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**Have you eaten? The long-run impact of the Great Leap Famine on recent trade**

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# Have you eaten? The long-run impact of the Great Leap Famine on recent trade *

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**Abstract**

This paper estimates the long-run transmission of the Great Leap Famine (1959-61) to the current trade of Chinese provinces. Based on the provincial dispersion of famine severity, we find that provinces more severely affected by the famine have smaller food exports compared to non-food exports, even after over forty years. We present several potential channels including food consumption patterns and risk-related domestic bias, to explain the observed lower food exports in those areas that experienced more intense famine. This study adds to the literature on the effects of the Great Leap Famine and contributes to research on the long-term impacts of historical events on trade.

**Keywords:** Great Leap Famine; Trade; Instrumental variables; Famine memory

**JEL:** F14, N55, N75, O24, Q17

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# 1 Introduction

"Have you eaten?", pronounced as "chi le ma?" in Mandarin, is one of the most common greetings in China. No matter what the respondent answers, the proposer would invite her or him to eat together. This implies not merely the hospitality of Chinese people but also the importance of eating in their minds. Indeed, nothing is more prioritized than satiety and nothing is more unforgettable than the memory of hunger.

After completing the land reform in 1953, China began its socialist transformation (first 5-year plan), which was specifically reflected in the transformation of agriculture, handicrafts, industry and commerce, and achieved preliminary success in late 1956 (Lin, 1990). Aiming for more rapid industrialization and modernization, the Great Leap Forward was initiated in 1958. In industry it centred on the nationwide "Great Steel Making" movement, striving to "catch up with and surpass the UK in the output of steel within 2 years" (Fan and Shi, 2013).[1] In agriculture, collectivization and people's communes were established in rural areas (Lin, 1990; Bai and Kung, 2014).

The drastic reforms brought by the Great Leap Forward severely disrupted food production in China. As a result, between 1959 and 1961, China experienced one of the deadliest famines in history. Poor agricultural policies, extreme weather conditions and flawed administrative decisions resulted in severe food shortages causing millions of deaths across the country.[2] Since this famine, coincided with the Great Leap Forward, it is known as the Great Leap Famine. It has left a profound mark on China's population, economy, and collective memory, with long-lasting effects that are still studied today (Bai and Kung, 2014; Chen et al., 2022; Guo et al., 2024). Our paper aims to study its long-lasting effect on China's contemporary trade between Chinese provinces and foreign partners. In particular, we compare food exports with non-food exports across provinces that experienced different levels of famine intensity. To do so we use adverse weather shocks as an instrumental variable to address the endogeneity issue arising in our analysis.

While the existing literature has explored both causes (Lin, 1990; Kueh, 1995; Houser et al., 2009; Meng et al., 2015) and consequences (Chen and Zhou, 2007; Bai and Kung, 2014; Ding et al., 2022; Guo et al., 2024) of this famine, to the best of our knowledge, no research has yet estimated its effect on contemporary trade patterns in China or examined the mechanisms of its transmission. Hence, the first contribution of this paper is to fill this gap and complement the literature on the long-term impact of the Great Leap

[1] In August 1958, the Central Committee of the Communist Party of China passed the resolution *The whole party and the whole people strive to produce 10.7 million tons of steel.*

[2] See Section 2.2 for an overview of the causes of the Great Leap Famine.

Famine.[3] Understanding the impact of the Great Leap Famine on trade is crucial for several reasons. First, trade is one of the factors contributing to economic development. Consequently, disruptions to trade can have long-lasting effects on a country's and/or a region's economic performance. In addition, by causing significant population loss, the famine affected labour supply and production capacities. This has likely impacted not only local economies but also China's position in the global economy. Second, regions affected by famine may have altered the mix of products exported, affecting both domestic and international trade flows. By studying these patterns, we can see whether the famine indirectly influenced China's long-term specialization and comparative advantage of different provinces. Based on recent trade data and measures of famine intensity from two sources, we uncover that provinces that suffered more during the famine have smaller food exports relative to non-food exports in the decades following the famine. This result is robust to different methodologies and instruments used.

One might ask how a historical famine could continue to affect trade years later. Several potential mechanisms could explain this influence. For example, a famine often creates concerns about food security among both policymakers and individuals. In response, policymakers may shift toward self-sufficiency (Guo et al., 2023). This can lead to a more risk-averse approach to food exports in order to protect domestic supply. At the household level, famine experiences may encourage risk-averse behaviours and lead to more precautionary actions (Chen et al., 2023), thus encouraging food hoarding and a greater focus on nutritional intake, leading to increased domestic consumption and a reduction in exportable surpluses.

Our second contribution is to examine the potential channels behind the effects of the famine on trade. The first channel is the increased local food consumption or reserves in areas that suffered more from the famine. Studies have shown the famine experience can affect victims' behaviours through preventive food reserve driven by the fear of hunger (Chamon and Prasad, 2010; Wei and Zhang, 2011; Ding et al., 2022) or compensatory overeating to make up for early-life losses (Cheng and Zhang, 2011; Gluckman et al., 2005; Kesternich et al., 2015). We find that households whose heads were born during or before the famine have higher staple food reserves and families from hard-stricken areas purchase more food than non-food products in monetary value. In addition, provinces that experienced harsher famine retained more crops instead of selling them and this phenomenon is more pronounced for food crops than non-food crops. This is reflected

[3] We also contribute to the broader literature on the long-term consequences of historical events on trade. These events include conflicts (Blomberg and Hess, 2006; Ouyang and Yuan, 2021), colonization (Head et al., 2010), official communications (Nitsch, 2007), international aid (Hu et al., 2023) and more.

in lower commodity rates for food crops. Consequently, we suggest higher food consumption and reserves in areas that experienced harsher famine to be the potential explanation for their smaller food exports relative to non-food exports.

Additionally, famine survivors tend to exhibit higher risk aversion, which may lead to a stronger domestic bias in trade—particularly in food trade, which is inherently riskier than non-food trade due to factors such as perishability, vulnerability to supply shocks (e.g., adverse weather conditions or disease), and stringent safety regulations. We show that domestic bias in export is stronger in (1) food and agricultural sectors; and (2) places that had higher death tolls during the famine. Eventually, we find that the domestic bias in food and agricultural sectors becomes more pronounced with the increase of the famine intensity. This could explain the observed smaller food exports in these areas. To some extent, this also provides a new explanation for the "border effect puzzle" that more trade happens domestically than internationally, which as argued by Obstfeld and Rogoff (2000), is one of the six puzzling phenomenons in the area of international economics. It might also give a hint to the problem of why some countries are reluctant to export food products.

The rest of this paper is organized as follows. A detailed review of the literature and a description of the data are presented in sections 2 and 3 respectively. Our identification strategy and results are discussed in section 4. Then in section 5, we focus on the potential channels through which this famine transmits its effects to trade. Several robustness checks are presented in section 6. The final section concludes.

## 2 Literature review

In this section, we first review the literature on various famines worldwide (subsection 2.1), we then shift our focus to the Great Leap Famine (subsection 2.2) and discuss our contributions to the existing literature on its impact (subsection 2.3), as well as the long-term effects of historical events on current trade (subsection 2.4).

### 2.1 Global famines: causes and consequences

As early as the eighteenth century, Malthusianism attributed wars and famines to imbalances between population and agricultural production caused by unrestricted population growth (Malthus, 1798). According to this theory and its later derivatives, famine is driven by a decline in food availability (FAD theory). However, this theory does not explain why famines can occur even when food supply has not declined. Instead of focusing on the food shortages, Sen (1981) argued that famine can also be triggered by the failure of exchange entitlements, whereby some people are unable to acquire food due to either a decline in their own entitlements or a rise in food prices. This theory explains why people from different professions or classes may experience famine differently.

Research on famines often focuses on the causes and consequences of specific historical famines. For instance, Sen (1981) and Ó Gráda (2010) both analyse the Bengal Famine of the 1940s but from different perspectives. Sen (1981) emphasizes that market failure, driven by rampant speculative behaviour during wartime, exacerbated a minor decline in food availability into a significant reduction in the food supply. In contrast, Ó Gráda (2010) attributes the primary cause to the government's lack of political will to prioritize famine relief over wartime efforts, rather than speculation. In another case, Naumenko (2021) examines the Ukrainian Famine of the 1930s, attributing it primarily to Soviet policies, particularly the collectivization of agriculture, while adverse weather conditions playing only a minor role.

Many studies have focused on the effects of famines, such as the papers on the impact of the Great Irish Famine on emigration, the depopulation of Ireland, and the Irish economy (Guinnane, 1994; O'Rourke, 1994; Ó Gráda and O'Rourke, 1997; Whelan, 1999). In addition, Narciso and Severgnini (2023) find that the Great Irish Famine had a long-term impact on political movements. Specifically, they show that the famine played a role in sparking the Irish Rebellion against British rule approximately 70 years later. Beyond these macro-level impacts, certain famines also affect micro-level outcomes, particularly the health and well-being of their victims. For instance, based on evidence from the famines in Ukraine, Western Netherlands, and China, Li et al. (2024) find that prenatal famine exposure is associated with a higher risk of developing type 2 diabetes in later years.

To sum up, these devastating famines have a profound impact on those who experience them, and this effect is often enduring and hard to forget.

## 2.2 Causes of the Great Leap Famine

"Three parts natural, seven parts man-made." is how the former president of China, Liu Shaoqi, characterized the causes of the Great Leap Famine during the Seven Thousand Cadres Conference in 1962 (Houser et al., 2009). This number was not based on statistical analysis but rather on conclusions drawn from interactions with rural workers, providing a crude overview of the Great Leap Famine. The official explanation attributes this famine to the mistakes made in both the Great Leap Forward and the Anti-Rightist Campaign, natural disasters and the betrayal of the Soviet Union.[4]

To date, scholars have explored each contributing factor in more detail. Most studies show that weather shocks contributed to this famine, but also agree that they were not the primary cause (Kueh, 1984; Kueh, 1995; Li and Yang, 2005, Houser et al., 2009, Bramall, 2011).[5] Kueh (1984), was among the early scholars testing the weather shock hypothesis. He suggests that bad weather led to a decline in grain production and thus aggravated the mortality during the famine. Later studies expanded this examination of climate shocks using more direct climate data (Houser et al., 2009; Bramall, 2011).

Other contributing factors have also been highlighted, particularly those closely related to the Great Leap Forward, which are considered potential primary causes. These include planned over-procurement and excessive purchasing of food, (Li and Yang, 2005; Fan and Shi, 2013; Meng et al, 2015), public canteens in people's communes leading to significant food waste (Yang, 1996; Chang and Wen, 1997), biased food distribution policies favoring city dwellers over villagers (Lin and Yang, 2000), and career incentive and radicalization of local leaders (Kung and Chen, 2011; Kung and Lin, 2010; Tao et al., 2014), etc. In addition, geographical features also played a role (Garnaut, 2014). For instance, Gooch (2019) shows that remoteness and terrain ruggedness may have offered protection from radical policies and the resulting famine. Moreover, social capital, especially within kinship-based clans, played a vital role in providing disaster relief during famines (Cao et al., 2022).

### 2.3 Impacts of the Great Leap Famine

A disaster of this magnitude inevitably has wide-ranging effects. For instance, Yang (1996) and Kung and Bai (2010) find that provinces more severely affected by the famine implemented agricultural de-collectivization earlier and were more proactive during China's economic reforms in the late 1970s. Bai and Kung (2014) find that harsher weather conditions during the famine accelerated this shift. In addition, studies have shown that this famine fostered a preference for sons within households, which negatively affects daughter's education

[4] *Resolution on Certain Historical Issues of the Communist Party of China since the Founding of the People's Republic of China* (1981).

[5] Figure 2 shows sown areas affected by natural disasters in China from the 1950s onward, in which "total" refers to all types of natural disasters and "other" stands for disasters other than drought and flood.

(Cheng et al., 2023), and that over-reporting of harvest during famine predicts financial misconduct today (Chen et al., 2022), among other effects.

Although few studies have examined the famine's effect on later exports, our research connects to previous findings. Famine experiences can increase risk-aversion after the famine (Chen et al., 2023),[6] leading to precautionary behaviors, such as higher savings (Chamon and Prasad, 2010; Wei and Zhang, 2011; Cheng and Zhang, 2011; Ding et al., 2022), or compensatory overeating (Cheng and Zhang, 2011; Gluckman et al., 2005; Kesternich et al., 2015). In the context of our research, both excess food reserves and overconsumption can result in a reduction in exportable food, thereby explaining the mechanism behind our observed effect that smaller food exports from those hard-stricken areas.

