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Essays on International Trade and Economic Development

by

Zhimin Li

A dissertation submitted in partial satisfaction of the
requirements for the degree of
Doctor of Philosophy

in

Agricultural and Resource Economics

in the

Graduate Division

of the

University of California, Berkeley

Committee in charge:

Professor Pierre-Olivier Gourinchas, Co-chair
Assistant Professor Thibault Fally, Co-chair
Professor Andrés Rodríguez-Clare
Professor Brian Wright

Spring 2018

Essays on International Trade and Economic Development

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Abstract

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Doctor of Philosophy in Agricultural and Resource Economics

University of California, Berkeley

Professor Pierre-Olivier Gourinchas, Co-chair

Assistant Professor Thibault Fally, Co-chair

This dissertation consists of three chapters regarding international trade and economic development. In the first two chapters I explore how China’s economic rise to the global stage affects resource allocations inside and outside the country, and in the third chapter I present a new method to infer risk sharing regimes pertinent to studying consumption behavior in developing countries.

The first chapter studies how the “China shock”—the remarkable growth in China’s productivity and trade activities since its accession to the World Trade Organization (WTO)—affects China’s labor market and real exchange rate dynamics. I apply a dynamic trade and spatial equilibrium model to jointly explain two distinctive features of China’s economic growth: the structural transformation, as characterized by the reallocation of labor from agriculture to manufacturing and services, and the sluggish appreciation of the real exchange rate, a puzzle from the perspective of a standard international economics model. The model highlights the role of the subsistence sector in shaping the patterns of the structural transformation and real exchange rate dynamics. Using inter-regional trade and migration data, I calibrate the model to decompose the “China shock” into productivity shocks and trade shocks and show that the two features above arise naturally from the interaction between the labor market and observed shocks to productivity and trade costs. I find that while productivity growth is the primary source of the structural transformation, the accession to the WTO explains about 35% of the rise in the employment share and 20% of the increase in the real wage in the manufacturing sector. Welfare gains from the “WTO entry” are 27% on average and would be larger if complemented by relaxing labor restrictions further. By accounting for trade costs, the subsistence sector, and labor market frictions, the model generates dynamics for China’s real exchange rate consistent with the data.

The second chapter studies the effects of real estate investments by foreign Chinese on local economies in the United States. This chapter is co-authored with Leslie S. Shen and Calving Zhang. We document an unprecedented surge in housing purchases by foreign Chinese in the US over the past decade and analyzes their effects on US local economies. Using

transaction-level data on housing purchases, we find that the share of purchases by foreign Chinese in the California real estate market increased more than tenfold during the period of 2007-2013 relative to earlier years. In particular, these purchases have been concentrated in zip codes that are historically populated by ethnic Chinese, making up for more than 10% of the total real estate transactions in these neighborhoods in 2013. We exploit the cross-sectional variation in the concentration of Chinese population settlement across zip codes during the pre-sample period to instrument for the volume of housing purchases by foreign Chinese. Our results show that housing purchases by foreign Chinese significantly increased local housing prices as well as local employment. Our evidence highlights the role of foreign investments in local employment, especially in times of economic downturns.

The third chapter proposes a novel approach to test alternative theories of risk sharing—full insurance, self-insurance, and private information—in a unified framework. Given the prevalence of informal insurance in developing countries to share consumption risks, studying risk sharing regimes is important. A distinguishing feature of the framework presented in this chapter is that it accounts for aggregate shocks and does not require data on interest rates, an important advantage for studying rural economies. Applying the approach to a longitudinal dataset from Tanzania, I reject models of full insurance and private information and find evidence of self-insurance. An incorrect inference on the insurance regime could underestimate the welfare loss from risk by as much as ten times.

This dissertation is dedicated to my parents, whose unyielding faith in me has been my constant source of strength.

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Chapter 1

The “China Shock” on China: Trade, Structural Transformation, and Real Exchange Rate Dynamics

1.1 Introduction

One of the most notable phenomena in international economics over the past two decades has been China’s economic transformation and mounting influence on the rest of the world, as evidenced by its rapid growth in productivity and trade activities (the so-called “China shock”). China’s export-oriented development process has led to impressive reallocations of resources inside the country as well as adjustments in relative prices.

Two distinctive features are salient regarding China’s recent economic rise:

Feature 1: The economy has undergone a structural transformation, characterized by the reallocation of labor from agriculture to manufacturing and services. As shown in figure 1.1, agriculture’s employment share declined from more than 50% in the 1990s to less than 30% in 2015, while industry’s employment share rose by almost 50% during the same period, with an inflection point around the time when China joined the World Trade Organization (WTO).^{1,2}

Feature 2: There has been a sluggish appreciation of the real exchange rate, despite rapid productivity growth in manufacturing. Figure 1.2 shows that China’s real exchange rate appreciated by only 60% in the decade following its accession to the WTO, despite the fact that its relative labor productivity in manufacturing rose more than threefold during the same period. Fast productivity growth in manufacturing did not translate to a rapid increase in relative prices or the real exchange rate with the rest of the world, which is puzzling with respect to a textbook Balassa-Samuelson model from international economics.

¹China became a member of the WTO on December 11, 2001.

²Industry consists of both manufacturing and mining sectors in figure 1.1.

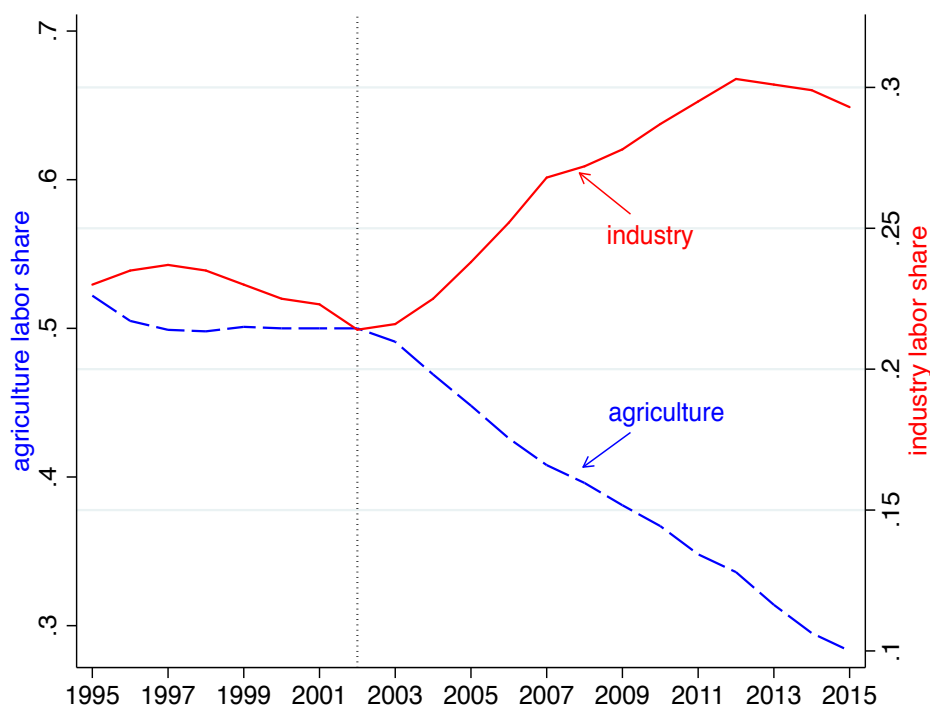


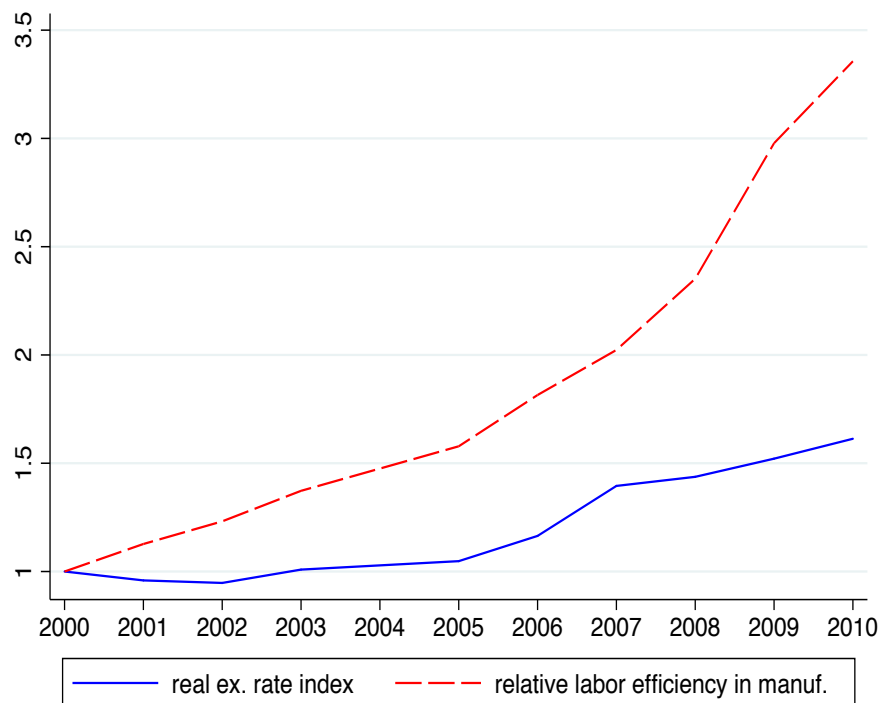
Figure 1.1: Employment Share Evolution

This figure plots the employment shares of the agriculture and industry sectors in China between 1995 and 2015. The left y-axis is agriculture’s employment share, and the right y-axis is industry’s employment share (consisting of employment in both manufacturing and mining). The vertical dotted line is the time when China joined the World Trade Organization. The figure shows that the economy has undergone a dramatic structural transformation, characterized by the reallocation of labor from agriculture to manufacturing and services. Data source: China Statistical Yearbooks.

This paper develops a framework to jointly explain the observed structural transformation and real exchange rate dynamics in China. The model highlights the role of the subsistence sector and its interaction with trade costs and labor market frictions in affecting labor market consequences and real exchange dynamics following a variety of relevant shocks. I apply the model to interregional trade and migration data in China and show that the prominent features of the structural transformation and the dampened appreciation in the real exchange rate arise naturally from the interaction between the labor market and observed shocks to productivity and trade costs.

To assess the effect of the WTO accession on the labor market, it is important to disentangle sources of the “China shock” as productivity shocks and trade shocks. Regions that benefited the most from trade cost reductions following China’s entry to the WTO may have also experienced higher productivity growth. Moreover, the Chinese government has enacted various migration reforms since the 1990s, which also affected labor reallocation across regions and sectors. I adopt a structural approach by applying a dynamic trade and spa-

Figure 1.2: Muted Balassa-Samuelson Effect



This figure plots the increase of the relative labor efficiency in the manufacturing sector between China and the rest of the world, as well as the appreciation of the real exchange rate in the Chinese currency, both normalized using year 2000 levels. It shows that there has been a sluggish appreciation of the real exchange rate, despite rapid productivity growth in manufacturing, a puzzle with respect to a textbook Balassa-Samuelson model from international economics. Data source: Penn World Table, China Statistical Yearbooks, World IO Table.

tial equilibrium model to decompose the “China shock” into productivity shocks and trade shocks, while accounting for changes in migration costs, and quantify their effects on the structural transformation and real exchange rate dynamics. This approach also allows me to conduct counterfactual experiments to examine the implications of China’s WTO accession on its labor market dynamics, real exchange rate adjustments, as well as welfare gains across regions and sectors.

My model builds on the dynamic trade and spatial equilibrium framework in Caliendo et al. (2015) and extends it along several dimensions. First, I explicitly account for a subsistence sector and examine its role in shaping the structural transformation and real exchange rate dynamics. Second, I allow for time-varying migration costs and develop a model-based method to estimate these costs. These extensions are especially relevant for developing countries such as China, where the subsistence sector constitutes a substantial part of the labor force and the labor market is subjected to ongoing migration reforms. Third, I add a tractable framework to incorporate an endogenous process of capital allocations. Doing

so allows me to not only purge potentially spurious effects of an economic shock on the estimates of the migration elasticity and productivity growth, but also to account for the role of China’s high savings and the resulting current account surplus in analyzing its real exchange rate dynamics.

The subsistence sector plays a critical role in shaping the effects of productivity and trade shocks on the dynamics of labor reallocations and the real exchange rate. Consider a scenario where there is unlimited labor surplus in the subsistence sector, migration is perfectly elastic with zero migration costs (as in the Lewis model; see Lewis (1954)), and there is diminishing marginal returns to labor in production. A productivity shock in manufacturing will draw labor from subsistence, and the additional labor supply to manufacturing will arbitrage away any potential gains in wages and keep them at the subsistence level. Due to the unlimited reserve of subsistence labor surplus, a productivity shock will not affect the wages and relative prices. In such a scenario, the economy will experience a structural transformation without any real exchange rate appreciation.

I extend this core intuition to a multi-sector, multi-region trade and spatial equilibrium framework which incorporates frictions in labor reallocation and in trade. In this more general setting, the response of labor reallocation to a shock in the economic environment is no longer immediate, and wages are no longer equalized across regions and sectors. A shock in the productivity or trade costs in the manufacturing sector will increase the real wage in manufacturing and services, which will then raise the demand for manufacturing and services goods. As a result, both manufacturing and services sectors will expand by drawing labor from the subsistence sector, while the subsistence sector shrinks, leading to a structural transformation.

The model also allows me to match China’s real exchange rate dynamics much better than a standard Balassa-Samuelson model. The textbook model tends to over-predict the extent of the real exchange rate appreciation for China, as it assumes the Law of One Price (LOOP) for tradable goods and fails to account for the role of the subsistence sector or frictions in goods trade and labor mobility. As a result, it posits that a productivity shock would translate fully to higher wages, higher prices of nontradable goods, and an appreciation in the real exchange rate. I relax these restrictive assumptions in the standard model to capture the downward pressures on relative prices due to trade costs and the structural transformation. Accounting for these other channels allows the model to generate predictions for China’s real exchange rate appreciation more consistent with the data.

I apply the model to regional trade and migration data from China and study the implications of the “China shock” for its labor market outcomes and the real exchange rate. I first decompose the “China shock” into productivity shocks and trade shocks and quantify their effects on the structural transformation and real exchange rate dynamics in China. I then use the calibrated model to conduct counterfactual policy experiments to examine the gains from the “WTO entry” with or without migration reforms, and to analyze the real exchange rate responses under different scenarios. My main findings include the following: (1) While productivity growth is the primary source of the structural transformation, the accession to the WTO explains about 35% of the rise in the employment share and 20% of

the increase in the real wage in the manufacturing sector; (2) Welfare gains from the “WTO entry” are 27% on average, and the gains would be larger if complemented by relaxing migration restrictions further; (3) The model could jointly explain the observed patterns in the structural transformation and real exchange rate dynamics in China.

The paper contributes to several strands of the literature. First, it is related to a growing series of recent articles that study the economic impacts of the “China shock.” Autor et al. (2013) is among the first studies to lead the discussion of the effect of import competition from China on local labor markets in the U.S. They find that rising imports from China lead to higher unemployment, lower labor force participation, and lower wages in import-competing labor markets in the U.S. Caliendo et al. (2015), Acemoglu et al. (2016), and Pierce and Schott (2016) find that the aggregate job loss in the U.S. due to the “China shock” totals from 0.8 million to more than 2 million, predominantly due to employment losses in manufacturing.³ All these studies focus on the U.S., and the literature about the labor market impact on the China side is relatively small, an area to which my paper aims to contribute. Han et al. (2012) studies how trade liberalization affects wage inequality in urban regions in China, and Li (2015) analyzes the effect on human capital accumulation. Tombe and Zhu (2015) examine how trade and migration costs contribute to the aggregate productivity in China and find that the reduction in those costs explains about 40% of aggregate productivity growth between 2000 and 2005. However, the model they use is static and does not take into account the transition costs due to labor adjustment.

Second, this paper contributes to a recent literature that moves away from static models to focus on the effects of trade on labor dynamics. Artuç et al. (2010) estimate a rational expectations model with labor adjustment costs and find high mean and variance of switching costs across sectors, which imply that the adjustment process in the labor market is slow. In a similar context, Dix-Carneiro (2014) studies trade-induced transitional dynamics in Brazil’s labor market and finds that mobility costs are more than 1.4 times annual wages with a high dispersion across workers. Methodologically, most related to my framework is Caliendo et al. (2015), who develop a dynamic trade model with frictions in labor and goods mobility to study the effect of China’s trade shocks on the decline in manufacturing employment in the United States.

Third, the paper is related to the literature on explaining the structural transformation. Herrendorf et al. (2013) explores various preference specifications to account for the structural transformation in the U.S. since 1947 and the associated changes in the expenditure shares across broad sectors. Comin et al. (2015) use a multi-sector growth model that accommodates demand and supply drivers of the structural change to match the decline in agriculture, the hump-shaped evolution of manufacturing and the rise of services in the U.S. However, these papers analyze the structural transformation in a closed-economy context. More related to my paper is Uy et al. (2013), who study the effect of international trade

³More recently, researchers started to examine the effect of the “China shock” beyond economics to the political realm. For example, Dorn et al. (2016) and Che et al. (2016) find that import competition from China affects partisan divisions in Congress, voter turnout, and the share of votes cast for Democrats.

on the structural transformation in South Korea. They calibrate an open-economy model to match the evolution of employment shares across agriculture, services, and manufacturing sectors and find international trade to be quantitatively important for explaining South Korea’s structural change.

Lastly, by examining the structural transformation and real exchange rate dynamics jointly, this paper links the literature in international trade with that in international macroeconomics. The international trade literature tends to focus on the “quantity” side such as trade flows and the labor reallocation, while the international macroeconomics literature on the “price” side such as the real exchange rate. The standard Balassa-Samuelson model posits that movements in real exchange rates over time are driven by relative productivity growth across countries (Balassa, 1964; Samuelson, 1964). While it is widely acknowledged that this theory often fails to explain real exchange rate dynamics except for the long run (Rogoff, 1996; Lothian and Taylor, 2008; Chong et al., 2012), the combination of fast growth in manufacturing productivity in China and slow appreciation in its real exchange rate for more than a decade since the early 2000s poses a puzzle. One may argue that the resolution to the puzzle lies in China’s high savings rate and large current account surplus (Tyers and Golley, 2008). Even if there are short-term rigidities in nominal prices, however, any shocks from the nominal side should have been neutralized by price inflations over a course of 15 years. A more plausible explanation may be that the standard Balassa-Samuelson model, given its restrictive assumption, is inadequate to explain the real exchange rate dynamics. Attempting to overcome this shortcoming, Berka et al. (2014) construct a dynamic stochastic general equilibrium model (DSGE) to examine the roles of sectoral productivity shocks and a labor market wedge in determining the real exchange rate for Eurozone countries. In a similar spirit, this paper presents a unified framework to extend the Balassa-Samuelson model by incorporating trade costs, labor market frictions, and structural transformation.

The rest of the paper is organized as follows. Section 1.2 presents a trade and spatial equilibrium model with labor dynamics and time-varying migration costs, along with a tractable solution method. In section 1.3, I discuss the data and model calibration. In section 1.4, I use the model to decompose the “China shock” into productivity shocks and trade shocks and quantify their effects on labor market dynamics and the real exchange rate. In addition, I conduct counterfactual experiments to examine the welfare gains from China’s WTO accession and analyze China’s real exchange rate dynamics under various scenarios. Section 1.5 concludes.

1.2 A Dynamic Trade and Spatial Model

The model is a multi-region multi-sector dynamic and spatial trade framework that accounts for labor mobility frictions, trade costs, and input-output linkages. I follow the basic setup in Caliendo et al. (2015), but I extend it by allowing for time-varying migration costs, explicitly accounting for a subsistence sector, and incorporating an endogenous capital allocation process. These extensions are critical for studying the joint patterns of the structural

transformation and real exchange rate dynamics in China.

The economy consists of spatially distinct markets—defined as sector-region pairs—with workers, mutual fund managers, and firms. In each market, a continuum of heterogeneous firms produces intermediate goods as in Eaton and Kortum (2002). They use labor, capital, and materials from all other markets in the production process. The intermediate goods are aggregated to produce final goods. On the labor supply side, forward-looking workers decide where to locate across markets, which I model using a dynamic discrete choice framework based on Artuç et al. (2010) and Caliendo et al. (2015). They could choose to work in the subsistence sector or non-subsistence (“modern”) sectors. Subsistence workers obtain consumption from subsistence production, while non-subsistence workers supply a unit of labor, receive the local market wage, and consume a bundle of final goods. Non-subsistence workers save a fixed fraction of their total income and invest it into a global mutual fund. The global mutual fund pools the savings from workers across all markets and allocates them to a continuum of asset managers, who then channel the savings to their most profitable use across markets, subject to idiosyncratic frictions. The investment allocations by asset managers supply capital to firms across markets, and the returns from capital are rebated back to the workers who provide the savings. The savings of the workers may exceed the total investment in a country, in which case there will be a current account surplus. The labor and capital allocations by workers and fund managers determine labor and capital supplies, which, combined with firms’ labor and capital demand, clear factor markets.

Set-up and Agents’ Problem

Regions and Sectors

There are $N + 1$ regions ($n = 0, 1, \dots, N$), one of them being the Rest of the World (ROW), and $S + 1$ sectors ($s = 0, 1, \dots, S$), one of them subsistence. Let region $n = 0$ denotes the ROW, sector $s = 0$ the subsistence sector. In the empirical exercise, the regions include 30 Chinese provinces and an aggregate ROW region, and the sectors include manufacturing, services, formal agriculture, and subsistence (i.e., informal agriculture). Manufacturing and formal agricultural goods are traded, while subsistence and service goods are not.

Regions are indexed by n or n' , sectors by s or s' . A market is defined as a region-sector pair. Let h denote workers.

Workers

I assume a random utility framework for the workers’ problem. At $t = 0$, there is a mass $L_{ns,0}$ of workers in region n and sector s . Workers are forward-looking and discount future utility at rate $0 \leq \beta \leq 1$. They seek to maximize their lifetime utility:

$$V_{ns,t}(a_{h,t}) = U(C_{hns,t}) + \max_{\{n',s'\}_{n'=0,s'=0}^{N,S}} \{ \beta \mathbb{E}_t[V_{n's',t+1}(a_{h,t+1})] - \kappa_{n's',ns,t} + v\epsilon_{hn's',t} \},$$

where $V_{ns,t}(a_{h,t})$ is the utility of worker h in market ns with asset $a_{h,t}$, $\kappa_{n's',ns,t}$ are migration costs (in terms of lifetime utility) for reallocating from market ns to $n's'$, and $\epsilon_{hn's',t}$ are idiosyncratic preference shocks with a dispersion parameter ν . The dispersion parameter ν , as explained below, is related to the migration elasticity, a key parameter that governs the patterns of the structural transformation and real exchange rate dynamics. This set-up is standard in dynamic discrete choice models, and it permits a tractable aggregation of the idiosyncratic labor reallocation decisions made by workers (Aguirregabiria and Mira, 2010).

The timing for the workers’ problem goes as follows. Workers observe the economic environment in all markets and the realizations of their own preference shocks in the current period, and they decide in which market to supply their labor. If they begin the period in a non-subsistence sector, they earn the local market wage; if they engage in subsistence work, they consume subsistence goods. This set-up of the subsistence sector is akin to the non-employment or home production sector in Caliendo et al. (2015), and it is a convenient way to capture the subsistence sector in the context of developing countries. Specifically, I assume the following instantaneous utility function for workers in market ns (note that $s = 0$ is the subsistence sector):

$$U(C_{hns,t}) = \begin{cases} \underline{y}_{n0}, & \text{if } s = 0 \\ \prod_{s'=1}^S (c_{hns,s',t})^{\alpha_{s'}}, & \text{if } s \neq 0 \end{cases}$$

where \underline{y}_{n0} is subsistence consumption (which is time-invariant, region-specific), $c_{hns,s',t}$ is the consumption of sector s' goods; $\alpha_{s'}$ is the expenditure share for final good s' , with $\sum_{s'=1}^S \alpha_{s'} = 1$. In other words, if the household currently works in subsistence, then they consume subsistence production; otherwise, they consume a bundle of “modern” goods.

Suppose workers in “modern” sectors save a constant fraction λ of the total income in each period. Let $y_{hns,t}$ be the total nominal income of worker h in market ns :

$$y_{hns,t} = w_{ns,t} + R_{n,t}a_{h,t},$$

where $w_{ns,t}$ is the local wage in market ns , $a_{h,t}$ is the asset of worker h , and $R_{n,t}$ is the rate of return for assets (it differs across regions for reasons to be explained shortly). Then the worker’s consumption and savings decisions are

$$\begin{aligned} P_{n,t}C_{hns,t} &= (1 - \lambda)y_{hns,t}, \\ a_{h,t+1} &= \lambda y_{hns,t}, \end{aligned}$$

where $P_{n,t}$ is the ideal price index in region n that aggregates the prices of sector s goods $P_{ns,t}$:

$$P_{n,t} = \prod_{s=1}^S \left(\frac{P_{ns,t}}{\alpha_s} \right)^{\alpha_s}.$$

Suppose that the idiosyncratic preference shocks are i.i.d. over time, have zero mean, and follow a Type-I Extreme Value distribution. Denote $\bar{V}_{ns,t}(a_{h,t}) \equiv \mathbb{E}_t[V_{ns,t}(a_{h,t})]$ as the

expected lifetime utility of worker h in market ns with an asset level $a_{h,t}$. The property of the Type-I Extreme Value distribution implies that (see the appendix for the proof)

$$\bar{V}_{ns,t}(a_{h,t}) = U(C_{hns,t}) + v \log \left[\sum_{n'=0}^N \sum_{s'=0}^S \exp \left(\frac{\beta \bar{V}_{n's',t+1}(a_{h,t+1}) - \kappa_{n's',ns,t}}{v} \right) \right]. \quad (1.1)$$

Equation 1.1 states that the value of working in a particular labor market is equal to the sum of current utility and the option value of reallocation in the next period. Then migration shares take the following Logit form (see the appendix for the proof)

$$\mu_{n's',ns,t}(a_{h,t+1}) = \frac{\exp \left(\frac{\beta \bar{V}_{n's',t+1}(a_{h,t+1}) - \kappa_{n's',ns,t}}{v} \right)}{\sum_{n'=0}^N \sum_{s'=0}^S \exp \left(\frac{\beta \bar{V}_{n's',t+1}(a_{h,t+1}) - \kappa_{n's',ns,t}}{v} \right)}, \quad (1.2)$$

where $1/v$ is migration elasticity. Equation 1.2 shows that labor markets offering higher utility (net of migration costs) attract more workers.

Equations 1.1 and 1.2 show that workers' value functions and migration decisions may depend on their asset levels. This potential dependence would make savings a state variable, which would greatly complicate the model. However, it turns out that if asset returns are indexed to local goods, workers' migration decisions are independent of their savings.

Proposition 1. *Suppose asset returns $R_{n,t}$ are indexed to the local basket of goods such that $R_{n,t} = P_{n,t}R_t$. Then the value function of workers can be decomposed as*

$$V_{ns,t}(a_{h,t}) = V_{ns,t} + f(a_{h,t}),$$

where $V_{ns,t}$ does not depend on workers' asset levels and $f(a_{h,t})$ is some function that does. Moreover, workers' migration decisions are independent of their asset levels:

$$\mu_{n's',ns,t}(a_{h,t}) = \mu_{n's',ns,t}(a_{h',t}) \quad \forall a_{h,t} \neq a_{h',t}.$$

Proof: See the appendix.

Proposition 1 implies that workers in the same market have a common probability of reallocating to other markets, irrespective of their asset levels. Henceforth, I maintain the assumption that $R_{n,t} = P_{n,t}R_t$. I denote the value function $V_{ns,t}$ net of savings and denote the common migration probabilities as $\mu_{n's',ns,t}$ without conditioning on asset levels.

The dynamics of labor distribution across markets is thus

$$L_{ns,t+1} = \sum_{n'=0}^N \sum_{s'=0}^S \mu_{ns,n's',t} L_{n's',t}. \quad (1.3)$$

Equation 1.3 characterizes the distribution of labor supply across markets over time.

Mutual Fund Managers

I assume that the savings of workers are pooled into a global mutual fund. The fund is allocated to a continuum of asset managers responsible for the investment decisions. Each manager possesses a social network with firms across different markets. Those managers allocate the savings to invest in markets that provide the highest returns, but they derive utility from lending to firms across markets that belong in their own social networks (akin to amenity values), on top of monetary returns. The returns are collected and rebated back to workers as part of their total income.

