land parcel quality (evaluated by the official-in-charge on a 20-point scale), a three-digit industry code of the buyer's firm, and names of sellers and buyers.

I construct the city-by-year measures of land sales by aggregating the land transactions by city and year. Specifically, the measures of interest are the city-level land sales revenue, land sales area (the size of the land sales), the average selling price per hectare of the land, and these three measures by different land usage types. Specifically, I consider three usage types of land: residential land, commercial land, and industrial land, as these are the main types of land sold in the land market, accounting for 76.11% of the land transactions during the sample period.

Auxiliary Data. I use other auxiliary data for controls and mechanism exploration, including city-level time-varying characteristics, city leaders' characteristics, real estate investment, and infrastructure building. Appendix B describes these data.

3 Empirical Strategy

This section describes the empirical strategy used to identify the effects of export slowdowns on construction employment. For clarity, the discussion focuses on construction employment as the main outcome; the empirical specifications for other outcomes follow the same structure.

3.1 Estimating Equation

I regress the city-level construction employment change on the export shock experienced by the city using the following baseline specification:

$$\Delta Construction\ Employment_{c,t+1} = \beta \Delta Export_{ct} + \delta \Delta X_{ct} + \lambda_c + \mu_{pt} + \epsilon_{ct} \tag{4}$$

where c denotes city, p province and t year. $\Delta Export_{ct}$ is the change in city c's manufacturing export per worker between year $t-1$ and year t defined in Equation 1. $\Delta Construction\ Employment_{c,t+1}$ is the change in the share of working-age population employed in the construction sector from t and $t+1$ defined in Equation 2. The one-year gap between the export shocks and the construction employment change is taken to account for the time that the labor market adjustment will take. The X_{ct} includes a series of time-varying city-level characteristics, such as population composition, which includes the share of college students and the share of non-hukou residents.[5] λ_c and μ_{pt} capture city fixed effect and province-year fixed effect.

Note that the regression in Equation 4 uses the first differences of both dependent and independent variables. The first-differencing removes the time-invariant determinants of construction employment share in city c. The city fixed effect captures the possible city characteristics affecting the change of construction employment share, or city-specific linear time trends in construction employment share. The province-year fixed effect controls for province-specific determinants on the change in construction employment share over time. I weight each observation by the city's working-age population in 2010 to make the results more representative and cluster the standard errors by provinces. In Section E.1, I show that the results are not sensitive to these particular choices of weighting and clustering level.

3.2 Instrumental Variable Approach

Estimating Equation 4 using ordinary least squares may lead to biased results for two reasons. First, reverse causality is a concern that cities with larger construction sectors may experience different manufacturing dynamics, which could have different export

[5] The control variables are obtained from the City Statistical Yearbooks. In some years, some cities have missing values in the control variables. In this instance, missing values are filled with the placeholder value of 999. To account for this imputation, a corresponding dummy variable is created for each control variable, indicating whether the value had been imputed. These dummy variables are then included in the regression alongside the original control variables.

exposures. Second, omitted variable bias may arise if some time-varying unobserved factors simultaneously affect both the export performances and construction employment

To address the potential endogeneity concern, I follow Campante et al. (2023) and adopt a shift-share (Bartik) instrument for the export change variable making use of the change in the global trade flows excluding China (referred to as the "rest of the world" or ROW hereafter). The instrument uses the city-level initial export mix across products as the share and the product-level trade flow change in the rest of the world as the shift. Specifically, the IV for $\Delta Export_{ct}$ is constructed as follows:

$$\Delta ExportROW_{ct} = \sum_{k} \frac{X_{ck,2010}}{\sum_c X_{ck,2010}} \frac{\Delta X_{kt}^{ROW}}{L_{c,2000}} \tag{5}$$

where $\Delta X_{kt}^{ROW} = X_{kt}^{ROW} - X_{k,t-1}^{ROW}$ is the change in product k's trade flows from ROW to ROW between year $t-1$ and t.[6] $\frac{X_{ck,2010}}{\sum_c X_{ck,2010}}$ is the initial city-level export share for product k. The weighted average of the rest of the world's trade shocks across products, $\sum_k \frac{X_{ck,2010}}{\sum_c X_{ck,2010}} \Delta X_{kt}^{ROW}$ is divided by the city-level working-age population in 2000, $L_{c,2000}$, to express the IV as export shock per worker (the unit is 1000 USD). The divided population of $\Delta ExportROW_{ct}$ is chosen in the year 2000 to avoid using the same population denominator of the population in 2010 in $\Delta Export_{ct}$ following Campante et al. (2023).

The validity of the IV in Equation 5 relies on the identification assumptions that (1) conditional on the control of time-varying city characteristics, city fixed effect, and province-year fixed effect, other time-varying city characteristics absorbed in the error term are not correlated with the IV $\Delta ExportROW_{ct}$; (2) there is strong correlation between the IV $\Delta ExportROW_{ct}$ and the key explanatory variable $\Delta Export_{ct}$; and (3) the IV satisfies the exclusion restriction. For (1), Borusyak et al. (2022) establish that the exogeneity assumption holds if the shocks are exogenous, allowing for the endogeneity of the shares. In this case, if the product-level export shocks are not correlated with the error term, the exogeneity assumption is valid. To validate this, I run a balance test recommended by Borusyak et al. (2022) (discussed in Appendix C) and the result indicates that export shocks for the rest of the world can be viewed as good as randomly assigned, which supports the exogeneity assumption. For the relevance assumption (2), the first-stage F statistic and the visualization of first-stage relationship (shown in Figure 2A) support that $\Delta ExportROW_{ct}$ is a strong IV. I assume the hold of exclusion restriction (Assumption (3)). The rationale is that the changing trade flows of different products in the rest of the world are determined

[6] The data source is UN Comtrade.

by the different recovery speeds of countries after the financial crisis, which is hard for cities in China to predict. Therefore, it is unlikely that the trade flows in the rest of the world would affect the city's construction-related measures through channels other than the export shocks experienced by their cities.

4 Export Slowdown and Construction Employment

This section presents evidence on how construction employment responds to the export slowdown. I begin by documenting the baseline relationship between export exposure and construction employment. I then examine heterogeneity in this response across local conditions associated with employment pressure, discuss the interpretation of the findings, and conduct robustness checks.

4.1 Main Result

Before showing the regression results, Figure 2 visualizes two key relationships: the relationships between city-level export changes and the rest-of-the-world export shock IV (first stage) and the relationship between the predicted city-level export changes using the IV and construction employment (second stage). The axes variables are residualized to remove the city fixed effect and province-year fixed effect and the export shocks variable is categorized into 50 bins. As shown in Figure 2A, there is a strong positive relationship between $\Delta Export$ and $\Delta ExportROW$, which is consistent with the high F statistic and supports the strong IV argument. Figure 2B presents a statistically significant negative relationship between export changes and construction employment changes, indicating that negative export shock is associated with an increase in construction employment. These patterns remain robust when excluding observations in the top and bottom tails of the export shock distribution.

Table 1 reports the IV regression results based on Equation 4. Columns (1) and (2) present the effect of the export slowdown on employment in the manufacturing sector, which is most directly exposed to the export shocks.[7] Column (1) presents the effect without time-varying city-level controls, while Column (2) incorporates these controls. On average, a one-standard-deviation increase in exposure to the export slowdown, which is

[7] Table A1 presents the immediate employment effects of the export slowdown across all industrial sectors. It shows that export slowdown immediately decreases manufacturing and transportation employment, with manufacturing employment reduction accounting for 95.1% of such employment decline.

equivalent to a reduction of $770 in export value per worker, leads to a decrease of 0.66 percentage points in the share of the working-age population employed in the manufacturing sector. However, in the subsequent period, cities more exposed to the export slowdown experienced a rise in construction employment, as evidenced in Columns (3) and (4). This increase in construction employment, amounting to 0.05 percentage points increase (around 2% of the average construction employment size) for a one-standard-deviation increase in export slowdown exposure, offsets about 7.6% of the employment loss in the manufacturing sector due to the export slowdown.[8] Note that the employment share is measured as the share of sectoral employment among the working-age population in 2010, so the increase in construction employment here is not mechanically driven by declines in manufacturing employment or by changes in population size.