The increased home bias seen in trade literature (McCallum, 1995) is also relevant, as food and agricultural exports come with higher risks such as perishability, stricter regulations, and price volatility (Hummels, 2007; OECD, 2017). This may lead risk-averse individuals to prioritize domestic markets, further reducing food exports.

In addition, famines have a profound impact on policymakers' decisions. Guo et al. (2024) find that politicians who experienced famine in their early years tend to prioritize agricultural development, food security, often increasing agricultural spending to ensure food sufficiency. Similarly, Chen et al. (2024) emphasize that officials traumatized by famine may adopt a scarcity mindset, leading to fiscal conservatism. In conjunction with these studies, we discuss the potential changes following the famine, particularly the possible increase in agricultural development, which may lead to a rise in food production and, to some extent, boost food exports. However, we also emphasize that this positive effect is insufficient to offset the larger decline in food exports resulting from more cautious and conservative food export policies and a heightened focus on food sufficiency among both officials and the public.

Gooch (2017) further examines the impact of the famine on recent GDP per capita, using the sequence of provincial takeovers by the People's Liberation Army (PLA) during the Civil War (1945-49) as an instrumental variable of dispersed famine severity. Gooch's rationale is that areas liberated later by the PLA were more likely to be assigned non-local leaders who were more radical in policy enforcement, thereby impacting the mortality rates. While we also employ an instrumental variables approach to address endogeneity, we base our analysis on weather shocks, as the sequence of PLA takeovers may influence recent trade through

[6] Or other disastrous events (Kim and Lee, 2014; Callen, 2015).

alternative channels.

### 2.4 Impacts of historical events on China's trade

The long-term impact of historical events on China's current trade patterns has garnered significant attention. For instance, Che et al. (2015) and Ouyang and Yuan (2021) show that regions in China with higher civilian casualties during the Japanese invasion engaged in less trade with Japan decades later, largely due to enduring anti-Japanese sentiment. Similarly, Hu et al. (2023) explore the effect of Soviet aid to China in the early 1950s on recent Sino-Russian trade, finding that regions receiving more Soviet support now engage in more trade with Russia, driven by a lasting affinity toward former Soviet states. These studies highlight how historical events—whether tragic or beneficial—can influence long-term trade through shifts in psychological factors such as negative sentiment or positive affiliation. Our research extends this literature by examining another tragic event that has led to trauma and influenced psychological attitudes, particularly by creating risk-averse behaviours such as food hoarding and increased domestic bias against food exports. These behaviours, in turn, significantly impact current trade patterns and structures. This, to some extent, explain why certain countries are more reluctant to export food than other products.

## 3 Data

In this section, we describe the data used for our study, including the provincial death toll data which measures the intensity of this famine, and the trade data that constitutes the dependent variable and other supplementary data.[7]

### 3.1 Death toll data

We use two measures of the severity of the famine that are commonly used in the previous Great Leap Famine research.

[7] We focus on provincial-level trade and famine intensity, rather than lower-level divisions, due to significant economic specialization within provinces. For instance, certain cities or counties may focus predominantly on industrial production, contributing little to agricultural output, while others may specialize in agriculture. Using city or county-level data in such cases could result in "zero" or very small values for food exports, which would make meaningful comparisons difficult or even unfeasible. Additionally, export decisions and food security policies are often made at the provincial level, which would affect the trade structure.

First, since there are no official statistics of deaths caused by this famine, scholars calculate the excess death rate during the famine (1959-61) based on provincial demographic data disclosed by the National Bureau of Statistics (NBS).[8] The national excess death rate in 1960 was around 1.4 percent, using the average level of 1956-58 as the baseline (Chen and Zhou, 2007; Ding et al., 2022).

Following Chen and Zhou (2007) and Ding et al. (2022) we define the excess death rate ($EDR_c$) as the gap between the death rate of a Chinese province $c$ in 1960 when the famine was deemed to be the most severe, and the average death rate of that province during the three years before (1956-58).[9] We use the following formula to calculate the excess death rate:

$$EDR_c = Death\,Rate_{c60} - \frac{\sum_{t=56}^{58} Death\,Rate_{ct}}{3} \tag{1}$$

In addition to being consistent with previous studies that also use 1956-1958 as a reference period (Chen and Zhou, 2007; Fan and Qian, 2015; Xu et al., 2016; Ding et al., 2022), we choose these three years instead of a longer period to avoid contamination from earlier upheavals, transitions, or disruptions. Before 1956, China was still coping with the aftermath of significant conflicts, such as the Civil War and the Korean War, as well as early Communist reforms like the Land Reform and the Socialist Transformation. By 1956, China had largely completed its socialist transformation and achieved initial success in collectivization (Lin 1990), resulting in a relatively stable and peaceful political and economic environment that persisted until 1958.

Since there is no consensus on the famine death toll, we use an additional source of death toll data for comparison and to minimize controversy. Specifically, we include the unexpected death rate ($UDR_c$) reassessed by Cao (2005), based on both the census data and information gathered from local gazetteers. According to his estimates, around 32 million unexpected deaths happened during the famine.[10] Cao's calculations focus on the unexpected death numbers in province $c$ during the whole famine period (1959-61) with respect to its population in 1958, one year before the famine. It can be described as follows:

$$UDR_c = \frac{\frac{\sum_{t=59}^{61} Unexpected\,Death_{ct}}{3}}{Population_{c58}} \tag{2}$$

[8] See e.g., Lin and Yang (2000), Kung and Lin (2003), Chen and Zhou (2007), Bai and Kung (2014), Ding et al., (2022).

[9] This data comes from the *China Compendium of Statistics 1949–2008* (NBS, 2010), in which the death rate for Xizang, Hainan and Guangdong is unavailable. Guangdong's statistics are obtained from the earlier version, *Comprehensive Statistical Data and Materials on 50 Years of New China* (NBS, 1999).

[10] Notably, this data has also been used in previous studies (see e.g., Gooch, 2017; Gooch, 2019; Kung and Zhou, 2021).

The NBS data allows us to calculate the excess mortality rate in 29 provincial administrative units while Cao's statistics cover 21. Hence, there are 21 overlapping provinces between these two sources. Table A1 in Appendix A.1 shows the summary statistics of these two measures. On average, Cao's death rate is higher than that calculated based on NBS's data.

Figure 1 plots the famine severity by province based on the NBS's excess death rate (panel a) in 1960 and Cao's unexpected death rate between 1959-1961 (panel b). Darker shades indicate higher excess or unexpected death rates (blank areas represented provinces without available statistics). As one may note, the severity levels are similar in both figures albeit under different statistics. The situation of Anhui was the harshest, with over five percent excess death rate in 1960 based on official statistics and over 18 percent unexpected death rate during the famine (1959-61) based on Cao (2005). Overall, the famine was more severe in the southwestern and central inland regions than in the coastal and northeastern China.

(a) NBS, 1960

(b) Cao, 1959-61

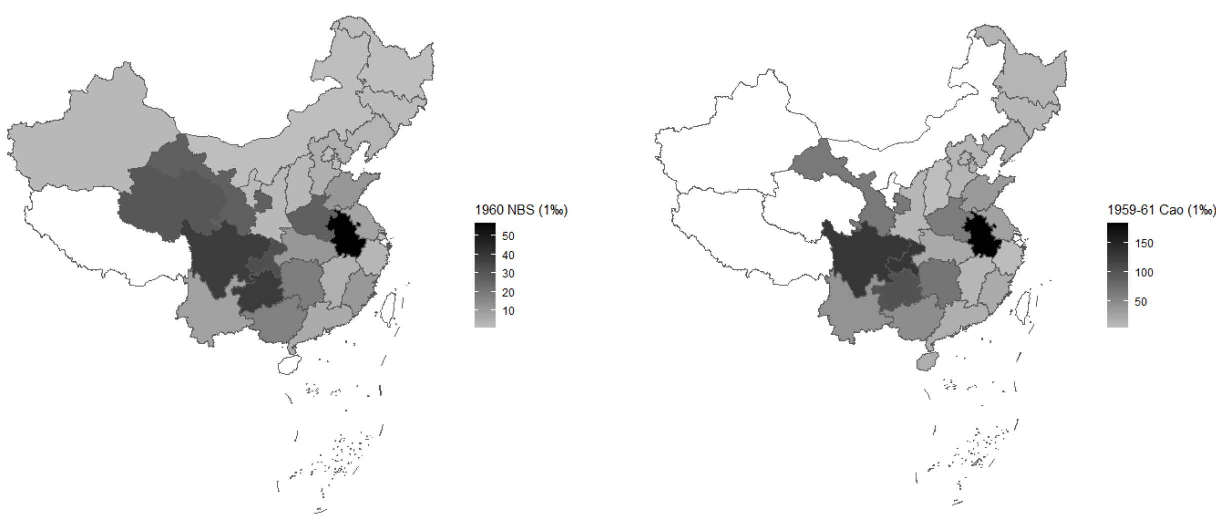



Figure 1: Comparison of Excess Death Rates (EDR) and Unexpected Death Rates (UDR) by Source.

## 3.2 Trade data

Our trade data comes from the statistical database of the Development Research Center of the State Council of China. It includes export statistics for over 1,200 product categories (HS4 level) from Mainland China provinces to 185 foreign countries or regions (Hong Kong, Macao and Taiwan regions are not included), ranging from 2002 to 2008.[11] For instance, the dataset could include the volume of frozen beef (HS4: 0202) exported from Shandong province to Malaysia in 2006. Our final data set includes over two million observations.[12]

### 3.3 Weather data

We use the weather shock data from the *Report on China's Natural Disasters [Zhongguo Zaiqing Baogao]* (NBS, 1995), which provides the historical data on "the area struck by natural disasters" across different types of natural disasters. In our robustness check, we also use direct meteorological information from historical weather stations reports collected in the National Oceanic and Atmosphere Administration (NOAA) database.

### 3.4 Other data

The latitude and longitude data required for calculating the geographical distance (great circle distance) come from the *World Urbanization Prospects: The 2018 Revision* (United Nations, 2018) and the R package "worldcities". The domestic trade data (used in the mechanism analysis) is calculated based on the *China 30-province Inter-regional Input-Output Table of 2007* compiled by Liu et al., (2012).[13] Consumption, food reserve, and characteristics of households come from the 2002 Chinese Household Income Project (CHIP 2002). The information on agricultural products and provincial characteristics in our mechanism analysis is sourced from *Compilation of Cost and Benefit Data of National Agricultural Products*, *Rural Statistical Yearbook of China*, *China Statistical Yearbook* and EPS Data platform.

[11] This choice aligns with previous studies that examine the long-term effects of historical events on current trade (Che et al., 2015; Ouyang and Yuan, 2021; Hu et al., 2023). Furthermore, in our robustness checks, we test the effects for each year to eliminate the possibility that the observed effects are influenced by shocks in any specific year.

[12] Chinese statistics distinguish two types of trade: ordinary and processing trade. The latter refers to the activity of importing all, or part of the raw or auxiliary materials from abroad, and reexporting the finished products after processing or assembly by companies within China. In this paper, only ordinary trade type is considered as processing trade does not necessarily reflect a region's intent or capacity to export specific commodities and is more likely influenced by policy factors.

[13] Key Laboratory of Regional Sustainable Development Modeling, China Academy of Science (2012). China 30-province Inter-regional Input-Output Table of 2007.

### 3.5 Summary statistics

Table 1 presents the summary statistics. Our baseline analysis includes 2,843,943 observations of product-level exports from Chinese provinces to foreign countries or regions between 2002 and 2008. Approximately twelve percent of these products are classified as food products. In Appendix A.3, we provide the summary statistics of the variables used in the mechanism analysis.