Specifically, mutual fund managers seek to maximize

$$V_t^K = \max_{\{n,s\}_{n=0,s=1}^{N,S}} \{r_{ns,t} + v^K \epsilon_{ns,t}^K\},$$

where I use the superscript K to denote variables related to the capital allocation problem, $r_{ns,t}$ is the return to capital (i.e., per unit of savings) in market ns , and $\epsilon_{ns,t}^K$ are the idiosyncratic benefits from investing in firms across markets in their social network. Similar to the workers’ problem, I assume that $\epsilon_{ns,t}^K$ are i.i.d. over time, have zero mean, and follow a Type-I Extreme Value distribution with a dispersion parameter v^K .

The share of savings allocated to market ns takes the following form (see the appendix for the proof):

$$\mu_{ns,t}^K = \frac{\exp\left(\frac{r_{ns,t}}{v^K}\right)}{\sum_{n=0}^N \sum_{s=1}^S \exp\left(\frac{r_{ns,t}}{v^K}\right)} \quad (1.4)$$

Note that $\frac{1}{v^K}$ determines the elasticity of capital allocations. Equation 1.4 shows that markets offering higher returns attract more capital.

The distribution of capital allocation across markets is thus⁴

$$K_{ns,t+1} = \mu_{ns,t+1}^K K_{t+1}. \quad (1.5)$$

where K_{t+1} is the aggregate capital stock at $t + 1$ and $K_{ns,t+1}$ is the allocation to market ns . Assuming full depreciation of capital in each period, the aggregate capital stock is determined by total savings from last period:

$$K_{t+1} = I_t = \sum_{n=0}^N \sum_{s=1}^S a_{ns,t+1} L_{ns,t}, \quad (1.6)$$

where I_t is workers’ total savings available for investment and $a_{ns,t+1}$ is average savings of workers in market ns . The returns from investment are collected by the mutual fund and distributed back to workers. Because returns for assets are indexed to the local basket of

⁴In the quantitative analysis, I do not allow international migration, but I allow international capital flows.

goods, when workers move across markets, they are paid with returns to their savings indexed to local goods in the new location. To determine the return for workers’ assets,

$$\sum_{n=0}^N \sum_{s=1}^S r_{ns,t+1} K_{ns,t+1} = R_{t+1} \sum_{n'=0}^N \sum_{s'=1}^S P_{n',t+1} \sum_{n=0}^N \sum_{s=1}^S \mu_{n's',ns,t} a_{ns,t+1} L_{ns,t},$$

where the left-hand-side is the total nominal returns collected from firms and the right-hand-side is the total nominal returns rebated to workers.

It can be shown (see the appendix for the proof) that

$$R_{t+1} = \left(\sum_{n=0}^N \sum_{s=1}^S r_{ns,t+1} \mu_{ns,t+1}^K \right) \frac{\sum_{n=0}^N \sum_{s=1}^S a_{ns,t+1} L_{ns,t}}{\sum_{n'=0}^N \sum_{s'=1}^S P_{n',t+1} \sum_{n=0}^N \sum_{s=1}^S \mu_{n's',ns,t} a_{ns,t+1} L_{ns,t}}.$$

The current account for China is the difference between total savings and total investment in the country (recall that $n = 0$ denotes the ROW and $n \in \{1, 2, \dots, N\}$ denotes regions in China):

$$CA_t = \sum_{n=1}^N \sum_{s=1}^S \lambda y_{ns,t} L_{ns,t} - \mu_{ns,t+1}^K I_t,$$

where I_t is computed from equation 1.6. If the total savings exceed the total investment in the country, there is a current account surplus.

Firms

The production side follows the framework in Eaton and Kortum (2002) and Caliendo et al. (2015). There are two types of goods: intermediate goods and final goods. The production of intermediate goods requires labor, capital, and intermediate inputs (which come from final goods). These intermediate goods are aggregated to produce final goods using Constant Elasticity of Substitution (CES) technology.

Intermediate Goods Production The production function for intermediate goods is

$$q_{ns,t}(z_{ns}) = z_{ns} [A_{ns,t} [k_{ns,t}(z_{ns})]^{\xi_n} [l_{ns,t}(z_{ns})]^{1-\xi_n}]^{\gamma_{ns}} \prod_{s'=1}^S [M_{ns,s',t}(z_{ns})]^{\gamma_{ns,s'}},$$

where $k_{ns,t}$ and $l_{ns,t}$ are capital and labor used by firms in region n and sector s , and $M_{ns,s',t}$ is material inputs from sector s' by firms in sector s and region n . Productivity includes two components: an exogenous sector-region specific term, $A_{ns,t}$, and an idiosyncratic and variety-specific term, z_{ns} . Following Eaton and Kortum (2002), I assume that the idiosyncratic productivity of producing a variety z_{ns} in region n and sector s is a random draw from a Fréchet distribution with shape parameter θ (common for all sectors). Material goods consist of a Cobb-Douglas aggregate of final goods produced locally. The parameter γ_{ns} is the share of value added in the production of sector s goods in region n , and $\gamma_{ns,s'}$ is the share of materials from sector s' in the production of sector s goods in region n . The production function is assumed to exhibit constant returns to scale such that $\sum_{s'=1}^S \gamma_{ns,s'} = 1 - \gamma_{ns}$.

Let P_{ns} denote the price of materials (which come from final goods), w_{ns} the wage, and r_{ns} the rental price of capital in market ns . An input bundle (consisting of labor, capital, and materials) costs

$$\chi_{ns,t} = B_{ns} \left(r_{ns,t}^{\xi_n} w_{ns,t}^{1-\xi_n} \right)^{\gamma_{ns}} \prod_{s'=1}^S P_{ns',t}^{\gamma_{ns,s'}}$$

where B_{ns} is a constant. So the unit cost of an intermediate good of variety z_{ns} is $\frac{\chi_{ns,t}}{z_{ns} A_{ns,t}^{\gamma_{ns}}}$.

These intermediate goods are traded across all regions in the economy, subject to trade frictions. Trade costs, $\tau_{ns,n'} \geq 1$ (with the normalization $\tau_{ns,n} = 1$) are of the “iceberg” type. In order for one unit of any variety of intermediate good s shipped from source region n' to arrive in destination region n , the source region n' has to produce $\tau_{ns,n'} \geq 1$ units. If a good is not tradable, then $\tau_{ns,n'} = \infty \forall n' \neq n$. Competition ensures that the price paid for any variety of good s by firms in region n is the minimum unit cost across regions, while taking into account trade costs. Let $z_s \equiv (z_{0s}, z_{1s}, \dots, z_{Ns})$ be the vector of productivity draws across regions. The price of a particular variety of intermediate s in region n is thus

$$p_{ns,t}(z_s) = \min_{n'} \left\{ \frac{\tau_{ns,n',t} \chi_{n's,t}}{z_{n's} A_{n's,t}^{\gamma_{n's}}} \right\}.$$

Final Goods Production The production of final goods requires intermediate goods from sector s traded across all regions. Let $Q_{ns,t}$ denote the quantity of final goods in region n and sector s , and $\tilde{q}_{ns,t}(z_s)$ be the quantity demanded of an intermediate good of variety z_s from the lowest-cost supplier. The production of final goods uses CES technology and takes the following form:

$$Q_{ns,t} = \left[\int [\tilde{q}_{ns,t}(z_s)]^{(\eta_{ns}-1)/\eta_{ns}} \phi(z_s) dz_s \right]^{\eta_{ns}/(\eta_{ns}-1)},$$

where $\phi(z_s) = \exp \left\{ -\sum_{n=0}^N z_{ns}^{-\theta} \right\}$ is the joint density function whose marginal density function distributed Fréchet: $\phi(z_{ns}) = \exp \left\{ -z_{ns}^{-\theta} \right\}$, and the integration is over space R_+^N . Due to perfect competition firms make zero profits for all time periods.

The expenditure shares in market ns of good s from region n' take the following form:⁵

$$\pi_{ns,n',t} = \frac{(\chi_{n's,t} \tau_{ns,n',t})^{-\theta} (A_{n's,t})^{\theta \gamma_{n's}}}{\sum_{n'=0}^N (\chi_{n's,t} \tau_{ns,n',t})^{-\theta} (A_{n's,t})^{\theta \gamma_{n's}}}. \quad (1.7)$$

Equation 1.7 shows that a region will import more from regions with lower bilateral trade costs or higher productivity.

⁵Equation 1.7 is known as the “gravity” equation in the international trade literature. See Caliendo et al. (2017) for a detailed derivation.

Price Index and Real Exchange Rate Given the properties of the Fréchet distribution, the price of the final good is

$$P_{ns,t} = \Gamma \left[\sum_{n'=0}^N (\chi_{n's,t} \tau_{ns,n',t})^{-\theta} (A_{n's,t})^{\theta \gamma_{n's}} \right]^{-1/\theta}, \quad (1.8)$$

where Γ is a constant.⁶ For goods in non-traded sectors, the price is

$$P_{ns,t} = \Gamma \chi_{ns,t} (A_{ns,t})^{-\gamma_{ns}}.$$

The real exchange rate is expressed as the ratio of (aggregated) price indexes between China and the ROW. I aggregate the regional price indexes at the national level by taking a weighted average of regional price indexes where the weights represent regional output shares:

$$P_{\text{China},t} = \sum_{n=1}^N \frac{Y_{n,t}}{Y_{\text{China},t}} P_{n,t},$$

where $Y_{n,t}$ is the output in region n and $Y_{\text{China},t} = \sum_{n=1}^N Y_{n,t}$ is national output in China.⁷ The real exchange rate is the ratio of price indexes between China and the ROW:

$$RER_t = \frac{P_{\text{China},t}}{P_{\text{ROW},t}}.$$

Market Clearing Let $X_{ns,t}$ be the total expenditure on good s in region n . The goods market clearing condition is

$$X_{ns,t} = \sum_{s'=1}^S \gamma_{ns',s} \sum_{n'=0}^N \pi_{n's',n,t} X_{n's',t} + \alpha_s (1 - \lambda) \sum_{s'=1}^S y_{ns',t} L_{ns',t}, \quad (1.9)$$

where the first term is the total demand for material inputs by firms of intermediate goods across all regions and sectors, while the second term is the consumption of final goods by local workers in region n with total income $\sum_{s'=1}^S y_{ns',t} L_{ns',t}$.

The labor demand function of firms is

$$l_{ns,t} = \frac{\gamma_{ns}(1 - \xi_n)}{w_{ns,t}} \sum_{n'=0}^N \pi_{n's,n,t} X_{n's,t}.$$

Equating this labor demand function with labor supply in equation 1.3 gives the market clearing condition for labor.

⁶This expression assumes that $1 + \theta > \eta_{ns}$, a technical assumption made by Eaton and Kortum (2002). The constant Γ is given by the Gamma function evaluated at $1 + (1 - \eta_{ns}/\theta)$.

⁷Recall that $n \in \{1, 2, \dots, N\}$ denotes regions in China.

The demand from firms for capital is provided by

$$k_{ns,t} = \frac{\gamma_{ns}\xi_n}{r_{ns,t}} \sum_{n'=0}^N \pi_{n's,n,t} X_{n's,t},$$

which, combined with the capital supply in equation 1.6, gives the market clearing condition for capital.

Equilibrium

The fundamentals of the economy are given by sector-region productivities $A_t = \{A_{ns,t}\}_{n=0,s=1}^{N,S}$, trade costs $\Upsilon_t = \{\tau_{ns,n',t}\}_{n=0,n'=0,s=1}^{N,N,S}$, and migration costs $\Gamma_t = \{\kappa_{n's',ns,t}\}_{n=0,s=0,n'=1,s'=0}^{N,S,N,S}$. Denote the collection of fundamentals by $\Theta_t \equiv (A_t, \Upsilon_t, \Gamma_t)$. Given (L_t, Θ_t) , I can determine wages $w_t = \{w_{ns,t}\}_{n=0,s=1}^{N,S}$ and rents $r_t = \{r_{ns,t}\}_{n=0,s=1}^{N,S}$. These equilibrium wages and rents $w_t = w(L_t, \Theta_t)$ and $r_t = r(L_t, \Theta_t)$ define the *temporary equilibrium* in each time period. The temporary equilibrium solves the optimality conditions of the firms' problem. Given that prices are functions of wages and rents, I can express real wages as $\omega_{ns}(L_t, \Theta_t) \equiv \frac{w_{ns,t}}{P_{n,t}}$.

Let $\mu_t = \{\mu_{n's',ns,t}\}_{n=0,s=0,n'=0,s'=0}^{N,S,S,N}$ and $V_t = \{V_{ns,t}\}_{t=0}^{\infty}$ be the migration shares and the lifetime utility of workers (net of savings), and let $\mu_t^K = \{\mu_{ns,t}^K\}_{n=0,s=1}^{N,S}$ be the capital allocation shares across markets. Then given an initial condition (L_0, K_0, Θ_0) , I can determine an equilibrium sequence $\{L_t, K_t, \mu_t, \mu_t^K, V_t, w(L_t, \Theta_t), r(L_t, \Theta_t)\}_{t=0}^{\infty}$ that satisfies the temporary equilibrium at each t and the optimality conditions of the workers' problem. This sequence define a *sequential competitive equilibrium*. The steady state is reached when the sequential equilibrium is constant over time. Furthermore, define a *baseline equilibrium* to be the sequential equilibrium corresponding to the case when fundamentals are constant over time, i.e., $\Theta_t = \Theta \forall t$.

Implication for Structural Transformation and Real Exchange Rates

The model has implications on how a shock in productivity or trade costs in the manufacturing sector affects the joint dynamics of the structural transformation and the real exchange rate.

Labor Reallocation Response to Shocks

Consider a positive shock in manufacturing (productivity shock or trade shock). The real wage in manufacturing rises, which induces migration from the subsistence sector, increasing employment in manufacturing. Service also draws labor from the subsistence sector due to increases in input demand from manufacturing via input-output linkages and increases in consumption demand from workers. In the end, both manufacturing and services expand, whereas the subsistence sector shrinks, leading to structural transformation.

For illustration, consider a simple case by abstracting away from dynamics and assuming there is a single region with three sectors—subsistence ($s = 0$), manufacturing ($s = 1$), and services ($s = 2$)—and a homogeneous migration cost $\kappa_{s',s} = \kappa \forall s \neq s'$. The subsistence sector pays a fixed wage y_0 , while the other sectors pay w_s . Let $\omega_s \equiv \mathbb{1}_{s=0}y_0 + \mathbb{1}_{s \neq 0}\frac{w_s}{P}$ denote the real wage for workers in market s . Following the discrete choice framework, the migration probability for a subsistence worker to move to a modern sector $s \neq 0$ is

$$\mu_{s,0} = \frac{\exp\left(\frac{\log \omega_s - \kappa}{v}\right)}{\exp\left(\frac{\log y_0}{v}\right) + \exp\left(\frac{\log \omega_1 - \kappa}{v}\right) + \exp\left(\frac{\log \omega_2 - \kappa}{v}\right)}.$$

A positive wage shock in manufacturing or services will draw migration flows away from subsistence. The aggregate consumption share for final good s , $\mu_{s,0}\alpha_s$, increases; in contrast, the consumption share of the subsistence good, $1 - \mu_{1,0} - \mu_{2,0}$, decreases. As a result, economic activities are reallocated from subsistence to manufacturing and services, leading to structural transformation.

Response of the Real Exchange Rate to Shocks

Consider how a productivity shock to the manufacturing (tradable) sector affects the price index and the real exchange rate. The change in the price index (denote $\hat{x}_t = \frac{x_{t+1}}{x_t}$ to be the time difference of a variable), $\hat{P}_{n,t+1} = \prod_{s=1}^S \hat{P}_{ns,t+1}^{\alpha_s}$, can be decomposed into three sources—the effect from factor costs, the effect from trade costs, and a productivity effect:

$$\hat{P}_{ns,t+1} = \left(\sum_{n'=0}^N \pi_{ns,n',t} \underbrace{\hat{\chi}_{n',s,t}^{-\theta}}_{\text{factor cost (+)}} \underbrace{\hat{\tau}_{ns,n',t}^{-\theta}}_{\text{trade cost(+)}}, \underbrace{\hat{A}_{n',s,t}^{\theta \gamma_{n',s}}}_{\text{direct(-)}} \right)^{-1/\theta}. \quad (1.10)$$

The decomposition in equation 1.10 highlights the critical roles of trade costs and labor market frictions in determining the dynamics of the real exchange rate. An increase in the productivity in the manufacturing sector (assuming trade costs remain constant) will have a direct effect on tradable prices (negative) and an indirect effect on nontradable prices due to higher wages and rents (positive). If cross-regional trade is frictionless, then the first effect is muted; if migration costs are zero and if there is unlimited labor supply from the subsistence sector, then the second effect disappears. The reserve army of labor surplus in the subsistence sector will arbitrage away potential wage gains in other sectors.

A textbook Balassa-Samuelson model does not account for frictions in goods and labor flows or the role of the subsistence sector. It posits that a productivity shock would translate fully to higher wages, higher prices of nontradable goods, and a higher real exchange rate, so it tends to over-predict the extent of real exchange rate appreciation following productivity growth. The framework in this paper relaxes the restrictive assumptions in the standard model to capture the downward pressures on relative prices due to trade costs and the role of the subsistence sector. These relaxations allow the model to generate predictions for China’s real exchange rate dynamics that match the data better.

Solution Method

I adopt a solution method based on time differences. Dekle et al. (2008) and Caliendo et al. (2015) show that by conditioning on the initial allocation, one can solve the model in time differences without knowing the levels of fundamentals. Importantly, this approach also allows me to conduct counterfactual analysis by calculating how a change in fundamentals affects the equilibrium. I adapt the solution method from Caliendo et al. (2015) to incorporate time-varying migration costs and endogenous capital allocations.

Let $\hat{x}_t = \frac{x_{t+1}}{x_t}$ denote the change of a variable in relative time differences, let $\Delta x_t \equiv (x_{t+1} - x_t)$ denote the first time difference of a variable, and let $\Omega(L_t, \Theta_t)$ denote the temporary equilibrium allocation consistent with labor distribution L_t and fundamentals Θ_t , i.e., the set of trade shares, value added, and gross output.

Proposition 2. (Adapted from Caliendo et al. (2015)) *Consider a sequence of unanticipated changes in fundamentals, $\hat{\Theta} = \{\hat{\Theta}_t\}_{t=1}^{\infty}$. Conditional on the initial allocation of the economy, $(L_0, K_0, \mu_0, \mu_0^K, \Omega(L_0, K_0, \Theta_0))$, the solution to the sequential equilibrium in relative time differences given $\hat{\Theta}$ does not require information on the level of fundamentals Θ , and solves the following system of nonlinear equations:*

$$\begin{aligned} \hat{\mu}_{n's',ns,t+1}(\hat{\Theta}) &= \frac{\exp\left[\frac{1}{v}\left(\beta\Delta V_{n's',t+2}(\hat{\Theta}) - \Delta\kappa_{n's',ns,t+1}\right)\right]}{\sum_{n'=0}^N \sum_{s'=0}^S \mu_{n's',ns,t}(\hat{\Theta}) \exp\left[\frac{1}{v}\left(\beta\Delta V_{n's',t+2}(\hat{\Theta}) - \Delta\kappa_{n's',ns,t+1}\right)\right]}, \\ \exp\left(\frac{1}{v}\hat{V}_{ns,t+1}(\hat{\Theta})\right) &= \exp\left(\frac{1-\lambda}{v}\Delta\left(\frac{w_{ns,t+1}}{P_{n,t+1}}\right)\right) \times \\ &\quad \sum_{n'=0}^N \sum_{s'=0}^S \mu_{n's',ns,t}(\hat{\Theta}) \exp\left[\frac{1}{v}\left(\beta\hat{V}_{n's',t+2}(\hat{\Theta}) - \Delta\kappa_{n's',ns,t+1}\right)\right], \\ L_{ns,t+1} &= \sum_{n'=0}^N \sum_{s'=0}^J \mu_{ns,n's',t} L_{n's',t}, \\ \hat{\mu}_{ns,t}^K &= \frac{\exp\left(\frac{1}{v^K}\Delta r_{ns,t}(\hat{\Theta})\right)}{\sum_{n=0}^N \sum_{s=1}^S \mu_{ns,t}^K \exp\left(\frac{1}{v^K}\Delta r_{ns,t}(\hat{\Theta})\right)}, \\ K_{ns,t+1} &= \mu_{ns,t+1}^K \sum_{n=0}^N \sum_{s=1}^S a_{ns,t+1} L_{ns,t}. \end{aligned}$$

Proof: See the appendix.

Proposition 2 shows that by taking time differences one can solve for the dynamic model using only a few parameters and the initial condition (the solution algorithm is presented

in the appendix). Proposition 2 allows me to run counterfactual experiments by assuming a specific sequence of changes in the fundamentals. I first calibrate the underlying changes in fundamentals such as productivity growth, trade costs, and migration costs by mapping model predictions with corresponding moments in the data. Then I decompose the economic shocks and examine how they, separately and jointly, affect the structural transformation and real exchange rate dynamics.

1.3 Model Calibration

I now apply the model to the data and perform quantitative analysis. Using inter-regional and international trade data as well as cross-region and within-region migration data from China, I first describe prominent features in migration and trade patterns between 2000 and 2010. I then use the theoretical framework to guide the calibration of the structural model.

Data

I obtain data on inter-regional and external trade, inter-regional and within-region migration, and real wages by province and sector from various sources. For data on trade within China and between China and the rest of the world, I use regional input-output tables for 2002 and 2007, as reported in Li (2010) and Zhang and Qi (2012). Li (2010) reports bilateral trade flows in 2002 at the province by sector level, and Zhang and Qi (2012) provide the bilateral trade flows between eight aggregate regions and the rest of the world (ROW) in both 2002 and 2007. These regional trade data are also used in Tombe and Zhu (2015) in their study of misallocation in China. Data on migration come from the 2000 and 2010 Population Censuses.⁸ Trade and output data in the rest of the world come from input-output tables from the World Input-Output Database (WIOD).

Data on nominal wages, labor, value added, and the Consumer Price Index (CPI) from 2000 to 2010 are extracted from China Statistical Yearbooks (various issues). I assume that regions inside China have the same savings rate, whose value I take from the data on household savings rate from Urban Household Surveys from National Bureau of Statistics as in Coeurdacier et al. (2015). The savings rate for the ROW is the average value from National Income and Product Accounts Tables (NIPA) for the United States. The real exchange rate index is constructed from the country-level price indexes in the Penn World Tables Feenstra et al. (2015).

Regions and Sectors

The final dataset consists of 31 regions and four sectors. The regions include 30 Chinese provinces and one aggregate region for the rest of the world (ROW).⁹ These 30 provinces

⁸I assume no international labor movement.

⁹Tibet is excluded due to the lack of data in the input-output tables.

are also categorized into eight aggregate regions: Northeast (Heilongjiang, Jilin, Liaoning), North Municipalities (Beijing, Tianjin), North Coast (Hebei, Shandong), Central Coast (Jiangsu, Shanghai, Zhejiang), South Coast (Fujian, Guangdong, Hainan), Central (Shanxi, Henan, Anhui, Hubei, Hunan, Jiangxi), Northwest (Inner Mongolia, Shaanxi, Ningxia, Gansu, Qinghai, Xinjiang), and Southwest (Sichuan, Chongqing, Yunnan, Guizhou, Guanxi).

Sectors include manufacturing, services, formal agriculture, and subsistence (informal agriculture).¹⁰ Manufacturing and formal agricultural goods are traded across provinces inside China as well as internationally. The subsistence sector produces goods consumed solely by subsistence workers, and these goods are not used as materials in the production of other goods. For the quantitative analysis of the structural transformation, I combine formal agriculture and subsistence sectors into an aggregate agriculture sector. The definition of a market is a region-sector pair, leading to a total number of 124 markets.

Migration in China

Institutional Background When the Chinese Communist Party (CCP) founded the People’s Republic of China and came to power in 1949, it promoted a command-and-control economy. In 1958, it enacted the family register (*hukou*) system to “maintain social stability” by containing the movement of people between rural and urban areas. Based on their region of residence, people were broadly categorized as “rural” or “urban.” Rural workers seeking non-agricultural work in urban areas would have to apply for permits, and they would not qualify for employer-provided housing or other benefits (social security or health care) in urban areas. The *hukou* system limited migration flows from the countryside to the cities. It also served as an instrument of central planning because it allowed the government to control the supply of low-cost workers to state-owned enterprises. Before the “opening-up” reform took off in the late 1970s, the government succeeded in regulating population growth in the cities.

However, the *hukou* system has been highly controversial and widely regarded as unfair. The government started to relax the policy since the 1990s. A provision was instated to allow rural residents to obtain “temporary urban residency permits” at a low fee to work legally in the cities. Since China joined the WTO, the demand for migrant workers in manufacturing and service industries increased in the cities, and many provinces began to eliminate the requirement of temporary permits for migrant workers. This policy change reduced migration costs significantly. By 2004, over 100 million rural citizens were working in urban areas, according to the estimate from the Chinese Ministry of Agriculture. Migration costs remain high, however, because migration workers without a local permanent residency still have limited access to social benefits in urban areas (for further details on the *hukou* system in China, see Chan (2010)). Because of the ongoing migration policy reforms during the past few decades, it is important to account for their role in analyzing the effects of

¹⁰The service sector subsumes all other nontradable sectors including construction.

productivity improvement and trade cost reductions on labor market outcomes and real exchange rate dynamics.

Migration Patterns Table 1.1 shows inter- and intra-regional migration shares in China between 2000 and 2010. Migration flows increased substantially during that decade: within-region migration shares rose by 45% and between-region migration shares roughly doubled compared to the year 2000 levels. This surge in migration is indicative of the reduced migration costs and increased demand for labor in urban areas.

Table 1.1: Migration Shares by Region between 2000 and 2010

Region	within region		across region	
	2000	2010	2000	2010
northeast	0.117	0.163	0.013	0.034
north municip.	0.156	0.193	0.006	0.014
north coast	0.067	0.112	0.014	0.035
central coast	0.112	0.162	0.014	0.015
south coast	0.119	0.164	0.007	0.013
central region	0.070	0.122	0.051	0.101
northwest	0.085	0.160	0.013	0.031
southwest	0.075	0.134	0.045	0.081

Note: This table displays migration shares (normalized by total population). Provinces are categorized into eight aggregate regions: Northeast (Heilongjiang, Jilin, Liaoning), North Municipalities (Beijing, Tianjin), North Coast (Hebei, Shandong), Central Coast (Jiangsu, Shanghai, Zhejiang), South Coast (Fujian, Guangdong, Hainan), Central (Shanxi, Henan, Anhui, Hubei, Hunan, Jiangxi), Northwest (Inner Mongolia, Shaanxi, Ningxia, Gansu, Qinghai, Xinjiang), and Southwest (Sichuan, Chongqing, Yunnan, Guizhou, Guanxi).

A common data limitation with migration data is that cross-sector migration flows are difficult to observe, but under a fairly general structure on migration costs, they can be imputed based on cross-region migration and employment changes in the destination region. Suppose that migration costs take the following additive structure and that migration costs to own region-sector are normalized to zero:

$$\kappa_{n's',ns,t} = \kappa_{n',n,t} + \kappa_{s,t} + \kappa_{s',t}, \text{ if } s \neq s' \quad (1.11)$$

$$\kappa_{n',n,t} = \kappa_{n,n',t}, \kappa_{n,n,t} = 0, \kappa_{ns,ns,t} = 0. \quad (1.12)$$

Then it can be shown that (see appendix for the proof)

$$\mu_{n's',ns,t} = \left(\sum_{s'=0}^S \mu_{n's',ns,t} \right) \times \left(\frac{\sum_{n=0}^N \sum_{s=0}^S \mu_{n's',ns,t} L_{n,t}}{\sum_{s'=0}^S \sum_{n=0}^N \sum_{s=0}^S \mu_{n's',ns,t} L_{n,t}} \right). \quad (1.13)$$

Equation 1.13 implies that I can impute the cross-sector migration data based on cross-region migration and the changes in employment shares by sector in the destination region. Specifically, I first calculate the relative change in the employment shares from the previous year by sector and destination region (which is the probability that a migrant worker moves to a certain sector in the destination region). Note that $\sum_{n'=0}^N \sum_{s'=0}^S \mu_{n's',ns,t} = 1$. I impute the cross-sector (from sector s' to s) cross-region (from region n' to n) migration flow share as

$$\mu_{n's',ns,t} = \mu_{n',ns,t} \times \frac{G_{n's',t}}{\sum_{s'=0}^S G_{n's',t}},$$

where $G_{n's',t} \equiv \sum_{n=0}^N \sum_{s=0}^S \mu_{n's',ns,t} L_{n,t}$ denotes the net job creation in the destination region across sectors. The cross-sector migration share within the same region is

$$\mu_{ns',ns,t} = \mu_{n,ns,t} \times \frac{G_{ns',t}}{\sum_{s'=0}^S G_{ns',t}}.$$

Trade Patterns

Prior to its accession to the WTO, China’s internal and external trade costs were prohibitively high, and market protections by local governments were prevalent (Young, 2000; Poncet, 2005; Bai et al., 2004). Since 2001, trade barriers have been lowered substantially both within China and between China and the rest of the world. Externally, following China’s entry into the WTO, other countries decreased import tariffs on Chinese goods, boosting China’s export growth; China also reduced input tariffs, which increased its imports of inputs from other countries (Amiti et al., 2017). Internally, trade costs between regions inside China declined considerably. The state council under then-premier Zhu Rongji curbed local market protections across provinces. The government also undertook reforms of the state-owned enterprises and shrunk the size of the state sector, which further decreased the incentives of local governments to engage in market protections. Moreover, the improvements in transport infrastructure and logistics facilitated trade flows across Chinese provinces.