Table 1. Export Shocks and Employment Outcomes

	Δ%Manufacturing Employment$_t$		Δ%Construction Employment$_{t+1}$	
	(1)	(2)	(3)	(4)
ΔExport	0.856***	0.854***	-0.069***	-0.069***
	(0.222)	(0.213)	(0.013)	(0.014)
City Controls	N	Y	N	Y
Province-year FE	Y	Y	Y	Y
City FE	Y	Y	Y	Y
First-stage F stat	106.575	113.050	106.575	113.050
Mean(%)	4.653	4.653	2.650	2.650
Observations	1137	1137	1137	1137

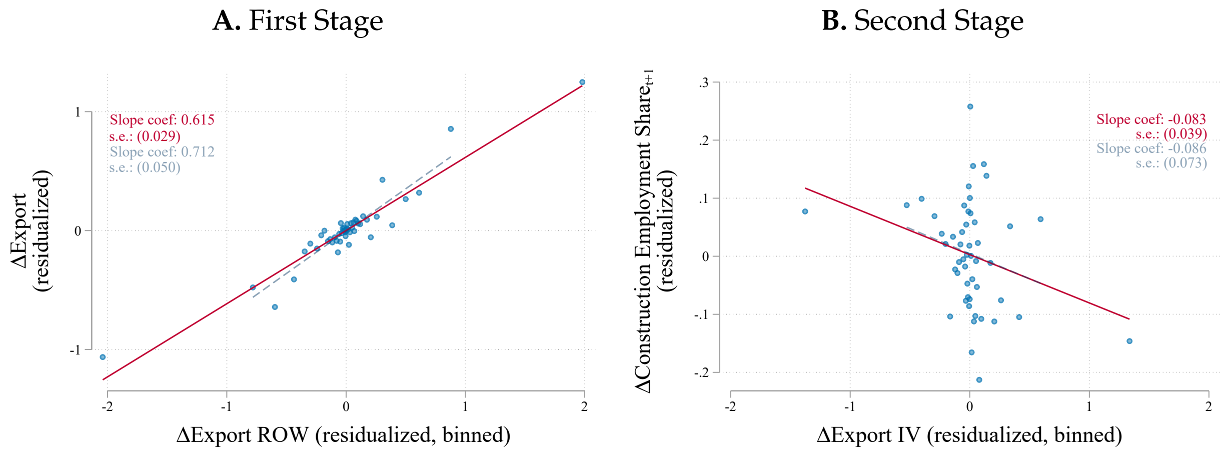
Note: The dependent variable is the change in the manufacturing employment between year $t-1$ and t (columns (1) and (2)) and the change in the construction employment between year t and $t+1$. Employment is defined as the ratio of total employed workers in the sector and city's working-age population. The key independent variable is the change in export values between year $t-1$ and t, normalized by the city's working-age population. The city controls include the changes in log college graduates and log urban population. All columns report the IV regression result and are weighted by the city's working-age population in 2010. The standard errors are clustered at the province level.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

To examine how employment adjusts across different sectors following the export slowdown, Figure 3 plots the coefficients of $\Delta Export_t$ for $\Delta Employment_{t+1}$ in all industrial sectors, estimated using Equation 4. The figure shows that construction is the only sector in which employment increases following the export slowdown. This pattern highlights

[8] 7.6% is calculates using 0.05/0.66.

the role of construction employment in absorbing labor after negative export shocks, when general employment is adversely affected.

Figure 2. Binned Scatter Plot: City Export Shocks and Construction Employment



Notes: All variables are residualized to remove the contribution of city fixed effect and province-year fixed effect. The export shock variable is categorized into 50 bins. The solid line fits all binned categories and the dashed line fits the binned categories excluding the top and bottom 2% of the sample.

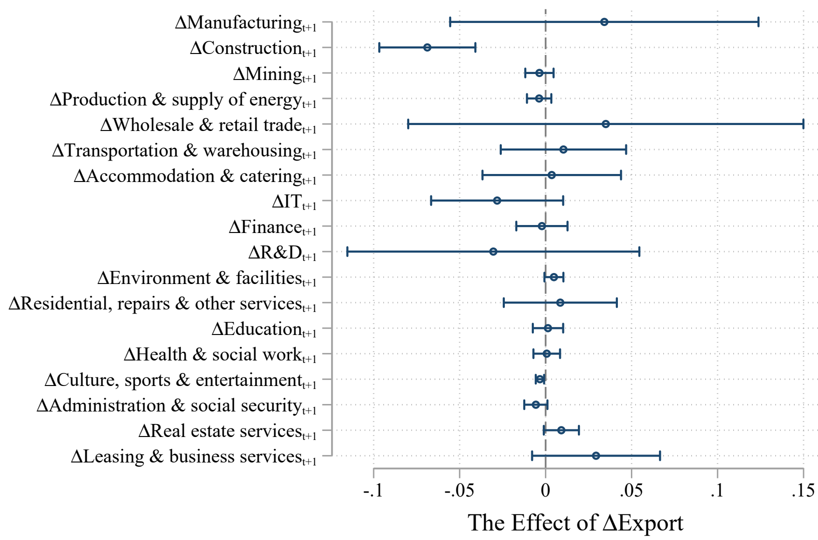
4.2 Heterogeneity by Employment Pressure

Having documented that cities respond to negative export shocks by expanding construction employment, this subsection examines whether the strength of this response varies with local conditions related to employment pressure. The underlying idea is that employment losses following the export slowdown may raise concerns about economic and social stability, leading some cities to respond more strongly than others.

Although local officials in China do not face electoral incentives, employment plays an important role in maintaining social stability and in the cadre evaluation system. In 2013, the Central Organization Department issued a notice reforming the performance evaluation system for local officials, emphasizing that, alongside GDP and its growth rate, assessments should prioritize high-quality and sustainable development, with particular attention to employment outcomes (Central Organization Department, 2013).[9] Employment matters for local leaders for two main reasons. First, it serves as a key indicator of local economic performance, reflecting officials' ability to sustain economic activity. Second, elevated

[9]The notice also highlighted additional dimensions such as environmental protection, innovation, education, social welfare, and public health.

Figure 3. Employment Following the Export Slowdown



Note: This figure plots the IV estimate of $\Delta Export_t$ on $\Delta Employment_{t+1}$ in all industrial sectors using specification as Columns (4) in Table 1.

unemployment can threaten social stability, which is central to regime legitimacy and has prompted substantial state investment in stability maintenance.[10]

I first examine heterogeneity in construction employment responses by characteristics of city leadership. If construction employment expansion reflects a response to employment pressure following the export slowdown, one would expect this response to be stronger in cities where local leaders are more responsive to such pressures. To capture differences in leaders' responsiveness, I exploit institutional age thresholds in the Chinese cadre system. The mandated retirement age for city leaders is 60, and the maximum promotion-eligible age is around 57 (Kou and Tsai, 2014). Therefore, younger leaders who have larger career incentives are expected to be more responsive. To measure such responsiveness, I define an indicator equal to one if the city party secretary is younger than 57.[11] Column (1) of Panel B in Table 2 shows that, conditional on exposure to the export slowdown, cities led by younger officials experience larger increases in construction employment in the subsequent period. This pattern indicates that the construction response is stronger in cities where leaders appear more responsive to employment-related pressures generated by the export shock.

I next examine heterogeneity by local labor unrest. As unemployment can heighten the risk of social instability, construction employment may serve as a response channel through which local governments address employment-related pressures. Column (1) of Panel C in Table 2 shows that, conditional on exposure to the export slowdown, cities experiencing larger increases in labor unrest exhibit larger expansions of construction employment in the subsequent period. This pattern indicates that the construction response is stronger in cities where employment pressures are more acute or more visible. I interpret this heterogeneity descriptively, as labor unrest itself may be affected by the export shock.

To further assess whether employment considerations underlying these construction responses are reflected in government policy discourse, I next examine city governments' emphasis on employment in their annual work reports. Each January, city governments deliver a work report to the People's Congress, summarizing accomplishments in the previous year and outlining policy priorities for the year ahead. These reports are widely viewed as articulating substantive policy directions for upcoming government actions (Jiang et al., 2019).

[10] For example, the state has made large investments in surveillance and security aimed at preventing social unrest.

[11] City party secretaries are treated as city leaders given their executive authority within the Chinese political system. The age cutoff at 57 is also used in prior work including Campante et al. (2023) and Jiang (2018).

Table 2. Heterogeneity of Construction Employment

	Δ*Employment focus*$_{t+1}$			
	Construction employment share	Employment count (log)	Employment focus (binary)	Employment focus (score)
	(1)	(2)	(3)	(4)
Panel A: Average effect				
ΔExport	-0.069***	-0.035	-0.030	-0.069
	(0.014)	(0.068)	(0.034)	(0.072)
Panel B: Differential effect by career incentive				
ΔExportIV	0.024	0.015	0.015**	0.073***
	(0.020)	(0.035)	(0.007)	(0.020)
ΔExportIV × Age $\leq$ 57	-0.055***	-0.073**	-0.040***	-0.133***
	(0.018)	(0.035)	(0.013)	(0.042)
Age $\leq$ 57	-0.212	0.142*	-0.005	0.168
	(0.141)	(0.082)	(0.082)	(0.206)
Panel C: Differential effect by labor unrest				
ΔExportIV	-0.009	-0.032	-0.012	-0.006
	(0.023)	(0.038)	(0.020)	(0.046)
ΔExportIV × ΔUnrest	-0.009**	-0.034***	-0.022**	-0.045*
	(0.004)	(0.012)	(0.008)	(0.022)
ΔUnrest	-0.015	-0.010	-0.001	-0.061
	(0.021)	(0.024)	(0.015)	(0.055)
Observations	1131	1076	1076	1076
Mean	2.656	9.264	0.910	2.923
City Controls	Y	Y	Y	Y
CPS Controls	Y	Y	Y	Y
Province-year FE	Y	Y	Y	Y
City FE	Y	Y	Y	Y

Note: The dependent variables are the change in construction employment (Column (1)), log employment counts in GWRs (Column (2)), a bianry variable on whether governments focus on employment stability and creation in GWRs (Column (3)), and the degree to which the governments focus on employment stability and creation in GWRs (Column (4)) between year t and $t+1$. Panel A examines the average effect using IV regression. Panels B and C examine the heterogeneity by city leaders' age and changes in cities' labor unrest. All regressions are weighted by the city's working-age population in 2010. The standard errors are clustered at the province level.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

I construct two measures of employment emphasis from these reports. The first measure counts the frequency of which governments mention "employment" ("就业") in their reports. Because some of such mentions could be purely descriptive, for example, reporting employment levels without policy intent, I also construct a text-based measure using a large language model. Specifically, I identify sections of each report that discuss employment-related topics, defined as sections containing references to "employment" ("就业") or "livelihood" ("民生").[12] These employment-related passages are then evaluated using a predefined scoring rubric that captures multiple dimensions of employment emphasis, including the urgency of employment stabilization and the strength of employment policy commitments. Appendix D provides details on the prompt. This approach yields two measures: (i) a binary variable for whether the report emphasizes maintaining or increasing

[12]Government work reports follow a standardized format, with each section typically addressing a distinct policy area.

employment, and (ii) an ordinal measure ranging from 1 to 5 reflecting the intensity of such emphasis.