Table 1: Summary statistics for the sample used in main regressions

| Variables | Obs | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| ***Product level trade:*** | | | | | |
| $\text{Export}_{cjpt}$ | 2,843,943 | 10.353 | 2.693 | 0 | 21.145 |
| ***Adverse death:*** | | | | | |
| Excess Death Rate $1960_c$ ($\text{EDR}_c$) | 29 | 1.269 | 1.475 | 0.060 | 5.668 |
| Unexpected Death Rate $1959\text{-}61_c$ ($\text{UDR}_c$) | 21 | 4.287 | 4.648 | 0.370 | 18.370 |
| ***Adverse drought:*** | | | | | |
| Adverse drought $1960_c$ | 24 | 4.686 | 14.028 | -0.985 | 69.500 |
| Adverse drought $1959\text{-}61_c$ | 24 | 5.047 | 15.930 | -0.580 | 79.000 |
| ***Product:*** | | | | | |
| $\text{Food}_p$ | 1,204 | 0.118 | 0.323 | 0 | 1 |

The summary statistics correspond to the sample used in the regression analysis in Column (1) of Table 2, with export volume in logarithmic form.

# 4 Identification

In this section, we describe our identification strategies, which include (1) Ordinary Least Squares (OLS) for the baseline model and (2) Instrumental Variables (IV) to address endogeneity issues. At the end of this section, we also discuss the implementation of different sets of fixed effects within both strategies.

### 4.1 OLS: baseline model

Since our aim is to compare food exports with non-food exports across Chinese provinces that experienced varying levels of famine intensity, we estimate the following baseline model

$$Export_{cjpt} = \beta_0 + \beta_1 EDR_c * Food_p + \gamma_{jpt} + \lambda_{cst} + \theta_{cjt} + \epsilon_{cjpt} \tag{3}$$

where $Export_{cjpt}$ is the export volume of a product $p$ from province $c$ to an importer (country) $j$ in a given year $t$. On the right-hand side, the variable of interest is an interaction term between the excess death rate $EDR_c$ and the $Food_p$ dummy (equals to one for a food product and zero otherwise). The coefficient $\beta_1$ compares food with non-food exports as the famine intensity increases.[14]

As described by Yotov et al. (2016), in a gravity model, the bilateral trade volume at the aggregate level is determined by the exporter's and importer's economic size and the relative trade frictions between them. However, when it comes to product-level trade, the determinants become product-level demand and supply, as well as, the bilateral trade costs. Thus, we introduce a set of interactive fixed effects to capture supply-side and demand-side unobservable determinants. $\gamma_{jpt}$ controls for all the characteristics that vary across the three dimensions: importer, product and year. In our case, we aim to capture the demand-side factors of each importer for each product in each year.[15] This allows us to control for the tariffs or non-tariff barriers an importing country sets towards a specific product from China, the encouragement or limitations of China towards each product's exports, the shocks to a certain product in a given year, the characteristics of importers or products, etc. For the supply side, we include the exporter($c$)-sector($s$)-year($t$) fixed effect $\lambda_{cst}$ primarily to capture factors such as the supply capability and comparative advantage of each province at the sector level.[16] $\theta_{cjt}$ is the year-specific importer-exporter pair fixed effect, which accounts for all the time-variant (or invariant) bilateral trade cost variables such as distance, common border, language gap, trade policy alterations, etc. The multilateral resistance terms which are indispensable in trade analysis and generally controlled for by exporter-time and importer-time fixed effect, have already been absorbed by the $\gamma_{jpt}$ and $\lambda_{cst}$ respectively (Hummels, 1999; Olivero and Yotov, 2012; Feenstra, 2015). It is important to note that since the $EDR_c$ and $Food_p$ are absorbed by the fixed effects, we did not include them into the regression equation.

Finally, $\epsilon_{cjpt}$ is the error term which we cluster by exporter-importer pair. Clustering errors at the trading pair level is a customary way to account for any trading pair level correlations in the gravity model as described by Yotov et al. (2016). We have also tried clustering at the exporter-$Food_p$ level. The results

[14]Please note that we test both $EDR_c$ and $UDR_c$ in all regressions requiring death toll variables for comparison, while we show only $EDR_c$ in the equations for brevity.

[15]Simultaneously, the three-way interactive fixed effects automatically account for individual fixed effects of each dimension and the two-way fixed effects consisting of each of the two dimensions.

[16]Including sector level instead of product level is to avoid perfect collinearity with our key independent variable. This setting also takes into consideration factors that vary within each separate dimension or across two dimensions among exporter, sector and year, such as the exporter's level of development in different years, its geographical features, its cultural customs; sector-level features or a shock in a given year; etc.

are presented in Table B1 of Appendix B.1.[17]

## 4.2 OLS: results

Table 2 displays the OLS results of the baseline model (Equation 3). Columns (2) and (3) include overlapping provinces in NBS's and Cao's (2005) data. The coefficients of the interaction terms in all specifications are negative and statistically significant, indicating that provinces with higher adverse death rates during the Great Leap Famine have smaller food exports than non-food exports after over forty years.

Table 2: OLS results: effects of the famine on food exports

| Specification | (1) | (2) | (3) |
|---|---|---|---|
| $EDR_c$*$Food_p$ | -0.074*** | -0.128*** | - |
| | (0.024) | (0.028) | |
| $UDR_c$*$Food_p$ | - | - | -0.039*** |
| | | | (0.009) |
| Constant | 10.356*** | 10.445*** | 10.445*** |
| | (0.001) | (0.001) | (0.001) |
| Exporter-Sector-Year FE | Y | Y | Y |
| Importer-Product-Year FE | Y | Y | Y |
| Pair-Year FE | Y | Y | Y |
| Number of exporters | 29 | 21 | 21 |
| Observations | 2,843,943 | 2,168,487 | 2,168,487 |
| R-squared | 0.530 | 0.549 | 0.549 |
| Data | NBS | NBS | Cao |

Dependent variable: log export volume. Robust standard errors, clustered by exporter-importer are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Taking column (2) as an example, for each percentage point increase in the excess death rate in 1960, food exports are 12 percent smaller than non-food exports ($e^{-0.128} - 1 \approx -0.120$). The results displayed in column (3) using Cao's data are relatively smaller in absolute value which can be explained by the fact that this death rate is higher than the one from NBS. This result indicates that current food exports are around 3.8 percent ($e^{-0.039} - 1 \approx -0.038$) smaller than non-food exports with a one percentage point increase in the unexpected death rate during 1959-61. More intuitively, a province with a population of around 30 million in 1958 (the average population per province based on Cao, 2005), would have contemporary food exports 3.8 percent smaller than non-food export with every additional 300,000 deaths.

Our results are comparable to those of previous papers analyzing the effects of historical events on recent

[17] We have also clustered the error term at the exporter-product level; the results remain robust and are available upon request.

trade based on similar estimation specifications. Ouyang and Yuan (2021) find that the coefficient of the interaction term between the massacre death intensity of Chinese civilians by the Japanese and a dummy variable which takes the value of one for Japan and zero for other countries, in the context of the recent China-Japan trade, is -0.114. Hu et al. (2023) find a coefficient on the interaction term between the aid intensity from the Soviet Union and a dummy variable indicating Russia, in the context of contemporary Chinese export to Russia, to be 0.142.

### 4.3 IV: source of endogeneity

One may worry about the endogeneity problem existing in our OLS regressions. First, it is reasonable to argue that famine intensity was not randomly assigned by "nature" albeit natural disasters played a role. Numerous studies have demonstrated that specific features of locations affect famine severity. For instance, remote and more rugged areas could be less affected, as their discretionary power regarding the Great Leap Forward policy is higher, and these areas have less trade. Besides, regional differences in radicalism may also affect both the famine severity and the current exporting strategy. Furthermore, calamities that each province suffered before the famine, may also form different levels of pre-disaster preparedness and ability to withstand the disaster and might have lasting effect on recent trade. Fortunately, these factors have been properly controlled for by the exporter fixed effect.

In our case, the biggest threat is the omission of the characteristics that vary with exporter and product, specifically the product-level comparative advantages (CAs henceforth) of a location, which is important to the current trade structure and the intensity of the famine shock. The literature has shown that this famine was more intense in grain-producing areas due to planned procurement and biased distribution of food (Meng et al., 2015), and if a province has more non-grain crops, the negative impact of famine was smaller (Fan and Meng, 2007).

Consider a province that naturally specializes in cultivating grains, a common target of collectivized procurement during the Great Leap Forward. Taking into account that the over-reporting of output during the Great Leap Forward was very common, this province was likely to have a higher death rate because its main production was collected and redistributed by the central government, leaving its inhabitants without other sources of calories. Since the natural endowment is unlikely to change much, even after nearly half a century, this province is still superior in terms of grain planting and thus will sustain its relative advantages in grain output and export. Therefore, the product-level CA of a province is a confounding factor that affects both the excess death rate and current exports.

### 4.4 IV: solution to endogeneity and results

In the previous section, we described the potential source of endogeneity. In this section, we explain how to solve this issue using the weather shock as an IV. According to the econometric theory, a suitable IV should satisfy two conditions: (1) relevance, which requires the IV to have a non-weak effect on the endogenous variable; (2) exclusion restriction, by which the IV should not correlate with the error term or the confounding factors. Combining these two requires the IV to affect the dependent variable only through the endogenous variable (Stock and Watson, 2020).

In Great Leap Famine literature, papers have used IV to address endogeneity, like the aforementioned case of Gooch (2017). She uses the sequence of PLA's takeover of provinces during the Chinese Civil War as an IV of famine intensity. However, this instrument is not a suitable choice for our case, since the PLA most likely determined the order of take-over based on regional characteristics including the CAs.[18]

As we have noted in the literature review, this famine has many causes, among which the weather conditions played a role, despite many studies finding that it is not the only nor the most important factor. Weather conditions largely affect crop production and the decrease in production caused by bad weather reduces the availability of food to people regardless of policy. In other words, the adverse weather shock would amplify the severity of the famine. In addition, as listed in the previous section, the unobservable confounding variable is the product-level CAs of an exporter. The sudden surge in adverse weather is unlikely to be associated with the CAs of a place nor any other factors that would affect the current export aside from the famine severity.

Starting in 1959, the area struck by natural disasters in China experienced a sudden surge, reaching its historical peak in 1960. This record has remained unbroken until the present day, as illustrated in Figure 2. Among all the disasters, the drought was particularly severe. Therefore, we collect the provincial drought data from *Report on China's Natural Disasters*.[19] Particularly, the adverse drought is measured by the deviation in the area affected by drought during the famine (1959-61) from the level in the three

[18] The earliest takeovers such as Hebei, Henan, and Shandong were all major agricultural production areas, while the north-eastern region, conquered soon afterwards, had developed both industrial and agricultural bases and was adjacent to the Soviet Union.

[19] This data was also used by Bai and Kung (2014) to analyze the effect of this famine on the later de-collectivization.

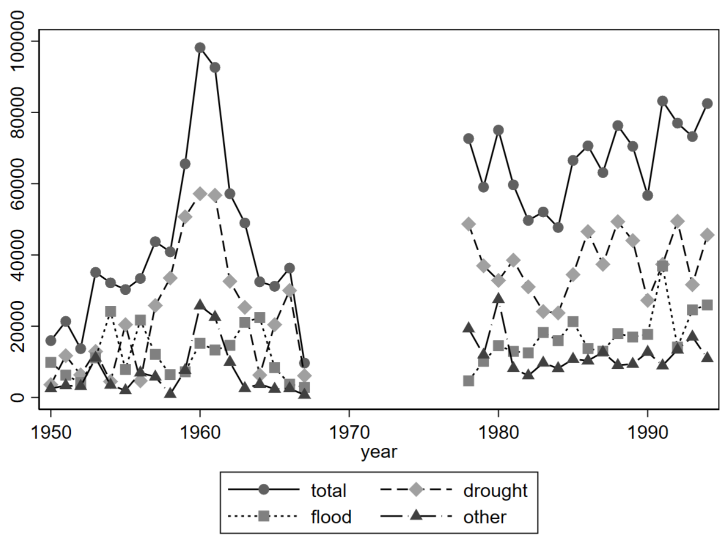



Figure 2: Natural disasters of China
Note: the source is *Report on China's Natural Disasters*. No statistics available during the Cultural Revolution.

years immediately preceding the famine (1956-58). In this case, the measure reflects the sudden increase in drought disasters during the famine, rather than the difference between drought conditions during the famine and their long-term average, such as the ten-year average. Using the latter approach could violate the IV's exclusion restriction, as the long-run average level of drought is likely related to a location's time-invariant CAs.