Table 1.2 shows that trade shares in manufacturing increased substantially between 2002 and 2007, both between regions inside China and between China and the rest of the world. The table displays the shares of trade flows normalized by the importing region’s total expenditures. Specifically, I construct trade shares for sector s goods as $\pi_{ns,n'} = \frac{X_{ns,n'}}{\sum_{n'=0}^N X_{ns,n'}}$, where $X_{ns,n'}$ denotes spending by region n on sector s goods imported from region n' . The diagonal entries, $\pi_{n,n}$, show expenditure shares spent by each region on goods produced in the same region. A smaller value means a higher degree of trade openness. From 2002 to 2007, the expenditure shares of trading with home regions decreased by an average of 10%,

implying that bilateral trade flows with other regions surged. For example, the Southwest region saw its trade share with other regions roughly doubled from 13% to 27%. Even more impressive was the increase in trade shares with the rest of the world: the expenditure share for an average region doubled from 2002 to 2007, six years after China’s entry into the WTO. Overall, inter-regional trade shares, especially export shares, rose considerably during that period, indicative of substantial reductions in external trade costs.

Table 1.2: Inter-Regional Trade Shares of China in Manufacturing

source/ destination	north- east	north municip.	north coast	central coast	south coast	central region	north- west	south- west	abroad
2002									
northeast	81.07	1.01	1.40	1.09	1.99	1.39	1.26	0.97	9.83
north municip.	4.59	49.89	10.25	3.03	3.18	3.46	1.29	0.94	23.37
north coast	2.23	2.3	78.16	2.99	1.85	5.05	1.09	0.88	5.41
central coast	0.31	0.21	0.77	74.09	2.09	2.69	0.65	0.53	18.65
south coast	0.48	0.68	0.66	3.28	55.96	2.33	0.40	1.77	34.44
central region	0.69	0.25	1.73	6.34	3.11	83.52	1.06	0.84	2.46
northwest	2.24	0.70	3.44	3.54	5.36	5.21	69.76	5.05	4.69
southwest	0.89	0.20	0.57	1.52	4.92	1.75	0.80	86.85	2.50
abroad	0.08	0.10	0.14	0.60	0.76	0.06	0.02	0.04	98.19
2007									
northeast	73.05	1.72	2.71	0.76	2.67	0.98	1.53	0.53	16.05
north municip.	4.12	46.61	12.28	2.01	3.42	2.11	2.09	0.52	26.83
north coast	2.16	3.33	76.86	1.51	2.01	4.11	2.01	0.76	7.25
central coast	1.22	0.67	1.69	69.54	2.37	5.22	1.86	1.00	16.44
south coast	1.51	0.67	1.95	5.84	58.67	4.41	1.91	3.23	21.80
central region	1.77	0.71	4.80	4.91	3.94	71.71	2.40	1.10	8.65
northwest	2.06	1.26	4.80	2.40	5.30	3.85	67.18	1.93	11.22
southwest	1.53	0.37	1.17	1.31	8.37	1.77	2.35	72.78	10.35
abroad	0.15	0.19	0.24	1.52	0.93	0.12	0.08	0.07	96.70

Note: This table displays the share of each importing region’s total spending originated from each source region. Provinces are categorized into eight aggregate regions: Northeast (Heilongjiang, Jilin, Liaoning), North Municipalities (Beijing, Tianjin), North Coast (Hebei, Shandong), Central Coast (Jiangsu, Shanghai, Zhejiang), South Coast (Fujian, Guangdong, Hainan), Central (Shanxi, Henan, Anhui, Hubei, Hunan, Jiangxi), Northwest (Inner Mongolia, Shaanxi, Ningxia, Gansu, Qinghai, Xinjiang), and Southwest (Sichuan, Chongqing, Yunnan, Guizhou, Guianxi).

Calibration Procedure

I apply the model to the data to study the effects of trade and productivity shocks on the dynamics of the labor market and the real exchange rate in China. I proceed in several steps. First, I calibrate a set of model parameters such as factor shares and consumption

shares to match the data in the year 2000 as the initial equilibrium. In particular, I match variables such as bilateral trade flows $\pi_{ns,n',0}$, value added $w_{ns,0}L_{ns,0} + r_{ns,0}K_{ns,0}$, and labor distribution $L_{ns,0}$. Second, I estimate the changes in key fundamental variables such as bilateral migration and trade costs as well as region-sector productivities using an approach consistent with the model. Intuitively, the bilateral migration and trade costs are estimated by matching bilateral trade flows (2002-2007) and bilateral migration flows (2000-2010), and region-sector productivities are estimated by matching the value added data (2000-2010). Third, based on the initial allocation and estimated changes in bilateral migration costs, trade costs, and region-sector productivity as estimated in the previous step, I estimate the elasticity of migration by matching labor distribution across regions and sectors. Finally, I use the estimated model to decompose the “China shock” into productivity and trade shocks, and analyze their effects on labor market outcomes and real exchange rate dynamics. I then conduct counterfactual experiments to assess welfare effects of the “WTO entry” and real exchange rate responses under various counterfactual scenarios. I detail each step below.

Step 1: Parameters on Factor Shares

The factor shares are calibrated to match the initial allocation from the data. I need to compute the shares of value added in gross output γ_{ns} , the shares of materials $\gamma_{ns,s'}$, the shares of labor in value added $1 - \xi_n$, final goods consumption shares α_s , and the savings rate λ .

Shares of Value Added in Gross Output γ_{ns} Based on the production function of intermediate goods, I calibrate γ_{ns} to be the shares of the value added (VA) in gross output values from the input-output tables. Recall that the intermediate goods production function is

$$q_{ns,t}(z_{ns}) = z_{ns} \underbrace{\left[A_{ns,t} [k_{ns,t}(z_{ns})]^{\xi_s} [l_{ns,t}(z_{ns})]^{1-\xi_n} \right]^{\gamma_{ns}}}_{\text{value added}} \underbrace{\left[\prod_{s'=1}^S [M_{ns,s',t}(z_{ns})]^{\gamma_{ns,s'}} \right]}_{\text{materials}},$$

so

$$\gamma_{ns} = \frac{VA_{ns}}{Output_{ns}}.$$

Shares of Materials $\gamma_{ns,s'}$ The shares of materials from sector s' demanded by firms in region n producing sector s goods, $\gamma_{ns,s'}$, is computed from the full input-output tables for each region. Note that by construction $\sum_{s'=1}^S \gamma_{ns,s'} = 1 - \gamma_{ns}$.

Shares of Labor Compensation in value added $1 - \xi_n$ The shares of labor compensations in the value added are calculated as the shares of the total wage bill in value added:

$$1 - \xi_n = \frac{VAL_{ns}}{VA_{ns}} \equiv \frac{Wage_{ns}}{VA_{ns}}.$$

The share of capital is one minus the share of labor compensation.

Savings rate λ I assume that regions inside China have the same savings rate. I take the information from Urban Household Surveys conducted by National Bureau of Statistics, as in Coeurdacier et al. (2015). The average household savings rate for China from 2000 to 2010 is 25%, the value I set for λ_{China} . The savings rate for the ROW is assumed to be 5%, the average value from National Income and Product Accounts Tables(NIPA) for the United States.

Shares of Final Goods Consumption α_s The shares of final goods consumption for sector s goods, α_s , are calculated from the market clearing condition for final goods in equation 1.9. Specifically, I compute α_s as the share of total spending on final good s in total income (the spending on final goods consumption is the total expenditure subtracted by the spending on intermediate goods):

$$\alpha_s = \frac{\sum_{n=0}^N \left(X_{ns} - \sum_{s'=1}^S \gamma_{ns',s} \sum_{n'=0}^N \pi_{n's',n} X_{n's'} \right)}{(1 - \lambda) \sum_{n=1}^N \sum_{s=1}^S y_{ns} + (1 - \lambda_0) \sum_{s=1}^S y_{0s}},$$

where $\sum_n \sum_{s'} \gamma_{ns',s} \sum_{n'} \pi_{n's',n} X_{n's'}$ is total spending on materials (to produce intermediate goods) and $(1 - \lambda) \sum_{n=1}^N \sum_{s=1}^S y_{ns} + (1 - \lambda_0) \sum_{s=1}^S y_{0s}$ is the total disposable income (net of savings) across all regions in the economy with λ being the savings rate in China and λ_0 the savings rate in the ROW.

Table 1.3 displays a summary of calibrated parameter values from this step.

Step 2: Changes in Fundamentals

In this step, I show how to use a model-based approach and infer changes in key fundamentals such as migration costs, trade costs, and region-sector productivity from the data. An advantage about this approach is that I do not have to solve the full dynamic model first. Otherwise, estimating the full matrix of migration costs, trade costs, and productivity changes by solving the full dynamic model would have been a challenging task because of the large dimensions of those matrices (migration costs $N \times (S + 1) \times (N \times (S + 1))$, trade costs $(N + 1) \times (N + 1) \times S$, productivity $(N + 1) \times (N + 1) \times S$). The intuition for my approach is that migration costs and trade costs can be inferred by taking appropriate log differences of bilateral migration and trade flows, and productivity changes can be inferred by matching the changes in labor-adjusted value-added data by region and sector.

Migration Costs Suppose that migration costs take an additive structure and that migration costs to the home region-sector are normalized to be zero:

$$\begin{aligned} \kappa_{n's',ns,t} &= \kappa_{n',n,t} + \kappa_{s,t} + \kappa_{s',t}, \text{ if } s \neq s' \\ \kappa_{n',n,t} &= \kappa_{n,n',t}, \kappa_{n,n,t} = 0, \kappa_{ns,ns,t} = 0. \end{aligned}$$

Table 1.3: Model Parameters

Parameter	Value	Description	Identification
$\frac{1}{\bar{v}}$	0.15	migration coef.	SMM, labor distribution
$\frac{1}{\bar{v}^K}$	1.28	capital allocation coef.	SMM, China’s current account growth
β	0.99	discount factor	assumption
θ	4	elasticity of trade	Simonovska and Waugh (2014)
λ_{China}	0.25	savings rate in China	UHS, Coeurdacier et al. (2015)
λ_{ROW}	0.05	savings rate in ROW	NIPA, Coeurdacier et al. (2015)
α_{ns}		final goods consumption share	data
γ_{ns}		share of value added in output	data
$\gamma_{ns,s'}$		shares of materials from sector j	input-output tables
$1 - \xi_n$		share of wages in value added	data
$\widehat{\kappa}_{ns,n's',t}$		bilateral migration cost	bilateral migration shares
$\widehat{\tau}_{ns,n',t}$		bilateral trade cost	bilateral migration shares
$\widehat{A}_{ns,t}$		labor productivity	labor-adjusted value-added data

Note: This table displays parameter values from model calibration, along with their sources of identification. See texts for more details regarding the calibration procedure of each parameter.

Then the migration cost matrix can be inferred by matching the full matrix of migration flows by region and sector.

Proposition 3. (*Inference of Migration Costs*) *Assume that migration costs take on an additive structure, with normalization as shown in equations 1.11 and 1.12. Then bilateral migration costs across regions and sectors can be inferred from the following expression:*

$$\kappa_{n's',ns,t} = \frac{1}{2}v \left[\log \left(\frac{\mu_{n's',n's,t}\mu_{ns,n's',t}}{\mu_{ns,n's',t}\mu_{n's',ns,t}} \right) + \log \left(\frac{\mu_{n's,n's,t}\mu_{n's',n's',t}}{\mu_{n's',n's,t}\mu_{n's,n's',t}} \right) \right]. \quad (1.14)$$

Proof: See the appendix.

The intuition of this approach is that the cross-regional component of migration costs can be identified from cross-regional migration flows and the cross-sectoral component from cross-sectoral migration flows. As a special case of equation 3, cross-sector within-region migration costs are computed as

$$\kappa_{n's',ns,t} = \frac{1}{2}v \log \left(\frac{\mu_{n's,n's,t}\mu_{n's',n's',t}}{\mu_{n's',n's,t}\mu_{n's,n's',t}} \right).$$

Tables 1.4 summarizes the average changes in migration costs within and across regions, as inferred using proposition 3. Migration frictions both within and across regions decreased, with the former declining considerably more than the latter. This pattern suggests the observed structural transformation between 2000 and 2010 originated more from the labor reallocation across sectors within provinces than from the labor reallocation across provinces.

Table 1.4: Average Change (%) in Migration Costs

source/destination	within region	across region
2001-2010		
northeast	11.5	3.2
north municip.	10.0	3.7
north coast	13.0	2.8
central coast	4.7	3.0
south coast	11.2	2.9
central region	14.2	3.1
northwest	14.1	3.3
southwest	12.2	3.1

Notes: This table displays the average percentage change in migration costs across regions. Provinces are categorized into eight aggregate regions: Northeast (Heilongjiang, Jilin, Liaoning), North Municipalities (Beijing, Tianjin), North Coast (Hebei, Shandong), Central Coast (Jiangsu, Shanghai, Zhejiang), South Coast (Fujian, Guangdong, Hainan), Central (Shanxi, Henan, Anhui, Hubei, Hunan, Jiangxi), Northwest (Inner Mongolia, Shaanxi, Ningxia, Gansu, Qinghai, Xinjiang), and Southwest (Sichuan, Chongqing, Yunnan, Guizhou, Guianxi).

Trade Elasticity A large body of literature in international trade estimates the parameter of trade elasticity, θ . This parameter governs the dispersion of productivity shocks across firms and the sensitivity of trade flows with respect to trade costs. This key parameter has been estimated using data from different levels of aggregation and with different approaches. Simonovska and Waugh (2014) use cross-country price data to estimate $\theta \approx 4$. Using tariff data, Parro (2013) estimates a parameter between 4.5 to 5 for manufacturing, and Tombe and Zhu (2015) estimates a parameter of 4.1 for agriculture and 4.6 for non-agriculture sectors. Bernard et al. (2003) use firm-level data to estimate a productivity dispersion parameter of 3.6 in the U.S. For the quantitative analysis below, I set this parameter to be the median value in the literature $\theta = 4$ for all sectors.

Trade Costs I follow the method in Head and Ries (2001) to estimate the average trade costs between region n' and n for sector s goods as

$$\bar{\tau}_{ns,n',t} \equiv \sqrt{\tau_{ns,n',t}\tau_{n's,n,t}} = \left(\frac{\pi_{ns,n,t}\pi_{n's,n',t}}{\pi_{ns,n',t}\pi_{n's,n,t}} \right)^{\frac{1}{2\theta}},$$

a direct implication of the trade share equation 1.7. With this approach, bilateral trade costs are inferred by taking the relative ratio of home shares versus bilateral trade shares, scaled by the trade elasticity. The intuition is that an observed increase in expenditure

shares on goods imported from other regions relative to goods produced in the home region implies lower trade costs. Notice that this approach assumes that trade costs are symmetric. A major advantage of this differencing method is that the estimated trade costs are not only consistent with the model, but they can be estimated from the observed trade flows without the full model being solved first. Another feature is that the estimation of bilateral trade costs is not affected by trade flows with other regions. I estimate trade costs in formal agricultural and manufacturing sectors for 2002 and 2007, the two years for which I have data on bilateral trade flows, and I assume that trade costs changed at a constant rate between 2000 and 2010.

Table 1.5 shows the change in trade costs in the manufacturing sector between 2002 and 2007. Trade costs for trading with home regions (the diagonal values) used as normalization: $\pi_{ns,n} = 1 \forall n, s$, so bilateral trade costs with other regions (the off-diagonal values) are relative to trade costs for trading with home regions.¹¹ Since 2002, bilateral trade costs have declined considerably, both between regions inside China and between Chinese regions and the rest of the world, with the latter decreasing by more. The reduction in trade costs varies across regions, with a wide range between 1% to 23%. In section 1.4, I quantify the heterogeneous effects of the reduction in trade costs, especially the external trade cost reduction following China’s entry into the WTO.

Table 1.5: Change in Trade Costs in Manufacturing

source/ destination	north- east	north municip.	north coast	central coast	south coast	central region	north- west	south- west	abroad
2002-2007									
northeast	1.00	0.93	0.91	0.86	0.83	0.90	0.97	0.97	0.85
north municip.	0.93	1.00	0.93	0.90	0.99	0.91	0.86	0.97	0.90
north coast	0.91	0.93	1.00	0.98	0.87	0.88	0.88	0.91	0.90
central coast	0.86	0.90	0.98	1.00	0.91	0.93	0.91	0.91	0.90
south coast	0.83	0.99	0.87	0.91	1.00	0.88	0.83	0.85	1.04
central region	0.90	0.91	0.88	0.93	0.88	1.00	0.91	0.93	0.77
northwest	0.97	0.86	0.88	0.91	0.83	0.91	1.00	0.96	0.76
southwest	0.97	0.97	0.91	0.91	0.85	0.93	0.96	1.00	0.77
abroad	0.85	0.90	0.90	0.90	1.04	0.77	0.76	0.77	1.00

Notes: This table displays the change in trade costs in manufacturing. Provinces are categorized into eight aggregate regions: Northeast (Heilongjiang, Jilin, Liaoning), North Municipalities (Beijing, Tianjin), North Coast (Hebei, Shandong), Central Coast (Jiangsu, Shanghai, Zhejiang), South Coast (Fujian, Guangdong, Hainan), Central (Shanxi, Henan, Anhui, Hubei, Hunan, Jiangxi), Northwest (Inner Mongolia, Shaanxi, Ningxia, Gansu, Qinghai, Xinjiang), and Southwest (Sichuan, Chongqing, Yunnan, Guizhou, Guanxi).

¹¹This normalization is standard in the international trade literature.

Productivity Changes In addition to changes in trade costs and migration costs, another key fundamental change occurring in China is the increase in productivity. I infer region-sector productivity changes by from value-added data by region and sector, deflated by sector-specific prices and adjusted for labor growth. Let $\text{QVA}_{ns,t} = \frac{\text{VA}_{ns,t}}{P_{s,t}}$ be value added in real terms in market ns . From the production function of intermediate goods and because $\widehat{r}_{ns,t}\widehat{k}_{ns,t} = \widehat{w}_{ns,t}\widehat{l}_{ns,t}$, I infer changes in productivity as

$$\widehat{A}_{ns,t} = \frac{\widehat{\text{QVA}}_{ns,t}}{\widehat{l}_{ns,t}^{1-\xi_n}\widehat{k}_{ns,t}^{\xi_n}} = \frac{\widehat{\text{QVA}}_{ns,t}}{\widehat{l}_{ns,t}(\widehat{w}_{ns,t}/\widehat{r}_{ns,t})^{\xi_n}}.$$

Using data for value added, sector-specific prices, labor distribution, wages, and rents, between 2000-2010, I calculate the right hand side as the change in productivity. Notice that this productivity measure partials out the effect from labor changes and endogenous capital allocation and thus captures the “Solow-residual” total factor of production (TFP).

I calculate the changes in region-sector labor productivity, $\widehat{A}_{ns,t}$, and take these productivity shocks as exogenous and feed them into the model for the quantitative analysis. Note that this approach assumes no “learning by doing” effects of trade on productivity.¹² Figure 1.3 plots the estimates of productivity growth in the three urban sectors in China: between 2000 and 2010, the productivity in the manufacturing and service sectors more than doubled, while the productivity in formal agriculture rose by more than 50%.

Step 3: Elasticity of Migration and Elasticity of Capital

I calibrate the elasticity parameters for migration and capital allocation $\frac{1}{v}$ and $\frac{1}{v^K}$ to match the labor distribution across sectors and regions and the increase in China’s current account from the data using Simulated Method of Moments (SMM).

The procedure goes as follows:

- a) Start with an initial value of v and v^K ;
- b) Input exogenous parameters: β, θ ; and factor shares: $\alpha_s, \gamma_{ns}, \gamma_{ns,s'}, \xi_n$;
- c) Input changes in fundamentals: $\widehat{\tau}_{ns,n',t}; \widehat{A}_{ns,t}; \widehat{\kappa}_{ns,n',s',t}(v)$; savings rate: λ_n . Note that $\widehat{\tau}_{ns,n',t}$ and $\widehat{A}_{ns,t}$ do not depend on unknown parameters, and that $\widehat{\kappa}_{ns,n',s',t}(v)$ depends on v .
- d) Given initial condition, solve the dynamic model in time differences to obtain $L_{ns,t}(v, v^K)$ and $CA_{\text{China},t}$ for 2000-2010
- e) Minimize $\sum_n \sum_s \sum_t \|L_{ns,t}^{\text{data}} - L_{ns,t}^{\text{model}}(v, v^K)\|$ and $\sum_t \|CA_{\text{China},t}^{\text{data}} - CA_{\text{China},t}^{\text{model}}(v, v^K)\|$ simultaneously using SMM.

I use a grid-search method for this calibration and obtain $\frac{1}{v} = 0.15$, $\frac{1}{v^K} = 1.28$. The result is summarized in table 1.3. There does not seem to exist any benchmark values for these elasticity parameters of labor and capital allocation in the literature, especially for developing countries. When converting these values to elasticities and comparing them to

¹²If there is learning by doing, then the trade liberalization effect is magnified. I explore the interaction between trade and productivity in future research.

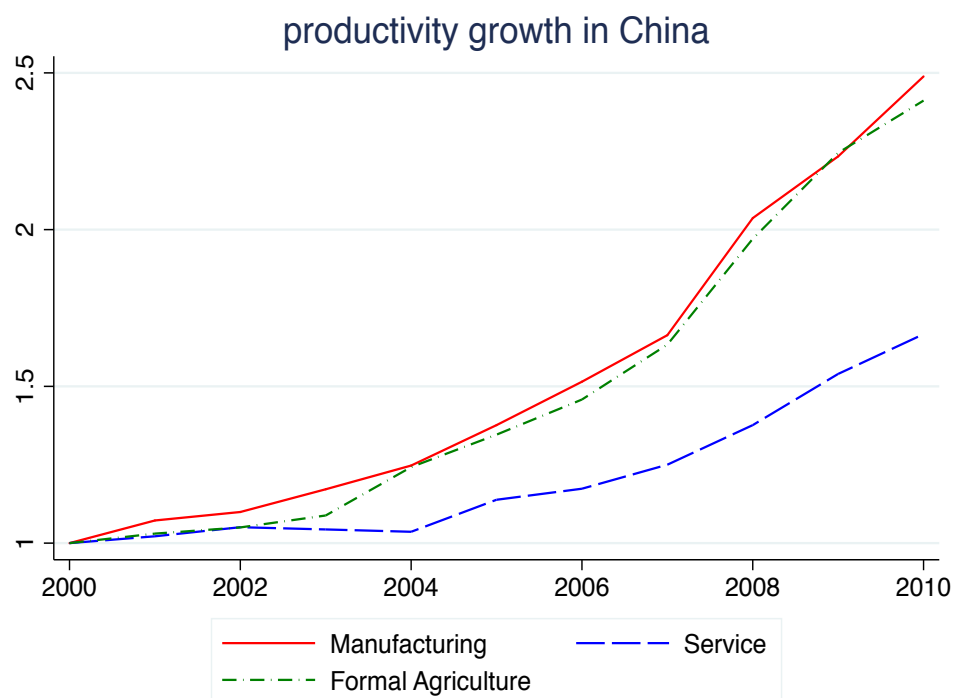


Figure 1.3: Estimate of Productivity Growth

This figure plots the estimated increase of the total factor of productivity (TFP) in manufacturing, service, and formal agriculture sectors, normalized using year 2000 levels. Source: author’s estimation.

estimates in Artuç et al. (2010) and Caliendo et al. (2015) for the U.S., my estimate of the migration elasticity for China is lower than the estimates from the U.S. data, which may result from a higher degree of migration frictions or labor misallocation in China caused by the *hukou* system. Regarding the elasticity parameter for the capital allocation, to the best of my knowledge, there are no other estimates in the literature with which to compare my estimate. However, the estimates suggest that the capital allocation is much more elastic than the labor movement, which seems to jibe with economic intuition.

Model Fit

For the model calibration and estimation, the moments that are targeted to match include labor distribution, migration flows, trade flows, value added and initial year equilibrium, while those that are not targeted include real wages and real exchange rate dynamics. These unmatched moments serve as a check on the model performance. The identification sources for the model parameters are summarized in table 1.3.

Moments Targeted

I first investigate the model fit for the following set of moments targeted to match using the calibration procedure: labor distribution across sectors and regions.

Labor Distribution The left panel in figure 1.4 displays the goodness of fit for the aggregate labor distribution across sectors. Overall, the model generates predictions on the dynamics of the structural transformation or the labor reallocation across manufacturing (top figure), services (middle figure), and agriculture (bottom figure) that fit the data quite well. Figure 1.5 shows the model fit for labor dynamics in manufacturing at the regional level. Overall, the model successfully captures the labor dynamics across sectors. The patterns of cross-regional labor dynamics are matched less precisely, but they still follow the overall trends in the data.

Current Account Dynamics Figure 1.6 shows the model fit for the evolution of China’s current account to GDP ratio. The model seems to over-predict capital account surplus in the first half of the 2000s, while it under-predicts in the second half. The reason for this mismatch is that there was a collapse in the current account surplus following the 2009 financial crisis, and the model is not rich enough to account for such a big shock to the financial system. Nonetheless, the model appears to fit the overall growth in China’s current account in the data between 2000 and 2010.

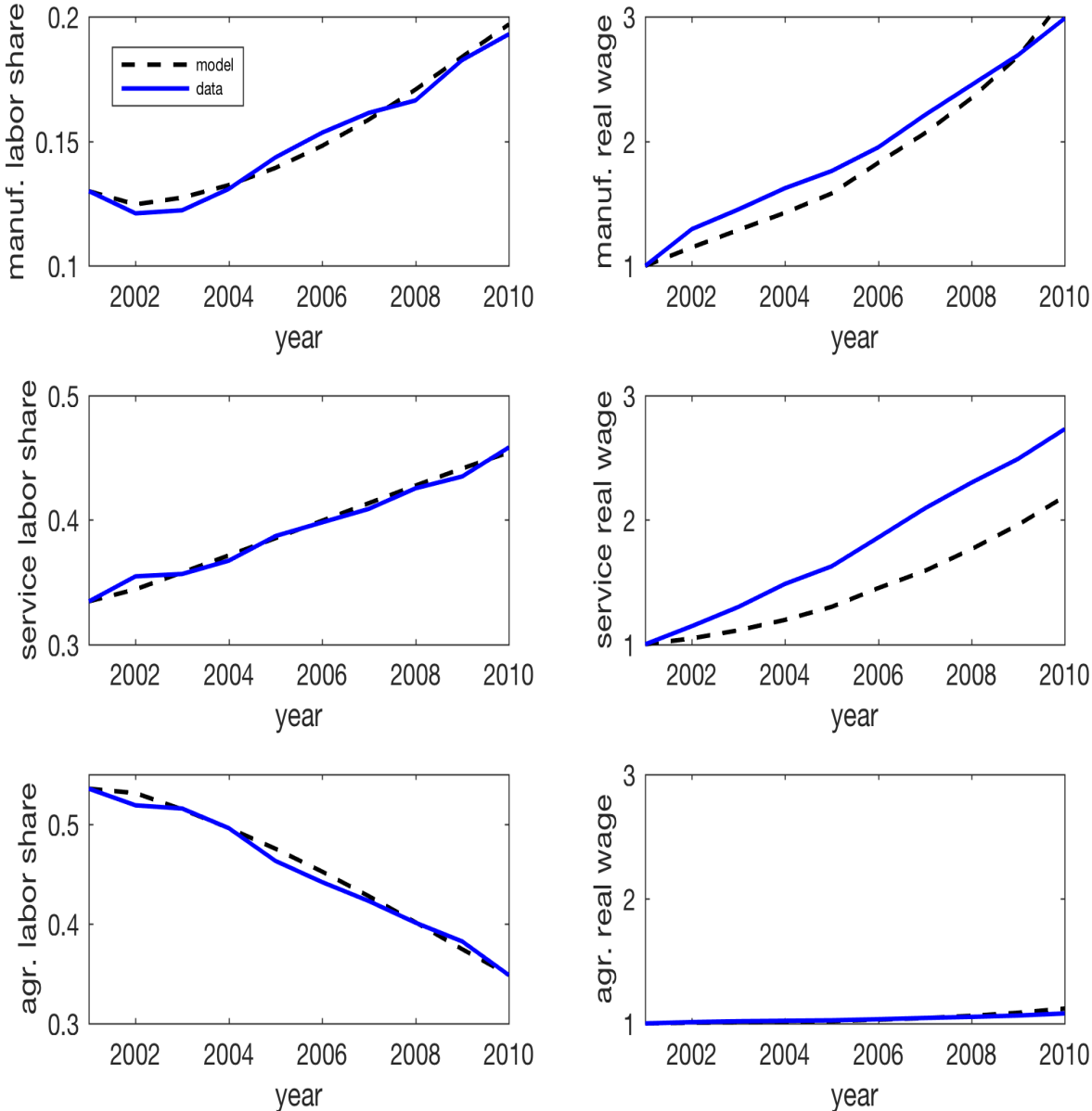
Some researchers argue that the slow pace of China’s real exchange rate appreciation may be due to the fact that the elevated savings rate and the resulting current account surplus depressed the nominal and real exchange rates (Tyers and Golley, 2008). However, one would expect that nominal shocks would have been neutralized by price inflations over a course of 15 years. By matching the dynamics of the current account surplus explicitly, I could account for the role of high savings in China when I examine its real exchange rate dynamics.