Columns (2) - (4) in Table 2 present the results on the impact of export slowdown on city governments' employment focus in the annual work reports. Panel A shows that, on average, exposure to the export slowdown does not significantly affect employment emphasis in government work reports. However, Panel B and C show substantial heterogeneity. Conditional on exposure to the export slowdown, cities led by younger leaders and cities experiencing larger increases in labor unrest place greater emphasis on employment in their work reports, both in terms of the frequency of employment-related mentions and the intensity of stated commitments to employment stabilization and creation. This heterogeneity mirrors the patterns observed for construction employment responses and supports the interpretation that construction expansion following the export slowdown is more pronounced in cities where employment-related pressures are greater.

4.3 Discussion of the Results

One potential concern is that the manufacturing sector in China employs large numbers of migrant workers without local household registration (*hukou*), raising the question of why local governments would respond to manufacturing job losses by creating employment for this group. I address this concern in two ways. First, although migrants constitute an important component of the manufacturing workforce, they do not dominate the sector: migrants account for approximately 34% of manufacturing workers in the 2010 Census.[13] As a result, employment losses in manufacturing directly affect a substantial share of local *hukou* holders as well. Second, even when displaced workers are migrants, local governments still have strong incentives to respond. Migrant workers are central participants in collective actions, labor disputes, and protests over layoffs (Friedman, 2014; Rho, 2023; Elfstrom, 2021), and maintaining social stability is a core agenda for local governments regardless of *hukou* status. From the perspective of local officials, this rising unemployment, whether among migrants or local residents, could be a direct threat to social stability.

At first glance, the increase in construction employment following the export slowdown, together with the finding that cities led by younger leaders exhibit larger

[13] This figure is calculated using the 2010 Census. For the construction sector, around 22% of the workers are migrants.

construction responses, could be interpreted as a standard counter-cyclical policy response. During economic downturns, governments often expand construction and infrastructure investment to stimulate economic activity, and leaders with stronger career concerns may respond more aggressively. Even under this interpretation, however, the evidence points to employment stability as a central consideration. Construction employment increases are significantly larger in cities experiencing greater labor unrest following the export slowdown, and, as shown in Table 2, leaders in these cities also place greater emphasis on employment stability and job creation in their government work reports. These heterogeneity patterns suggest that local governments respond not only to adverse economic conditions, but also to labor market instability, with stronger responses where threats to employment stability are more salient.

Table 3. Automation Shocks and Employment Outcomes

	Δ%Manufacturing Employment$_t$		Δ%Construction Employment$_{t+1}$	
	(1)	(2)	(3)	(4)
ΔRobot	-1.625***	-1.633***	0.109*	0.115**
	(0.395)	(0.398)	(0.054)	(0.055)
City Controls	N	Y	N	Y
Province-year FE	Y	Y	Y	Y
City FE	Y	Y	Y	Y
First-stage F stat	54.447	53.920	54.447	53.920
Mean(%)	4.692	4.692	2.679	2.679
Observations	1121	1121	1121	1121

Note: The dependent variable is the change in the manufacturing employment between year $t-1$ and t (columns (1) and (2)) and the change in the construction employment between year t and $t+1$. Employment is defined as the ratio of total employed workers in the sector and city's working-age population. The key independent variable is the change in industrial robots between year $t-1$ and t, normalized by the city's working-age population. The city controls include the changes in log college graduates and log urban population. All columns report the IV regression result and are weighted by the city's working-age population in 2010. The standard errors are clustered at the province level.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Moreover, this employment stability interpretation cannot be fully explained by counter-cyclical economic pressure alone. Construction employment expansion is not simply a by-product of aggregate economic stimulus. To distinguish between these two channels, I examine construction responses to automation-induced labor demand shocks. As shown in Table 3, robot exposure leads to substantial declines in manufacturing employment, while the construction employment in these cities increases in the following period.[14] This pattern closely mirrors the employment response observed in the setting of export slowdowns, despite automation shocks do not hurt the economic growth rate (Table F1 presents the impact of automation shocks and export slowdowns on nigh light intensity as a comparison). As in the setting of export slowdowns, the construction response to automation shocks is stronger in cities experiencing larger increases in labor unrest, and these cities also place greater emphasis on employment stability and employment creation in their government work reports (Table F4). Together, these patterns indicate that construction employment expansion reflects responses to employment pressure even in the absence of economic downturns.

Another related question is why local governments respond to employment losses through the construction sector. As discussed in Section 5.1, construction is a labor-intensive sector, and expansion is administratively straightforward because local governments control land allocation and can stimulate construction activity through land sales. This does not imply that construction is the only channel through which governments can create employment; for example, governments may also expand employment through state-owned enterprises (Wen, 2022; Huang et al., 2021). Rather, construction represents a feasible and scalable response channel through which local governments can address employment pressures in the short run.

4.4 Robustness Checks

This section performs a series of robustness checks to validate the result.

Specification Checks. Column (1) of Table E1 first shows that the result remains stable when the regression is unweighted. Column (2) additionally includes the controls of city leaders' characteristics, including age, the square term of their age, tenure, and the dummies of their educational degrees. Column (3) uses a different construction of the dependent variable. Instead of using the working-age population from the 2010 Census as the base to construct the construction employment share, Column (3) uses the population data obtained from the CSY as the base to construct the construction employment share. The result remains robust across different specifications.

Influential Observations. To check if the result is driven by any specific province or any specific industry, I leave out a province and an HS section at a time and re-estimate

[14] Appendix F presents more results on the impact of automation in employment across different industrial sectors.

Equation 4. Figure E1 plots coefficients of export shocks when each province is dropped from the sample and Figure E2 plots coefficients of export shocks when each HS section is dropped when constructing the export shock variable and the SSIV variable. The estimate is stable and remains negative and statistically significant to the exclusion of any province and any HS section, suggesting the result is not driven by any outlier of industry or province.

Alternative Inferences. Finally, I check whether the result is robust by clustering the standard errors at several alternative levels. Column (1) in Table E2 reports the result clustered at the provincial level. Column (1) also reports the 95% confidence interval based on the wild cluster bootstrap-t procedure recommended by Cameron et al. (2008) in the concern of the small number of clusters that my sample has 26 provinces.[15] I also implement the "tF inference" for IV proposed by Lee et al. (2022) to confirm the statistical significance of the IV estimate. The tF confidence intervals are reported at the bottom of Column (1). Column (2) in Table E2 clusters the standard error at the city level to allow for the within-city and across-year correlation.

As pointed out by Adao et al. (2019), the regression residuals in the shift-share specification would be correlated across regions with similar sectoral composition, regardless of their geographic proximity, in the presence of unobserved sectoral shifts. As a consequence, clustering standard errors at the geographic unit level will lead to over-rejection of the null hypothesis. To address this concern, I follow Campante et al. (2023) and use alternative clusters based on the similarity of the city's export structure.[16] Following Campante et al. (2023), the city-level similarity index takes the following form:

$$SimilarityIndex_{c,j}^{ROW} = \sum_k min\{\frac{X_{ck}^{ROW}}{X_c^{ROW}}, \frac{X_{jk}^{ROW}}{X_j^{ROW}}\} \quad (6)$$

where $\frac{X_{ck}^{ROW}}{X_c^{ROW}}$ is export share of product k in city c's total exports. The index is constructed using the provincial capital cities as the reference group, with j denoting the provincial capital city. The index takes a value between 0 and 1, with 0 denoting the two cities having no similarity in their export structure. In Column (3), the cluster group is created by assigning each city to the group of the provincial capital city that is most similar to it. In Column (4), the cluster group is created by assigning each city to the group of the

[15] Beijing, Shanghai, Tianjin and Chongqing are excluded in my main sample as these four are provincial cities.

[16] Note that the standard-error correction approach proposed in Adao et al. (2019) cannot be applied in my context since the number of products is far larger than the number of cities.

provincial capital city that is outside its province and most similar to it. The baseline result remains robust to these alternative clustering choices.

5 Strategy and Suggestive Consequences of Construction Employment Creation

Having established that the construction sector absorbs part of the employment losses following negative export shocks, this section examines how city governments generate construction employment and discusses the potential downstream consequences of relying on construction as an employment-absorbing mechanism.