The formula below describes the calculation of adverse drought $AD_c$ of an exporter $c$ during the famine relative to its average over the three preceding years (1956-58). Again, to make it consistent with the death toll data, we instrument $EDR_c$ from the NBS data with the adverse drought of 1960, while for Cao's $UDR_c$ we instrument it with the adverse drought during 1959-61. An example of the calculation of the adverse drought of 1960 is presented in Equation 4.

$$AD_c = \frac{(D_{c,60} - 1/T \sum_{t=56}^{58} D_{c,t})}{(1/T \sum_{t=56}^{58} D_{ct})} \tag{4}$$

We then estimate the IV equation:[20]

$$Export_{cjpt} = \beta_0 + \beta_1 \widehat{EDR_c * Food_p} + \gamma_{jpt} + \lambda_{cst} + \theta_{cjt} + \epsilon_{cjpt} \tag{5}$$

Since the drought data is only available for 24 provinces, 24 and 21 provinces are included in the specifications using NBS's and Cao's data respectively. The number of overlapping provinces is again 21.

The first three columns of Table 3 present the results under the above IV settings. The $F$ statistics from the first stage show that our instruments are strong. The coefficients are still significantly negative across all specifications. For instance, the coefficient of -0.364 in column (2) means that for each percentage point increase in the excess death rate of 1960 the food export are 30.5 percent smaller than non-food exports.

Compared to the OLS, the IV estimation yields a more negative coefficient. This can be explained by the source of endogeneity in our OLS model, which we believe to be the product-level CA of a province. Since the CA is positively correlated with both famine intensity and current exports, omitting it biases the OLS results towards zero, making the coefficient less negative. Once we correct for this endogeneity using the IV, we observe a stronger and more negative true effect.

To ensure robustness, we also collect historical temperature and precipitation data from weather stations, using the Global Summary of the Month datasets provided by the NOAA.[21] This data is used to conduct an alternative IV. For a detailed analysis and results, please refer to Appendix B.5.

In addition, in Appendix B.2, we further compare major food exports with non-food exports,[22] observing a more pronounced decline in major food exports relative to non-food exports in regions more severely affected by the famine.

## 4.5 Potential "bad control": source and solutions

In the previous section, we described the use of the IV to deal with the confounding factor: product-level CAs. Nevertheless, the CAs can be disentangled into two components: (1) the time-invariant CAs, which are determined mostly by the natural endowments and do not change over the past 50 years; (2) the time-variant

[20] For the first stage, we use $AD_c * Food_p$ to generate the predicted value of $EDR_c * Food_p$, namely the $\widehat{EDR_c * Food_p}$.

[21] `https://www.ncei.noaa.gov/`

[22] Please refer to Appendix A.2 for the classification of major food, which is based on the "Major food consumption" indicators of the *China Statistical Yearbook*. For instance, while horse meat is edible and thus included in previous regressions, it is less commonly consumed and thus excluded from the subsequent regressions using major food. In contrast, beef and chicken are included in both cases as they are more frequently consumed.

Table 3: IV regression results: causal effects of the famine on food exports

| Specification | Dealing with endogeneity | | | Avoiding potential "bad control" | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| ***Second-stage:*** | | | | | | |
| EDR$_c$*Food$_p$ | -0.346*** | -0.364*** | - | -0.236*** | -0.227*** | - |
| | (0.084) | (0.090) | | (0.075) | (0.076) | |
| UDR$_c$*Food$_p$ | - | - | -0.098*** | - | - | -0.065*** |
| | | | (0.025) | | | (0.022) |
| ***First-stage:*** | | | | | | |
| Adverse drought$_c$*Food$_p$ | 0.040*** | 0.039*** | 0.121*** | 0.037*** | 0.037*** | 0.118*** |
| | (0.001) | (0.002) | (0.004) | (0.001) | (0.001) | (0.004) |
| Kleibergen-Paap F-stat | 739.990*** | 656.921*** | 839.246*** | 743.128*** | 664.702*** | 933.930*** |
| Pair-Year FE | Y | Y | Y | Y | Y | Y |
| Exporter-Year FE | Y | Y | Y | Y | Y | Y |
| Exporter-Sector-Year FE | Y | Y | Y | - | - | - |
| Importer-Product-Year FE | Y | Y | Y | Y | Y | Y |
| Number of exporters | 24 | 21 | 21 | 24 | 21 | 21 |
| Observations | 2,209,768 | 2,168,487 | 2,168,487 | 2,210,057 | 2,168,717 | 2,168,717 |
| Data | NBS | NBS | Cao | NBS | NBS | Cao |

Dependent variable: log export volume. Robust standard errors, clustered by exporter-importer are in parentheses. The period ranges from 2002 to 2008. The Kleibergen-Paap F-statistics are used to test for weak instruments. When using the NBS's excess death rate of 1960 ($EDR$) the weather shock is calculated based on 1960's weather conditions relative to 1956-58, whereas when using Cao's unexpected death rate of 1959-61 ($UDR$) the adverse weather is the average weather condition of 1959-61 relative to that of 1956-58. *** p<0.01, ** p<0.05, * p<0.1.

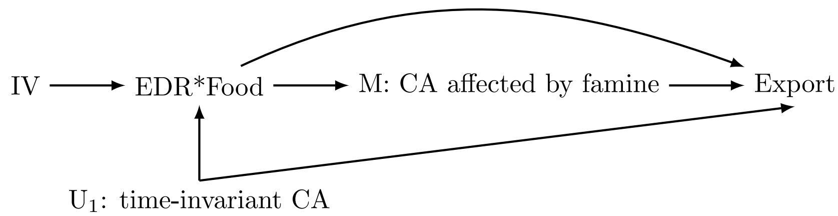



Figure 3: Endogeneity and "bad control"

CAs that changed because of the famine either through specific policies or individual incentives.

For example, places or people from areas that experienced harsher hunger might invest more in food or agricultural sectors to be more prepared for the future, given that during the reform era, the local governments were granted increasing economic independence by the central government (World Bank 1994; World Bank, 2002; Song, 2013). Guo et al. (2024) mention that with the increase of the early-life famine severity experienced by the county officials, the fiscal expenditure on agriculture increases, and the agricultural tax reduces, thus boosting grain production. Consequently, the inclusion of exporter-sector-year joint fixed effects in the models described in the previous section might block parts of the overall effect and lead to possible underestimation of the coefficient, as it absorbs time-variant sectoral CAs of a province.[23]

Figure 3 briefly summarizes the context. An exogenous IV would be a solution to address the endogeneity arising from not taking into account the provincial product-level CAs while the inclusion of exporter-sector-year fixed effect might potentially block part of the indirect effect from the famine to recent trade.

Following the rationale of the IV model described in Section 4.4, we make a modification to our model in the subsequent step. The dependent variables and the set of interactive fixed effects closely resemble those in Equation 3 or 5, except that the exporter-year fixed effects $\lambda_{ct}$ replace the exporter-sector-year fixed effects $\lambda_{cst}$. This adjustment is made to prevent potentially blocking part of the overall impact of the famine. The results generated by this setting are displayed in the last three columns of Table 3 confirming the negative impact of famine intensity on current food exports compared to non-food exports. Taking column (6) as an example, food exports would be 6.3 percent ($e^{-0.065} - 1 \approx -0.063$) smaller than non-food exports if the unexpected death rate rises by one percentage point. For the first stage regressions, the coefficient is

[23] Although we consider it possible that famine could have changed the CAs of certain areas, we have not found direct evidence in the literature. Therefore, it remains a suggestive approach to the potential "bad control" problem.

0.118 which can be interpreted as if the average area affected by the drought during 1959-61 was double the average level of 1956-58 (i.e., adverse drought equals one), the excess death rate would be around 0.12 percentage points higher. More intuitively, if a province had 1,000 acres of land affected by drought during the famine, twice the 1956-58 average (e.g., 500 acres), the province's excess mortality rate during 1959-61 would increase by 0.12 percentage points. Given the average population in each province sampled by Cao (2005) was around 30 million in 1958, 0.12 percentage points imply around 36,000 excess deaths.

In Section 4.6, we provide an example to summarize the different results generated by the fixed effects settings under OLS and IV.

### 4.6 Summarizing FE settings under OLS and IV

In this section, we explain why it is necessary to include exporter-sector fixed effects in OLS regressions, and why doing so under IV estimation might block the indirect effect. Table 4 presents a comparison of OLS and IV results under different sets of fixed effects. One can recognise the importance of controlling for exporter-sector-year fixed effects in OLS regressions. Failure to do so would result in a statistically positive coefficient as shown in column (1). This is because famine primarily occurred in grain-producing or agricultural provinces, which still have a comparative advantage in agriculture today. If we do not control for factors that vary with exporters and sectors, such as the agricultural productivity of each province, we would observe a positive effect. Similar results are found when using Cao's data in column (5).

Furthermore, focusing on columns (2) and (4), one may observe that the inclusion of exporter-sector-year fixed effects in the latter could potentially obscure part of the overall impact of famine on trade. The coefficient in column (4) is -0.346, whereas in column (2) it is -0.236. This difference suggests that factors positively influencing food export volume may be absorbed by the exporter-sector-year fixed effect. Consider a province that suffered more during the famine; it might allocate additional resources or investments toward the development of its food and agricultural industries in the post-famine period (Guo et al., 2024). This could provide the province with a CA, potentially increasing its exports. However, this increase is insufficient to offset the overall reduction in food exports caused by the famine. Still, the overall effect of the famine on trade would appear more negative if we account for this CA through fixed effects, as it represents a potential channel through which the famine could have boosted contemporary food exports. Again, similar findings are observed when comparing columns (6) and (8) under Cao's data.

Consequently, in the following sections, we use the exporter-year instead of the exporter-sector-year fixed effects to avoid the potential "bad control" problem.

Table 4: OLS and IV results with different fixed effects

| Specification | NBS | | | | Cao | | | |
|---|---|---|---|---|---|---|---|---|
| | OLS (1) | IV (2) | OLS (3) | IV (4) | OLS (5) | IV (6) | OLS (7) | IV (8) |
| $EDR_c$*$Food_p$ | 0.086*** | -0.236*** | -0.108*** | -0.346*** | - | - | - | - |
| | (0.021) | (0.075) | (0.027) | (0.084) | | | | |
| $UDR_c$*$Food_p$ | - | - | - | - | 0.029*** | -0.065*** | -0.039*** | -0.098*** |
| | | | | | (0.007) | (0.022) | (0.009) | (0.025) |
| Kleibergen-Paap F-stat | - | 743.128*** | - | 739.990*** | - | 933.930*** | - | 839.246*** |
| Exporter-Year FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Exporter-Sector-Year FE | - | - | Y | Y | - | - | Y | Y |
| Importer-Product-Year FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Pair-Year FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Number of exporters | 24 | 24 | 24 | 24 | 21 | 21 | 21 | 21 |
| Observations | 2,210,057 | 2,210,057 | 2,209,768 | 2,209,768 | 2,168,717 | 2,168,717 | 2,168,487 | 2,168,487 |

Dependent variable: log export volume. Robust standard errors, clustered by exporter-importer are in parentheses. The period ranges from 2002 to 2008. The Kleibergen-Paap F-statistics are used to test for weak instruments. When using the NBS's excess death rate of 1960 ($EDR$) the weather shock is calculated based on 1960's weather conditions relative to 1956-58, whereas when using Cao's unexpected death rate of 1959-61 ($UDR$) the adverse weather is the average weather condition of 1959-61 relative to that of 1956-58. *** p<0.01, ** p<0.05, * p<0.1. Please note by virtue of our estimation commands (*reghdfe* and *ivreghdfe*), which include high dimensional fixed effects and drop those singletons, the number of observations might change with specifications.

# 5 Mechanisms

In the previous sections, we found that the overall impact of the Great Leap Famine on food exports compared to non-food exports is negative. Since this research focuses on the long-term influence of a historical event, it is essential to test the possible mechanisms through which the famine affects food exports. In this section, we describe four potential mechanisms driving this effect.

## 5.1 Suffered more, consume more?

One possible explanation is that an increased domestic food consumption would reduce the supply of food available for export, for a given level of food production. It has been documented that famine survivors exhibit higher risk-aversion reflected in a higher household saving rate (Cheng and Zhang, 2011; Chen et al., 2018), more conservative corporate policies among CEOs who suffered from the famine (Feng and Johansson, 2018), and a strong preference for self-sufficiency and social security among the politicians who experienced the famine in their early life (Guo et al., 2024). In addition, Gluckman et al. (2005) mention that compensatory overeating often occurs later in life among famine survivors, leading to increase in food consumption or retention by families. As Cao (2005) states, surviving families might be more prepared for the future, which makes it reasonable to infer that they have excess food reserves or purchase more food to hedge against future risks.