Moments Not Targeted

Next, I examine the model fit for the following set of moments not targeted to match by the calibration procedure: real wages and real exchange rate dynamics.

Real Wages The right panel in figure 1.4 displays the goodness of fit for aggregate real wage dynamics across sectors. It shows that the model generates predictions for the real wages growth across sectors that are broadly in line with the data, even though these moments are not targeted directly by the model calibration procedure. Overall, the model fits the real wage dynamics almost perfectly for the manufacturing sector, and it also explains most of the real wage dynamics in the agriculture (80%) and non-tradable sectors (78%). Figure 1.7 shows the model fit for labor and wage dynamics in manufacturing at the regional

Figure 1.4: Model Fit for Labor and Real Wage Evolution



This figure displays the goodness of fit of the calibrated model. The left panel plots the model fit for the aggregate labor distribution across sectors, and the right panel plots the fit for the real wage dynamics across sectors (real wages are normalized using 2001 levels).

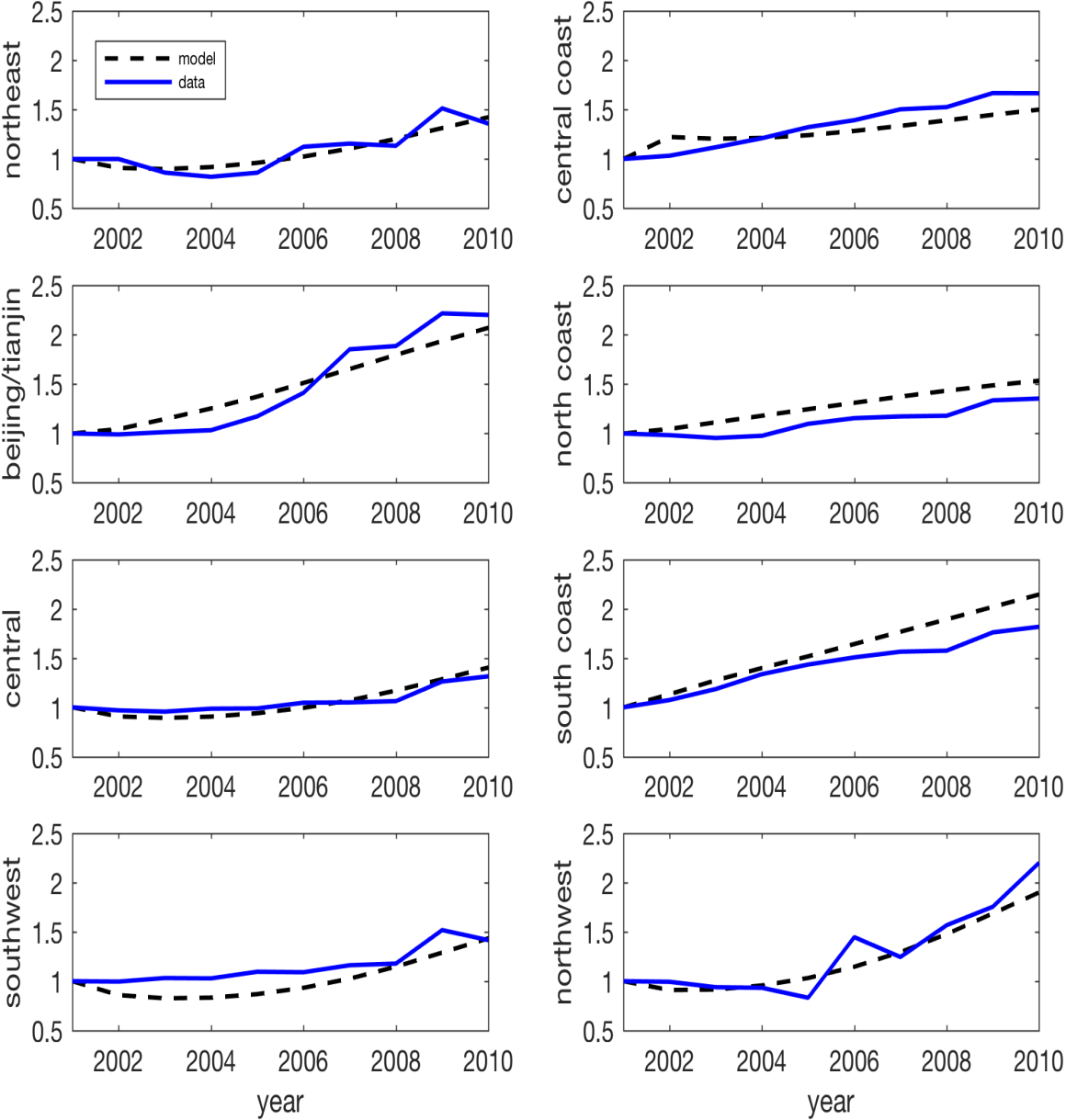


Figure 1.5: Model Fit for L in Manufacturing by Region

This figure displays the goodness of fit of the calibrated model in terms of the increase in manufacturing employment shares across regions, normalized using 2001 levels.

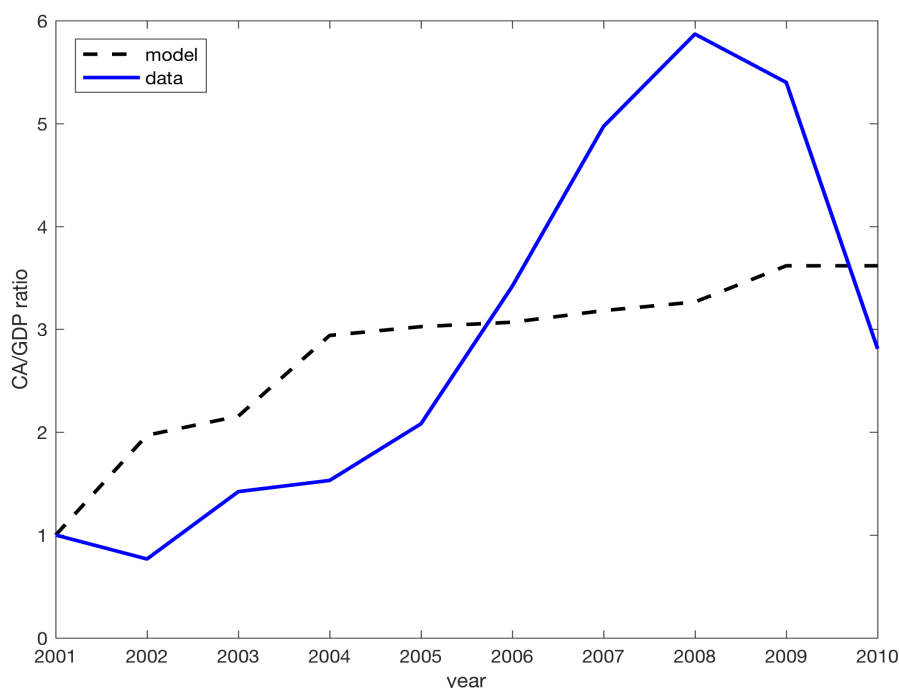


Figure 1.6: Model Fit for Current Account to GDP Ratio

This figure displays the goodness of fit of the calibrated model in terms of the increase in China’s current account surplus relative to its GDP, normalized using 2001 levels.

level. The match for the patterns of cross-regional wage dynamics is noisier, but they still follow the overall trends in the data.

Real Exchange Rate Dynamics Figure 1.8 plots the model fit for the evolution of the real exchange rate. The blue line shows the real exchange rate from the data, and the black dotted line shows the model fit. The figure shows that the model over-predicted the extent of real exchange rate appreciation in the first half of the decade for 2000-1010, but it matches the evolution of the real exchange rate for the whole period reasonably well. The purple dotted line shows the prediction based on the “standard” Balassa-Samuelson model by isolating the component of relative nontradable prices. Specifically, I construct a real exchange rate index only from the relative prices of service goods, while ignoring the relative prices of agriculture and manufacturing goods because the latter are assumed to equalize prices across countries in the standard Balassa-Samuelson model. The “standard” Balassa-Samuelson effect would have predicted that the real exchange rate would appreciate by 100%, rather than only 60% as observed in the data. Therefore, by incorporating the trade costs—thus relaxing the LOOP assumption—and labor market frictions—which accounts for structural transformation—the overall model fit for real exchange dynamics is improved.

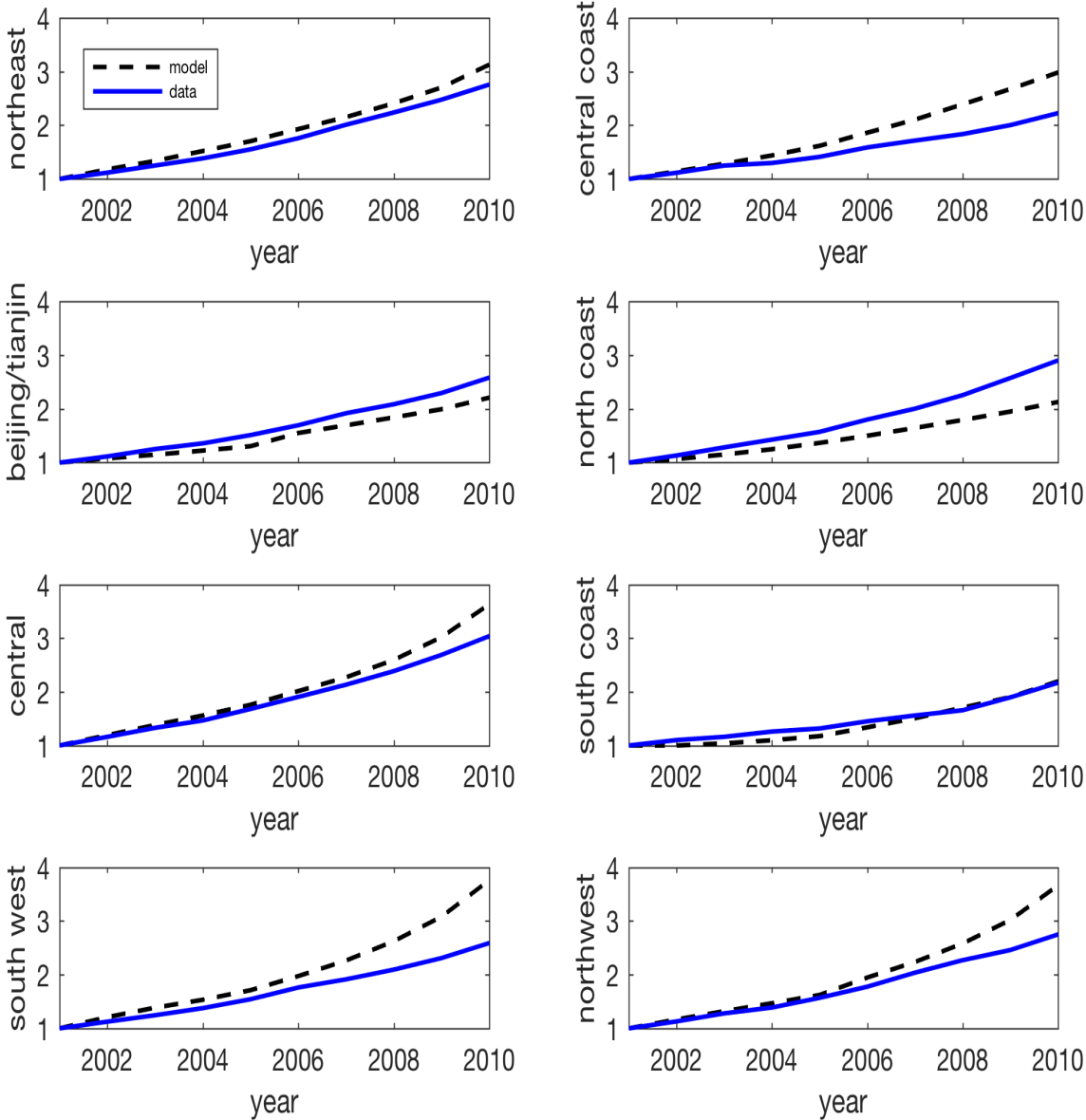


Figure 1.7: Model Fit for Real Wages in Manufacturing by Region

This figure displays the goodness of fit of the calibrated model in terms of the increase in manufacturing real wages across regions, normalized using 2001 levels.

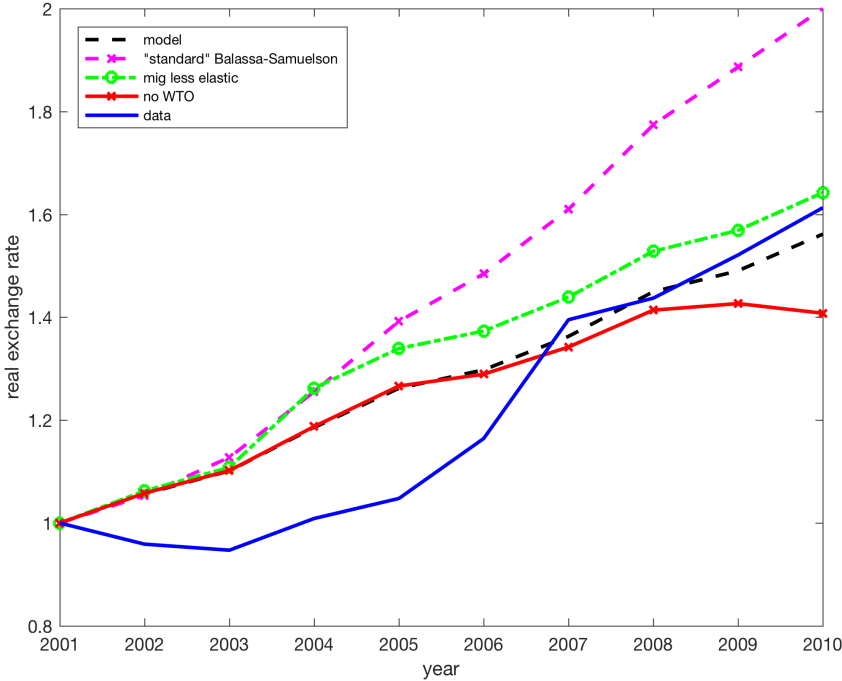


Figure 1.8: Counterfactual: Effects on Real Exchange Rate

This figure plots the model fit for the evolution of the real exchange rate, as well as the effects on the real exchange rate under various counterfactual scenarios, normalized using 2001 levels. The blue line shows the real exchange rate from the data, and the black dotted line shows the model fit. The purple dotted line shows the prediction based on the “standard” Balassa-Samuelson model by isolating the component of relative nontradable prices. Specifically, I construct a real exchange rate index only from the relative prices of service goods, while ignoring the relative prices of agriculture and manufacturing goods because the latter are assumed to equalize across countries in the standard Balassa-Samuelson model. The “standard” Balassa-Samuelson effect would have over-predicted that the real exchange rate substantially. The red line shows the case where China did not “enter the WTO,” and the green line shows the case where migration costs remained at their 2000 levels (i.e., no migration reforms undertaken since 2000).

1.4 Quantitative Analysis

Equipped with the calibrated parameters for the model, I now conduct quantitative analysis. I first decompose the effects of “China shock” on the labor market— structural transformation and real wage dynamics—into sources from productivity shocks versus trade shocks. Next, I investigate the effects on the labor market and real exchange rate dynamics under various counterfactual scenarios.

Decomposition

I decompose the effects on labor and wage dynamics into three sources: 1) secular convergence, 2) productivity growth, and 3) trade cost reductions. Specifically, for 1), I keep productivity and trade costs at the 2000 level and assume they do not change; for 2), I allow productivity to change over time as estimated from the data, but I keep trade costs (external and internal) at the 2000 level; and for 3), I allow trade costs (external and internal) to change over time as estimated from the data, but I assume there is no productivity growth. This exercise enables me to isolate the labor market effects coming from channels through productivity growth versus trade cost reductions.

Secular Convergence

Since the initial allocation may not be the steady state, there could be convergence in the economy even without external shocks. The purple line in figure 1.9 shows the evolution of labor distribution (left panel) and real wages (right panel) under the scenario of no shocks. This scenario shows the secular convergence of labor and wages based on the initial migration matrix. The figure shows that without any productivity or trade shocks, there would be some degree of structural transformation: the agricultural labor would decrease from 53% to about 47% from 2000 to 2010, and most of this labor outflow would go toward the service sector, making its employment share rise from 35% to about 40%. However, the employment share in the manufacturing sector would remain mostly unchanged.

Regarding the real wages, however, the secular convergence has only small effects. From 2000 to 2010 the real wage in the agricultural sector would remain almost the same. The real wage in the manufacturing sector would increase by only 13%, while that in the service sector would decrease by roughly 7%.

Productivity and Trade Shocks

The red line and green line in figure 1.9 show the effects of productivity growth and trade shocks, respectively. The left panel plots the impact on the labor reallocation across broad sectors or the structural transformation, and the right panel plots the effects on real wage dynamics. From the bottom graph in the left panel, one can notice that productivity growth has a more significant impact on structural transformation than trade cost reductions overall.

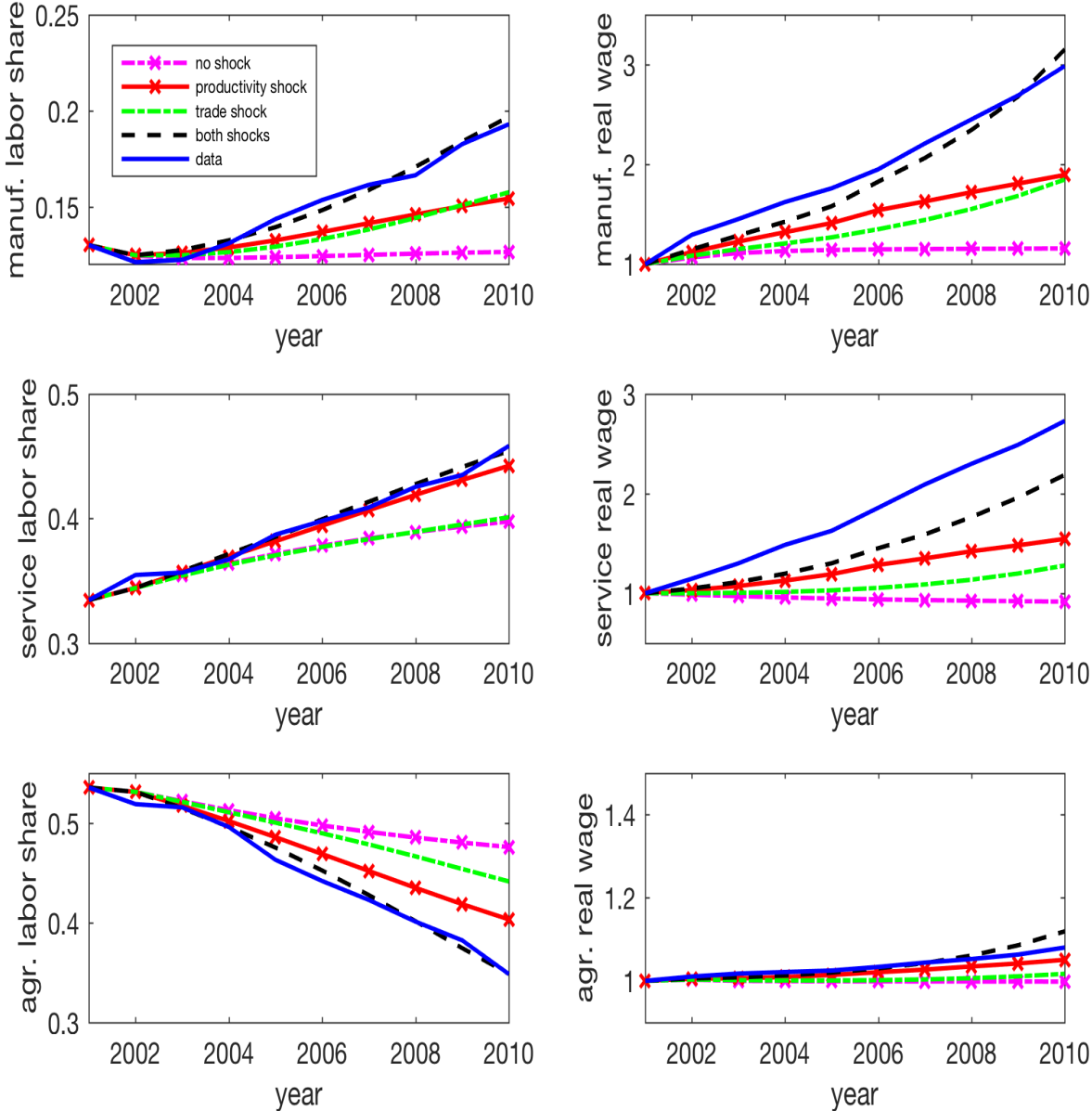


Figure 1.9: Decomposition of “China Shock” and Labor Market Dynamics

This figure plots the labor market effects when the “China shock” is decomposed into three sources: 1) secular convergence, 2) productivity growth, and 3) trade cost reductions. Specifically, for 1), I keep productivity and trade costs at the 2000 level and assume they do not change; for 2), I allow productivity to change over time as estimated from the data, but I keep trade costs (external and internal) at the 2000 level; and for 3), I allow trade costs (external and internal) to change over time as estimated from the data, but I assume there is no productivity growth. The left panel plots the effect on labor dynamics across sectors, and the right panel plots the effect on real wage dynamics across sectors (real wages are normalized using 2001 levels).

During 2000-2010, the employment share in agriculture decreased from more than 50% to 33%, and productivity growth explains about 65% of this decline. The right panel of figure 1.9 shows the decomposition effects on real wage growth in China. For the manufacturing sector, productivity and trade cost reductions played an equally important role in explaining the wage rise, whereas, for the wage increase in services, productivity appears to have a more prominent effect. Note that the trade shock in this decomposition exercise consists of a combination of trade cost reductions that are both internal (across regions inside China) and external (between China and the ROW). In a counterfactual exercise below, I further isolate the external component by examining the effect of the “WTO entry.”

Counterfactual Analysis

No “WTO Entry”

For this exercise, I allow productivity and internal trade costs to change between 2000 and 2010 as estimated from the data, but I keep the external trade costs at the initial level. I interpret the labor market effects in this scenario as the “WTO entry” effect.

Figure 1.10 shows the impact on structural transformation and real wages across sectors under the situation of no “WTO entry.” From the left panel, notice that “WTO entry” does not seem to affect the overall structural transformation much, especially the labor reallocation from the agriculture sector to the service sector. This result is consistent with previous findings in the literature that the main source of structural transformation comes from productivity growth (Caselli, 2005; Restuccia et al., 2008). However, the effect of “WTO entry” is significant for the manufacturing sector. Trade cost reductions following China’s accession to the WTO explain about 35% of the observed rise in the employment share and about 20% of the increase in real wages in the manufacturing sector, whereas productivity growth explains most of the rise in the employment share and real wages in the service sector.

Figures 1.11 and 1.12 show the effects of the “WTO entry” on employment shares and real wages in manufacturing across regions. Overall, the manufacturing sector would expand less across all regions. However, there is considerable heterogeneity across regions: the effect seems largest in the Central and Northwest regions, while smallest in the North Coast region. The effects on the real wages are qualitatively similar: real wages in manufacturing would have risen less if China did not “join the WTO” and experience the corresponding external trade cost reduction, and the effects are heterogeneous across regions.

Effects on Real Exchange Rate

Figure 1.8 shows what would happen to the dynamics of the real exchange rate under counterfactual scenarios of no “WTO entry” and no migration reforms. As the red line shows, if China did not “enter the WTO,” the real exchange rate would have appreciated by 40%, instead of 60% as observed in the data. The reason why the real exchange rate for China

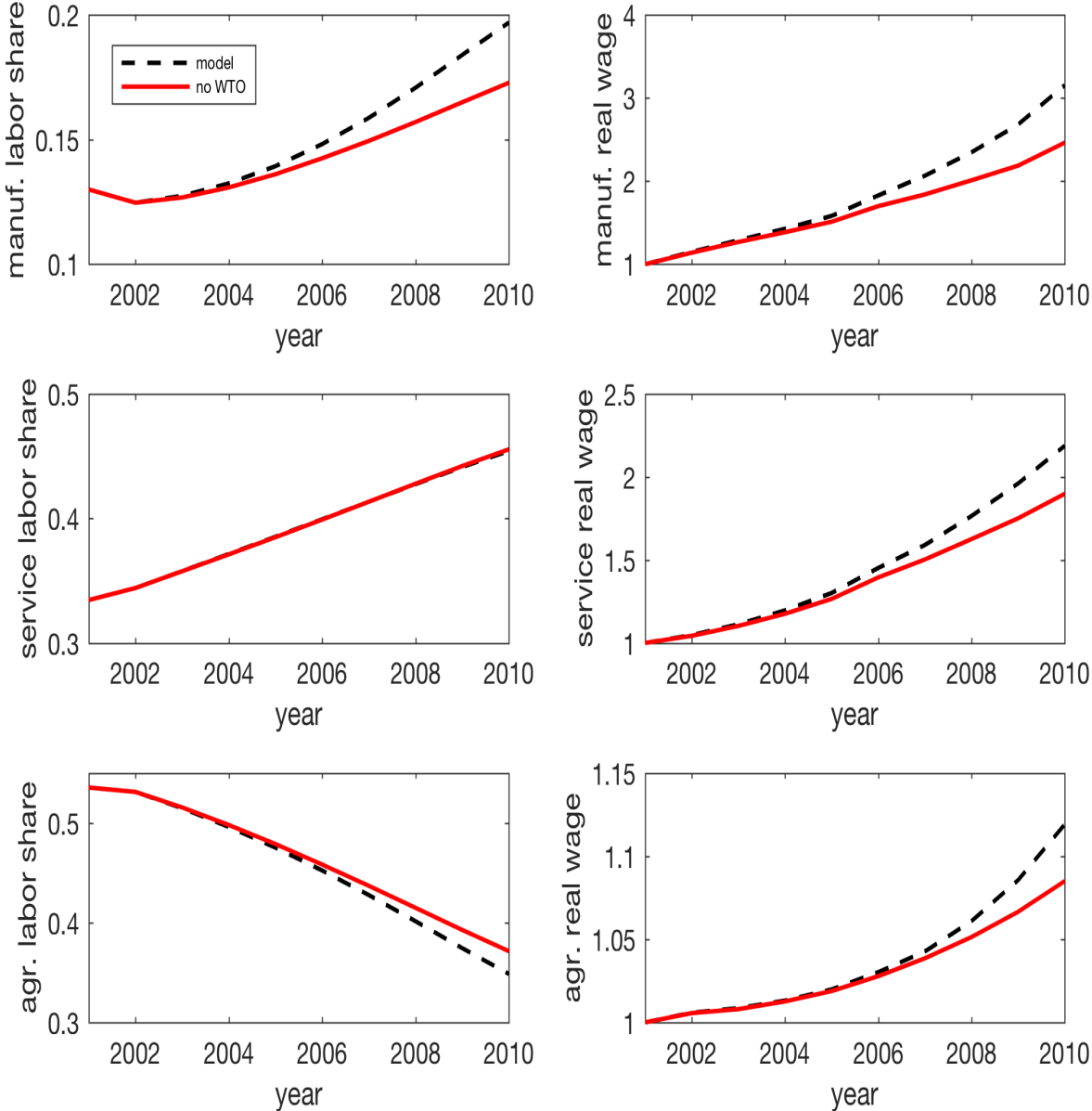


Figure 1.10: Labor and Real Wage Evolution with No “WTO Entry”

This figure plots the labor market effects under the counterfactual scenario in which China did not join the WTO. The left panel plots the effect on labor dynamics across sectors, and the right panel plots the effect on real wage dynamics across sectors (real wages are normalized using 2001 levels). For this exercise, I allow productivity and internal trade costs to change between 2000 and 2010 as estimated from the data, but I keep the external trade costs at the initial level. I interpret the labor market effects in this scenario as the “WTO entry” effect.