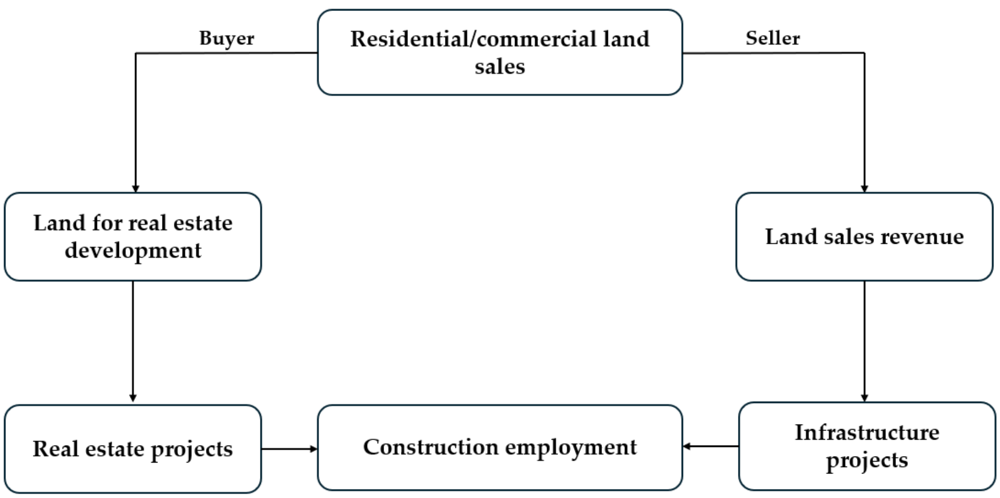
5.1 Land Sales As A Strategy

What drives the observed increase in construction employment following adverse labor shocks? Given the institutional setting and the role of employment-related pressures documented earlier, how do local governments create these jobs? This subsection examines one strategy local governments use to expand construction employment: land sales.

Government land sales can increase construction employment through two main channels, as illustrated in Figure 4. First, city governments can sell land intended for real estate development, enabling real estate developers to initiate housing construction projects. Second, revenue from land sales expand local fiscal capacity to finance infrastructure projects, which directly generate construction employment. Although land transfer revenue can be used across several designated categories, regulations generally earmark it toward land-related and urban development spending—such as land acquisition and demolition compensation, land development, and urban construction (State Council, 2006). In practice, local governments have relied heavily on land-related revenues to finance urban infrastructure investment (Cai et al., 2013). An increase in land sales revenue therefore provides cities with greater capacity to undertake construction projects.

To examine whether land sales operate as a channel through which construction employment expands following negative export shocks, Table 4 analyzes how export slowdown exposure affect the government land sales and related construction projects. Column (1) of Table 4 shows that city governments more exposed to negative export shocks have larger land sales revenue. Table A3 further decomposes the land sales by land

Figure 4. Conceptual Figure



Notes: This figure illustrates how government land sales can create construction employment.

use and shows that this increase is driven by greater sales of residential and commercial land—those most directly linked to real estate development—while industrial land sales remain unchanged.

Consistent with the channels illustrated in Figure 4, Column (2) shows that cities more exposed to the export slowdown also exhibit higher real estate investment, reflecting an increase in real estate projects. Moreover, because higher land sales revenue expands local fiscal capacity for infrastructure investment, Columns (3) - (5) show that these cities undertake more infrastructure construction projects, including a larger number of newly built intersections and bridges, as well as higher government expenditure on public housing. Public housing project (*Penghuqu*) are typically government-financed and labor-intensive urban construction projects, making them a common instrument through which local governments expand construction activity.

Table 4. Export Shocks and Construction Projects

	ΔLand sales	ΔReal estate	$\Delta\text{Infrastructure}_{t+1}$		
	(1) Log Revenue	(2) Log Investment	(3) Num Intersection	(4) Num Bridge	(5) Log Public housing
ΔExport	-0.077***	-0.025***	-2.168**	-11.318**	-0.102***
	(0.015)	(0.009)	(0.861)	(4.823)	(0.025)
City Controls	Y	Y	Y	Y	Y
Province-year FE	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y
First-stage F stat	112.914	112.876	92.926	106.637	67.402
Mean	8.944	0.015	1.024	8.372	1338.579
Observations	1138	1135	746	1090	1083

Note: The dependent variable is the change in log government land sales revenue (Column (1)), log real estate investment (Column (2)), number of newly constructed intersections (Column (3)), number of newly constructed bridges (Column (4)), and log government expenditure on public housing (Column (5)). The key independent variable is the change in export values between year $t-1$ and t, normalized by the city's working-age population. The city controls include the changes in log college graduates and log urban population. All columns report the IV regression result and are weighted by the city's working-age population in 2010. The standard errors are clustered at the province level. The mean is taken at the level instead of the change in level.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

5.2 Longer-run Consequences

So far, I have shown that city governments respond to negative export shocks by expanding construction activity through land sales. This response helps absorb part of the manufacturing employment loss in the short run and contributes to employment stabilization. However, reliance on land-financed construction may also entail longer-run costs. This subsection examines whether such responses are associated with increased real estate risks in subsequent years.

One potential longer-run concern is that government incentives to expand residential land sales may encourage housing supply to grow faster than underlying market demand. Such supply expansion can weaken developers' cash flows, especially when housing demand slows. Moreover, real estate developers in China often rely heavily on debt financing to acquire land and fund construction. Government-driven increases in residential and commercial land sales may therefore contribute to higher leverage among developers, raising their exposure to financial distress. When credit conditions tighten and housing demand weakens, highly leveraged developers face elevated risks of liquidity shortages, which can lead to project delays or suspensions.

I examine the potential longer-term consequence on the real estate risk in the context of the central government's tightening of regulations on real estate developers' debt beginning in 2020. For years prior, Chinese real estate developers have had relatively easy access to credit. However, in 2020, the central government imposed strict measures to curb excessive borrowing, requiring developers to reduce leverage before expanding debt (Economic Daily, 2021). This regulation, along with the sluggish housing demand, can increase financial stress among developers who had relied on debt to sustain ongoing construction projects. With many apartments being presold,[17] the financial strain of those real estate developers resulted in unfinished but sold housing projects, provoking collective protests from homeowners who needed to pay mortgages on the unfinished apartments.

To proxy for city-level real estate risk, I use data on homeowners' collective protests against unfinished housing projects. Specifically, I draw on a crowdsourced repository, "WeNeedHome", which collects information on properties where collectives of homeowners have initiated or threatened to request a loan suspension for their mortgages on the unfinished apartments.[18] As of 2023, the dataset records 348 properties across 94

[17] According to The New York Times (2022), about 90 percent of new homes in China were "presold."

[18] The GitHub page can be found in https://github.com/WeNeedHome/SummaryOfLoanSuspension. Data were retrieved in September 2023.

cities where homeowners have taken collective loan suspension for unfinished housing protests. I construct a city-level binary variable, with one denoting at least one such protest occurred in the city, which serves as a proxy for heightened real estate risk.

To examine the longer-run consequences of the government response to the export slowdown, I estimate the following regression:

$$Protest_{c,p} = \beta \Delta Export_{c,cum} + \Gamma X_c + \lambda_p + \epsilon_c \tag{7}$$

where c denotes city and p denotes province. Equation 7 uses a cross-sectional regression with $Protest_{c,p}$ equal to 1 if city c has experienced at least one event of homeowners' collective protests against unfinished housing following the post-2020 tightening of real estate financing regulations. $\Delta Export_{c,cum}$ is the cumulative change in export values per worker between 2012 and 2016. λ_p denotes the province fixed effect, and standard errors are clustered at the province level. $\Delta Export_{c,cum}$ is instrumented using the culmulative IV specified in Equation 5. ΓX_c are the city-level controls including whether the city is a provincial city, the cumulative change in college enrollment share, mobile phone users share, and Internet users share, and cumulative change in urban population.

Table 5 presents the results. Columns (1) and (2) show that cities with greater cumulative exposure to the export slowdown experienced higher cumulative land sales revenue, consistent with the short-run evidence in Table 4. Columns (3) and (4) then link this cumulative export exposure to the subsequent real estate risk. Cities more exposed to export slowdowns are significantly more likely to experience protests over unfinished housing projects after 2020. It is important to acknowledge that these estimates capture the reduced-form relationships, as export slowdowns may affect real estate protests through other channels beyond land-sales-driven construction. Nonetheless, the findings suggest a potential tradeoff between short-run employment stabilization through construction expansion and longer-run instability in the housing sector.

6 Concluding Remarks

This paper studies how city governments in China respond to negative labor market shocks by expanding construction activity. Exploiting variation in cities' exposure to the mid-2010s export slowdown, I show that more exposed cities experience substantial manufacturing employment losses followed by increases in construction employment.

Table 5. Longer-run Consequence

	Cum Land Revenue		Real Estate Protest	
	(1)	(2)	(3)	(4)
$\Delta\text{Export}_{cum}$	-0.259*	-0.123***	-0.074**	-0.042**
	(0.141)	(0.030)	(0.029)	(0.015)
City Controls	N	Y	N	Y
Province FE	Y	Y	Y	Y
First-stage F stat	10.259	11.899	10.259	11.899
Mean(%)	8.699	8.699	0.272	0.272
Observations	328	248	328	248

Note: The dependent variable is the cumulative city-level land sales revenue between 2012 and 2016 (Columns (1) - (2)) and a binary variable on whether the city experienced at least one protest over unfinished housing since 2020 (Columns (3) - (4)). The key independent variable is the cumulative change in export values between 2012 and 2016, normalized by the city's working-age population. The city controls includ whether the city is a provincial city, the cumulative change in college enrollment share, mobile phone users share, and Internet users share, and cumulative change in urban population. All columns report the IV regression result and are weighted by the city's working-age population in 2010. The standard errors are clustered at the province level.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

This construction response is stronger in cities led by younger officials with stronger career incentives and in cities experiencing greater labor unrest, and it is accompanied by increased emphasis on employment stability in government work reports. Together, these patterns suggest that construction serves as an important margin through which local governments stabilize employment during downturns.