Based on these findings, we provide three measures related to the consumption of food in terms of household food reserves, household expenditure, as well as, the commodity rate of agricultural products. We then regress these three measures on different interaction terms of $EDR_c$, controls, and fixed effects using both OLS and IV.[24] Table 5 provides an overview of the regressions in this subsection.

Table 5: Mechanism analysis - list of variables

| Outcome variable ($Y$) | Interaction term ($M$) | Controls ($X'$) | Fixed effects ($FEs$) |
|---|---|---|---|
| $Food\,Reserve_{ch}$ | $Post_h$ | household-level $X'_h$ | province $\gamma_c$ |
| $Expense_{chk}$ | $Food_k$ | household-level $X'_h$<br>province-level $X'_c$ | - |
| | | - | province $\gamma_c$<br>household $\gamma_h$<br>expense type $\gamma_k$ |
| $Commodity\,Rate_{cpt}$ | $Food_p$ | $Crop\ acreage\ pc_{cpt}$<br>$Output\ per\ mu_{cpt}$ | product-year $\gamma_{pt}$<br>province-year $\gamma_{ct}$ |

$Food\,Reserve_{ch}$ is the log monetary value of staple food reserve of household $h$ from province $c$.
$Post_h$ takes the value of one for household $h$ whose head was at least 44 years old in late 2002 (i.e. born before the famine) and zero otherwise.
$Expense_{chk}$ is the monetary value a household $h$ from province $c$ spends on goods belonging to type $k$.
$Food_k$ takes the value of one for food expenses (staple and non-staple food) and zero for other types of expenses (alcohol, tobacco, clothes, daily necessities, durable goods) and zero otherwise.
$Commodity\,Rate_{cpt}$ is the commodity rate (share of crops is sold rather than retained) of crop $p$ in province $c$ in year $t$.
$Food_p$ takes the value of one if crop $p$ is edible and zero otherwise.
$Crop\ acreage\ pc_{cpt}$ is the yearly $t$ planting area per capita of a crop $p$ of a province $c$; $Output\ per\ mu_{cpt}$ is the output per unit area of a crop $p$ for a given year $t$ of a province $c$. Both are log-transformed.

Similarly to previous sections, we estimate the following models where $Y$ encompasses the three outcome variables. In these models, $M$ serves as a component of the interaction term, while $X'$ stands for different sets of control variables, and $FEs$ represents fixed effects. We once again use the adverse drought $AD_c$ and interact it with $M$ as the IV. We estimate the following general models

$$EDR_c * M = \alpha_0 + \alpha_1 AD_c * M + \alpha X' + FEs + errors \tag{6}$$

$$Y = \alpha_0 + \alpha_1 \widehat{EDR_c *} M + \alpha X' + FEs + errors \tag{7}$$

[24]We present IV results only, OLS results will be available upon request.

We use the data from CHIP 2002 to estimate the impact of this famine on household's food consumption.[25]

#### 5.1.1 Households' food reserve

The first variable described in Table 5 is the family food reserve, which reflects how much excess food a family purchases or retains in a given year. In CHIP 2002, there is a section asking the respondent "how much staple food reserve do you have at the end of 2002?". From this, we obtain the food storage data of each household from over 100 counties.[26] As in the previous sections, we use the adverse drought as the IV for the excess death rate to address the endogeneity problem. The IV results are presented in the first two columns of Table 6.[27]

The coefficient of the interaction term of excess death and the dummy *Post* is significantly positive in the second stage of IV estimations, indicating that families whose heads experienced a more severe famine shock have a larger staple food reserve. Taking column (2) as an example, the coefficient of 0.016 suggests that families whose heads suffered from the famine have 1.6 percent higher staple food reserve, in monetary value, compared with those whose heads did not experience the famine, for each one percentage point increase in their province's excess death rate. The average excess death rate under Cao (2005) in this sample is 4.6 percent, indicating that, in areas with this average famine intensity, households whose heads were born in or before late 1958 have approximately 7.4 percent higher staple food reserves, in monetary value, compared to those whose heads did not experience the famine. Under a given level of grain output, these extra reserves might affect the relative supply capability for food export compared to non-food export. After all, people do not seem eager to stock up on products such as durable or non-edible manufactured goods.

#### 5.1.2 Household expenditure

It is worth noting that our storage data is limited to four types of edible crops (wheat, rice, corn and tuber) without taking into account other food and non-edible products. Recall that in the main regressions, we compare food exports with non-food exports in provinces that experienced different famine intensities.

[25] http://www.ciidbnu.org/chip/

[26] It includes the weight data (in kgs) of four types of staple food reserves, which we convert into monetary values according to the price disclosed by the Ministry of Agriculture, and Cheng and Zhang (2011).

[27] To minimize the potential risk of comparing households with younger heads to those with older heads, we create age brackets around the cutoff of 44 years (born during the famine). Specifically, we compare households headed by individuals aged 44 to 54 with those headed by individuals aged 33 to 43, and the results remain robust. Furthermore, we include cohort fixed effects to control for potential confounding factors. For detailed results, please refer to Appendix B.3.

Table 6: Effects of the famine on food storage and expenditure of households

| Specification | $Food\,Reserve_{ch}$ | | $Expense_{chk}$ | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| ***Second-stage:*** | | | | |
| EDR$_c$*Post$_h$ | 0.051** | - | - | - |
| | (0.021) | | | |
| UDR$_c$*Post$_h$ | - | 0.016*** | - | - |
| | | (0.006) | | |
| EDR$_c$*Food$_k$ | - | - | 0.122*** | - |
| | | | (0.024) | |
| UDR$_c$*Food$_k$ | - | - | - | 0.030*** |
| | | | | (0.006) |
| ***First-stage:*** | | | | |
| Adverse drought$_c$*Post$_h$ | 0.034*** | 0.110*** | - | - |
| | (0.003) | (0.008) | | |
| Adverse drought$_c$*Food$_k$ | - | - | 0.036*** | 0.114*** |
| | | | (0.003) | (0.007) |
| Kleibergen-Paap F-stats: | 132.910*** | 191.348*** | 178.762*** | 265.810*** |
| Province FE | Y | Y | Y | Y |
| Household FE | - | - | Y | Y |
| Household-level controls | Y | Y | - | - |
| Expense type FE | - | - | Y | Y |
| Number of provinces | 19 | 19 | 19 | 19 |
| Observations | 7,117 | 7,117 | 50,242 | 50,242 |
| Death Toll Data | NBS | Cao | NBS | Cao |

Dependent variable: log monetary value of staple food reserve and log expenditure. Robust standard errors, clustered by counties are in parentheses. The Kleibergen-Paap F-statistics are used to test for weak instruments. When using the NBS's excess death rate of 1960 ($EDR$) the weather shock is calculated based on 1960's weather conditions relative to 1956-58, whereas when using Cao's unexpected death rate of 1959-61 ($UDR$) the adverse weather is the average weather condition of 1959-61 relative to that of 1956-58. *** p<0.01, ** p<0.05, * p<0.1.

Therefore, to make it consistent with the main regressions, we use two indicators to analyze the mechanism.

First, we extract the families' expenditure data from the CHIP 2002 to analyze if a harsher famine experience makes families spend more (or less) on food products than on non-food products. As discussed earlier, the experience of famine can lead households to engage in precautionary savings through food reserve or higher food consumption. Additionally, as argued by Gooch (2017), famine may worsen the economic situation in certain areas, leading to food expenditures accounting for the majority of household expenditures, with less ability to purchase other commodities. This may also make local food exports relatively smaller than non-food exports. To account for this effect, we use the $Expense_{chk}$ variable described in Table 5, which represents the expenditure of a family $h$ from province $c$ on goods belonging to type $k$. In addition, we include provincial controls such as $Grain\ province_h$ and household-level characteristics.[28] We also apply different sets of fixed effects accordingly.

The last two columns of Table 6 present the IV estimation results for family expenditure. Both columns (3) and (4) show positive and significant coefficients, indicating that households from provinces that experienced harsher famine spend more on food than on non-food after controlling for household and expenditure type fixed effects. Taking column (3) as an example, the coefficient of the interaction term is 0.122, indicating that a one percentage point increase in the excess death rate in 1960 makes the households purchase 13 percent more food products than non-food products, in monetary value. In this case, higher domestic food consumption crowds out the supply available for export, leading to lower food exports relative to non-food exports.

#### 5.1.3 Commodity rate of crops

Commodity rate is another proxy that could be applied here as a measure of how much output is being sold or retained. It represents the share of a crop that is sold as a commodity rather than retained for own use by farmers. We use the commodity rate of 39 edible and non-edible agricultural products of each province available from 2004 to 2008, overlapping with most of the years in our main regressions (2002 to 2008). The following formula shows the definition of the commodity rate

$$Commodity\ Rate = \frac{Commodity}{Total\ Output} = \frac{Total\ Output - Retained\ Output}{Total\ Output} = \frac{Sold\ Output}{Total\ Output} \qquad (8)$$

[28] $Grain\ province_h$ is a dummy equal to one if the province is one of the thirteen main grain-producing provinces (Heilongjiang, Henan, Shandong, Sichuan, Jiangsu, Hebei, Jilin, Anhui, Hunan, Hubei, Inner Mongolia, Jiangxi, Liaoning) and zero otherwise.

Our underlying assumption is that farmers will only consider selling their produce to domestic or international buyers once they have enough food for their own use. In other words, in harvest season producers will decide to retain parts of their harvest and then determine how much to sell. A higher commodity rate reflects, first, a lower share for own use and, second, a higher share allocated for exchange. The order here is crucial, as it indicates that more consumption demand leads to less selling and reduced export supply, rather than the other way around. This helps to alleviate the threat of reverse causality between local consumption and export.

In addition, we include non-edible products, which enables us to compare them with food. We first regress the commodity rate of a product $p$ of a province $c$ in year $t$ on the excess death toll and a set of controls. We then test its heterogeneous effect on food and non-food products. As shown in Table 5, we incorporate the annual planting area per capita for a crop in a province and the output per unit of area of a certain crop for a given year in a province as controls.

Table 7 shows the results of our IV regressions.[29] It shows that the excess death rate has a negative impact on the commodity rate, irrespective of the death toll data source, implying the retained rate of crops is higher in more affected areas. Taking specification (1) as an example, a one percentage point increase in the excess death rate of 1960 results in around 4.7 percentage point decrease in the commodity rate of agricultural crops, all else being equal. In columns (3) and (4) the negative coefficients are statistically significant, indicating that provinces with higher excess death rates, on average, have lower commodity rates of food crops than non-food crops. In other words, farmers in provinces with more intense famine experience retain more of their produce for personal use rather than selling it, and this effect is more pronounced for food crops than non-food ones.

To summarise, the first channel between famine and contemporary trade could be that the famine experience makes people consume or retain more food than non-food for the purpose of precautionary savings, which would lead to a relatively lower supply of food exports of these provinces. It may also be attributed to the long-term negative impact of famine on the economy that household expenditures on food accounted for a larger proportion, while the local consumption of other products was limited, thus making room for exports. However, these findings can only serve as suggestive evidence of the transmission channel as more

[29] Note that product-year fixed effects are included in all specifications while province-year fixed effects are included in specifications (3) and (4). The dummy of the grain-producing province is included when the province-year fixed effect is not added.