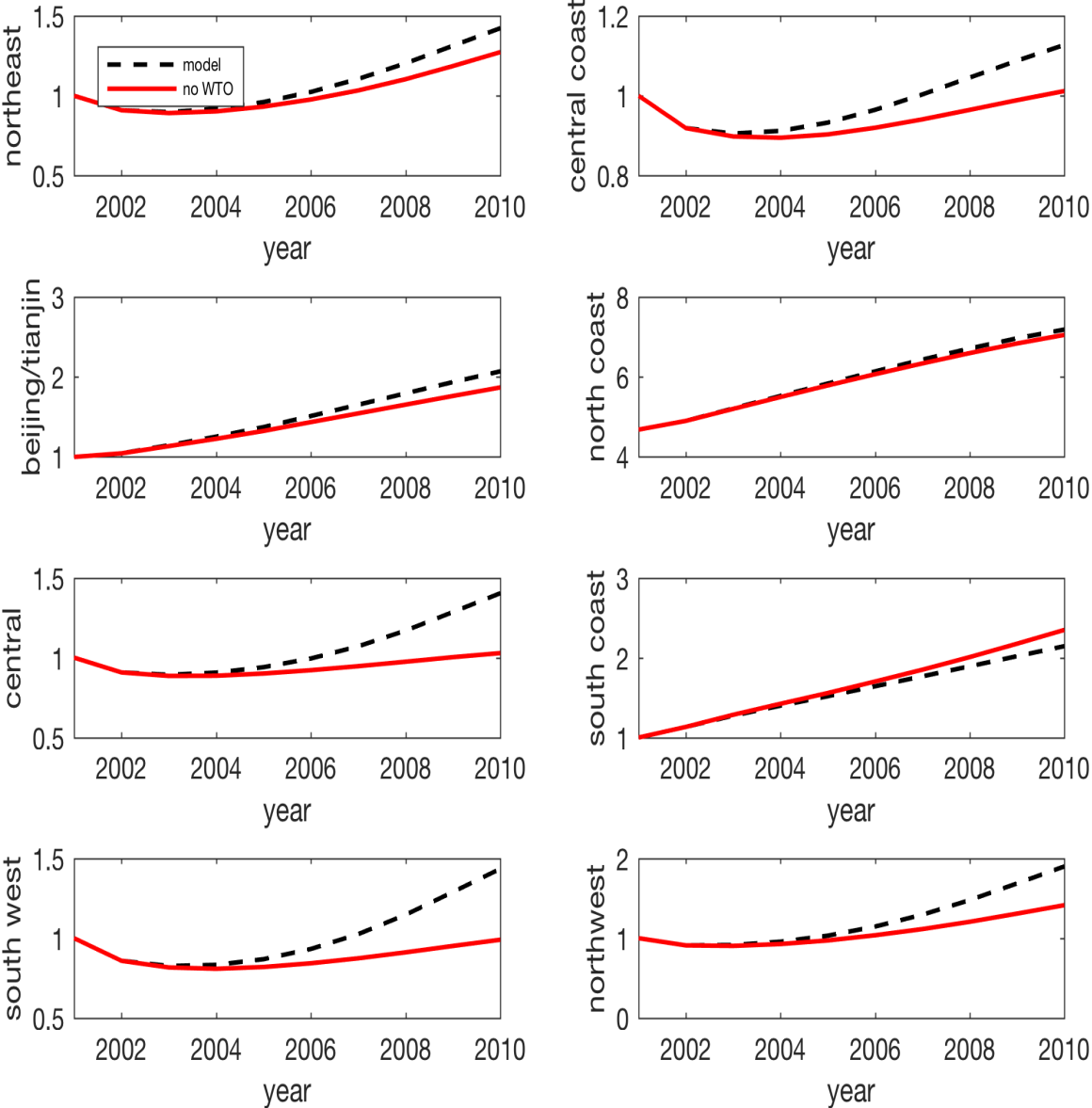


Figure 1.11: Labor Evolution by Region with No “WTO Entry”

This figure plots the labor dynamics in the manufacturing sector across regions under the counterfactual scenario in which China did not join the WTO, normalized using 2001 levels. For this exercise, I allow productivity and internal trade costs to change between 2000 and 2010 as estimated from the data, but I keep the external trade costs at the initial level. I interpret the labor market effects in this scenario as the “WTO entry” effect.

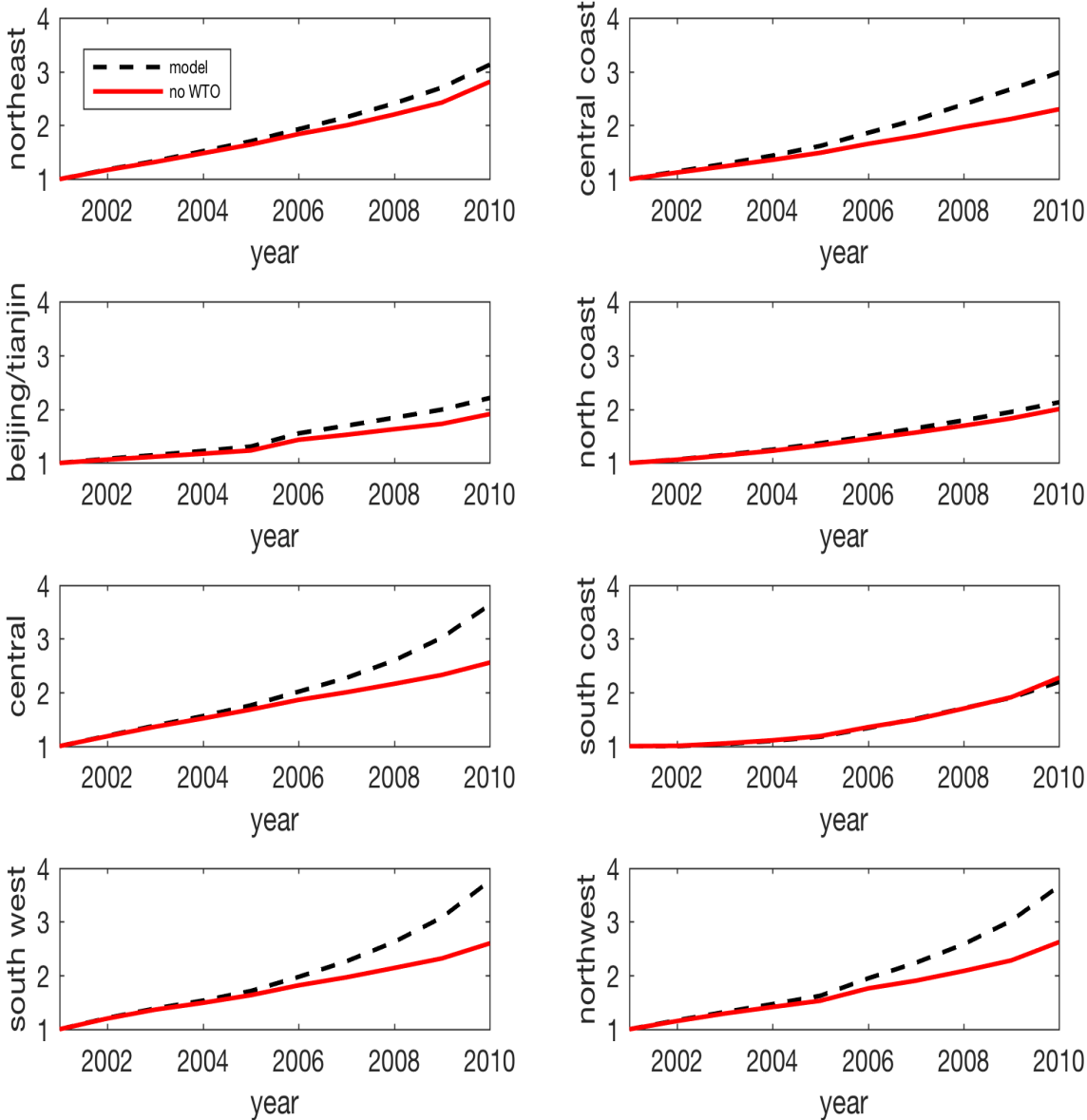


Figure 1.12: Wage Evolution by Region with No “WTO Entry”

This figure plots the real wage dynamics in the manufacturing sector across regions under the counterfactual scenario in which China did not join the WTO, normalized using 2001 levels. For this exercise, I allow productivity and internal trade costs to change between 2000 and 2010 as estimated from the data, but I keep the external trade costs at the initial level. I interpret the labor market effects in this scenario as the “WTO entry” effect.

would rise more with the “WTO entry” is that an external trade cost reduction would transmit the downward price effect from productivity growth to the rest of the world to a greater extent than the case without “WTO entry.” On the other hand, if migration costs remained at their 2000 level without any reforms to the *hukou* system, then the real exchange rate for China would have appreciated more. This is because there would be a decrease in labor reallocation from the subsistence sector to urban sectors to absorb wage increases, leading to higher prices and a higher real exchange rate than the case with less migration restrictions.

Welfare Gains from “WTO Entry”

The aggregate welfare gain can be calculated by comparing the labor-weighted value function with and without “WTO entry”. Specifically, the long term aggregate welfare gain from “WTO entry” is

$$Gain = (V_{ns,t}L_{ns,t} - V_{ns,t}^0L_{ns,t}^0)_{t \rightarrow \infty},$$

where the superscript 0 denotes the variables under the no “WTO entry” scenario.

To calculate the welfare gain, I first freeze productivity and trade costs at 2010 levels and let the dynamics in the model play out over time. Figure 1.13 plots the evolution of aggregate welfare gains from “WTO entry.” The long term welfare gain from “WTO entry” is 27%. If migration costs were to stay constant, i.e., no migration reforms occurred, the welfare gain would be 8% less.

1.5 Conclusion

This paper investigates the implications of China’s export-oriented development process—a process that involves extraordinary increases in productivity and exchanges of goods with the rest of the world—on the labor market and the real exchange rate dynamics in China. I apply a dynamic trade and spatial equilibrium model to jointly explain two prominent features regarding China’s recent economic growth: the structural transformation and the sluggish real exchange rate appreciation. The model highlights the crucial role of the subsistence sector in determining the patterns of the structural transformation and real exchange rate dynamics. Calibrating the model to the trade and migration data in China, I decompose the “China shock” into productivity shocks and trade shocks. I find that while productivity growth is the primary source of the structural transformation, trade cost reductions following China’s accession to the WTO account for 35% of the rise in the employment share and 20% of the increase in the real wage in the manufacturing sector. My counterfactual policy experiments show that welfare gains from the “WTO entry” are 27% on average, and the gains would be larger if complemented by migration policy reforms. Moreover, by taking into account trade costs, labor market frictions, and the current account surplus, the model extends the standard Balassa-Samuelson framework and produces dynamics for China’s real exchange rate consistent with the data.

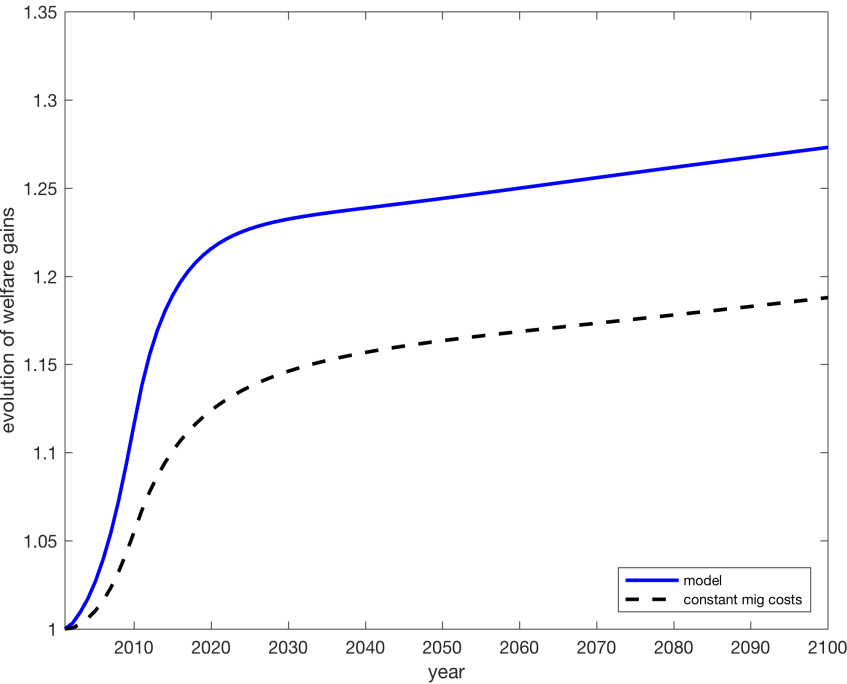


Figure 1.13: Welfare Gain from “WTO Entry”

This figure plots the evolution of aggregate welfare gains from the “WTO entry” for China (normalized using pre-WTO 2001 levels). It is calculated by comparing the labor-weighted value function with and without “WTO entry.” To calculate welfare gains, I first freeze productivity and trade costs at 2010 levels and let the dynamics in the model play out over time.

Chapter 2

A “China Shock” on the Finance Side: Evidence from Chinese Housing Investment in the US

2.1 Introduction

The rise of China in the global economic scene has been one of the most notable economic phenomena over the past two decades, which a growing literature has dubbed as the “China shock.” While much of the literature focuses on the “China shock” on the real side, specifically the effects of China’s rising international trade activities on local economies in the US (e.g., Autor et al. (2013)), China’s intention to play a more active role in global finance in recent years has prompted a new question: As China becomes more financially integrated into the global economy and allow capital to flow in and out of the country more freely, what are the economic effects and welfare implications of a “China shock” on the finance side for the rest of the world? Our paper is one of the first academic works that studies this increasingly relevant question. In this paper, we call attention to a specific “China shock” on the finance side. We document an unprecedented surge in residential housing purchases by foreign Chinese in the US since 2007 and analyze the effects of these purchases on the US local housing and labor markets.

The surge of housing purchases by foreign Chinese¹ in the US over the past decade has grabbed many headlines in the press. According to the National Association of Realtors, foreign Chinese have taken the lead among all foreign buyers of US real estates by a wide margin, as measured by both value and quantity, and they tend to concentrate the purchases in regions that have been more populated by ethnic Chinese historically such as California and leave them vacant.² While these purchases have been widely reported by the media, to

¹In this paper, we define “foreign Chinese” as Chinese who do not regularly reside in the US, and “ethnic Chinese” as Chinese who live in the US.

²Foreign Chinese buyers spent \$28.6 billion on residential property in the US in 2014, which is a 30%

the best of our knowledge, no academic study has provided a formal quantification of the phenomenon and explored its implications for the US real economy.

In this paper, we first document two stylized facts about purchasing behavior by foreign Chinese in the US housing market using detailed transaction-level data covering all real estate transactions in the three largest core-based statistical areas (CBSA) in California. First, house purchases by foreign Chinese increased more than tenfold over the 2007-2013 period relative to earlier periods. Figure 2.1 plots the share of purchases in the US real estate market by foreigners as measured by dollar value over the 2001-2013 period. While the percentage of all housing transactions made by foreign Chinese was small (around 0.3%) and comparable to that of other foreigners over the 2001-2006 period, it began to increase sharply in 2007 and reached more than 5% of total housing purchases in California by 2013, overtaking all other groups as the lead group of foreign buyers in the market. Note the year 2007 was when home prices in the US began to slump, thus our analysis on the effects of housing purchases by foreign Chinese on US local economies also delves into the question of whether housing investments by foreign Chinese played a stabilizing role during the housing market crash of 2007-2011.³

Second, the increase in house purchases by foreign Chinese has been concentrated in zip codes that are historically populated by ethnic Chinese. Figure 2.2 dissects Figure 2.1 by zooming in on housing purchases by foreigners in zip codes in the top quartile of the Chinese population based on the 2000 Census. Evidently, the surge of housing purchases by foreign Chinese has been concentrated in zip codes that are historically populated by ethnic Chinese: in 2013, they made up more than 10% of the total real estate transactions in these neighborhoods. As we describe in detail below, we exploit this observation in our empirical strategy to assess the effects of housing purchases by Chinese on US local economies.

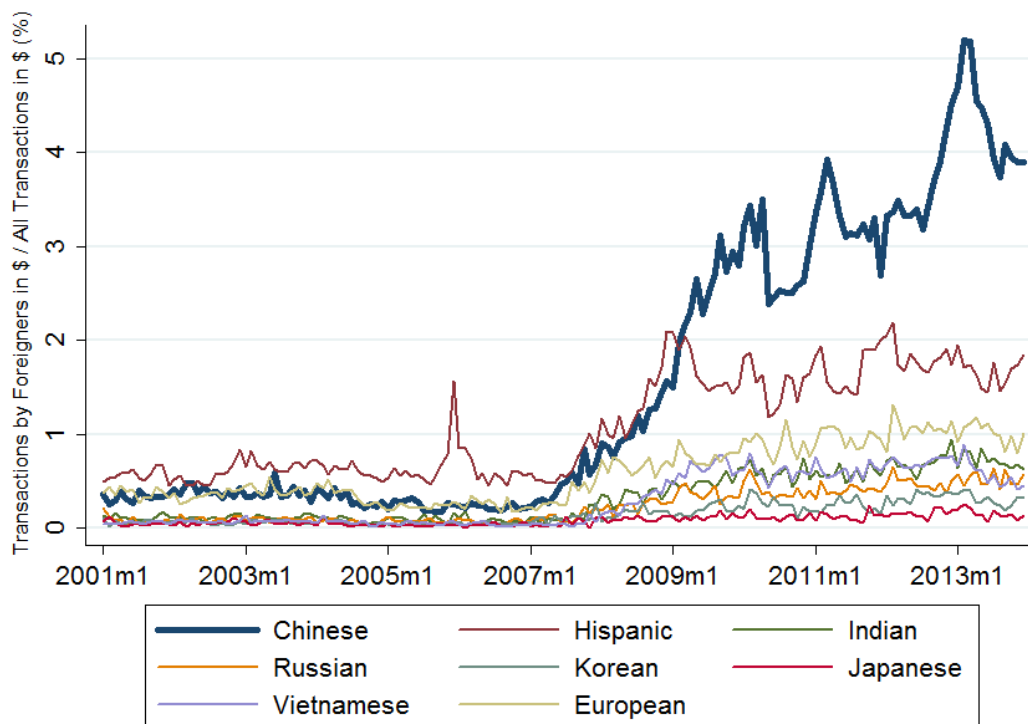
Motivated by these two facts, we proceed to study the effects of housing purchases by foreign Chinese on US local economies in this paper in two steps. First, we estimate the

increase from the previous year and more than two and a half times the amount spent by Canadians, the next biggest group of foreign buyers of real estate in the US. Furthermore, a survey published by the California Association of Realtors found that Chinese bought 32% of homes sold to foreigners in California, and a recent RealtyTrac report found that 80% of new construction homes in the city of Irvine were sold to Chinese buyers. Studies by Rosen et al. (2017) and Simons et al. (2016) find that foreign Chinese real estate buyers tend to neither use the purchased properties as primary residences nor rent it out. They show that housing purchases by foreign Chinese in the US has been accompanied by a rise in the number of Chinese investors in the EB-5 Immigrant Investor Visa Program, and they are primarily interested in obtaining a green card for their children instead of actual returns to their real estate investments. The tendency of foreign Chinese real estate buyers to leave housing properties vacant may not be surprising in light of a similar practice in China: Glaeser et al. (2017) show that housing vacancy rates in China are much higher than in the US, reaching more than 20% in major Chinese cities in 2012.

³Besides the housing market crash in the US, the 2007/2008 period was also the time that the real estate market in China began to boom significantly and the Chinese government increased the limit on how much Chinese citizens can exchange yuan to other currencies annually (up from \$20,000 to \$50,000). All of these factors likely played a role in inducing the surge of housing purchases by foreign Chinese in the US. Nevertheless, the main focus of this paper is to understand the implications of these purchases on the US economy.

causal impact of these purchases on local housing markets and labor markets in the US. Then we develop a model that rationalizes the empirical results in which we highlight the housing wealth channel through which foreign housing purchases impact US local economies.

Figure 2.1: Share of Housing Purchases (\$) by Foreigners

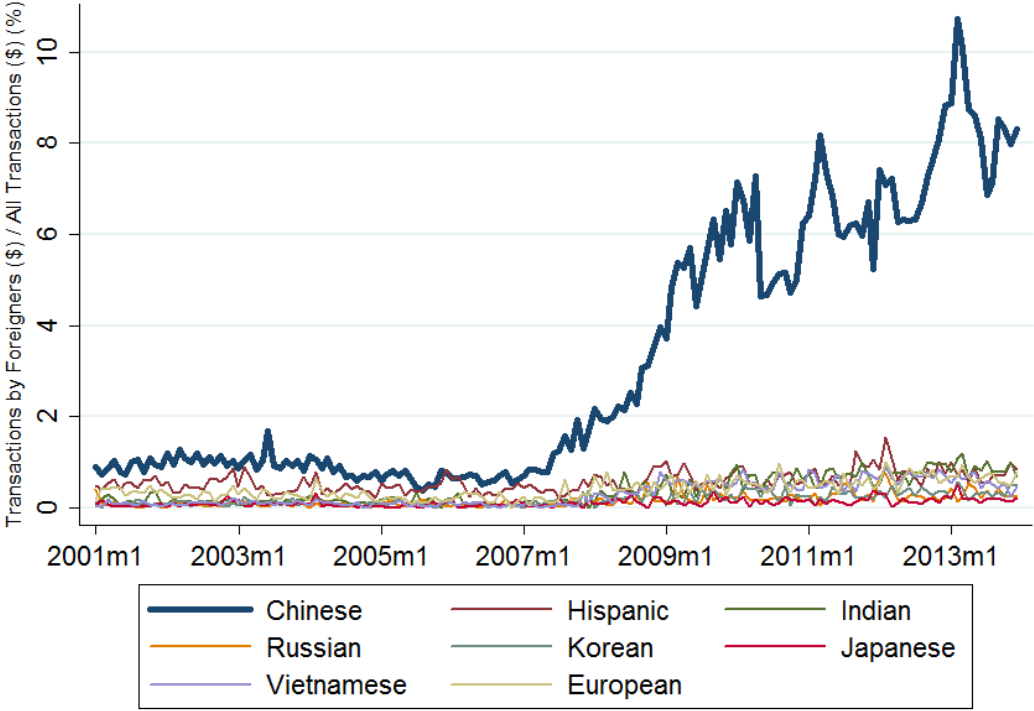


Notes: This figure plots the share of total monthly transaction value of home purchases in the 3 largest CBSAs in California between 2001 and 2013 by buyer ethnicity. Data source: DataQuick.

Empirically establishing the causality from Chinese purchases to local housing markets is challenging due to an issue of endogeneity: it is difficult to distinguish if increasing purchases by foreign Chinese are driving up home prices or if foreign Chinese just happen to be buying in areas that are more likely to experience higher home prices. To deal with this issue, we make use of the second stylized fact by exploiting historical cross-market variation in the concentration of Chinese population across zip codes to analyze the effects of the surge in housing purchases by Chinese buyers since 2007 on local housing prices and employment. Given Chinese buyers are more likely to buy homes in neighborhoods that are populated by a higher pre-existing percentage of ethnic Chinese, we use the percentage of ethnic Chinese for each zip code in 2000 as an instrument for the volume of housing purchases by foreign Chinese.

Our results show that zip codes that witnessed a higher volume of real estate purchases by foreign Chinese exhibit significantly higher increases in housing prices. We find that a

Figure 2.2: Share of Housing Purchases (\$) by Foreigners in Top Chinese Zip Codes



Notes: This figure plots transitions value of home purchases made by each ethnicity monthly in the 3 largest CBSAs in California between 2001 and 2013 for zip codes in the top quartile of ethnic Chinese population based on the 2000 Census. Data source: DataQuick.

1% increase in the housing demand by foreign Chinese as measured by transaction value induces a 0.074% increase in home prices between 2007 and 2011 (the period of the housing market crash), which corresponds to an increase of \$433 per home, and a 0.102% increase during 2012 and 2013 (the recovery period), which corresponds to \$597 per home. During the housing market crash of 2007-2011, zip codes that experienced more real estate purchases by foreign Chinese exhibit a lower decline in housing prices, suggesting foreign cash inflow during economic downturns can have a stabilizing effect.

To understand the real effects of the surge of real estate purchases by foreign Chinese, we then proceed to study the impact of the resulting increase in home prices on local labor markets. A number of papers have pointed to a significant link between housing investment and the real economy (e.g., Green (1997), Parker (2000)); in particular, recent papers by Mian et al. (2013) and Mian and Sufi (2014) show that deterioration in housing net worth played a significant role in the sharp decline in US employment between 2007 and 2009, or what they call the housing net worth channel. They argue that housing net worth affect employment by changing consumer demand through either a direct wealth effect or less

binding borrowing constraints driven by the rise in collateral value.

In our estimation on the relationship between higher housing prices driven by higher foreign Chinese purchase and employment, we find evidence of greater total employment in zip codes that experienced a higher volume of foreign Chinese housing purchases: a 1% increase in housing demand by foreign Chinese in terms of transaction value induces a 0.102% increase in a zip code’s total employment levels during the housing market crash years and a 0.149% increase during the recovery years. Moreover, we find that zip codes that experience more real estate purchases by foreign Chinese since 2007 exhibit a significantly higher increase in the non-tradable sector employment relative to earlier periods. This result in particular supports the housing net worth channel, which suggests the impact of spending changes in an area due to housing net worth fluctuations on local employment should show up foremost in non-tradable sector employment of that area, since non-tradable sector employment depends primarily on local demand, while the tradable sector is more diversified in its geographic origins of demand.

We build a simple model that incorporates the housing net worth channel to aid our thinking about the economic mechanism and interpreting the empirical estimates. This model shows how a nominal shock through housing wealth affects tradable versus non-tradable employment in the local economy. A key prediction of the housing net worth channel is that changes in housing net worth should be positively related to changes in non-tradable employment and not significantly related to changes in tradable employment. The intuition is that a positive housing wealth shock through housing purchases by foreign Chinese will increase the local demand for non-tradable goods and hence local non-tradable employment because demand for non-tradable goods are centralized in local economies, whereas the increased demand for tradable goods can be supplied by the production elsewhere, diffusing the effect on local employment in the tradable sector. Our results support this prediction as we find that foreign Chinese purchases significantly impact employment in the non-tradable sectors but not the tradable sectors.

This paper is related to several strands of literature and contains important policy implications. First, it contributes to the literature that aims to better understand the impacts and implications of China’s increasing integration into the global economy on the rest of the world. A growing literature explores the effects of China’s rapid growth in trade activities on US local economies, starting with the paper by Autor et al. (2013) who study the effects of rising Chinese import competition on US local labor markets and find that such competition explains one-quarter of the aggregate drop in US manufacturing employment. A number of subsequent papers find that Chinese import competition significantly affect innovation (Autor and Shu (2017)), electoral consequences (Autor and Majlesi (2017)), and marriage market outcomes (David Autor et al. (2018)) in the US. While China’s integration into the global economy indeed has been most acutely manifested in its trade activities over the past two decades, China has been seeking to open up its capital markets, which has prompted growing interests in the academic, policy and business community to better understand the implications of a “China shock” on the finance side for the rest of the world. This paper is one of the first academic papers on that front. We focus on a specific source of “China

shock” on the finance side, the surge of cash inflows from China to the US for residential real estate purchases, and analyze its economic impacts on the US local economies.