I further document that land sales play an important role in facilitating this construction expansion response. Cities more exposed to export slowdowns increase land sales for real estate development, which in turn is associated with higher real estate investment and greater infrastructure construction. These findings highlight how an institutional feature of China's local public finance system enables governments to rapidly expand construction activity in response to adverse labor market conditions.

While construction employment creation helps mitigate employment loss in the short run, the paper also points to a potential longer-run consequence of this strategy. Cities with greater cumulative exposure to export slowdowns are more likely to experience protests over unfinished housing projects following the tightening of real estate financing regulations. These results suggest a tradeoff between short-run employment stabilization and longer-run financial vulnerabilities associated with land-financed construction expansion.

The findings contribute to a broader literature on government responses to negative economic shocks by showing how employment considerations shape policy choices even outside democratic settings. More broadly, the paper illustrates how political incentives can be associated with policy responses that deliver immediate employment benefits but may also entail longer-term costs—a pattern that is not unique to China and resonates with evidence from a wide range of institutional contexts.

I conclude this paper by noting some limitations. First, land sales are unlikely to be the only channel through which local governments expand construction employment during economic downturns, and land sales themselves may reflect motives beyond employment stabilization. Future research could explore alternative policy tools and disentangle their relative importance. Second, the institutional mechanisms emphasized in this paper, particularly government control over land supply, are specific to China, and the strategies and longer-run implications may differ in other settings. Finally, while the paper documents suggestive evidence of longer-run real estate risks associated with land-financed construction expansion, a comprehensive cost–benefit analysis and welfare assessment of these policies lies beyond the scope of this study.

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Online Appendices

Contents

A Additional Tables

Table A1. Export Shocks and Employment in the Current Period

	ΔEmployment$_t$					
	(1) Manufacturing	(2) Construction	(3) Mining	(4) Energy	(5) Transportation	(6) Services
ΔExport	0.673***	-0.153	-0.009	-0.001	0.035*	-0.016
	(0.167)	(0.139)	(0.009)	(0.003)	(0.020)	(0.163)
City Controls	Y	Y	Y	Y	Y	Y
Province-year FE	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y
First-stage F stat	112.914	112.914	105.460	112.914	112.914	112.589
Mean(%)	4.652	2.649	1.024	0.384	0.641	8.093
Observations	1138	1138	1041	1138	1138	1152

Note: The dependent variable is the change in the employment between year $t-1$ and t in (1) the manufacturing sector, (2) the construction sector, (3) the mining sector, (4) the energy and utility sector, (5) the transportation sector, and (6) services sectors. Employment is defined as the ratio of total employed workers in the sector and the city's working-age population. The key independent variable is the change in export values between year $t-1$ and t. The city controls include the changes in log college graduates and log urban population. All columns report the IV regression result and all regressions are weighted by the city's working-age population in 2010. The standard errors are clustered at the province level.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table A2. Export Shocks and Employment in the Next Period

	ΔEmployment$_{t+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
	Manufacturing	Construction	Mining	Energy	Transportation	Services
ΔExport	0.027	-0.054***	-0.003	-0.003	0.008	0.036
	(0.034)	(0.011)	(0.003)	(0.003)	(0.014)	(0.078)
City Controls	Y	Y	Y	Y	Y	Y
Province-year FE	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y
First-stage F stat	112.904	112.904	67.526	112.904	112.904	112.589
Mean(%)	4.651	2.648	1.017	0.385	0.642	8.093
Observations	1139	1139	1045	1139	1139	1152

Note: The dependent variable is the change in the employment between year t and $t+1$ in (1) the manufacturing sector, (2) the construction sector, (3) the mining sector, (4) the energy and utility sector, (5) the transportation sector, and (6) services sectors. Employment is defined as the ratio of total employed workers in the sector and the city's working-age population. The key independent variable is the change in export values between year $t-1$ and t. The city controls include the changes in log college graduates and log urban population. All columns report the IV regression result and all regressions are weighted by the city's working-age population in 2010. The standard errors are clustered at the province level.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table A3. Export Shocks and Government Land Sales

	ΔRevenue (log)			ΔArea (log)		
	(1)	(2)	(3)	(4)	(5)	(6)
	Residential	Commercial	Industrial	Residential	Commercial	Industrial
ΔExport	-0.071***	-0.186***	0.033	-0.035**	-0.065	-0.003
	(0.016)	(0.045)	(0.027)	(0.016)	(0.041)	(0.027)
City Controls	Y	Y	Y	Y	Y	Y
Province-year FE	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y
First-stage F stat	112.914	115.706	113.098	112.914	119.243	113.098
Mean	8.331	7.380	6.744	5.413	4.733	5.726
Observations	1138	1136	1135	1138	1137	1135

Note: The dependent variable is the change in log government land sales revenue for residential land, commercial land, and industrial land (Column (1) - (3)) and change in log government land sales area for residential land, commercial land, and industrial land (Column (4) - (6)). The key independent variable is the change in export values between year $t-1$ and t, normalized by the city's working-age population. The city controls include the changes in log college graduates and log urban population. All columns report the IV regression result and are weighted by the city's working-age population in 2010. The standard errors are clustered at the province level. The mean is taken at the level instead of the change in level.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

B Auxiliary Data

City-level Controls. The data on city-level characteristics are obtained from China's City Statistical Yearbooks. In this paper, I use information on city-level share of college students, urban population, and the share of households using the Internet and mobile phones.

City Leaders' Characteristics. This paper considers city party sectaries as city leaders as they hold the top authority and executive discretion in a city given the leading position of Chinese Communist Party.[1] I collect information on the characteristics and career trajectories of city leaders by compiling data from Yao et al. (2022) and Jiang (2018), which provide information on each official's education, political ranking, birth city, political experiences, and career history.

Construction Projects. Data on construction projects are obtained from China's City Statistical Yearbooks. I focus on two types of construction projects: real estate projects and infrastructure projects. I use information on the city's investment in real estate projects to proxy for real estate projects. Infrastructure projects are measured using the area of constructed roads, constructed bridges, and constructed intersections in the subsequent period, which are obtained from the Urban Construction Statistical Yearbook.

Real Estate Risk. To measure real estate risk, I use the incidence of homeowners' collective protests against paying mortgages on unfinished apartments, leveraging data from a crowdsourced list titled "WeNeedHome" on GitHub.[2] This repository collects information on properties where collectives of homeowners have initiated or threatened to request a loan suspension for their mortgages on the unfinished apartments. As of the data retrieved in 2023, the list includes 348 properties across 94 cities in China where homeowners have taken collective loan suspension for unfinished housing protests.

[1] Previous literature also regards local party sectaries as local leaders. See, for example, Persson and Zhuravskaya (2016); Campante et al. (2023); Wang et al. (2020).

[2] The GitHub page can be found in https://github.com/WeNeedHome/SummaryOfLoanSuspension.. The data used is retrieved in September, 2023.

C Validity of the Bartik Instrument

The validity of the IV relies on the identification assumptions that conditional on the control of time-varying city characteristics, city fixed effect, and province-year fixed effect, other time-varying city characteristics absorbed in the error term are not correlated with the shift-share IV. According to Borusyak et al. (2022), this assumption holds when the shifts at the product level are as good as randomly assigned.

In particular, the identification assumption can be written as

$$\sum_{k} s_k g_{kt} \phi_k \xrightarrow{p} 0 \tag{C1}$$

where $g_{kt} = \frac{\Delta X_{kt}^{ROW}}{\sum_c X_{ck,2010}}$ is the shift of product k from the rest of the world divided by the total exporting value of product k in China in 2010. $s_k = \sum_c e_c s_{ck}$ is the weighted average of export exposure to product k across city, where $s_{ck} = \frac{X_{ck,2010}}{L_{c,2000}}$ is city c's initial exposure of product k and e_c is the regression weights in the city-level regression models. $\phi_k = \frac{\sum_c (e_c s_{ck} \epsilon_c)}{\sum_c (e_c s_{ck})}$ is an exposure-weighted expectation of city c's initial characteristics. Equation C1 states the condition of as good as randomly assigned shocks that when weighted by s_k, the correlation of g_{kt} and ϕ_k goes to zero when the sample is large. This can be tested by regressing g_{kt} on ϕ_k weighted by s_k and checking whether the coefficient of ϕ_k is zero.

I consider two sets of city's initial characteristics that may enter ϵ_c hence ϕ_k: (i) city's initial characteristics in 2010, including the share of college graduates, the share of construction employment, the share of manufacturing employment, export to GDP ratio, the share of the non-hukou population, log GDP per capita, and log fiscal revenue per capita; and (ii) pretrends in the outcomes of interest including the change in construction employment share, the change in manufacturing employment share, the change in real estate investment (logged), the change in constructed roads (logged), the change in land sales revenue (logged), the change in land sales area (logged), and the change in land price (logged). Table C1 reports the coefficients and the standard errors for these two sets of city characteristics. All coefficients are not statistically significant, which assures the exogeneity of shocks.