Table 7: Commodity rate of agricultural crops: IV

| Specification | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| ***Second-stage:*** | | | | |
| $\text{EDR}_c$ | -4.741*** | - | - | - |
| | (1.706) | | | |
| $\text{UDR}_c$ | - | -1.304*** | - | - |
| | | (0.472) | | |
| $\text{EDR}_c$*$\text{Food}_p$ | - | - | -5.960*** | - |
| | | | (2.137) | |
| $\text{UDR}_c$*$\text{Food}_p$ | - | - | - | -1.437** |
| | | | | (0.578) |
| Crop acreage $\text{pc}_{cpt}$ | 9.134*** | 9.913*** | 13.913*** | 14.074*** |
| | (1.793) | (1.579) | (2.896) | (2.618) |
| Output per $\text{mu}_{cpt}$ | -1.626 | -1.172 | -0.173 | -0.214 |
| | (2.245) | (2.066) | (1.988) | (2.004) |
| Grain $\text{province}_c$ | 11.287*** | 11.137*** | - | - |
| | (3.357) | (3.223) | | |
| ***First-stage:*** | | | | |
| Adverse $\text{drought}_c$*$\text{Food}_p$ | 0.029*** | 0.090*** | 0.034*** | 0.106*** |
| | (0.002) | (0.007) | (0.003) | (0.008) |
| Kleibergen-Paap F-stats: | 144.371*** | 168.130*** | 139.546*** | 185.823*** |
| Product-Year FE | Y | Y | Y | Y |
| Province-Year FE | - | - | Y | Y |
| Number of Provinces | 21 | 21 | 21 | 21 |
| Observations | 1,032 | 1,032 | 1,032 | 1,032 |
| Death Toll Data | NBS | Cao | NBS | Cao |

Dependent variable: Commodity rate. Robust standard errors, clustered by product are in parentheses. The Kleibergen-Paap F-statistics are used to test for weak instruments. The same controls are used in both stages. When using the NBS's excess death rate of 1960 ($EDR$) the weather shock is calculated based on 1960's weather conditions relative to 1956-58, whereas when using Cao's unexpected death rate of 1959-61 ($UDR$) the adverse weather is the average weather condition of 1959-61 relative to that of 1956-58. *** p<0.01, ** p<0.05, * p<0.1.

domestic consumption or a higher commodity rate might be the consequence of smaller international exports.

### 5.2 Risk-aversion and home bias

The home bias or border effects literature in international trade, pioneered by McCallum (1995) and followed up by many others (Wei, 1996; Anderson and Wincoop, 2003), indicates that much more trade occurs domestically than internationally. In general, international trade involves more uncertainties and costs compared to intra-national trade, including issues related to jurisdictions, exchange rates, and trade policies (Simmons, 2005; Ghazalian, 2012; Parsley and Wei 2001; Taglioni, 2002). These uncertainties help to explain why people tend to prefer trading within rather than across borders (Novy and Taylor, 2020; Matzner et al., 2023).

Compared to other exports, food and agricultural exports are naturally associated with more risk, higher relative cost and increased price volatility than non-food products (Hummels, 2007; OECD, 2017; Beghin and Schweizer, 2021). First, many food and agricultural products are low-value, perishable, and bulky, which induces more risk and higher costs relative to farm-gate value in international agricultural trade compared to domestic transactions. Moreover, since the quality of food and agricultural products can impact human health and environment, importing countries normally impose strict policies and standards (Essaji, 2008; Disdier and van Tongeren, 2010; Beghin et al., 2015). Consequently, companies exporting food to foreign markets face a higher risk of border rejection, affecting their export decision (Baylis et al., 2010; Beestermöller et al., 2018).[30] These factors contribute to the risks faced by exporters and increase trade costs, expressed as a share of the total value of traded goods, for agricultural and food products compared to high-value manufacturing goods (Beghin and Schweizer, 2021).

Second, food trade can impact a country's food security. Agricultural trade liberalization has been frequently debated as one of the factors making developing countries worse off in terms of food security (Gonzalez, 2002; Matthews, 2014; Mary, 2019).

The literature has found that the survivors of the Great Leap Famine exhibit higher risk aversion in decision-making, both among the general public and the politicians (Chen et al. 2023; Guo et al., 2024; Chen et al., 2024). This phenomenon is consistent with existing literature about the long-term impacts of

[30] Chinese enterprises are no exception, for instance, Chen et al. (2008) find that stricter food safety standards in terms of chemical residue on agricultural and fishery products set by the importers impede the corresponding exports from China.

disasters on risk aversion (Kim and Lee, 2014; Callen, 2015). Hence, if people or politicians from more affected provinces are more risk-averse, they may engage in less trade with foreign countries, showing a stronger preference for the domestic market in general. If more risk is associated with food trade, it will lead to relatively smaller food exports than non-food exports. In this section, our objective is to test the heterogeneous effect of excess death on the home-country bias of food sectors using international and intra-national trade data of Chinese provinces in 2007. We first estimate the domestic bias of Chinese provinces and then elaborate on its heterogeneity. Equation 9 estimates the heterogeneous home bias of Chinese provinces concerning food and agricultural products.

$$Export_{cjs} = \alpha_0 + \alpha_1 Distance_{cj} + \alpha_2 International_{cj} * Food_s + \sigma_{cs} + \omega_j + \epsilon_{cjs} \tag{9}$$

The dependent variable $Export_{cjs}$ is the log of the export volume of sector $s$ from a Chinese province $c$ to a domestic or a foreign partner $j$. The variable $International_{cj}$ takes the value of zero for domestic trade and one for international trade. We include exporter-sector fixed effects $\sigma_{cs}$, importer fixed effect $\omega_j$ and geographical distance $Distance_{cj}$. The $Food_s$ dummy equals one for the agricultural sector and food sector and zero otherwise.[31] Subsequently, we analyze the heterogeneity of home bias with respect to the famine intensity.

In column (1) of Table 8, the coefficient of $International_{cj}$, at -0.927 indicates that international exports from 21 sampled Chinese provinces are 60.4 percent smaller than domestic exports, which proves the existence of the domestic bias. In column (2), the negative sign of the interaction between $International_{cj}$ and $Food_s$ suggests that, compared with non-food sectors, food sectors have smaller international exports than domestic exports. In other words, the agricultural and food sectors have greater domestic bias than other sectors. Similarly, in columns (3) and (4) we uncover the heterogeneous border effect with respect to the severity of the famine. Taking column (3) as an example, provinces that were more severely affected by the famine export less to international partners than to domestic partners.

In Equation 10, we incorporate a three-way interaction term of $International_{cj}$, $Food_s$ and the death

[31] It also equals to one for the tobacco and beverage sectors since they are integrated with the food sector in the input-output tables.

Table 8: Food, EDR and home country bias - OLS

| Specification | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Distance$_{cj}$ | -1.139*** | -1.392*** | -1.386*** | -1.395*** |
| | (0.052) | (0.065) | (0.068) | (0.067) |
| International$_{cj}$ | -0.927*** | - | - | - |
| | (0.125) | | | |
| International$_{cj}$*Food$_s$ | - | -2.657*** | - | - |
| | | (0.066) | | |
| International$_{cj}$*EDR$_c$ | - | - | -0.207*** | - |
| | | | (0.024) | |
| International$_{cj}$*UDR$_c$ | - | - | - | -0.068*** |
| | | | | (0.008) |
| Constant | 23.596*** | 25.233*** | 25.191*** | 25.268*** |
| | (0.366) | (0.555) | (0.573) | (0.571) |
| Exporter-Sector FE | Y | Y | Y | Y |
| Importer FE | - | Y | Y | Y |
| Importer-Sector FE | - | - | Y | Y |
| Number of exporters | 21 | 21 | 21 | 21 |
| Observations | 50,083 | 50,083 | 50,083 | 50,083 |
| R-squared | 0.393 | 0.665 | 0.781 | 0.781 |
| Death Toll Data | - | - | NBS | Cao |

Dependent variable: log export volume. The individual terms $International_{cj}$, $Food_s$ and $EDR_c$ are not included in column (2) to (4) as they would be absorbed by the fixed effects. Robust standard errors, clustered by exporter-importer are in parentheses. The $Distance_{cj}$ variable is in log. *** p<0.01, ** p<0.05, * p<0.1.

toll. Furthermore, to address potential endogeneity we instrument the excess death with the adverse drought.

$$Export_{cjs} = \alpha_0 + \alpha_1 International_{cj} * EDR_c * Food_s + \sigma_{cs} + \lambda_{js} + \omega_{cj} + \epsilon_{cjs} \tag{10}$$

As shown in Table 9 the coefficients are all negative in both specifications. This indicates that the relative international export over domestic export is smaller for food and agricultural sectors than that for other sectors, and this effect is more pronounced when the excess death rate increases. Another interpretation could be the domestic bias is higher in more severely affected areas by the famine and this phenomenon is more obvious in their food sectors.

In summary, this section demonstrates that provinces that faced more severe famine shocks between 1959 and 1961 exhibit a stronger domestic bias in their exports patterns. This tendency is particularly pronounced in the food and agricultural sectors compared to other industries. Such behavior could be influenced by the risk-averse attitudes of both individuals and policymakers. Consequently, food exports are relatively smaller than other exports in the seriously affected provinces, which explains the effect found in previous sections.

Table 9: Food, EDR and home country bias - IV

| Specification | (1) | (2) |
|---|---|---|
| *Second-stage:* | | |
| International$_{cj}$*EDR$_c$*Food$_s$ | -0.249** | - |
| | (0.111) | |
| International$_{cj}$*UDR$_c$*Food$_s$ | - | -0.083*** |
| | | (0.023) |
| *First-stage:* | | |
| International$_{cj}$*Adverse drought$_c$*Food$_s$ | 0.038*** | 0.116*** |
| | (0.006) | (0.016) |
| Pair FE | Y | Y |
| Exporter-Sector FE | Y | Y |
| Importer-Sector FE | Y | Y |
| Number of exporters | 21 | 21 |
| Observations | 49,834 | 49,834 |
| Death Toll Data | NBS | Cao |
| Kleibergen-Paap F-stats: | 41.970*** | 55.123*** |

Dependent variable: log export volume. Robust standard errors, clustered by exporter-$Food$ are in parentheses. When using the NBS's excess death rate of 1960 ($EDR$) the weather shock is calculated based on 1960's weather conditions relative to 1956-58, whereas when using Cao's unexpected death rate of 1959-61 ($UDR$) the adverse weather is the average weather condition of 1959-61 relative to that of 1956-58. *** p<0.01, ** p<0.05, * p<0.1.

## 6 Robustness checks

In previous sections, we tested the robustness of our findings by using two different sources of death toll data: the NBS and Cao (2005). In this section, we conduct additional robustness checks. First, we present the yearly regression results and perform a placebo test. Additionally, in Appendix B.4 we apply a different regression method (PPML) and in Appendix B.5 we re-estimate the observed effects using an alternative IV. Our findings remain consistent across these checks.

### 6.1 Yearly regressions

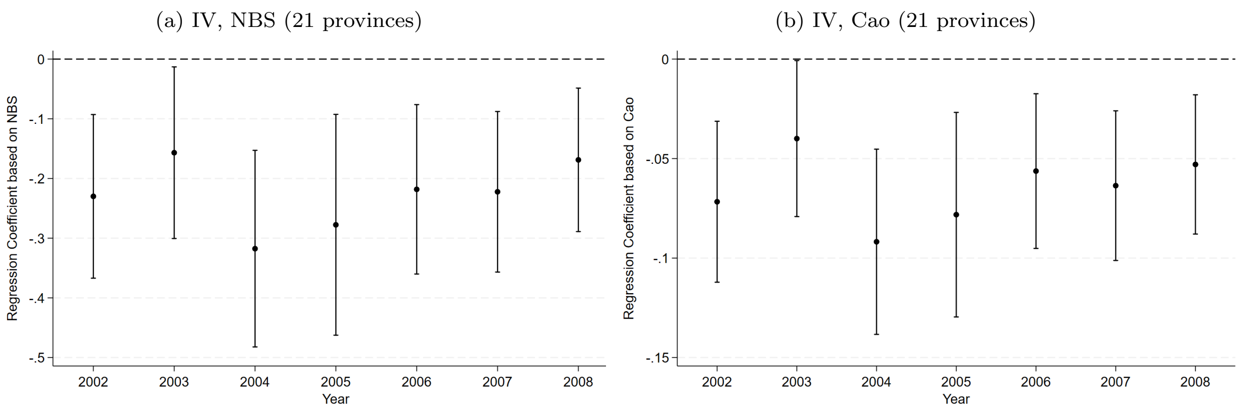
In Figures 4 we present the results of the yearly regressions using the IV method. All the specifications yield negative coefficients.

The yearly IV results confirm our findings from previous sections and rule out the possibility that the observed effect is caused by random shocks in specific years (although the year fixed effects added in previous models have already alleviated this concern). In other words, the long-run impact of this famine on current trade indeed exists across different years. What is more, the negative impact of this famine was most pronounced in 2004. After that year it is getting gradually weaker, possibly due to the fact that those who experienced the famine are getting older. This finding is consistent with the results by Ouyang and Yuan (2021) on the effects of massacres by the Japanese during the Second Sino-Japanese War. They find that its effects on recent trade patterns are diminishing. Their explanation is, however, based on a more integrated international markets. In our case, this could also be the reason for the attenuating effect.