Our paper is also related to a growing literature that studies the effects of housing purchases by foreigners on local housing markets. Badarinza and Ramadorai (2015) examines the effects of housing demand by foreigners on domestic housing prices in London. Using political shocks in a source country as an exogenous instrument, they estimate the effects of foreign buyers on house prices in London neighborhoods with a large pre-existing share of residents born in that source country and find substantial price effects in such areas. Sa (2016) also studies the effect of foreign investment on UK house prices and home ownership rates, using a different data set. Cvijanovic and Spaenjers (2015) finds that non-resident foreigners induce house prices to rise and crowd out residents in highly desirable neighborhoods of Paris. They also show empirically that relatively few properties bought by non-residents are rented out, which corresponds to reports on foreign Chinese and validates an important assumption we make in our model. Favilukis and Van Nieuwerburgh (2017) develop a spatial equilibrium model of a city with heterogeneity among residents to study the welfare implications out-of-town buyers of local housing markets. Our paper contributes to this literature by going beyond the price effects of foreign housing purchases and examines the consequences on local employment as well as the underlying mechanisms. We aim to bridge the literature in the macro-finance and urban economics by presenting empirical evidence on how a foreign shock on the finance side affects the real economy.

To that end, our paper is related to the line of research that explores the effects of housing investments on the real economy. Green (1997) and Parker (2000) are among the earlier works that point out a significant link between real estate investment and the macro-economy. Recent papers by Mian et al. (2013) and Mian and Sufi (2014) argue that deterioration in household balance sheets, the housing net worth channel, played a significant role in the sharp decline in US spending and employment during the 2007-2009 financial crisis. Our paper presents results that support the housing net worth channel in the context of a positive housing net worth shock driven by foreign Chinese demand.

More broadly, our paper is related to papers that study the impact of foreign investments on domestic local economy, including papers that look into the effects of foreign direct investment on domestic economic growth (e.g., Borensztein et al. (1998)). Our analysis quantifies the effect of foreign housing investment, a specific form of capital inflow that has not been emphasized in the international finance literature, on the local economy and draws a link between international capital inflow to the housing sector and domestic economy. Moreover, given the surge in housing purchases by foreign Chinese coincided with the housing market crash in the US, our results show that investments by foreigners can play a stabilizing role in times of economic downturns. Our work also is related to papers that estimate the effects of stabilization policies such as fiscal stimulus on local economies during economic downturns, including Ramey (2011), Nakamura and Steinsson (2014), and Chodorow-Reich et al. (2012).

The remainder of the paper is organized as follows. Section 2 describes the data and the empirical methodology. Section 3 presents our empirical results. Section 4 presents the

model we use to interpret the empirical results. Section 5 concludes.

2.2 Data and Methodology

Data

Our main data source for housing transaction data is DataQuick, from which we obtain the universe of housing transaction records in the California from 2001 to 2013.⁴ For each transaction, we can observe the address of the house, the names of the buyer and seller, the transaction price, the transaction date, and characteristics of the house. We restrict our sample to single family residential homes as the focus of this study is residential real estate purchases not business purchases.

Given our objective is to study the impact of housing demand by foreign Chinese on the local economy, we need to generate a measure for foreign Chinese housing transaction value (*CHTV*) in the sample. To this end, we proceed in three steps.

First, we identify the ethnicity of the house buyers in our sample using Bill Kerr’s ethnic name-matching algorithms. Kerr (2008) originally created the algorithm to identify the ethnicity of inventors who were granted patents by the US Patent and Trademark Office, and Kerr and Lincoln (2010) used this algorithm to investigate the impact of H-1B Visa reforms on Indian and Chinese inventors and patents. This algorithm exploits the fact that certain names are unique or more common to one ethnicity and assigns each person a probability of belonging to a specific ethnicity, with the probabilities summed up to 100%. If a name is unique to one ethnicity, the person with that name will be assigned with 100% to one ethnicity. For names that are common among multiple ethnicities, the algorithm uses the demographic breakdown in the MSA in which the corresponding buyers reside to assign probabilities. For example, a person named Yi Chen would be assigned to the Chinese ethnicity with 100% probability, while someone with the surname Lee, which could be of Chinese, Korean or American ethnicity, would be assigned to each of the three ethnic groups with probabilities based on the proportion of Chinese, Koreans, and Americans in the MSA in which person resides.⁵ In order to ensure that our final foreign Chinese housing demand measure is of the highest accuracy possible, we consider a transaction to be made by an ethnic Chinese buyer if the name matching process assigns that buyer as 100% ethnic Chinese.

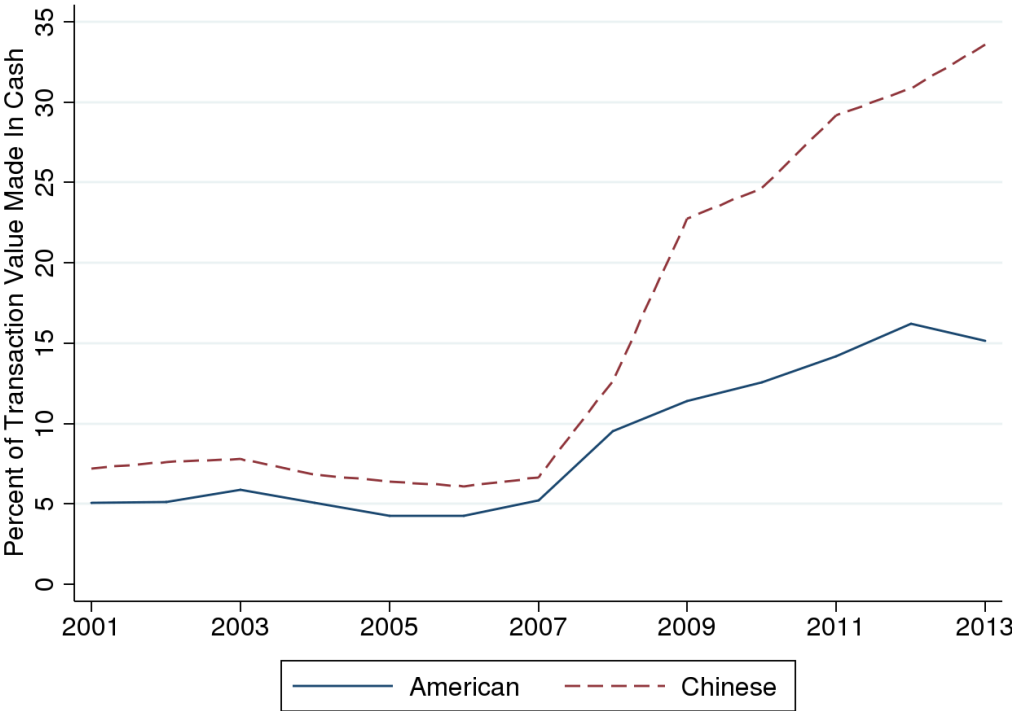
Next, we only keep transactions that were made in cash by ethnic Chinese buyers. This filtering is motivated by the fact that foreign Chinese cannot qualify for mortgage when buying homes in the US, which means they must pay in cash. We therefore assume that all Chinese buyers in the sample that have mortgages attached are ethnic Chinese who regularly lives in the US.

⁴In our analysis, we focus on housing transactions in the three largest core-based statistical areas (CBSAs) in California, Los Angeles-Long Beach-Riverside, San Jose-San Francisco-Oakland, and San Diego-Carlsbad-San Marcos, as those are the areas that have witnessed more purchases by foreign Chinese since 2007.

⁵See Kerr (2008) for more comprehensive details on the names matching process and descriptive statistics from their matching exercises.

Third, we recognize that restricting the sample to cash purchases by ethnic Chinese is a necessary but not sufficient condition for identifying foreign Chinese housing purchases because ethnic Chinese also can pay cash. To address this concern, we make an assumption that ethnic Chinese who live in the US behave similarly to Americans and take out cash transactions that are likely to be made by Americans for the *CHTV* measure. As shown in Figure 2.3, the percentage of all transactions that are made in cash for Americans and for ethnic Chinese were comparable prior to 2007. After 2007, the probability of cash transactions increased much faster for ethnic Chinese than for Americans, which is likely driven by the increase in cash purchases by foreign Chinese based on figures reported by the National Association of Realtors. Given this observation, we adjust the ethnic Chinese cash transaction figure by taking out the probability that the cash purchases were made by Americans for each zip code-year to arrive at the final *CHTV* measure.

Figure 2.3: US and Chinese Cash Purchase Trends



Notes: This figure plots the percentage of home transaction values bought in cash by both Americans and Chinese between 2001 and 2013. Homes were classified as being purchased by American or Chinese if Kerr’s ethnic name matching process assigns a 100% match for each corresponding ethnicity for the buyer. Based on the trends in this graph, we can calculate an adjusted foreign Chinese housing transactions (*CHTV*) as: $CHTV_{zt} = ethnic\ Chinese\ Cash_{zt} * (1 - Prob(American\ Cash)_{zt})$ for each zipcode-year *zt*.

To study the impact of foreign Chinese housing transactions on the local economy, we merge the housing transactions data with multiple zip code level datasets, including Zillow for local housing values, the 2000 Census for historical ethnic Chinese population, the Census Zip Code Business Patterns for employment size, and the IRS for income. Similar to Mian et al. (2013), we further decompose the employment size measure into two categories, tradable and non-tradable, using the four-digit industry classification code.

Table 2.1 presents the summary statistics of our dataset. In total, we have 9,986 zip code-year observations over the period 2001-2013. We break down the sample into three sub-periods: the housing market boom period (2001-2006), the housing market crash period (2007-2011) and the housing market recovery period (2012-2013). As shown in the top four rows, there was a dramatic increase in housing transactions by foreign Chinese during the post-2007 period relative to earlier years. On average, while each zip code witnessed 0.8 housing transactions by foreign Chinese for a total value of \$0.45 million per year between 2001-2006, those figures jumped to 11 transactions and \$5 million by 2013, respectively. The share of Chinese transaction out of all housing transactions in California in terms of counts and values also increased from 0.28% to 4.5% and from 0.28% to 4.36% respectively. The bottom four rows of Table 2.1 show that the average local economic conditions, as measured by home prices, employment and income, were similar across the three periods. Given the surge in housing purchases by foreign Chinese began in 2007, we focus on the the sample period 2007-2013 in the subsequent empirical analysis.

Table 2.1: Summary Statistics

	N (total)	2001-2006		2007-2011		2012-2013	
		Mean	SD	Mean	SD	Mean	SD
Foreign Chinese Housing Transaction							
Counts	9,986	0.80	2.21	7.87	13.33	10.95	16.90
Value (\$)	9,986	0.45M	1.30M	3.18M	5.49M	5.00M	8.91M
Counts (%)	9,986	0.28	0.73	3.26	4.23	4.50	5.56
Value (%)	9,986	0.28	0.75	3.08	4.15	4.36	5.62
Zillow Single Family Home Price Index	9,986	0.54M	0.36M	0.54M	0.36M	0.54M	0.40M
Log of Non-Tradable Employment	9,986	7.34	1.26	7.63	0.97	7.61	1.00
Log of Tradable Employment	9,986	5.88	1.99	5.89	1.92	5.80	1.93
Average Household Income	9,986	68,562.23	57,776.78	76,097.31	62,394.53	85,152.74	82,349.33

Notes: This table presents summary statistics and counts of key variables for 2001-2013 and further broken down into the housing market boom period (2001-2006), the housing market crash period (2007-2011) and the housing market recovery period (2012-2013). The unit of observation is at the zip code by year level.

Methodology

Our goal is to estimate the impact of the increase in housing transactions by foreign Chinese on the local economy. However, establishing causality is difficult due to an issue of

endogeneity: it is difficult to distinguish if the increase in foreign Chinese purchases drives up home prices or if foreign Chinese seek to buy homes in zip codes that are more likely experience higher rates of home price appreciation. To address this issue, we implement an instrumental variable approach and use the ethnic Chinese population percentage share reported in the 2000 Census in each zip code as an instrument for the foreign Chinese housing transaction value measure ($CHTV$). This instrument is motivated by the observation in Figure 2.2 that foreign Chinese prefer to buy homes in areas that have a higher percentage of pre-existing ethnic Chinese in the population. The identification assumption is that percentage of ethnic Chinese in the pre-existing population in 2000 is independent from factors that may affect local housing prices after 2007.⁶ This strategy is equivalent to a Bartik instrument, whose source of identification is cross-sectional (Goldsmith-Pinkham et al., 2018). Since this percentage was measured prior to the sample period of the empirical analysis, it is unlikely to be correlated with other factors that could be driving up home prices in later periods. We also control for population, education, and pre-trends to alleviate concerns about omitted variables bias.

Figure 2.4 provides evidence that this instrumental variable has significant predictive power for foreign Chinese housing purchases. In the graph, we plot the $CHTV$ measure normalized by total transaction value (left plot) and total income (right plot) for each zip code decile based on the percentage of the ethnic Chinese population in the zip code in 2000. In both plots, zip codes in the top two deciles have noticeably higher foreign Chinese housing transaction values.

As an additional illustration of the statistical power of our instrument, we plot the quarterly Zillow Home Value Index for zip codes in the top two deciles by ethnic Chinese population percentage in 2000 (treated group) versus zip codes in the bottom eight deciles (control group), with the Index normalized to 1 in 2007Q1 in Figure 2.5. As shown, while the patterns of home prices between the two zip code groups were similar prior to 2007, a price gap between the two groups began to emerge in 2007 and continued to increase thereafter, with the home prices of the treated group at an increasingly higher level than that of the control group. The positive relationship between the share of ethnic Chinese population and home prices further suggests that the share of ethnic Chinese population as an instrumental variable has significant predictive power for foreign Chinese housing purchases.

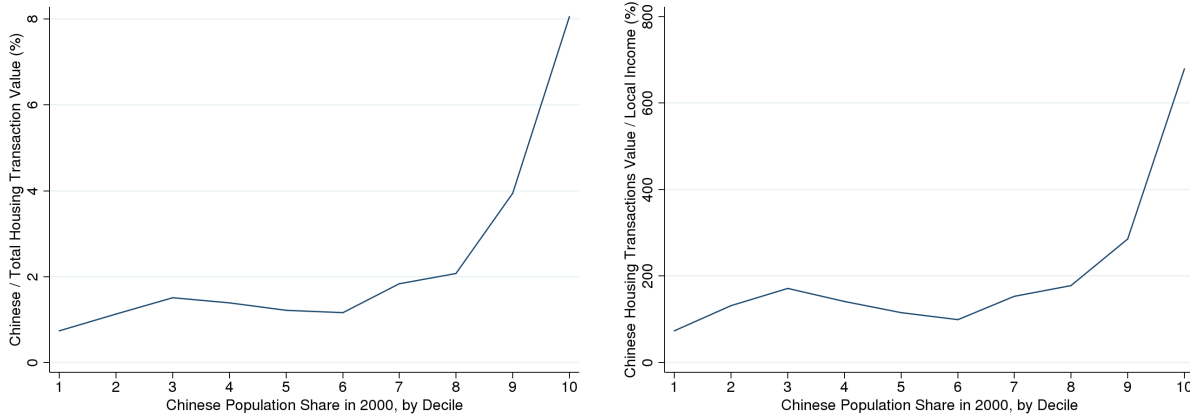
Using the foreign Chinese housing transaction ($CHTV$) measure and data on local economic conditions, we estimate the impact of the increase in housing transactions by foreign Chinese on the local housing market and labor market using the following specification:

$$\ln(Y_{zt}) = \alpha + \theta \ln CHTV_{zt} + \beta \ln CHTV_{zt} \times \mathbb{I}\{year \geq 2007\} + \gamma X_z + \eta_{ct} + \varepsilon_{zt} \quad (2.1)$$

where Y_{zt} is the Zillow Home Value Index (in log) or employment size (in log) for zip code z in year t , $CHTV_{zt}$ is the foreign Chinese housing transactions value measure (in log), $\mathbb{I}\{year \geq 2007\}$ is an indicator variable if the year is 2007 or later, X_z are time-invariant

⁶A similar instrument has been used to study the impact of immigrants on the labor markets by Card (2001).

Figure 2.4: Variation in foreign Chinese Housing Purchases by Historical Ethnic Chinese Population Percentage



Notes: This figure shows two plots on foreign Chinese housing purchases between 2007 and 2013 for each zip code decile based on the year 2000 ethnic Chinese population percentage. The left figure normalizes foreign Chinese purchases measure by total transaction value, and the right figure normalizes the measure by total income.

zip code level controls including population, education measured as the percentage of the population with a bachelor degree and a pre-sample trend variable for the dependent variables calculated as the difference between Zillow Home Value Index or employment in 1996 and 2000, and η_{ct} are county-year fixed effects. β is the coefficient of interest.

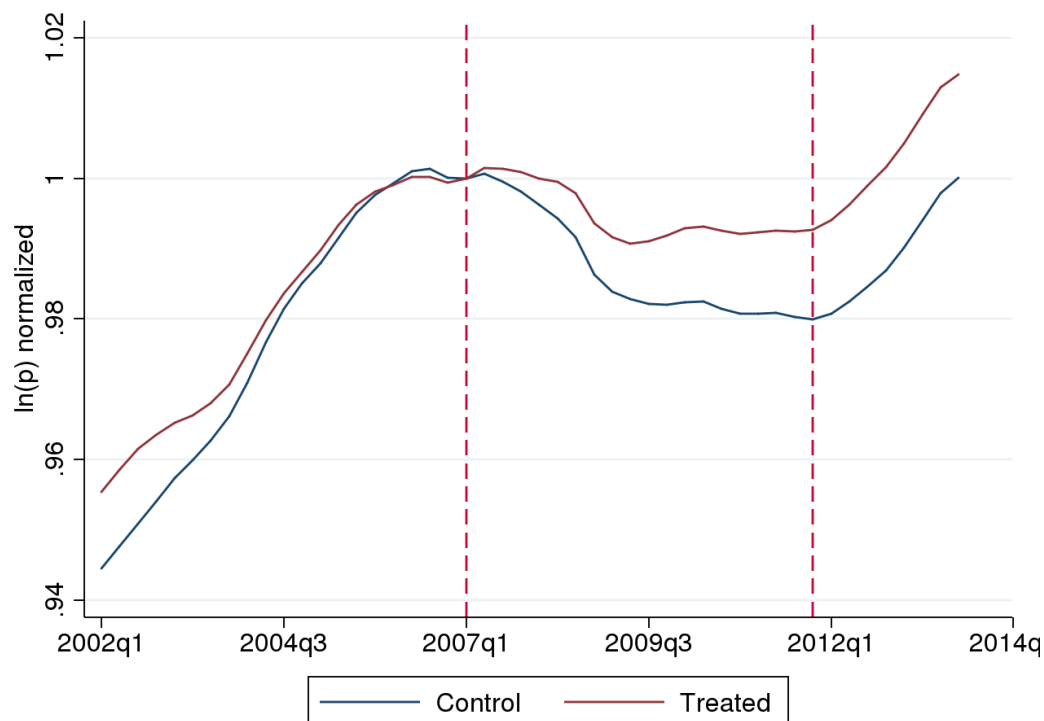
To mitigate endogeneity concerns regarding the foreign Chinese housing transaction value measure ($CHTV$), we instrument for it using the ethnic Chinese population percentage share reported in the 2000 Census in each zip code. The first stage regression is as follows:

$$\ln(CHTV_{zt}) = \tilde{\alpha} + \tilde{\theta}CH_Share_{zt} + \tilde{\beta}CH_Share_{zt} \times \mathbb{I}\{year \geq 2007\} + \tilde{\gamma}X_z + \tilde{\eta}_{ct} + \tilde{\varepsilon}_{zt} \quad (2.2)$$

where CH_Share_{zt} is the share of ethnic Chinese population in 2000, and the other controls are the same as those in 2.1. The identification assumption is that conditional on the county-time fixed effects and our zip code level controls the cross-sectional variation in the concentration of ethnic Chinese in the pre-existing population in 2000 across local areas (zip codes) does not correlate with factors that may affect local housing prices and employment after 2007.

We conjecture the coefficient of impact, β , to be positive for both housing market and labor market effects. Increasing housing purchases by foreign Chinese pushes up the demand for homes, which we predict would increase home prices as a first order effect. In addition, a change in home prices can also impact local labor markets through the housing net worth channel.

Figure 2.5: Zillow Home Price Index by Historical Ethnic Chinese Population Percentage



Notes: This figure shows the average quarterly Zillow Home Value index for zip codes in the top two deciles based on the year 2000 Chinese population percentage versus those in the bottom eight deciles. For both groups, the index is normalized to one in the first quarter of 2007.

2.3 Empirical Results

Housing Price and Employment Effects

In Table 2.2, we show our main regression results based on Equation 2.1 with log Zillow Home Value Index as the dependent variable. Column 1 shows results over the housing market crash period of 2007-2011, and Column 2 presents results for the housing market recovery period of 2011-2013, respectively. All the regressions control for log population, education, and a pre-trend of housing prices. The F-statistics on the first stage regression are highly significant, which indicates that the instrument has strong predictive power for foreign Chinese housing purchases. The coefficient in the first row is the estimated impact of foreign Chinese housing purchases on local house prices.

The results support our conjecture that foreign Chinese housing purchases have a significant effect on local housing prices in the US. We find zip codes that witnessed a higher volume of real estate purchases by foreign Chinese exhibit significantly higher increases in housing

prices: a 1% increase in the housing demand by foreign Chinese as measured by transaction value induces a 0.074% increase in local home prices. 0.074% during the 2007-2011 period. Using a mean Zillow Home Value Index of \$584,553 during the 2007-2011 period, the 0.074% home price increase is equal to an increase of \$432.57 per home.

We can also use this estimate to roughly compare how home prices reacted across zip codes with different levels of changes in *CHTV*. Between 2007 and 2011, while the median zip code experienced an average annual increase in *CHTV* of 47%, a zip code in the 90th percentile experienced an annual increase in *CHTV* of 139%. Having a 92% higher increase in *CHTV* leads to 6.8% higher home prices for the 90th percentile zip code compared to the median zip code. During the housing market crash period of 2007-2011, housing prices declined across all zip codes but zip codes that experienced more real estate purchases by foreign Chinese exhibit a lower decline in housing prices. This suggests cash inflow from foreign Chinese during economic downturns played a stabilizing role for US local economies over the period.

In addition to comparing the housing boom years to the housing crash years, we also compare the boom years to the recovery years of 2012 and 2013. The results in Column 2 shows that a 1% increase in *CHTV* increases home prices by 0.102% during the recovery years. During the recovery years, the median zip code experienced an annual increase in *CHTV* of 36% while a zip code in the 90th percentile experienced an annual increase in *CHTV* of 174%. This difference leads to a 14.1% difference in home prices.

Furthermore, we also estimate Equation 2.1 using housing transaction prices from DataQuick as the dependent variable. Results are presented in Table 2.3. In addition to the set of controls specified in Equation 2.1, we also control for home characteristics, which includes the number of bathrooms, the square footage, and age of the home. We obtain similar results for both periods, although the coefficient estimates on the interaction term are slightly larger in magnitude compared to the estimates in Table 2.2.

We then proceed to study if the increase in home prices driven by higher demand from foreign Chinese significantly affect the local real economies. Specifically, we estimate Equation 2.1 with zip code level employment size as the outcome variable. As shown in Table 2.4, zip codes that experienced a higher volume of foreign Chinese housing purchases exhibit greater total employment: a 1% increase in housing demand by foreign Chinese in terms of transaction value induces an increase of 0.10% during the housing market crash period of 2007-2011 and of 0.15% during the recovery period of 2012-2013 in a zip code's total employment levels.

Employment Effects by Sector

We explore the channels that potentially give rise to the relationship between higher housing prices driven by higher foreign Chinese purchase and local employment. Recent papers by Mian et al. (2013) and Mian and Sufi (2014) argue that higher home prices can lead to higher rates of employment through the housing net worth channel: higher housing wealth could affect employment by changing consumer demand through either a direct wealth effect

Table 2.2: Home Price Effects Using Zillow Home Price Index

	(1)	(2)
$\ln(\text{CHTV}) \times \mathbb{I}\{\text{year} \geq 2007\}$	0.074*** (0.014)	0.102*** (0.015)
$\ln(\text{CHTV})$	0.001 (0.021)	-0.004 (0.023)
$\ln(\text{Population})$	-0.043*** (0.017)	-0.031* (0.016)
$\Delta \ln(\text{HNW}), 00-96$	1.232*** (0.204)	1.304*** (0.242)
Education	4.134*** (0.251)	4.250*** (0.303)
County Year Fixed Effects	X	X
Post Period	2007-2011	2012-2013
Model Statistics:		
First Stage F-statistic	98.95	85.53
Observations	3474	2470

Notes: This table presents results from the IV regression testing for impact of home purchases made by foreign Chinese on home prices as measured by the Zillow Home Value Index. *CHTV* denotes foreign Chinese housing transaction values instrumented by historical share of ethnic Chinese. Education is measured as the percentage of the population with a bachelor degree. Additional control variable includes a pre-sample trend variable for the dependent variable calculated as the difference between Zillow Home Value Index in 1996 and 2000. Columns 1 shows results for the housing crash period 2007-2011, Column 2 for the recovery period 2012-2013. Standard errors are clustered at the zip code level. *, **, *** denote 10%, 5% and 1% significance respectively.

or less binding borrowing constraints driven by the rise in collateral value. One of the key predictions of the housing net worth channel is that the impact of demand changes in an area due to housing net worth fluctuations on local employment should show up foremost in the non-tradable sector employment of that area, since non-tradable sector employment depends primarily on local demand while the tradable sector is more diversified in its geographic origins of demand.

To test for this effect, we categorize the employment measure into tradable employment and non-tradable employment based on 4-digit SIC codes, following the practice in Mian and Sufi (2014), and estimate the following regression:

$$\ln(\text{Emp})_{zt} = \alpha + \beta_1 \ln(\tilde{\text{CHTV}}_{zt}) + \beta_2 \ln(\tilde{\text{CHTV}}_{zt}) \times \mathbb{I}\{\text{year} \geq 2007\} + \gamma X_z + \eta_{ct} + \varepsilon_{zt} \quad (2.3)$$

where Y_{zt} is tradable or non-tradable sector employment (in log) for zip code z in year t , $\tilde{\text{CHTV}}_{zt}$ is the foreign Chinese housing transactions value measure (in log) instrumented by

Table 2.3: Home Price Effects Using Transaction Prices

	(1)	(2)
$\ln(\text{CHTV}) \times \mathbb{I}\{\text{year} \geq 2007\}$	0.121*** (0.013)	0.119*** (0.013)
$\ln(\text{CHTV})$	-0.046*** (0.017)	-0.036** (0.017)
$\ln(\text{Population})$	-0.003 (0.013)	0.009 (0.013)
$\Delta \ln(\text{HTV}), 00-96$	0.219*** (0.073)	0.250*** (0.077)
Education	3.475*** (0.169)	3.335*** (0.172)
County Year Fixed Effects	X	X
Post Period	2007-2011	2012-2013
Model Statistics:		
First Stage F-statistic	124.27	103.64
Observations	3699	2631

Notes: This table presents results from the IV regression testing for impact of home purchases made by foreign Chinese on home prices as measured by the average zip code level transaction values from DataQuick. *CHTV* denotes foreign Chinese housing transaction values instrumented by historical share of ethnic Chinese. Education is measured as the percentage of the population with a bachelor degree. Additional control variables include a pre-sample trend variable for the dependent variable calculated as the difference between average zip code level transaction values in 1996 and 2000, number of bathrooms, square footage and age. Columns 1 shows results for the housing crash period 2007-2011, Column 2 for the recovery period 2012-2013. Standard errors are clustered at the zip code level. *, **, *** denote 10%, 5% and 1% significance respectively.

the share of ethnic Chinese population in 2000, $\mathbb{I}\{\text{year} \geq 2007\}$ is an indicator variable that takes the value 1 if year is post-2007 and 0 otherwise, X_z are time-invariant zip code level controls including population, education measured as the percentage of the population with a bachelor degree, and a pre-sample trend variable for the corresponding dependent variables calculated as the difference between tradable/non-tradable employment in 1996 and 2000, and η_{ct} are county-year fixed effects.

The results from Equation 2.3 are reported in Table 2.5. We find that a 1% increase in *CHTV* increases zip code level non-tradable employment by 0.122% and 0.137% during the housing market crash period and housing market recovery period, respectively, as shown in Columns 1 and 3. On the other hand, estimates in Columns 2 and 4 show that the increase in housing purchases by foreign Chinese have no statistically significant impact on local tradable employment.