Borusyak et al. (2022) also establish that the effect of the export slowdown can also be estimated using product-level regression, and the magnitude should be identical to the city-level regression. To check this, I run a regression of $\Delta Construction\ employment_{kt}^{\perp}$ on

Table C1. Balance Tests of Product Shocks

	(1) Coef	(2) SE
Predetermined City Characteristics:		
Share of college graduates (%)	0.0059	0.0044
Share of construction employment (%)	0.2194	0.1693
Share of manufacturing employment (%)	0.9650	0.7263
Export to GDP ratio (%)	0.1231	0.0942
Share of non-Hukou population (%)	0.0827	0.0611
Log GDP per capita	0.0010	0.0008
Log fiscal revenue per capita	0.0016	0.0012
Pretrend in Outcomes:		
ΔShare of construction employment (%)	0.0696	0.0521
ΔShare of manufacturing employment (%)	0.0081	0.0323
ΔLog Real estate investment	-0.0192	0.0136
ΔLog Constructed road	-0.0064	0.0050
ΔLog Land revenue	0.0491	0.0426
ΔLog Land area	-0.0537	0.0447
ΔLog Land price	0.0010	0.0008

Note: This table reports coefficients and standard errors (multiplied by 10,000 for readability) from regressing product-specific weighted averages of pre-export-slowdown period's city characteristics and outcome variables on HS6 product-level export shocks, which is recommended by Borusyak et al., 2022. Standard errors are clustered by HS 4-digit codes. All regressions are weighted by the average HS6 product-level export exposure across cities. The predetermined city characteristics are in the year 2010 and the pretrend outcomes are chosen in the year 2011-2012. The shock is constructed starting in the year 2013.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

$\Delta Export^{\perp}_{kt}$ and use $\frac{\Delta X^{ROW}_{k}}{\sum_c X_{ck,2010}}$ as IV, where superscript $\perp$ refers to the product-level analog of the city-level variables.[3] Table C2 presents the product-level regression result. The coefficient of $\Delta Export^{\perp}_{kt}$ is equal to the coefficient of $\Delta Export$ in the city-level regression.

Another concern on the shift-share IV is related to the "incomplete share" problem brought up in Borusyak et al. (2022) that the initial export exposure could be correlated with the time trends in construction employment share.[4] The city fixed effects remove any time-invariant effects of city's initial exposure share. To address the potential time-varying effect of initial exposure share, I further control the initial exposure share-year fixed effects. I separately control for the deciles, quintiles, quartiles, and terciles of the initial export exposure by year fixed effect. Table C3 shows that the effect of export slowdown on construction employment share remains robust when taking the "incomplete share" problem into account.

Table C2. Product-level Regression

	(1)
	ΔConstruction Employment$^{\perp}_{k,t+1}$
ΔExport$^{\perp}_{kt}$	-0.069***
	(0.022)
First-stage F stat	11.974
Observations	17596

Note: This table reports the result of the product-level IV regression. The dependent variable is product-level analogous to change in construction employment share. $ExpShock^{\perp}_{kt}$ is product-level analogous of export change in city's export change. Standard errors are clustered at HS 2-digit codes.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

[3] Specifically, $\Delta Construction\ employment^{\perp}_{kt} = \sum_c e_c s_{ck} \Delta Construction\ employment^{\perp}_{c}$ and $\Delta Export^{\perp}_{kt} = \sum_c e_c s_{ck} \Delta Export^{\perp}_{c}$, where $\Delta Construction\ employment^{\perp}_{c}$ and $\Delta Export^{\perp}_{c}$ are the residualized land sales revenue and export shock after controlling the city time-varying characteristics, city fixed effects and province-year fixed effects.

[4] The equivalence of exogenous shocks and condition of IV validity builds on the assumption of constant share among observations

Table C3. Controlling for Incomplete Share

	ΔConstruction Employment$_{t+1}$			
	(1)	(2)	(3)	(4)
ΔExport	-0.150**	-0.060**	-0.069***	-0.068***
	(0.054)	(0.024)	(0.024)	(0.017)
City Controls	Y	Y	Y	Y
Exposure-year FE	Y	Y	Y	Y
Province-year FE	Y	Y	Y	Y
City FE	Y	Y	Y	Y
First-stage F stat	60.669	92.562	93.244	102.982
Mean	1123	1123	1123	1123

Note: The dependent variable in this table is the change in log land sales revenue. Column (1) controls the deciles of initial exposure share by year fixed effect. Column (2) controls the quintiles of initial exposure share by year fixed effect. Column (3) controls the quartiles of initial exposure share by year fixed effect. Column (4) controls the terciles of initial exposure share by year fixed effect. Standard errors are clustered by HS 2-digit codes.

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

D Construction of the LLM-based Employment Focus Measure

To get the score of governments focus on maintaining and increasing employment, I feed the extracted text to GPT-4.1 using a structured prompt and requiring the model to generate four outputs:

1. Binary employment focus indicator
2. Ordinal employment focus score (1-5)
3. The reason for the score
4. Direct quote on keywords on which the model gives the score

In the rubric, I instruct the model to distinguish between **routine reporting** (e.g., employment statistics, training numbers), which reflects standard administrative reporting and does not signal employment concern, and **genuine employment concern and policy actions**, including mentioning expanded hiring efforts, employment stabilization measures, and language elevating employment as a priority.

The model is instructed to base its evaluation on semantic intensity and policy intent, instead of a simple word frequency. Specifically, the full prompt is as follows.

Task Description

Your task is to evaluate the text from the Government Work Report for its level of "employment focus".

Specifically, the evaluation focuses on whether the government:

- Whether the government expresses employment pressure.
- Whether it proposes stabilizing employment, protecting employment, or expanding employment.
- Whether it shows intent to absorb labor or create jobs.
- Whether it treats employment as a political priority.
- Whether it uses policy-intensifying language.

Judgment should be based on **semantic intensity** and **policy intent**, explicitly distinguishing between routine reporting and genuine employment concern.

Definition of Routine Content

The following types of content are routine content and not counted as employment focus or concern.

- Reporting employment statistics (e.g., “added X new jobs", “unemployment rate is x").
- Standard numerical updates (re-employment numbers, training statistics).
- Pure reporting without policy intent.

Core rules of languages related to employment concern

Employment focus and concern is identified based on the presence of at least one of the following:

- Expressions of employment stabilization or employment pressure. (e.g., “就业压力",“保就业", “就业形势严峻")
- Expansion of employment or labor absorption. (e.g., “扩大就业",“吸纳就业", “创造岗位")
- Elevating employment as a priority. (e.g., “就业优先",“就业是最大民生")
- Non-routine employment policy actions (e.g., programs, projects, engineering work to absorb labor) (e.g., “扶持就业项目")

Examples of employment-focused language include:

> "expanding employment," "stabilizing and expanding employment," "employment assistance," "promoting employment for key groups".

For each input text, you will need to give

1. a binary classification on whether the text reflects employment focus and concern.
2. an ordinal score from 1-5 on the extent to which the report highlights employment focus and concern.
3. a short explanation justifying the classification.
4. quoted phrases from the text on which you give the assessment.

Rules for Binary classification (0/1/"NA")

- **1**: contains any employment concern/ focus related languages.
- **0**: only routine numerical reporting on employment statistics or no employment-related languages at all.

- **NA**: insufficient information to determine or hard to determine.

Rules for Ordinal Score (1-5/"NA")

- **1**: very weak (routine reporting only or no employment-related languages)
- **2**: weak (employment mentioned without policy emphasis)
- **3**: moderate (clear employment policy actions)
- **4**: strong (use of intensifying verbs for the policy) (e.g., 大力、坚决切实、突出 + 就业)
- **5**: very strong (employment mentioned as a core task or linked to stability) (e.g., 把就业作为民生之本，全力扩大就业)
- **NA**: insufficient information to determine or hard to determine.

E Robustness Check

E.1 Robustness Check on Construction Employment

Table E1. Robustness: Specification

	Δ%Construction Employment$_{t+1}$		
	(1) No weight	(2) CPS control	(3) Alt. D.V.
ΔExport	-0.098***	-0.074***	-0.092*
	(0.024)	(0.026)	(0.046)
City Controls	Y	Y	Y
Province-year FE	Y	Y	Y
City FE	Y	Y	Y
First-stage F stat	50.927	88.940	88.940
Mean(%)	2.648	2.655	2.655
Observations	1139	1068	1068

Note: The dependent variable is the change in the construction employment share from year t to year $t+1$. All regressions report IV estimates. Column (1) is the unweighted regression. Column (2) adds the city leader characteristics as controls. Column (3) uses the time-varying city population as the base to construct the construction employment share. Regressions in Columns (2) and (3) are weighted by the city's working-age population in 2010. The mean is the mean value of the urban construction employment share in the city working-age population (with % as the unit). The city controls include the change in log college graduates and the change in log urban population. The standard errors are clustered at the province level.