### 6.2 Placebo test

We use the death rate from 1950 to 1958 from the NBS to construct a linear trend.[32] This allows us to estimate the predicted death rate for the period 1959-1961, assuming the famine had not occurred. Based on this, we can calculate the counterfactual "excess death rate" that would have been observed in the absence of the famine. Figure 5 plots the predicted counterfactual and actual death rate (in percent) for 21 provinces in 1960.

[32]Please note that as we do not have the demographic data for 1950-58 for Cao' data so we can only test it based on the NBS data.




*We report 90% confidence intervals. The robust standard errors are clustered at the importer-exporter pair.*

Figure 4: Yearly regressions results

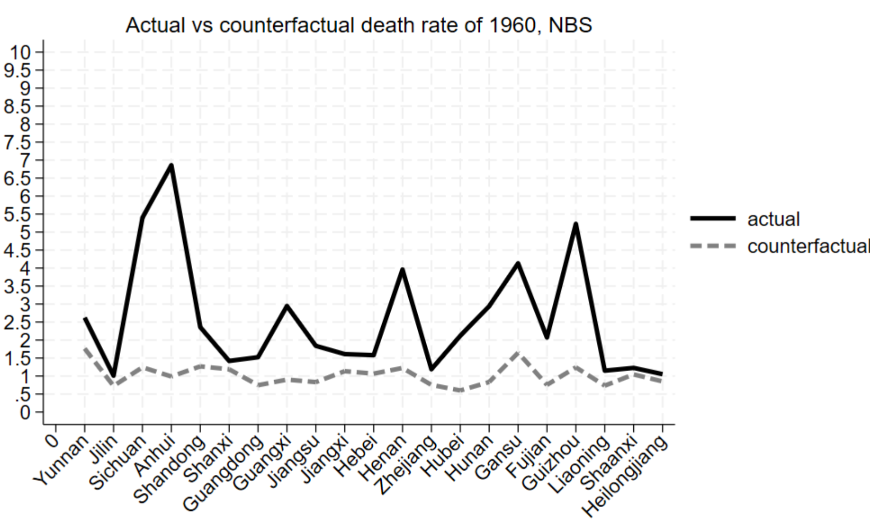



Figure 5: Counterfactual EDR (%), NBS

Table 10 displays the results generated by applying the predicted counterfactual excess death rate to the OLS regressions. All the specifications turn significantly positive, which suggests that if the famine had not happened, current food exports of the areas that suffered more, would be larger than non-food exports. Consequently, the placebo test supports our findings.

Table 10: OLS - counterfactual excess death rate

| Specification | (1) | (2) |
|---|---|---|
| Predicted $EDR_c$*$Food_p$ | 1.257*** | - |
| | (0.319) | |
| Predicted $EDR_c$*$Major_p$ | - | 2.635*** |
| | | (0.543) |
| Constant | 10.446*** | 10.421*** |
| | (0.002) | (0.000) |
| Exporter-Sector-Year FE | Y | Y |
| Importer-Product-Year FE | Y | Y |
| Pair-Year FE | Y | Y |
| Number of exporters | 21 | 21 |
| Observations | 2,168,487 | 2,100,872 |
| R-squared | 0.549 | 0.550 |
| Data | NBS | NBS |

Dependent variable: log export volume. Robust standard errors, clustered by exporter-importer are in parentheses. The period ranges from 2002 to 2008. *** p<0.01, ** p<0.05, * p<0.1.

# 7 Conclusion

Uncovering the impacts of historical events such as conflicts, aids, and exchanges on recent trade is popular in the field of international economics and development economics. One of the devastating events, the Great Leap Famine of China, happened in the late 1950s and has long been discussed by scholars in terms of its causes and consequences on health, labor market outcomes, or institutional changes. However, the impacts of this famine on recent trade have never been analyzed. Based on product-level trade data between Chinese provinces and foreign partners, we find that provinces that suffered more during the famine have smaller food exports than non-food exports after over forty years, and this effect is more pronounced for major food items that are commonly consumed. In order to address the endogeneity and avail causal inference, we apply the IV method by using the adverse weather shock, which is one of the exogenous contributors to the famine. The results are robust to different methods and instruments. In the final step, we run yearly regressions and find that the captured impact is getting weaker with time.

In the ensuing analysis, we explore several potential channels explaining our results. First, famine-induced consumption or preventive food reserves might play a role. Households that experienced famine have larger food storage and higher food expenditure over non-food expenditure. Second, provinces that suffered more severely from famine retain more food crops than non-food crops rather than selling them. Finally, individuals and policymakers who experienced famine tend to exhibit greater risk aversion later in life. International trade, especially in food, is associated with higher risk. Consequently, people in areas more severely affected by famine are likely to have a stronger domestic bias in trade, with this preference being more pronounced in food sectors than non-food sectors.

In sum, this paper complements the literature on the long-term impact of the Great Leap Famine and shows that history matters in understanding China's current trade patterns. We show that the influence of this famine extends beyond areas such as demography, health, labour, and institutional reform, also affecting current trade structures and patterns. This can help explain the formation of the current trade patterns, whether from the perspective of famine-induced changes in comparative advantage across regions or from shifts in the public attitudes toward food safety and risk preferences resulting from the famine. At the same time, we hope that by highlighting the profound impact of this famine, both the public and decision-makers will recognize the importance of avoiding such crises, particularly by addressing the man-made factors that contribute to them. To prevent the recurrence of a famine of this magnitude, a comprehensive study of its causes and impacts is essential. By reflecting on the experiences and lessons learned from the planned economic system, we can apply these insights to modern society.

Throughout history, even prominent figures are often only briefly acknowledged, much less ordinary individuals who may appear "insignificant". However, each of these individuals is a celebrity in their own right, holding great importance within their families. This paper also aims to ensure that people who suffered from the famine are remembered from an economic perspective.

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# A Appendix: Additional data description

## A.1 Adverse death rate

Table A1: Summary statistics of adverse death rate (percentage)

| | Source | Provinces include | Mean | Std.dev. | Min | Max |
|---|---|---|---|---|---|---|
| Excess death rate 1960 ($EDR_c$) | NBS | 29 | 1.269 | 1.475 | 0.060 | 5.668 |
| | NBS | 21 | 1.423 | 1.514 | 0.062 | 5.668 |
| Unexpected death rate 1959-61 ($UDR_c$) | Cao (2005) | 21 | 4.287 | 4.648 | 0.370 | 18.370 |

## A.2 Major food categories

Table A1: Major food list

| HS4 | Product |
|---|---|
| 102 | Bovine animals; live |
| 103 | Swine; live |
| 104 | Sheep and goats; live |
| 105 | Poultry; live, fowls of the species Gallus domesticus, ducks, geese, turkeys and guinea fowls |
| 201 | Meat of bovine animals; fresh or chilled |
| 202 | Meat of bovine animals; frozen |
| 203 | Meat of swine; fresh, chilled or frozen |
| 204 | Meat of sheep or goats; fresh, chilled or frozen |
| 301 | Fish; live |
| 302 | Fish; fresh or chilled, excluding fish fillets and other fish meat of heading 0304 |
| 407 | Birds' eggs, in shell; fresh, preserved or cooked |
| 701 | Potatoes; fresh or chilled |
| 702 | Tomatoes; fresh or chilled |
| 703 | Onions, shallots, garlic, leeks and other alliaceous vegetables; fresh or chilled |
| 704 | Cabbages, cauliflowers, kohlrabi, kale and similar edible brassicas; fresh or chilled |
| 705 | Lettuce (lactuca sativa) and chicory (cichorium spp.) fresh or chilled |
| 706 | Carrots, turnips, salad beetroot, salsify, celeriac, radishes and similar edible roots; fresh or chilled |
| 707 | Cucumbers and gherkins; fresh or chilled |
| 708 | Leguminous vegetables; shelled or unshelled, fresh or chilled |
| 803 | Bananas, including plantains; fresh or dried |
| 805 | Citrus fruit; fresh or dried |
| 806 | Grapes; fresh or dried |
| 807 | Melons (including watermelons) and papaws (papayas); fresh |
| 808 | Apples, pears and quinces; fresh |
| 809 | Apricots, cherries, peaches (including nectarines), plums and sloes, fresh |
| 1001 | Wheat and meslin |
| 1005 | Maize (corn) |
| 1006 | Rice |
| 1101 | Wheat or meslin flour |
| 1202 | Ground-nuts; not roasted or otherwise cooked, whether or not shelled or broken |
| 1205 | Rape or colza seeds; whether or not broken |
| 1206 | Sunflower seeds; whether or not broken |
| 1501 | Pig fat (including lard) and poultry fat, other than that of heading 0209 or 1503 |
| 1507 | Soya-bean oil and its fractions; whether or not refined, but not chemically modified |
| 1508 | Ground nut oil and its fractions; whether or not refined, but not chemically modified |
| 1701 | Cane or beet sugar and chemically pure sucrose, in solid form |

## A.3 Summary statistics - mechanism analysis

Table A2: Summary statistics for mechanism analysis

| Variables | Obs | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| **Food reserve:** column (2) of Table 6 | | | | | |
| Food reserve$_{ch}$ | 7,117 | 7.277 | 1.141 | 0.095 | 10.898 |
| Post$_h$ | 7,117 | 0.586 | 0.493 | 0 | 1 |
| Gender of head$_h$ | 7,117 | 1.033 | 0.180 | 1 | 2 |
| Age of head$_h$ | 7,117 | 46.241 | 10.217 | 16 | 87 |
| Years of schooling$_h$ | 7,117 | 7.280 | 2.454 | 0 | 16 |
| Employed$_h$ | 7,117 | 0.920 | 0.271 | 0 | 1 |
| Family size$_h$ | 7,117 | 4.151 | 1.267 | 1 | 11 |
| Dependency$_h$ | 7,117 | 0.217 | 0.211 | 0 | 1 |
| Net income per family member$_h$ (NI pc$_h$) | 7,117 | 7.648 | 0.673 | 4.159 | 10.460 |
| Assets per family member$_h$ (Assets pc$_h$) | 7,117 | 8.701 | 0.894 | 5.481 | 12.530 |
| **Expenditure:** column (4) of Table 6 | | | | | |
| Expense$_{chk}$ | 50,242 | 5.529 | 1.517 | 0 | 10.810 |
| Food$_k$ | 50,242 | 0.336 | 0.472 | 0 | 1 |
| **Commodity rate:** column (4) of Table 7 | | | | | |
| Commodity rate$_{cpt}$ | 1,032 | 81.794 | 21.640 | 12.600 | 100.000 |
| Food$_p$ | 1,032 | 0.625 | 0.484 | 0 | 1 |
| Output per mu$_{cpt}$ | 1,032 | 6.905 | 0.813 | 3.678 | 10.179 |
| Crop acreage per capita$_{cpt}$ (Crop acreage pc$_{cpt}$) | 1,032 | 0.392 | 0.533 | 0 | 2.873 |
| **Home bias:** column (2) of Table 9 | | | | | |
| Export$_{cjs}$ | 49,834 | 13.273 | 3.290 | -10.192 | 22.877 |
| International$_{cj}$ | 49,834 | 0.750 | 0.433 | 0 | 1 |
| Food$_s$ | 49,834 | 0.093 | 0.291 | 0 | 1 |

Export volume, food reserve, expense, net income, assets, crop acreage per capita and output per mu are in logs (in China, mu is a unit of land area and one mu is approximately equal to 667 square meters).

# B Appendix: additional results

## B.1 Different clustering methods

In this section, we test the robustness of our baseline OLS and IV results by clustering the standard error at the level of exporter-$Food_p$. Since we have 21 overlapping provinces in Cao (2005) and NBS, we end up with 42 clusters. The results are robust to the ones generated by clustering the standard errors by importer-exporter pair presented in the main text.