Table 2.4: Total Employment Effects

	(1)	(2)
$\ln(\text{CHTV}) \times \mathbb{I}\{\text{year} \geq 2007\}$	0.102** (0.044)	0.149*** (0.051)
$\ln(\text{CHTV})$	0.028 (0.079)	0.018 (0.082)
$\ln(\text{Population})$	0.752*** (0.079)	0.741*** (0.090)
$\Delta \ln(\text{Emp}), 00-96$	0.380* (0.197)	0.332 (0.210)
Education	2.246*** (0.680)	2.402*** (0.714)
County Year Fixed Effects	X	X
Post Period	2007-2011	2012-2013
Model Statistics:		
First Stage F-statistic	110.97	93.24
Observations	3712	2643

Notes: This table presents results from the IV regression testing for impact of home purchases made by foreign Chinese on total employment. *CHTV* denotes foreign Chinese housing transaction values instrumented by historical share of ethnic Chinese. Education is measured as the percentage of the population with a bachelor degree. Additional control includes a pre-sample trend variable for the corresponding dependent variable calculated as the difference between employment in 1996 and 2000. Column 1 shows results for the housing crash period 2007-2011, Column 2 for the recovery period 2012-2013. Standard errors are clustered at the zip code level. *, **, *** denote 10%, 5% and 1% significance respectively.

Robustness

To address potential additional concerns related to endogeneity between foreign Chinese housing purchases and local employment, we perform a placebo test to examine if changes in housing purchases by foreign Chinese after 2007 is related to local employment prior to 2007. To do so, we estimate the following regression of ex-post foreign Chinese housing purchases on ex-ante local employment:

$$\ln(\text{Emp}, 01-06)_z = \alpha_0 + \beta \ln\left(\sum_{2007}^{2013} \text{CHTV}\right)_z + \gamma X_z + \varepsilon_{zt} \quad (2.4)$$

where $\ln(\text{Emp}, 01-06)_z$ is the zip code level change in employment between 2001 and 2006 and $\ln\left(\sum_{2007}^{2013} \text{CHTV}_z\right)$ is the log of the total value of Chinese purchases between 2007 and

Table 2.5: Tradable and Non-Tradable Employment Effects

	(1)	(2)	(3)	(4)
	ln(NT Emp)	ln(T Emp)	ln(NT Emp)	ln(T Emp)
ln(CHTV) $\times \mathbb{I}\{year \geq 2007\}$	0.122*** (0.043)	0.046 (0.099)	0.137*** (0.044)	0.144 (0.116)
ln(CHTV)	-0.057 (0.078)	0.246 (0.175)	-0.060 (0.076)	0.259 (0.181)
ln(Population)	0.894*** (0.071)	0.889*** (0.146)	0.887*** (0.070)	0.822*** (0.158)
$\Delta \ln(\text{NT/T Emp}), 00-96$	-0.074 (0.136)	-0.153 (0.120)	-0.103 (0.129)	-0.113 (0.121)
Education	2.524*** (0.655)	-4.738*** (1.352)	2.570*** (0.611)	-5.102*** (1.453)
County Year Fixed Effects	X	X	X	X
Post Period	2007-2011	2007-2011	2012-2013	2012-2013
Model Statistics:				
First Stage F-statistic	111.49	107.49	122.57	90.85
Observations	3708	3668	4876	2607

Notes: This table presents results from the IV regression testing for impact of home purchases made by foreign Chinese on both tradable and non-tradable employment. *CHTV* denotes foreign Chinese housing transaction values instrumented by historical share of ethnic Chinese. Education is measured as the percentage of the population with a bachelor degree. $\Delta \ln(\text{NT/T Emp}), 00-96$ is a pre-sample trend variable for the corresponding dependent variables calculated as the difference between tradable/non-tradable employment in 1996 and 2000. Columns 1 and 2 shows results for the housing crash period 2007-2011, Column 3 and 4 for the recovery period 2012-2013. Standard errors are clustered at the zip code level. *, **, *** denote 10%, 5% and 1% significance respectively.

2013 in each zip code. The results in Table 2.6 show that ex-post foreign Chinese purchases do not predict ex-ante employment, which support the findings that foreign Chinese home purchases induced a significant change in local employment, and they were not targeting zip codes that had previously experienced a home price growth.

A Summary of Empirical Results

We summarize the findings of our empirical results. Using an instrumental variables approach, we find that an influx of foreign Chinese housing investment increases local housing prices and local employment in nontraded sectors. However, we do not find statistically significant evidence that local employment in the tradable sector is affected. These results support the notion that the housing net worth channel played an important role: regions

Table 2.6: Placebo Test

	(1)	(2)
ln(CHTV, 07-13)	-0.000 (0.009)	0.001 (0.010)
ln(Population)	-0.074*** (0.028)	-0.077*** (0.030)
Education		-0.049 (0.154)
First Stage F-statistic	413.02	328.32
Observations	717	717

Notes: This table presents results from the IV regression testing for impact of total home purchases made by foreign Chinese between 2007-2013 on the growth in aggregate employment between 2001-2006. This specification is used to confirm that foreign Chinese home purchases induced a change in employment and that they were not targeting zip codes that had previously experienced a home price growth. Standard errors are clustered at the zip code level. *, **, *** denote 10%, 5% and 1% significance respectively.

with more housing purchases by foreign Chinese experience higher housing prices, which raise consumer demand through either a direct housing wealth effect or a relaxation of borrowing constraints due to the rise in collateral value. A higher local demand raises local employment, and the employment effect should reflect more prominently in the nontradable sector since non-tradable sector employment depends on local demand while the supply for tradable goods is spread across regions. In the next section, we attempt to provide an explanation of these features using a simple model.

2.4 A Simple Model

We develop a simple partial equilibrium framework to show how housing purchases by foreign Chinese affect house prices and employment in the local economy. We then discuss how the model predictions match our empirical findings.

Baseline

Consider an economy consisting of Z equally-sized regions indexed by z . Each region produces two types of goods, tradable (indexed by T) and non-tradable (indexed by N). The tradable good is nationally traded and serves as a numeraire good with $P^T = 1$. There is a fixed stock of housing in each region (indexed by H). Regions can freely trade the tradable good, but must consume the non-tradable good produced locally. For simplicity, we impose

the restriction that labor cannot move across islands but can move freely between the tradable and non-tradable sectors within an island. Let D_z denote the nominal income in each region, which consists of wages and rental income (rebated to local workers).

Preference Workers in region z have Cobb-Douglas preferences over tradable and non-tradable goods as well as housing (C_z^N , C_z^T , and C_z^H) with prices P_z^N , P^T , and P_z^H , and they spend income shares α , β , and $1 - \alpha - \beta$ on the three goods.

Budget Constraint The budget constraint of workers is $P_z^N C_z^N + C_z^T + P_z^H C_z^H = D_z$. From the Cobb-Douglas preference specification, $P_z^N C_z^N = \alpha D_z$, $C_z^T = \beta D_z$, and $P_z^H C_z^H = (1 - \alpha - \beta) D_z$ on the nontradable, tradable, and housing consumption, respectively.

Output All regions face the same tradable good price, while the non-tradable good price may be region-specific since non-tradable good are produced locally. Production is governed by a constant returns technology for tradable and non-tradable goods with employed labor, e as the only factor input and produces output according to $y_z^T = b e_z^T$, and $y_z^N = a e_z^N$, respectively, where b and a are productivity parameters. The housing supply is fixed at H_z .

Employment Total employment in each region is normalized to one with $e_z^T + e_z^N = 1$. Wages in the non-tradable and tradable sectors are given by $w_z^N = a P_z^N$ and $w_z^T = b P^T = b$. Free mobility of labor across sectors equates the two wages, which implies $w_z = w = b$ and $P_z^N = \frac{b}{a}$.

Equilibrium In equilibrium the goods markets clear. For nontradable goods, $y_z^N = C_z^N$ in each region. For tradable goods, the total demand equate to the total production across all regions: $\sum_{z=1}^Z y_z^Z = \sum_{z=1}^Z C_z^T$. We solve the model with a symmetry assumption that, in the initial state, all regions have the same housing stock $H_z = H_0$ and that the economy achieves full employment. The housing demand is equal to the supply in equilibrium: $C_z^H = H_0$. Since the nominal income is $D_z = w + P_z^H H_0$, we could obtain equilibrium house prices and the nominal income. The equilibrium variables in this simple framework are collected as follows:

$$\text{Prices :} \quad P_z^{*N} = \frac{b}{a}; \quad P^{*T} = 1; \quad P_z^{*H} = \frac{1 - \alpha - \beta}{\alpha + \beta} \frac{b}{H_0} \equiv P_0;$$

$$\text{Employment :} \quad e_z^{*N} = \frac{\alpha}{\alpha + \beta} \equiv e_0^N; \quad e_z^{*T} = \frac{\beta}{\alpha + \beta} \equiv e_0^T;$$

$$\text{Wages :} \quad w_z^{*N} = w_z^{*T} = b \equiv w;$$

$$\text{Nominal income :} \quad D_z^* = w + P_0 H_0 = b + \frac{1 - \alpha - \beta}{\alpha + \beta} b \equiv D_0.$$

Effects of House Demand by Foreigners

Suppose now that there is heterogeneous housing demand by foreign Chinese across regions (denoted by $C_{\text{chn},z}^H$):

$$H_0 = C_z^H + C_{\text{chn},z}^H,$$

where C_z^H is the housing demand by local workers and C_{chn}^H is the (exogenous) demand by foreign Chinese. Since $C_z^H = (1 - \alpha - \beta) \frac{D_z}{P_z^H}$ and $D_z = b + P_z^H H_0$, we obtain the housing prices:

$$P_z^H = \frac{(1 - \alpha - \beta)b}{(\alpha + \beta)H_0 - C_{\text{chn},z}^H},$$

which shows that regions with more housing purchases from foreign Chinese have higher house prices (a housing boom). Consider two regions, one with a house demand from foreigners (treated region, $C_{\text{chn},z}^H > 0$) and one without (control region, $C_{\text{chn},z}^H = 0$). The cross-sectional difference in house prices between the two regions is

$$P_{z,\text{treated}}^H - P_{z,\text{control}}^H = \frac{(1 - \alpha - \beta)b}{(\alpha + \beta)H_0 - C_{\text{chn},z}^H} - P_0,$$

which is an increasing function of $C_{\text{chn},z}^H$ with

$$\frac{\partial(P_{z,\text{treated}}^H - P_{z,\text{control}}^H)}{\partial C_{\text{chn},z}^H} = \frac{(1 - \alpha - \beta)b}{[(\alpha + \beta)H_0 - C_{\text{chn},z}^H]^2} > 0. \quad (2.5)$$

The prediction from Equation 2.5 is confirmed by our empirical analysis.

The nominal income now becomes

$$D_z = b + P_z^H H_0 = b + \underbrace{\frac{(1 - \alpha - \beta)bH_0}{(\alpha + \beta)H_0 - C_{\text{chn},z}^H}}_{\text{housing net worth channel}},$$

so the house demand by foreign Chinese raises the nominal demand via a housing net worth channel. Now the non-tradable employment becomes

$$e_z^N = \frac{\alpha}{b} D_z = \alpha + \frac{\alpha(1 - \alpha - \beta)H_0}{(\alpha + \beta)H_0 - C_{\text{chn},z}^H},$$

which shows that the nontradable sector expands in regions with higher house demand from foreigners. The cross-sectional difference in local employment in the nontradable sector between the treated and control regions is an increasing function of $C_{\text{chn},z}^H$:

$$\frac{\partial(e_{z,\text{treated}}^N - e_{z,\text{control}}^N)}{\partial C_{\text{chn},z}^H} = \frac{\alpha(1 - \alpha - \beta)}{[(\alpha + \beta)H_0 - C_{\text{chn},z}^H]^2} > 0. \quad (2.6)$$

The prediction on the employment effect in the nontradable, as shown in Equation 2.6, is confirmed by our empirical results. Based on the full employment condition, however, output and employment in the tradable sector, will shrink in treated regions:

$$e_z^T = 1 - e_z^N = 1 - \alpha - \frac{\alpha(1 - \alpha - \beta)H_0}{(\alpha + \beta)H_0 - C_{\text{chn},z}^H},$$

so the cross-sectional difference in local employment in the tradable sector between the treated and control regions is a decreasing function of $C_{\text{chn},z}^H$:

$$\frac{\partial(e_{z,\text{treated}}^T - e_{z,\text{control}}^T)}{\partial C_{\text{chn},z}^H} < 0. \quad (2.7)$$

In our partial equilibrium setup, the increased demand for tradable good is met by imports from other regions outside the local economy since we assume that the tradable good is nationally traded with a fixed price $P^T = 1$. So the inflow of Chinese real estate investment acts as financial transfers to recipient regions, allowing them run a trade deficit. To see this, note that we could obtain the deficit as the difference between consumption and output in the traded sector:

$$\begin{aligned} \text{Deficit}_z &= C_z^T - be_z^T \\ &= \beta D_z - b \left(1 - \frac{\alpha}{b} D_z\right) \\ &= (\alpha + \beta) D_z - b \\ &= (\alpha + \beta) D_z - D_z + P_z^H H_0 \\ &= P_z^H H_0 - (1 - \alpha - \beta) D_z \\ &= P_z^H H_0 - P_z^H C_z^H \\ &= P_z^H C_{\text{chn},z}^H. \end{aligned}$$

In the aggregate, the production and employment in the tradable sector decrease due to the inflow of real estate purchases by foreign Chinese.⁷ Unfortunately, the prediction in Equation 2.7 has not been confirmed by our empirical analysis as we find statistically insignificant effect of Chinese real estate purchases on the employment in the tradable sector.

Overall, our simple model predicts that housing purchases by foreign Chinese has the following effects: 1) raise local house prices; 2) increase local employment in the nontradable sector via a housing net worth channel; and 3) local employment in the tradable sector. Predictions 1) and 2) are consistent with our empirical results, but 3) is not. It does not seem obvious how to generate a null effect on the tradable employment in the model without introducing some friction such as economic slack or allowing migration. In that regard, the static and partial equilibrium nature of our model is not completely satisfactory because it fails to capture the effect on the tradable sector. Nonetheless, it delivers an intuition on the economic mechanism underlying the effects of house purchases from foreigners on house prices and nontradable employment in the local economy.

⁷This negative impact on the tradable sector is a form of a “Dutch disease.”

Discussion

Our model has made many simplifications such as assuming no migration or commuting across regions. A more general framework should relax these assumptions. In such a setting, competing forces will arise in driving the effects of an increase in housing demand by foreigners on local employment across sectors. Suppose that prices and wages are flexible and workers can move and commute across regions. We have to consider the differential effects of an injection of foreign housing demand on local homeowners versus renters. A positive housing price shock in the local economy through housing purchases by foreign Chinese will increase the wealth of local homeowners, whose increased spending on nontradable goods tends to raise local employment in the nontradable sector. However, due to the higher rents, renters will move out of treated regions and into cheaper areas (control regions), which tends to lower the consumption demand and employment for nontradable goods in the treated region. If the positive force from housing net worth channel exceeds the negative force from the outflow of renters (subject to migration and commuting costs), then nontradable employment in treated regions will still increase, a prediction matching our empirical results.

On the other hand, the effect on the employment in the tradable sector is less clear. Homeowners’ increased demand for tradable goods in treated regions can be supplied by the production elsewhere, so the employment effect of a rising real estate demand from foreign Chinese in the tradable sector is more diffused than the effect on the nontradable sector. But to have a model with a more general setup than our current one predict a null effect on tradable employment—a result from our empirical analysis—we may need to ensure that the tradable sector in both treated and the control regions expand to the same extent, despite that fact that living costs in treated regions have risen, a prediction that is difficult to generate in a general equilibrium framework with flexible prices and full employment. For that to happen, we may need to introduce agglomeration spillovers in the treated region. Otherwise, the model may even predict a reduction in the tradable employment in treated regions, contradicting our empirical findings. We are currently working to extend our simple framework to formalize these intuitions.

2.5 Conclusion

In this paper, we document an unprecedented surge in housing purchases by foreign Chinese in the US over the past decade and analyzes the effects of the purchases on US local economies. Using detailed transaction-level housing purchase data, we utilize an instrumental variable method that exploits cross-zip code variation in the concentration of Chinese population stemming from pre-sample period differences in Chinese population settlement to instrument for the volume of housing purchases by foreign Chinese. We find that housing investment by foreign Chinese significantly induces higher local area housing net wealth, and it leads to higher local employment, particularly in the non-tradable sectors. We then develop a simple model that helps to illustrate how housing purchases by foreign Chinese

affect the local employment through the housing wealth channel.

This paper is one of the first academic papers that studies the effects of a “China shock” on the finance side for US local economies. Given China has been seeking to open up its capital markets, a better understand the implications of a “China shock” on the finance side for the rest of the world is of utmost importance. Our results point to potential welfare gains and losses that come with China’s opening up for the rest of the world. Moreover, our evidence highlights the role of capital inflow and foreign investments on the domestic output and employment, especially in times of economic downturns. During the housing market crash period between 2007-2011, the improvement in household balance sheet resulting from capital inflows of housing investment played a mitigating role for the US local economies.

Chapter 3

Inference of Risk Sharing Regimes and Welfare Costs of Risk in Village Economies

3.1 Introduction

Informal insurance, such as payments from relatives and neighbors when family members get sick or when crops fail, enable poor households in the developing countries to share risk. Yet, this informal insurance is incomplete—the poor still face substantial fluctuations in consumption due to adverse idiosyncratic shocks (Gertler and Gruber, 2002). This phenomenon suggests there is room of trade that can Pareto-improve the consumption allocation, contrary to the prediction of a model with complete markets.

Alternative theories have been proposed to explain why insurance is incomplete. These theories consider specific forms of market frictions that limit the extent of risk sharing. The first theory is the self-insurance model in which households insure against risk through the credit market but not through inter-household income pooling (Hall, 1978; Bewley, 1977). Another theory is the private information model in which households do not perfectly observe other households' income or effort (Rogerson, 1985; Kocherlakota, 2005). These market frictions prevent households from achieving full risk sharing. Distinguishing between specific market frictions that impede risk sharing has been difficult, not least because the idiosyncratic shocks are often hard to measure. However, it could help design effective development policies because different policies tend to interact with existing informal insurance regimes differently depending on the nature of the frictions. For example, a work-guarantee program such as India's National Rural Employment Guarantee Act could complement insurance constrained by private information about household income because it will discourage households from misreporting their income (since it becomes common knowledge that the probability of a household receiving a very low income is small due to the work-guarantee program) (Kinnan, 2012).

In this paper I present a novel framework to distinguish between alternative theories of incomplete insurance and estimates the welfare costs of risk. The proposed testing approach exploits the prediction about intertemporal consumption patterns under alternative models in a unified framework. Furthermore, it is semi-parametric and does not require solving the dynamic models fully. In particular, it combines the advantages of testing strategies proposed in Ligon (1998) and Kocherlakota and Pistaferri (2009), and this combination yields a testing approach that has two distinct advantages. First, unlike Ligon (1998) it accounts for aggregate shocks explicitly and is robust to a fairly broad class of classical measurement error processes. Second, unlike Ligon (1998) and Kocherlakota and Pistaferri (2009) it does not require data on interest rates. This feature is especially important in the context of developing economies if information on interest rates is unavailable or unreliable or if people in rural economies face a different interest rate than the formal rate offered by banks.

I apply the proposed testing approach to a longitudinal dataset from rural household surveys in Tanzanian villages and test full risk sharing as well as alternative models of endogenously constrained risk sharing such as self-insurance and private information. I reject models of full insurance and private information, and find evidence consistent with self-insurance. Using estimated and calibrated coefficients of risk aversion under alternative regimes based on the dataset, I calculate the welfare costs of risk and decompose it into aggregate and idiosyncratic sources. A comparison of welfare estimates suggests that an incorrect inference on the insurance regime could underestimate the welfare loss from risk by as much as ten times.

Relation to the Literature

The typical approach to testing risk sharing models in the literature is to propose and test a specific model of full insurance, limited enforcement or moral hazard (Lim and Townsend, 1998; Ligon et al., 2002; Attanasio and Pavoni, 2011). Relatively fewer studies empirically distinguish *between* information regimes of partial risk sharing, with notable exceptions being Ligon (1998), Kinnan (2012), and Karaivanov and Townsend (2013).

Using data on Thai households, Karaivanov and Townsend (2013) test full insurance against models of permanent income and moral hazard using linear programming and maximum likelihood. They find that for rural households the permanent income model provides the best fit for the data on consumption, business assets, investment, and income, while for urban households the moral hazard model fits data on consumption the best. Using the same dataset, Kinnan (2012) adopts a reduced-form approach to test alternative models. Her main idea is to test whether the lagged consumption is a sufficient statistics for current consumption to distinguish barriers to insurance. She rejects model of full insurance, limited enforcement, and moral hazard and finds evidence that data are consistent with the hidden income (private information) model.

Ligon (1998) and Kocherlakota and Pistaferri (2009) take a unified testing approach by leveraging the first-order conditions (i.e., the Euler equations) derived from the models of

different information regimes. Specifically, they test which Euler equation from the specific models they consider fits the data the best using GMM estimation. The idea of Ligon (1998) is to distinguish the self-insurance model from the private information regime by the sign of a key coefficient in the moment condition (this coefficient is related to the degree of risk aversion). He applies this method to the ICRISAT longitudinal data of Indian villages and finds that overall the private information model is most consistent with the data. Similarly, using repeated cross-sectional consumption data from the US, the UK, and Italy, Kocherlakota and Pistaferri (2009) compare the goodness fit, as measured by the minimand of the GMM criterion function, of three alternative models—the standard incomplete market model with uninsurable idiosyncratic risk, the representative agent model, and the private information model—and find that the private information model best fit their asset pricing and consumption data.

The approach I take in this paper combines some reduced form tests as in Kinnan (2012) and structural tests as in Ligon (1998) and Kocherlakota and Pistaferri (2009). This hybrid approach allows me to combine the advantages of reduced form tests—they are generally easier to implement—with those of structural estimation—they allow the inference of preference parameters and calculation of welfare loss from risk (Chetty, 2009). A key distinction of my approach and the above approaches is that it accounts for aggregate shocks explicitly and is robust to a fairly broad class of measurement error processes. Another advantage of this approach is that it does not require data on interest rates, which is important in the context of developing economies if information on interest rates is unavailable or unreliable or if people in rural economies face a different interest rate than the formal rate offered by banks. This is a key methodological difference between the estimation approach in Ligon (1998) and mine. Ligon (1998) estimates “strict” versions of the self-insurance and the private information models: he imposes a steady-state condition that equates the discount rate and the interest rate and assumes that the principal is risk neutral.¹ In contrast, my estimation approach does not impose these restrictions and allows aggregate shocks for the interest rate by exploiting the relationship between the interest rate and cross-sectional consumption variation (for examples that use a similar approach in different contexts, see Ligon (2010) and Kocherlakota and Pistaferri (2009)). Another important advantage of utilizing the cross-sectional consumption inequality is that the estimation is more robust to measurement error (as discussed in the next section).

This study is also related to literature on estimating the welfare costs of risk or on estimating “vulnerability.” A well-known example of calculating welfare costs of consumption fluctuations is Lucas (1987). Lucas computes the variation of aggregate time series consumption data between 1947 and 2001 from the US and argues that under the usual assumptions for the degree of risk aversion the cost of business cycles on consumer welfare is extremely small. A disadvantage of aggregate data, however, is that they mask the underlying het-

¹Perhaps this decision is due to the lack of information on the interest rate in Indian village. This issue is irrelevant for Kocherlakota and Pistaferri (2009) because they test models in asset pricing in rich countries and have data on interest rates.

erogeneity of consumption risk, and studies based on micro-level data tend to find larger welfare costs. Using household level data from Bulgaria, Ligon and Schechter (2003) propose an approach of measuring vulnerability in a static model and decomposing it into three components: poverty, aggregate risk, and idiosyncratic risk. They find that aggregate shocks reduce welfare more than idiosyncratic risk does. In this paper, I combine the decomposition approach of Ligon and Schechter (2003) and the calculation of Lucas (1987) to estimate the distribution of welfare loss from overall, aggregate, and idiosyncratic sources of consumption risk in a dynamic setting.

3.2 Theoretical Framework

I start by describing the environment and the first-order conditions of alternative risk sharing models and relate these conditions to unify the testing approach. As these models are standard in the literature on dynamic contracts, I will mainly describe their equilibrium conditions drawn from the literature to the extent they are relevant to my tests. The environment and notations I adopt are adapted from Kocherlakota and Pistaferri (2009) and Attanasio and Pavoni (2011).

Environment

Consider a village economy which consists of N households with homogeneous von Neumann-Morgenstern preferences that are separable in time and consumption-effort decisions. They order a stream of consumption and effort bundles by maximizing

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t [u(c_{it}) - v(e_{it})],$$

where \mathbb{E} is the expectation operator, $u(\cdot)$ the flow utility function of consumption, $v(\cdot)$ the flow disutility function of effort, c_{it} consumption, and e_{it} effort.² Suppose households exhibit constant relative risk aversion (CRRA) preferences over consumption:

$$u(c) = \begin{cases} \frac{c^{1-\eta}}{1-\eta} & \text{if } \eta > 0 \text{ and } \eta \neq 1, \\ \ln c & \text{if } \eta = 1. \end{cases}$$

Household i 's production function depends on its idiosyncratic shock $\theta^{it} \in \Theta^t$ and is constant returns to scale:

$$y_{it} = F(\theta^{it}, e^{it}),$$

where F is homogeneous of degree 1. Household-specific shocks, θ_{it} , may be illness or crop failure, for example. Different assumptions on the observability of idiosyncratic shocks,

²“Effort” is to be interpreted more generally than its literal meaning. In the context of asymmetric information, for example, it can be interpreted as the agent’s disutility of reporting his true type.

effort, and output give rise to different information regimes. When θ^{it} is private information, I define a reporting strategy to be $\sigma : \Theta^t \rightarrow \Theta^t$, where $\sigma(\theta^t) = \sigma(\hat{\theta}^t)$ for some $\hat{\theta}^t$ (Golosov et al., 2003).

The timing works as follows: first, households observe their own type and then make consumption and portfolio decisions. Assume that the social planner has access to an external credit market with an exogenous interest rate r . A feasible allocation is a triplet $(c_{it}, e_{it}, y_{it})_{t=0}^{\infty}$ such that

$$\sum_{i=1}^N \sum_{t=0}^{\infty} \frac{1}{(1+r)^t} c_{it}(\theta^{it}) \leq \sum_{i=1}^N \sum_{t=0}^{\infty} \frac{1}{(1+r)^t} y_{it}(\theta^{it}, e^{it}).$$

Models of Risk Sharing

This section illustrates models of full insurance, self-insurance, and partial risk sharing constrained by limited enforcement and private information.

Full Insurance

As a benchmark, I start with a model with Arrow-Debreu complete markets. Assume that θ^{it} , e^{it} , and y^{it} are publicly observable. In equilibrium the economy achieves full risk sharing with the hallmark result that the marginal utility is equated across households in all states of the world:

$$\left(\frac{c_{it}(\theta^{it})}{c_{jt}(\theta^{jt})} \right)^{-\eta} = \frac{\lambda_j}{\lambda_i},$$

where λ_i is the Pareto weights for household i prescribed by the social planner. Sum consumption across households and rearrange terms to get

$$c_{it}(\theta^{it}) = \frac{\lambda_i^{1/\eta}}{\sum_j \lambda_j^{1/\eta}} C_t,$$

where $C_t \equiv \sum_j c_{jt}(\theta^{jt})$ denotes aggregate consumption in the risk sharing network. Taking the logarithmic transformation yields

$$\log c_{it}(\theta^{it}) = \frac{1}{\eta} \log \lambda_i + \log \left(\frac{C_t}{\sum_j \lambda_j^{1/\eta}} \right). \quad (3.1)$$

This condition of equal marginal utility, together with the feasibility constraint, leads to a strong prediction: under full insurance, each household's consumption is independent of idiosyncratic income and depends only on aggregate resources. It suggests a test for full insurance in a regression framework. Once household fixed effects (the first term) and aggregate resources (the second term) are controlled for, household consumption should not depend on time-varying idiosyncratic shocks such as income of the household.