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

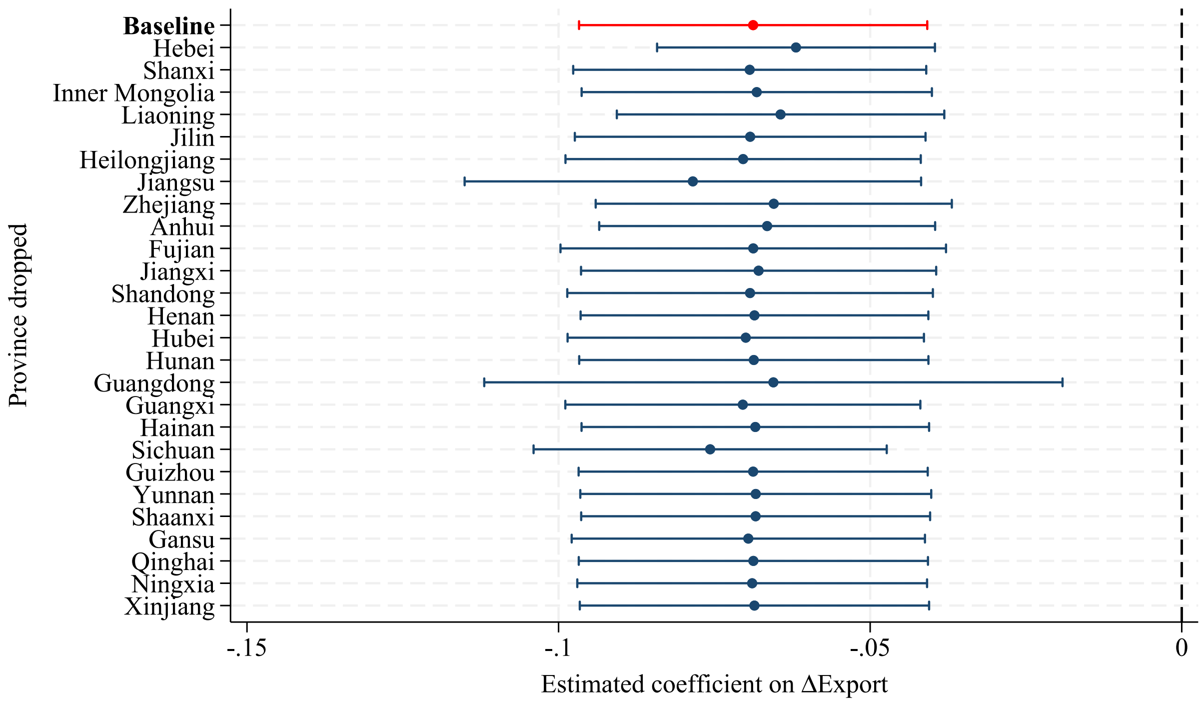


Figure E1. Robustness: Dropping One Province Each Time

This figure reports the estimated coefficient on ΔExport from Equation 4, using the entire sample less one province. For comparison, the baseline estimated coefficient using the entire sample is also presented (in red). The solid points are point estimates, and the caps are 95 percent confidence intervals. Standard errors are clustered at the province level.

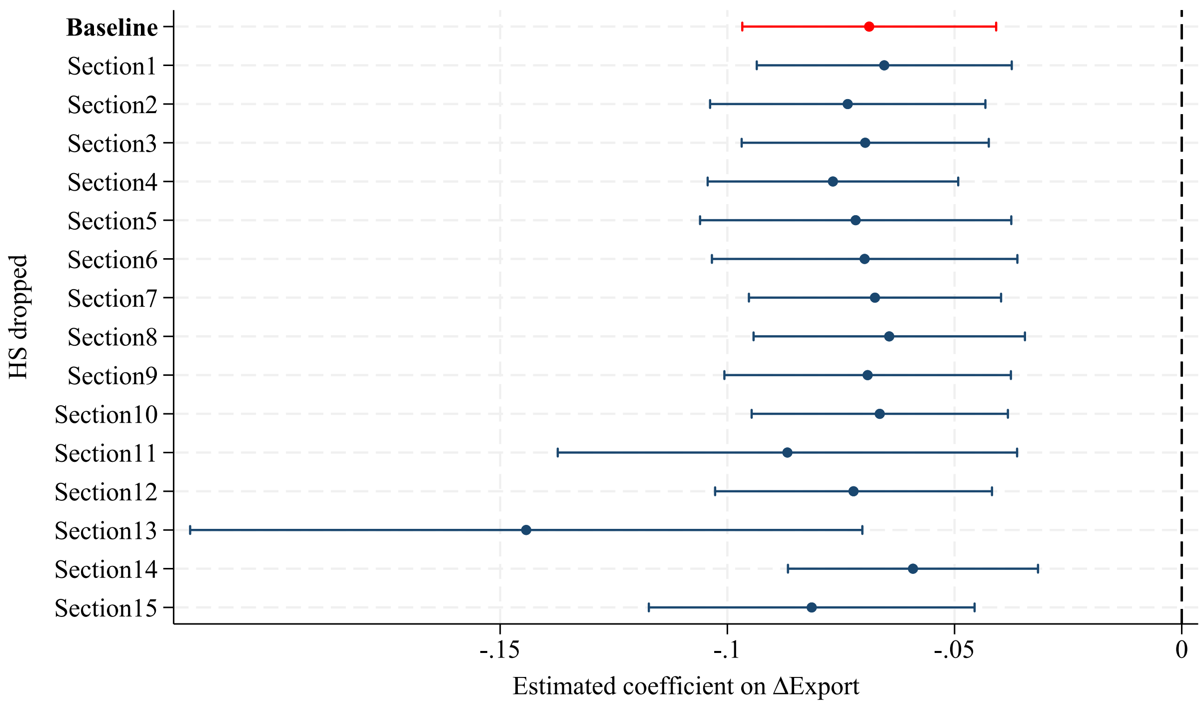


Figure E2. Robustness: Dropping One HS Section Each Time

This figure reports the estimated coefficient on ΔExport from Equation 4, the independent variable ΔExport and its IV are constructed using the entire exporting sample less products from one HS Section. For comparison, the baseline estimated coefficient is also presented (in red). The solid points are point estimates, and the caps are 95 percent confidence intervals. Standard errors are clustered at the province level.

Table E2. Robustness: Inference

	Δ%Construction Employment$_{t+1}$			
	(1)	(2)	(3)	(4)
	Province level	City level	Export similarity	Export similarity outside prov.
ΔExport	-0.069***	-0.069**	-0.069**	-0.069***
	(0.014)	(0.033)	(0.027)	(0.022)
City Controls	Y	Y	Y	Y
Province-year FE	Y	Y	Y	Y
City FE	Y	Y	Y	Y
Wild cluster bootstrapt 95% CI	[-0.137, -0.037]			
tF 95% CI	[-0.103, -0.035]			
Observations	1123	1123	1123	1123

Note: The dependent variable is the change in urban employment share. All regressions report IV estimates and are weighted by the city's working-age population in 2010. Column (1) reports the regression clustered at the province level used in the baseline regression. 95% confidence interval is reported through a wild bootstrap-t procedure following Cameron et al. (2008), due to the small number of clusters (28). The tF test for IV proposed by Lee et al. (2022) is also implemented in Column (1)'s baseline regression. Standard errors in Column (2) are clustered at the city level. For Columns (3) and (4), the standard errors are clustered at the export similarity level and the level of the export similarity with cities outside the province.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

F Robot Exposure and Construction Employment

F.1 Measuring Robot Exposure

To measure the city-level robots exposure, I follow Giuntella et al. (2025) and exploit the city-level variations in the pre-existing employment distribution across industries and the industry-level changes in the amount of robots adopted in China to measure robots exposure. Data on China's robot adoption is obtained from the International Federation of Robotics (IFR) (International Federation of Robotics, 2016), which provides operational stock of industrial robots at the level of year, county, and industry. The pre-existing employment distribution across industries is obtained from China's 2000 census. Specifically, the robots exposure measure is represented as

$$\Delta Robot_{ct} = \sum_{s \in S} l_{cs}^{2000} \frac{\Delta R_{st}}{L_{s,2000}} \tag{F1}$$

where s denotes sector, c city, and t year. R_{st} is the total number of operational industrial robots used in sector s and year t. $\Delta R_{st} = R_{st} - R_{s,t-1}$, is the annual change of industry i's robots use. The exposure in robots is normalized by the number of workers employed in sector s in 2000, $L_{s,2000}$. l_{cs}^{2000} is the share of employment in sector s in city c in 2000.

To mitigate the concern that the adoption of industrial robots correlate with factors affecting the employment outcomes, I follow Giuntella et al. (2025) and instrument the $\Delta Robot_{ct}$ in Equation F1, leveraging the sector-level robots adoption in other countries. Specifically, I use the average sector-level robot adoption in European Union countries and the instrument is defined as:

$$\Delta RobotIV_{ct} = \sum_{s \in S} l_{cs}^{2000} (\frac{\Delta R_{st}}{L_{s,2000}})_{EU_{Avg}} \tag{F2}$$

where s represents each sector in the IFR data, l_{cs}^{2000} is sector s's employment share in city c, and ΔR_{st} is the average of robot usage among EU countries in sector s and year t.

To identify the impact of automation shocks, I estimate Equation 4 using $\Delta RobotIV_{ct}$ as an instrument for $\Delta Robot_{ct}$.

F.2 Robots Exposure and Construction Employment

This section examines how automation-induced labor demand shocks affect city-level employment outcomes. Export slowdowns and automation shocks differ in their aggregate economic effects: export slowdowns reduce economic activity, while robot exposure is associated with stable or increasing nighttime light intensity (Table F1). Both shocks, however, generate employment losses in manufacturing.