Table B1: Baseline OLS and IV results: clustering by exporter-$Food_p$

| Specification | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| ***Second-stage:*** | | | | |
| $\text{EDR}_c$*$\text{Food}_p$ | -0.128** | - | -0.364*** | - |
| | (0.048) | | (0.093) | |
| $\text{UDR}_c$*$\text{Food}_p$ | - | -0.039** | - | -0.098*** |
| | | (0.016) | | (0.023) |
| Constant | 10.445*** | 10.445*** | - | - |
| | (0.002) | (0.002) | | |
| ***First-stage:*** | | | | |
| Adverse $\text{drought}_c$*$\text{Food}_p$ | - | - | 0.039*** | 0.121*** |
| | | | (0.005) | (0.012) |
| Kleibergen-Paap F-stat | - | - | 75.449*** | 104.982*** |
| Exporter-Sector-Year FE | Y | Y | Y | Y |
| Importer-Product-Year FE | Y | Y | Y | Y |
| Pair-Year FE | Y | Y | Y | Y |
| Number of exporters | 21 | 21 | 21 | 21 |
| Observations | 2,168,487 | 2,168,487 | 2,168,487 | 2,168,487 |
| R-squared | 0.549 | 0.549 | - | - |
| Method | OLS | OLS | IV | IV |
| Death Toll Data | NBS | Cao | NBS | Cao |

Dependent variable: log export volume. Robust standard errors, clustered by exporter-$Food_p$ are in parentheses. The period ranges from 2002 to 2008. The Kleibergen-Paap F-statistics are used to test for weak instruments. When using the NBS's excess death rate of 1960 ($EDR$) the weather shock is calculated based on 1960's weather conditions relative to 1956-58, whereas when using Cao's unexpected death rate of 1959-61 ($UDR$) the adverse weather is the average weather condition of 1959-61 relative to that of 1956-58. *** p<0.01, ** p<0.05, * p<0.1.

## B.2 Major food

In this section, we use a $Major$ dummy which takes the value of one for products belonging to the major food category and zero for non-food products. We anticipate the effect of famine on food exports to be greater when only major food items are compared with non-food products. The classification of major food is based on the "Major food consumption" indicators of the *China Statistical Yearbook*. Detailed categories are provided in Table A1. Table B2 shows the corresponding results. The negative impact of famine on food exports relative to non-food exports is more pronounced when we consider major food items only. For instance, compared to column (6) of Table 3 the coefficient in column (3) of Table B2 is approximately doubled.

Table B2: IV results - major food items (excluding non-major food)

| Specification | (1) | (2) | (3) |
|---|---|---|---|
| ***Second-stage:*** | | | |
| EDR$_c$*Major$_p$ | -0.450*** | -0.446*** | - |
| | (0.156) | (0.164) | |
| UDR$_c$*Major$_p$ | - | - | -0.135*** |
| | | | (0.052) |
| ***First-stage:*** | | | |
| Adverse drought$_c$*Major$_p$ | 0.037*** | 0.036*** | 0.107*** |
| | (0.002) | (0.002) | (0.007) |
| Kleibergen-Paap F-stat | 272.835*** | 239.094*** | 253.108*** |
| Exporter-Year FE | Y | Y | Y |
| Importer-Product-Year FE | Y | Y | Y |
| Pair-Year FE | Y | Y | Y |
| Number of exporters | 24 | 21 | 21 |
| Observations | 2,139,462 | 2,101,111 | 2,101,111 |
| Data | NBS | NBS | Cao |

Dependent variable: log export volume. Robust standard errors, clustered by exporter-importer, are in parentheses. The period ranges from 2002 to 2008. The Kleibergen-Paap F-statistics are used to test for weak instruments. When using the NBS's excess death rate of 1960 ($EDR$) the weather shock is calculated based on 1960's weather conditions relative to 1956-58, whereas when using Cao's unexpected death rate of 1959-61 ($UDR$) the adverse weather is the average weather condition of 1959-61 relative to 1956-58. *** p<0.01, ** p<0.05, * p<0.1.

## B.3 Food reserve - age brackets and age cohort fixed effects

To reduce the risk of comparing households led by younger heads to those led by older heads, we created age brackets centred around the cutoff of 44 years. Specifically, we compare households headed by individuals aged 44 to 54 with those headed by individuals aged 33 to 43, ensuring that the main results remain robust. Additionally, we incorporate cohort fixed effects to account for potential confounding factors.

Table B3: Effects of the famine on food storage

| Specification | $Food\,Reserve_{ch}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| ***Second-stage:*** | | | | |
| $\text{EDR}_c$*$\text{Post}_h$ | 0.053** | - | 0.058** | - |
| | (0.022) | | (0.024) | |
| $\text{UDR}_c$*$\text{Post}_h$ | - | 0.017*** | - | 0.018*** |
| | | (0.006) | | (0.006) |
| ***First-stage:*** | | | | |
| Adverse $\text{drought}_c$*$\text{Post}_h$ | 0.034*** | 0.110*** | 0.035*** | 0.111*** |
| | (0.003) | (0.008) | (0.003) | (0.008) |
| Kleibergen-Paap F-stats: | 129.658*** | 187.636*** | 133.203*** | 188.230*** |
| Province FE | Y | Y | Y | Y |
| Household-level controls | Y | Y | Y | Y |
| Age cohort FE | Y | Y | - | - |
| Age brackets | - | - | Y | Y |
| Number of provinces | 19 | 19 | 19 | 19 |
| Observations | 7,117 | 7,117 | 5,023 | 5,023 |
| Death Toll Data | NBS | Cao | NBS | Cao |

Dependent variable: log monetary value of staple food reserve. Columns (1) and (2) include additional controls for age cohort fixed effects. Columns (3) and (4) compare households headed by individuals aged 45 to 54 with those headed by individuals aged 33 to 43. Robust standard errors clustered by counties are in parentheses. All specifications include province fixed effects.The Kleibergen-Paap F-statistics are used to test for weak instruments. When using the NBS's excess death rate of 1960 (EDR), the weather shock is calculated based on 1960's weather conditions relative to 1956-58, whereas when using Cao's unexpected death rate of 1959-61 (UDR), the adverse weather is the average weather condition of 1959-61 relative to 1956-58. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

## B.4 PPML

Since the OLS estimation with logarithmic variables inevitably omits observations containing zeros, considered to include useful information, we use the Poisson Pseudo Maximum Likelihood (PPML) method, as recommended by Silva and Tenreyro (2006). We estimate Equation 3 with the dependent variable changed to the level of the export value. Table B4 presents the results, showing that the coefficients in columns (2) and (4) of the interaction are still significantly negative and similar in magnitude to those estimated by OLS in columns (1) and (3).

Table B4: Robustness check - PPML regressions to address zero trade volume

| Specification | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $EDR_c$*$Food_p$ | -0.128*** | -0.133** | - | - |
| | (0.028) | (0.059) | | |
| $UDR_c$*$Food_p$ | - | - | -0.039*** | -0.059*** |
| | | | (0.009) | (0.018) |
| Constant | 10.445*** | 15.733*** | 10.445*** | 15.735*** |
| | (0.001) | (0.003) | (0.001) | (0.002) |
| Exporter-Sector-Year FE | Y | Y | Y | Y |
| Importer-Product-Year FE | Y | Y | Y | Y |
| Pair-Year FE | Y | Y | Y | Y |
| Number of exporters | 21 | 21 | 21 | 21 |
| Observations | 2,168,487 | 11,720,518 | 2,168,487 | 11,720,518 |
| R-squared | 0.530 | - | 0.549 | - |
| Death Toll Data | NBS | NBS | Cao | Cao |
| Method | OLS | PPML | OLS | PPML |

Dependent variable: log export volume for OLS regressions; export volume for PPML regressions. Robust standard errors clustered by exporter-importer are in parentheses. The period ranges from 2002 to 2008. *** p<0.01, ** p<0.05, * p<0.1.

## B.5 Alternative instrument - direct weather data

In this section, we use an alternative source of weather data obtained from the Global Summary of the Month datasets of the NOAA. The data includes monthly historical precipitation and temperature records between 1956 and 1961, collected from 185 weather stations in China. By averaging sub-provincial level data, we obtain the average yearly precipitation and temperature data for 21 overlapping provinces. However, this approach may introduce the following issues: (1) provinces that experienced both drought and flood might have a seemingly "normal" precipitation due to the offsetting effect of the averaging process; (2) data collected from weather stations in remote and sparsely populated areas may not be reliable. Previous literature has identified these problems in Sichuan province, which is considered an outlier (Houser et al., 2009; Bramall, 2010). Therefore, we exclude the stations located in mountainous areas of central and western Sichuan and include those from the eastern basins and plains, following Bramall (2010).

Following the logic used in calculating the adverse drought, we compute the deviation of average precipitation and temperature during the famine period from the average level of three preceding years (1956-58) and use both as instruments in the two-stage least squares regressions. Specifically, we use the precipitation and temperature of 1960 normalized by the average level of three years before the famine as a proxy for the 1960 excess death rate of NBS. For Cao's unexpected death rate during 1959-61, we instrument it using the deviation of 1959-61's weather conditions from the average of three preceding years. The calculation of instruments is illustrated in Equations 11 and 12. Table B5 presents the estimated results using direct weather data, accounting for the distinctiveness of Sichuan in columns (2) and (4).

$$Adverse\,Precipitation_c = \frac{(Precipitation_{c,60} - 1/T\sum_{t=56}^{58} Precipitation_{ct})}{(1/T\sum_{t=56}^{58} Precipitation_{ct})} \tag{11}$$

$$Adverse\,Temperature_c = \frac{(Temperature_{c,60} - 1/T\sum_{t=56}^{58} Temperature_{ct})}{(1/T\sum_{t=56}^{58} Temperature_{ct})} \tag{12}$$

Starting with the first stage regressions of specifications (1) and (3), we see that provinces with more precipitation and higher temperatures have lower excess death rates, which corroborates the findings using adverse drought data, that provinces experiencing higher drought have higher excess death rates. The coefficient of the precipitation variable in column (1) indicates that if a province's 1960s precipitations was zero (i.e., $AdversePrecipitation_{ct}$ equals -1), the excess death rate would be around 2.4 percentage points

Table B5: Robustness check: analysis using direct weather data

| Specification | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| ***Second-stage:*** | | | | |
| EDR$_c$*Food$_p$ | -0.213*** | -0.190*** | - | - |
| | (0.071) | (0.068) | | |
| UDR$_c$*Food$_p$ | - | - | -0.161*** | -0.158*** |
| | | | (0.031) | (0.030) |
| ***First-stage:*** | | | | |
| Adv precipitation$_c$*Food$_p$ | -2.385*** | -2.532*** | -15.546*** | -15.719*** |
| | (0.258) | (0.262) | (1.661) | (1.660) |
| Adv temperature$_c$*Food$_p$ | -7.228*** | -7.282*** | -6.663*** | -6.634*** |
| | (0.913) | (0.918) | (0.744) | (0.739) |
| Kleibergen-Paap F-stat | 124.173*** | 126.782*** | 62.454*** | 63.225*** |
| Exporter-Year FE | Y | Y | Y | Y |
| Importer-Product-Year FE | Y | Y | Y | Y |
| Pair-Year FE | Y | Y | Y | Y |
| Number of exporters | 21 | 21 | 21 | 21 |
| Observations | 2,168,717 | 2,168,717 | 2,168,717 | 2,168,717 |
| Death Toll Data | NBS | NBS | Cao | Cao |

Dependent variable: log export volume. Robust standard errors clustered by exporter-importer are in parentheses. The period ranges from 2002 to 2008. Column (2) and (4) take into account the distinctiveness of Sichuan. The Kleibergen-Paap F-statistics are used to test for weak instruments. When using the NBS's excess death rate of 1960 ($EDR$) the weather shock is calculated based on 1960's weather conditions relative to 1956-58, whereas when using Cao's unexpected death rate of 1959-61 ($UDR$) the adverse weather is the average weather condition of 1959-61 relative to that of 1956-58. *** p<0.01, ** p<0.05, * p<0.1.

higher. In column (3), the adverse weather shock is calculated using the average precipitation from 1959-61 relative to the three preceding years, the coefficient of the precipitation is greater in absolute value. This can be interpreted as if a province's average precipitation during the whole famine was zero, the excess death rate would increase by approximately 15.5 percentage points. Moving to the second-stage regressions, the coefficients of the variables of interest are all negative and significant, similar to our previous results using adverse drought. The negative effect of famine intensity on trade is more pronounced when using the direct weather shock as the instrument for Cao's excess death rate.

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