Table F1. Automation, Export Slowdown, and Economic Growth

	ΔLog Nightlight Intensity$_t$			
	(1)	(2)	(3)	(4)
ΔExport	0.012**	0.014***		
	(0.005)	(0.005)		
ΔRobot			0.034***	0.034***
			(0.010)	(0.010)
City Controls	N	Y	N	Y
Province-year FE	Y	Y	Y	Y
City FE	Y	Y	Y	Y
First-stage F stat	106.469	112.914	54.429	53.906
Mean(%)	0.015	0.015	0.015	0.015
Observations	1138	1138	1122	1122

Note: The dependent variable is the city-level change in log night light intensity between year $t-1$ and t (Columns (1)- (4)), obtained from Campante et al. (2023). The key independent variables are the change in export values between year $t-1$ and t (Columns (1) - (2)) and change in industrial robots (Columns (3) - (4)) between year $t-1$ and t, normalized by the city's working-age population. The city controls include the changes in log college graduates and log urban population. All columns report the IV regression result and are weighted by the city's working-age population in 2010. The standard errors are clustered at the province level.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table 3 reports the effect of robot exposure on the city's employment. Columns (1) and (2) show that robot exposure decreases manufacturing employment.[5] On average, a one-standard-deviation increase in the exposure to robot leads to a decrease of 1.631 percentage points in the share of the working-age population employed in the manufacturing sector.

[5]Table F2 presents the immediate employment effects of robot exposure across all non-agricultural sectors. It shows that increasing robot exposure immediately decreases manufacturing, transportation and services employment, with manufacturing employment reduction accounting for around 80% of such employment decline.

However, similar to the context of export slowdown, in the subsequent period, cities more exposed to the robot exposure experienced a rise in construction employment, as evidenced in Columns (3) and (4). This increase in construction employment, amounting to 0.115 percentage points increase (around 4% of the average construction employment size) for a one-standard-deviation increase in the robot exposure, helps mitigate 7.05% of the employment loss in the manufacturing sector due to the export slowdown.[6]

Table F2. Automation Shocks and Employment in the Current Period

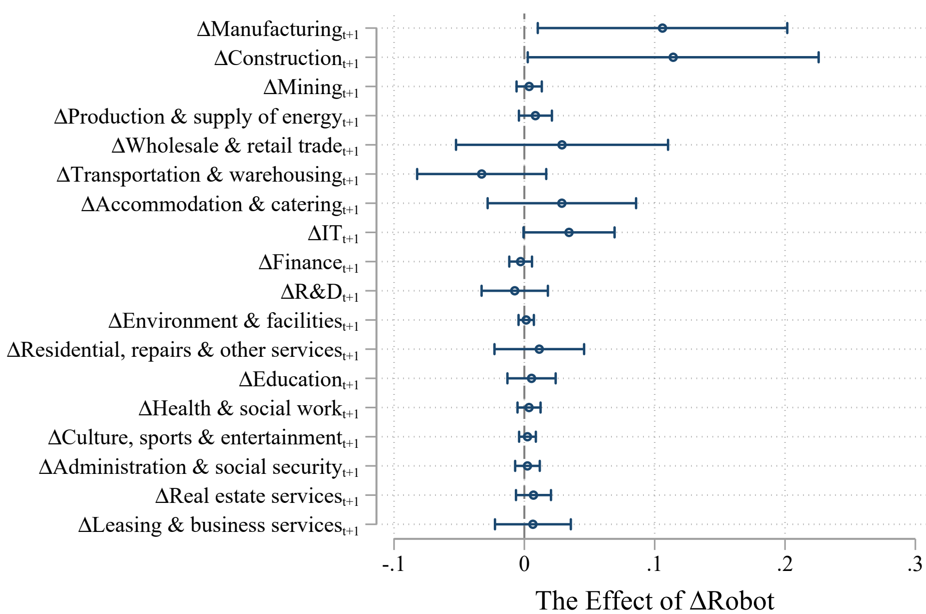
	$\Delta \text{Employment}_t$					
	(1) Manufacturing	(2) Construction	(3) Mining	(4) Energy	(5) Transportation	(6) Services
ΔRobot	-1.631***	-0.112	0.022	-0.017	-0.030**	-0.373**
	(0.399)	(0.124)	(0.020)	(0.012)	(0.015)	(0.139)
City Controls	Y	Y	Y	Y	Y	Y
Province-year FE	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y
First-stage F stat	53.906	53.906	44.184	53.906	53.906	54.051
Mean(%)	4.691	2.679	1.019	0.383	0.644	8.105
Observations	1122	1122	1029	1122	1122	1136

Note: The dependent variable is the change in the employment between year $t-1$ and t in (1) the manufacturing sector, (2) the construction sector, (3) the mining sector, (4) the energy and utility sector, (5) the transportation sector, and (6) services sectors. Employment is defined as the ratio of total employed workers in the sector and the city's working-age population. The key independent variable is the change in export values between year $t-1$ and t. The city controls include the changes in log college graduates and log urban population. All columns report the IV regression result and all regressions are weighted by the city's working-age population in 2010. The standard errors are clustered at the province level.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Figure F1 plots the effects of robot exposure on employment across all industrial sectors in the following year. In contrast to the export-shock setting—where construction is the only expanding sector—robot exposure is associated with increases in both construction and manufacturing employment in the following period. This pattern is consistent with the idea that, while automation initially displaces labor, productivity gains may partially restore manufacturing labor demand over time.

[6] 7.05% is calculated using 0.115/1.631.

Figure F1. Employment Following the Robot Shocks



Note: This figure plots the IV estimate of $\Delta Robot_t$ on $\Delta Employment_{t+1}$ in all industrial sectors using specification as Columns (4) in Table 1.

Table F3. Automation Shocks and Employment in the Following Period

	ΔEmployment$_{t+1}$					
	(1) Manufacturing	(2) Construction	(3) Mining	(4) Energy	(5) Transportation	(6) Services
ΔRobot	0.106**	0.114**	0.004	0.008	-0.033	0.116
	(0.046)	(0.054)	(0.005)	(0.006)	(0.024)	(0.123)
City Controls	Y	Y	Y	Y	Y	Y
Province-year FE	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y
First-stage F stat	54.243	54.243	46.798	54.243	54.243	54.051
Mean(%)	4.690	2.678	1.012	0.383	0.645	8.105
Observations	1123	1123	1033	1123	1123	1136

Note: The dependent variable is the change in the employment between year $t1$ and $t+1$ in (1) the manufacturing sector, (2) the construction sector, (3) the mining sector, (4) the energy and utility sector, (5) the transportation sector, and (6) services sectors. Employment is defined as the ratio of total employed workers in the sector and the city's working-age population. The key independent variable is the change in export values between year $t-1$ and t. The city controls include the changes in log college graduates and log urban population. All columns report the IV regression result and all regressions are weighted by the city's working-age population in 2010. The standard errors are clustered at the province level.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

F.3 Heterogeneity and Employment Emphasis

To assess whether construction responses to automation are shaped by employment pressure, I conduct heterogeneity analyses paralleling those in Table 2. Table F4 reports the results.

Construction employment responses to robot exposure do not differ systematically between cities led by younger versus older leaders. However, conditional on robot exposure, cities experiencing larger increases in labor unrest exhibit significantly larger expansions in construction employment. Turning to governments' employment emphasis, Columns (2)–(4) show that robot exposure does not affect governments' employment emphasis on average. However, cities with larger increases in labor unrest place stronger emphasis on employment stability and job creation in their government work reports, both in terms of frequency of employment-related references and expressed policy commitments.

Compared with responses to export slowdowns, younger leaders do not differentially expand construction employment following automation shocks. One interpretation is that export slowdowns combine employment losses with economic contraction, making construction expansion attractive both as job creation and as economic stimulus. Automation shocks, by contrast, reduce employment while raising productivity and aggregate output, dampening incentives for leaders to expand construction unless employment instability becomes salient. Consistent with this view, construction responses to automation are concentrated in cities experiencing greater labor unrest.

Table F4. Robots: Heterogeneity of Construction Employment

	Δ*Employment focus*$_{t+1}$			
	Construction employment share	Employment count (log)	Employment focus (binary)	Employment focus (score)
	(1)	(2)	(3)	(4)
Panel A: Average effect				
ΔRobot	0.115**	0.007	0.041	0.041
	(0.055)	(0.034)	(0.036)	(0.090)
Panel B: Differential effect by career incentive				
ΔRobotIV	0.180	-0.017	0.055	-0.048
	(0.156)	(0.157)	(0.120)	(0.306)
ΔRobotIV $\times$ Age $\leq$ 57	-0.003	0.127***	0.032	0.081*
	(0.030)	(0.031)	(0.020)	(0.045)
Age $\leq$ 57	-0.186	0.105	-0.004	0.169
	(0.135)	(0.079)	(0.078)	(0.199)
Panel C: Differential effect by labor unrest				
ΔRobotIV	0.265*	0.457**	0.356***	0.543***
	(0.130)	(0.196)	(0.094)	(0.159)
ΔRobotIV $\times$ ΔUnrest	0.011*	0.044***	0.036***	0.081***
	(0.006)	(0.010)	(0.003)	(0.012)
ΔUnrest	-0.013	-0.029	-0.018	-0.113*
	(0.023)	(0.025)	(0.014)	(0.056)
Observations	1115	1062	1062	1062
Mean	2.685	9.275	0.910	2.923
City Controls	Y	Y	Y	Y
CPS Controls	Y	Y	Y	Y
Province-year FE	Y	Y	Y	Y
City FE	Y	Y	Y	Y

Note: The dependent variables are the change in construction employment (Column (1)), log employment counts in GWRs (Column (2)), a bianry variable on whether governments focus on employment stability and creation in GWRs (Column (3)), and the degree to which the governments focus on employment stability and creation in GWRs (Column (4)) between year t and $t+1$. Panel A examines the average effect using IV regression. Panels B and C examine the heterogeneity by city leaders' age and changes in cities' labor unrest. All regressions are weighted by the city's working-age population in 2010. The standard errors are clustered at the province level.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$