Self-Insurance (Permanent Income)

As another benchmark, I consider the case where households do not engage in mutual insurance with other households and only self-insure against adverse shocks through borrowing and lending (Hall, 1978; Bewley, 1977). Suppose the interest rate for borrowing and lending is r_t in period t . The household chooses consumption and effort bundles by solving the utility function subject to an intertemporal budget constraint

$$A_{it+1} = y_{it} - c_{it} + (1 + r_t)A_{it},$$

where A_{it} is asset at time t . Assume that households start with initial asset A_0 and they have to honor their debt, i.e., $\lim_{t \rightarrow \infty} \frac{1}{1+r_t} A_{it} \geq 0$. The first-order condition gives rise to the usual Euler condition

$$(c_{it}(\theta^{it}))^{-\eta} = \beta(1 + r_t)\mathbb{E}_t[(c_{it+1}(\theta^{it+1}))^{-\eta}], \quad (3.2)$$

where the expectation operator is over the information set at time t .

Private Information

Suppose now enforcement is not a problem, but there is hidden action or hidden information. In particular, idiosyncratic shocks (θ^{it}) and effort (e^{it}) are not observed, but output (y^{it}) is. The household's choice of effort affects the distribution of output. Any insurance contract has to be incentive-compatible to induce agents to exert effort or report true types; that is, for a household with type θ^{it} at time t ,

$$\mathbb{E}_t \sum_{s=t}^{\infty} \beta^{s-t} U[(c_i(\sigma(\theta^{is})), e_i(\sigma(\theta^{is})))] \geq \mathbb{E}_t \sum_{s=t}^{\infty} \beta^{s-t} U[(c_i(\sigma(\hat{\theta}^{is})), e_i(\sigma(\hat{\theta}^{is})))], \quad \forall \hat{\theta}^{it} \in \Theta^t.$$

I invoke the revelation principle that in equilibrium truthful reporting is utility maximizing. In this private information regime, a result known as the “inverse Euler equation” holds (Rogerson, 1985; Kocherlakota, 2005):

$$(c_{it}(\theta^{it}))^\eta = \frac{1}{\beta(1 + r_t)} \mathbb{E}_t[(c_{it+1}(\theta^{it+1}))^\eta]. \quad (3.3)$$

Note that this Euler equation differs from that under the life-cycle model. From the concavity of the utility function and Jensen's inequality, equation 3.3 implies that

$$(c_{it}(\theta^{it}))^{-\eta} \leq \beta(1 + r_t)\mathbb{E}_t[(c_{it+1}(\theta^{it}))^{-\eta}],$$

where the strict inequality holds for households whose incentive-compatibility constraint binds. This inequality condition is analogous to a case where households face a *savings* constraint and there exists a distortion on the savings behavior (Golosov et al., 2003). The intuition for such a distortion is that the planner needs to prevent households of high types from saving too much so as to keep them in the risk sharing contract.³

³See Kocherlakota and Pistaferri (2009) for a more formal exposition on why consumption-smoothing is distorted in the private information model.

Classification of Risk Sharing Regimes

The moment conditions implied by the first-order conditions in models of full insurance (equation 3.1), self-insurance (equation 3.2), and private information (3.3) are distinct from each other, which potentially allows us to distinguish between these information regimes. Table 3.1 summarizes these equilibrium conditions for risk sharing in different information regimes.

Table 3.1: Equilibrium Conditions in Different Information Regimes

Regime	Equilibrium condition
Full insurance	$\log c_{it}(\theta^{it}) = \frac{1}{\eta} \log \lambda_i + \log \left(\frac{C_t}{\sum_j \lambda_j^{1/\eta}} \right)$
Self-insurance	$(c_{it}(\theta^{it}))^{-\eta} = \beta(1+r_t)\mathbb{E}_t[(c_{it+1}(\theta^{it+1}))^{-\eta}]$
Limited enforcement	$(c_{it}(\theta^{it}))^{-\eta} \geq \beta(1+r_t)\mathbb{E}_t[(c_{it+1}(\theta^{it+1}))^{-\eta}]$
Private information	$(c_{it}(\theta^{it}))^\eta = \frac{1}{\beta(1+r_t)}\mathbb{E}_t[(c_{it+1}(\theta^{it+1}))^\eta]$

3.3 Data

To test risk sharing models, I use a panel dataset from household surveys in the Kagera region in Tanzania from 1991 to 1994. This region (with a population of about 2 million in 2004) is primarily rural with the north mainly producing bananas and coffee and the south mainly rain-fed annual crops such as maize, sorghum, and cotton. This longitudinal survey was jointly conducted by the Population and Human Resources Department and the Africa Technical Department of the World Bank and interviewed about 800 households from nearly 50 communities in all five districts of Kagera (for detailed information on the sampling design, see Ainsworth (2004)). The main objective of the survey was to estimate the economic impact of adult mortality and morbidity on surviving household members, so it contained detailed questions about household consumption, income, and demographic information such as the gender and schooling of the household head.

As households in the region are primarily engaged in agricultural production, rainfall is a key determinant for income. To measure this important source of aggregate risk, I have obtained the monthly rainfall data from Tanzania Meteorological Agency for years 1980-2004, and matched them with the survey data based on the nearest weather station according to direct-line estimates from the GIS data on village centers and rainfall stations. The region has two rainy seasons, a long rainy season usually between March and May and a short rainy season usually between October and December. I have constructed average monthly z-score deviations of rainfall during the most recent two rainy seasons preceding the interview.

This dataset is well suited for studying consumption fluctuation and informal risk sharing because about 74% of households have received non-zero monetary transfers during the

survey period. This fact suggests that informal risk sharing is prevalent in the region. Moreover, the income of households in Kagera is subject to substantial variation arising from uncertainty in rainfall. Based on preliminary calculation, I find that one standard deviation increase in average rainfall during the rain seasons is associated with an average increase of 38.3% in household income. This degree of income variation, both within and across villages, implies potentially large gains from trading risk.

Table 3.2 shows summary statistics. Consumption, transfers, and income are annualized and expressed in 2004 Tanzanian Shillings. To adjust for family size and the ages of household members, consumption is expressed in per adult equivalent terms. Notice that there are substantial fluctuations both across households and within households over time. This suggests that insurance against consumption risk is far from complete and that the welfare loss from incomplete insurance may be substantial. In the next section I formally test the model of full insurance and alternative models of constrained risk sharing.

Table 3.2: Summary of Statistics

	Observations	Mean	Std. deviation
Household income	3008	670211	1441116
Income fluctuation	3008	537565	1210794
Consumption (per adult-equiv.)	3008	189240	287425
Consumption fluctuation	3008	125893	229420
Incoming transfer	3008	53430	482221
HH head is female	3008	0.274	0.446
HH head received schooling	3008	0.804	0.397
HH head age	3008	50	17
Days HH head is sick	3008	7.49	16.90
Rainfall	3008	187.32	46.52
Rainfall dispersion	3008	0.245	0.129

Note 1: Income and consumption fluctuation variables refer to the standard deviation of each household over four rounds of interviews. Consumption, income, and transfers are annualized and expressed in 2004 Tanzanian Shillings (TZS). 1 USD = 1,029 TZS as of January 1, 2004.

Note 2: Consumption is measured in per adult equivalent terms. The scheme employed here is the same as that in Ligon and Schechter (2003): it assigns adult males a weight of 1 and adult females a weight of 0.9 (adults are at the ages of sixteen or older). Children of ages 0 to 4 receive a weight of 0.32, ages 5 to 9 a weight of 0.52, and ages 10 to 15 a weight of 0.67.

Note 3: The rainfall variable (measured in millimeters) is time series (1980-2004) averages of the two rain seasons (March-May and October-December). It is matched to villages based on the nearest weather station. Dispersion is defined to be the ratio of the time series standard deviation to the mean.

3.4 Estimation and Testing

Risk Sharing is Incomplete

The full insurance model suggests the following estimating equation to test full insurance (Townsend, 1994; Kinnan, 2012):

$$\log c_{it} = \alpha_0 \log y_{it} + \delta_i + \phi_t + \varepsilon_{it}, \quad (3.4)$$

where c_{it} and y_{it} are household i 's consumption and income at time t , δ_i household fixed effects, ϕ_t time fixed effects, and ε_{it} an error term (due to measurement error or unobserved preference heterogeneity). The time fixed effects controls economy-wide shocks to aggregate resources or to the interest rate. Full insurance implies that $\alpha_0 = 0$.

I also add village-year fixed effects to capture the aggregate resource in each village by estimating

$$\log c_{ivt} = \alpha_0 \log y_{ivt} + \delta_{iv} + \phi_{vt} + \varepsilon_{ivt}, \quad (3.5)$$

where ϕ_{vt} are village-year fixed effects. For robustness checks, I also include time-varying demographic control variables of households to capture idiosyncratic preference shifters that may affect consumption. Full insurance implies that $\alpha_0 = 0$.

Note the conceptual difference between the underlying assumptions regarding the nature of risk sharing arrangements embodied in the two testing equations above. In equation 3.5, risk sharing happens only within each village, but there is no inter-village insurance. In contrast, in equations 3.4 the risk sharing network consists of all villages. A comparison of the coefficients on household income may suggest how important inter-village insurance is in the economy.

Table 3.3 shows the testing results. A few notes are in order. First, across all specifications, full insurance has been rejected. This is not surprising given the vast amount of evidence in the literature against full insurance (e.g., Townsend (1994); Gertler and Gruber (2002); Kinnan (2012)). Second, time-varying household characteristics such as the age of the household head or whether the household head is female do not appear to affect how household consumption responds to income. Third, whether the risk sharing entity is specified to be a village or the whole region does not seem to matter.

Inferring Risk Sharing Regimes via Euler Equation

Given that full insurance has been rejected, what insurance regime is most consistent with the data? The first-order conditions of alternative risk sharing models imply natural moment conditions that potentially allow us to distinguish between different regimes. The moment conditions implied by the Euler conditions are distinct under different models, and they must hold in equilibrium *regardless of the joint distribution of the underlying idiosyncratic shocks*. Testing which Euler condition describes the data the best is equivalent to testing which information regime describes the economy the best (Ligon, 1998; Kocherlakota and

Table 3.3: Testing the Full Insurance Model

lhs: $\ln c_t$	(1)	(2)	(3)	(4)
Log household income	0.3996*** (0.0336)	0.4025*** (0.0342)	0.3829*** (0.0327)	0.3855*** (0.0333)
Demographic controls	No	Yes	No	Yes
Household FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Village-year FE	No	No	Yes	Yes
N	2999	2999	2999	2999

Note 1: The balanced panel has a total 3008 observations, nine of which have negative household income and are dropped for the tests here.

Note 2: Demographic controls include the age of the household head and two indicators for whether the head is female and has received any formal schooling.

Note 3: Standard errors (in parenthesis) are clustered at the village level. *** $p < 0.01$.

Pistaferri, 2009). This observation affords us a key advantage: I do not have to solve the general equilibrium models fully in order to test alternative models.

Before describing the tests, I need to resolve an important issue: the interest rate in the village economies is not observed. It turns out that under the mild assumption that households from the region face the same interest rate, I can utilize the cross sectional consumption to infer information about the discount factor and the interest rate. Let's first consider the self-insurance model. I sum across households on both sides of the Euler equation and rearrange terms to obtain

$$\frac{1}{\beta(1+r_t)} = \mathbb{E}_t \left[\frac{\sum_i (c_{it+1}(\theta^{it+1}))^{-\eta}}{\sum_i (c_{it}(\theta^{it}))^{-\eta}} \right].$$

In the private information regime, I obtain an analogous condition:

$$\beta(1+r_t) = \mathbb{E}_t \left[\frac{\sum_i (c_{it+1}(\theta^{it+1}))^\eta}{\sum_i (c_{it}(\theta^{it}))^\eta} \right].$$

Despite their similar appearance, these two conditions are quite distinct from each other. In particular, one does not imply the other because the inverse function cannot go through the expectation operator. These expressions are very useful for at least two reasons. First, they provide a theoretically consistent way to link cross-sectional consumption growth to the risk facing households. Two notable examples that also exploit this advantage are Kocherlakota and Pistaferri (2009) and Ligon (2010).⁴ Second, these conditions enable us to estimate risk aversion from the moment condition of the Euler equation without having to observe interest rates.⁵ This result is well suited to the context of developing economies where data

⁴Kocherlakota and Pistaferri (2009) estimates risk aversion using asset prices and repeated cross sectional consumption data, and Ligon (2010) measures risk by looking at inequality in cross-sectional consumption.

⁵The downside is that the discount factor cannot be identified separately.

on interest rates are either unavailable or unreliable. Substituting these expressions into the Euler equations, I obtain key moment conditions for the self-insurance model,

$$\mathbb{E}_t \left[\left(\frac{c_{it+1}(\theta^{it+1})}{c_{it}(\theta^{it})} \right)^{-\eta} - \frac{\sum_i (c_{it+1}(\theta^{it+1}))^{-\eta}}{\sum_i (c_{it}(\theta^{it}))^{-\eta}} \right] = 0,$$

and for the private information model,

$$\mathbb{E}_t \left[\left(\frac{c_{it+1}(\theta^{it+1})}{c_{it}(\theta^{it})} \right)^\eta - \frac{\sum_i (c_{it+1}(\theta^{it+1}))^\eta}{\sum_i (c_{it}(\theta^{it}))^\eta} \right] = 0.$$

For the limited enforcement regime I cannot sign an analogous moment condition explicitly, but I can test this regime using over-identification tests. In particular, if there is no η that can (almost) zero out the moment conditions implied by the self-insurance or the private information regimes, then it constitutes evidence that limited enforcement may be important in constraining risk sharing. The above moment conditions therefore provide a unified framework for testing the information regimes.

To proceed to empirical estimation, let the information set available at time t be denoted by Z_t . By rational expectation, Z_t is orthogonal to the Euler forecast error, so I can transform the conditional moments into unconditional ones. I can apply the GMM estimator to estimate the risk aversion coefficient using an approach similar to that in Hansen and Singleton (1982). The idea is to use the first-order necessary conditions to form the moment condition for estimation. A key advantage of this approach is that I do not need to solve the complete model of dynamic contracts in order to test the models. Specifically, let

$$\mathbb{E}[\zeta_{it}(\varphi) \cdot z_{it}] = 0, \tag{3.6}$$

where $\zeta_{it}(\varphi) \equiv \left(\frac{c_{it+1}(\theta^{it+1})}{c_{it}(\theta^{it})} \right)^{-\varphi} - \frac{\sum_i (c_{it+1}(\theta^{it+1}))^{-\varphi}}{\sum_i (c_{it}(\theta^{it}))^{-\varphi}}$ and $z_{it} \in Z_{it}$. Note that $\varphi = \eta$ if the economy is in the self-insurance or credit market regimes, and $\varphi = -\eta$ if it is in the private information regime.

Following Ligon (1998), I can infer the insurance regime by the sign of the parameter estimate $\hat{\varphi}$. If $\hat{\varphi} > 0$, then I reject the private information model; if $\hat{\varphi} < 0$, then I reject the self-insurance model.⁶ Table 3.4 summarizes the model testing strategy.

Empirical Estimation and Model Testing

The sample analog of the moment condition (3.6) is

$$\frac{1}{T} \frac{1}{N} \sum_t \sum_i [g(\varphi)] = 0,$$

⁶Note that if all households are risk neutral, i.e., $\varphi = 0$, this case is degenerate as the Euler moment condition always holds. This degeneracy is not economically meaning, and, as explained later, motivates the choice of a continuously-updating GMM estimator.

Table 3.4: Model Testing Strategy

$\hat{\varphi}$	Model testing
> 0	Reject private information
< 0	Reject self-insurance

$$\text{with } g(\varphi) \equiv \zeta_{it}(\varphi) \cdot z_{it},$$

where N is the number of households, T the number of time periods, and $z_t \in Z_t$ denotes the variables that enter the information set at time t .

I apply a continuously-updating GMM estimator (Hansen et al., 1996; Imbens et al., 1998) and estimate φ as⁷

$$\hat{\varphi} = \arg \min_{\tilde{\varphi} \in [\underline{\varphi}, \bar{\varphi}]} \left(\frac{1}{T} \frac{1}{N} \sum_t \sum_i g(\tilde{\varphi}) \right)' W(\tilde{\varphi}) \left(\frac{1}{T} \frac{1}{N} \sum_t \sum_i g(\tilde{\varphi}) \right), \quad (3.7)$$

where $W(\tilde{\varphi}) = \left(\frac{1}{T} \frac{1}{N} \sum_t \sum_i g(\tilde{\varphi}) g(\tilde{\varphi})' \right)^{-1}$ is the optimal weighting matrix. Because our tests hinge on the estimate of φ , there are two important issues to consider. The first issue is the choice of variables to enter the information set. All lagged variables are in households' information set at time t which can be used to form the moment conditions for estimation. These variables need not be “exogenous,” they only need be “predetermined.” To achieve the highest power of model testing, it is desirable to choose variables that are informative for households when making consumption plans. It is not advisable to choose variables that are “random,” because even at false parameter values the correlation between the Euler forecast error and the “random” variables will be close to zero—leading to weak identification (Stock et al., 2002).⁸ For this reason, lagged consumption and income are desirable variables to enter the information set because they provide good information in households' consumption decisions due to consumption-smoothing motives.

Table 3.5 shows the results from GMM estimation and model testing. (The estimation is performed in Python using a grid-search method.) Across all specifications of the information set, the estimate $\hat{\varphi}$ is around 0.15, and it is quite stable across specifications. The fact that it is positive and statistically from 0 at the 99% significance level means that I reject $\varphi < 0$ at any conventional significance level and hence I reject the private information regime, but not the self-insurance regime.

A note of caution, however, is that the self-insurance model may not be the unique regime generating the data. There may well be other models that I have not considered also

⁷The continuously-updating GMM estimator appears to have better properties than the traditional two-step or iterated GMM estimator, although they are asymptotically equivalent (see Hansen et al. (1996) and Imbens et al. (1998) for further discussions). This estimator is robust to the the issue of degeneracy of the moment condition at $\varphi = 0$.

⁸The continuously-updating GMM estimator, the estimator used in this study, is partially robust to weak identification. Another estimator that is also partially robust is the generalized empirical likelihood estimator. For a discussion, see Stock et al. (2002).

Table 3.5: GMM Estimation Results and Model Testing

Information set	$\hat{\varphi}$
Consumption	0.14013*** (0.00441)
Consumption, income	0.14776*** (0.00451)
Consumption, income, household size	0.15394*** (0.00468)
Consumption, income, rainfall	0.14352*** (0.00430)
Consumption, income, rainfall, household size	0.15141*** (0.00451)
N	3008
Robustness checks: measurement error in income	
Information set	$\hat{\varphi}$
Consumption, household size	0.14998*** (0.00469)
Consumption, rainfall	0.13668*** (0.00420)
Consumption, household size rainfall	0.14794*** (0.00452)

Note 1: The variables that enter the information set are lagged by one period. All information sets include a vector of constants.

Note 2: The estimation is performed in Python using a grid-search method.

Note 3: Standard errors are shown in parenthesis in column 2. ***p<0.01.

consistent with the observed pattern of intertemporal household consumption. Throughout this paper, I have restricted attention to identifying a single mechanism from several well-known models in the literature.

Robustness and Limitations of the Testing Approach

Before calculating welfare costs of risk, I discuss a few issues related to robustness and limitations of the testing approach.

Measurement Error in Consumption Data

Measurement error in consumption data can potentially cause bias the estimate of the risk aversion coefficient. Fortunately, it turns out that the estimation procedure outlined above is robust to a broad class of measurement errors. Suppose that the measured consumption contains multiplicative measurement error, $\tilde{c}_{it}(\theta_t) = c_{it}^*(\theta_t) \exp(\nu_{it})$, where \tilde{c}_{it} and c_{it}^* are, respectively, measured and true consumption levels. One may deal with measurement error by either assuming a parametric distribution or imposing a non-parametric structure for the measurement error process (Ventura, 1994; Hong and Tamer, 2003; Chioda, 2004; Alan et al., 2009). Let's first consider a case with a parametric structure. In particular, suppose $\nu_{it} \sim \mathcal{N}(0, \sigma_\nu^2)$ iid.⁹ From

$$\begin{aligned} \mathbb{E} \left[\left(\frac{c_{it+1}(\theta^{it+1})}{c_{it}(\theta^{it})} \right)^\varphi \right] &= \mathbb{E} \left[\left(\frac{c_{it+1}^*(\theta^{it+1})}{c_{it}^*(\theta^{it})} \right)^\varphi \frac{\exp(\varphi \nu_{it+1})}{\exp(\varphi \nu_{it})} \right] \\ &= \mathbb{E} \left[\left(\frac{c_{it+1}^*(\theta^{it+1})}{c_{it}^*(\theta^{it})} \right)^\varphi \right] \mathbb{E} [\exp(\nu_{it+1} - \nu_{it})] \\ &= \mathbb{E} \left[\left(\frac{c_{it+1}^*(\theta^{it+1})}{c_{it}^*(\theta^{it})} \right)^\varphi \right] \exp(\sigma_\nu^2), \end{aligned}$$

and

$$\begin{aligned} \mathbb{E} \left[\frac{\sum_i (c_{it+1}(\theta^{it+1}))^\varphi}{\sum_i (c_{it+1}(\theta^{it}))^\varphi} \right] &= \mathbb{E} \left[\frac{\sum_i (c_{it+1}^*(\theta^{it+1}))^\varphi}{\sum_i (c_{it+1}^*(\theta^{it}))^\varphi} \right] \mathbb{E} \left[\frac{\exp(\nu_{it+1})}{\exp(\nu_{it})} \right] \\ &= \mathbb{E} \left[\frac{\sum_i (c_{it+1}^*(\theta^{it+1}))^\varphi}{\sum_i (c_{it+1}^*(\theta^{it}))^\varphi} \right] \exp(\sigma_\nu^2), \end{aligned}$$

I obtain

$$\mathbb{E} \left[\left(\frac{c_{it+1}(\theta^{it+1})}{c_{it}(\theta^{it})} \right)^\varphi - \frac{\sum_i (c_{it+1}(\theta^{it+1}))^\varphi}{\sum_i (c_{it+1}(\theta^{it}))^\varphi} \right] = \mathbb{E} \left[\left(\frac{c_{it+1}^*(\theta^{it+1})}{c_{it}^*(\theta^{it})} \right)^\varphi - \frac{\sum_i (c_{it+1}^*(\theta^{it+1}))^\varphi}{\sum_i (c_{it+1}^*(\theta^{it}))^\varphi} \right] \exp(\sigma_\nu^2),$$

so with a log-normally distributed measurement error process, setting the empirical moment condition with observed error-ridden consumption to zero is equivalent to setting an analogous condition with true consumption to zero.

The estimation approach above is actually robust to not only to parametric error structures, but also to fairly general non-parametric assumptions about the process of measurement error. My approach is adapted from Chioda (2004) who shows that the parametric and non-parametric structures of the measurement error process can be resolved in a unified GMM framework. Suppose ν_{it} is independent from idiosyncratic shocks θ_{it} and independent

⁹One may assume a more flexible parametric distribution of measurement error such as Laplace (Hong and Tamer, 2003), but a similar result to that with a log-normal distribution holds. See Chioda (2004) for a detailed exposition.

across households.¹⁰ The moment condition for estimation using observed consumption will still be valid. Let $\kappa \equiv \mathbb{E} \left[\frac{\exp(\nu_{it+1})}{\exp(\nu_{it})} \right]$. Then

$$\mathbb{E} \left[\left(\frac{\tilde{c}_{it+1}(\theta^{it+1})}{\tilde{c}_{it}(\theta^{it})} \right)^\varphi \right] = \mathbb{E} \left[\left(\frac{c_{it+1}^*(\theta^{it+1})}{c_{it}^*(\theta^{it})} \right)^\varphi \right] \kappa,$$

where the second and third steps follow from the independence assumptions of the measurement error process, and hence

$$\mathbb{E} \left[\left(\frac{c_{it+1}(\theta^{it+1})}{c_{it}(\theta^{it})} \right)^\varphi - \frac{\sum_i (c_{it+1}(\theta^{it+1}))^\varphi}{\sum_i (c_{it+1}(\theta^{it}))^\varphi} \right] = \mathbb{E} \left[\left(\frac{c_{it+1}^*(\theta^{it+1})}{c_{it}^*(\theta^{it})} \right)^\varphi - \frac{\sum_i (c_{it+1}^*(\theta^{it+1}))^\varphi}{\sum_i (c_{it+1}^*(\theta^{it}))^\varphi} \right] \kappa,$$

so again setting the empirical moment condition with observed error-ridden consumption to zero is equivalent to setting the analogous condition with true consumption to zero.

Measurement Error in Income Data

While the testing approach is robust to a fairly broad class of measurement error processes, one may still worry about measurement error in income data. To examine whether the results are sensitive to measurement error in income data, I drop income in the information set when forming the moment conditions for estimation. The lower panel of table 3.5 shows that the results are robust to this alternative specification of the information set.

Specification of Preferences

The moment condition is robust to time-invariant preference shifters.¹¹ To see this, suppose the utility function takes the form

$$u(c) = \frac{c^{1-\eta}}{1-\eta} \exp(X'_i \alpha),$$

where X'_i is the vector of time-invariant household characteristics that may shift the household's preferences. The moment condition is unaffected because

$$\begin{aligned} \tilde{\zeta}_{it}(\varphi) &= \left(\frac{c_{it+1}(\theta^{it+1})}{c_{it}(\theta^{it})} \right)^{-\varphi} \frac{\exp(X'_i \alpha)}{\exp(X'_i \alpha)} - \frac{\sum_i (c_{it+1}(\theta^{it+1}))^{-\varphi} \exp(X'_i \alpha)}{\sum_i (c_{it+1}(\theta^{it}))^{-\varphi} \exp(X'_i \alpha)} \\ &= \left(\frac{c_{it+1}(\theta^{it+1})}{c_{it}(\theta^{it})} \right)^{-\varphi} - \frac{\sum_i (c_{it+1}(\theta^{it+1}))^{-\varphi}}{\sum_i (c_{it+1}(\theta^{it}))^{-\varphi}} \\ &= \zeta_{it}(\varphi). \end{aligned}$$

¹⁰These assumptions about the structure of the measurement error are not completely innocuous, of course. But I do not need to impose any functional form or make any assumption about the magnitude of the measurement error.

¹¹Since consumption is converted to adult equivalence levels, the specification in this study accounts for potential changes in preferences due to family size and ages of household members.

In this sense, the estimator using the above moment condition is analogous to a fixed effects estimator in a linear regression model.

However, the testing approach above is not robust to non-homothetic preferences. When preferences are not homothetic, demand is not Gorman-aggregable and thus utility cannot be expressed as a function of a composite consumption as is assumed in this paper.

3.5 Welfare Costs of Risk

Given that households in the rural villages fail to achieve complete risk sharing, how large are the welfare costs of risk? And how large would be the potential bias in welfare estimates if one infers the insurance regime incorrectly?

To calculate welfare loss from risk, I need an estimate for risk aversion, an important statistic for welfare analysis. In fact, given information on consumption fluctuation, it is a sufficient statistic for calculating welfare loss (Chetty, 2009). I use the estimates from models of self-insurance and private information and compare welfare estimates across the models. Such a comparison allows me to examine the potential bias in welfare estimates if one uses “incorrect” regime.

For the self-insurance regime, I use $\eta = 0.15$, the estimate from the data. Since this estimate is the unique solution to the GMM criterion function in equation 3.7, I cannot use the same criterion function to estimate risk aversion based on the model of private information. Under the steady state condition $\beta(1 + r_t) = 1 \forall t$ (neither the discount factor β nor the interest rate r_t are observed in my data), however, I can calculate the implied coefficient under the regime of private information. I apply the Law of Iterated Expectation to the first-order condition (equation 3.3) and rearrange terms to obtain its sample analogue

$$\xi(\eta) \equiv \frac{1}{T} \frac{1}{N} \sum_t \sum_i \left[\left(\frac{c_{it+1}(\theta^{it+1})}{c_{it}(\theta^{it})} \right)^\eta - 1 \right] = 0. \quad (3.8)$$

Figure 3.1 shows the calibrated coefficient of relative risk aversion under different regimes, along with the estimate from the self-insurance model ($\eta = 0.15$). The private information model implies $\eta = 1.44$.

I calculate the welfare cost of risk by using a similar approach to Lucas’ calculation of the cost of business cycles but applying it micro data. Specifically, let λ_i be the equivalent variation (EV) expressed as the share of annual consumption that household i has to be compensated for it to be indifferent between a consumption path that is fluctuating and alternative path that is smooth at the same expected consumption level; this measure represents the welfare cost of risk, and by definition,

$$\int \beta^t \left\{ \frac{[(1 + \lambda_i)c_{it}]^{1-\eta}}{1 - \eta} \right\} dF_i(c) = \beta^t \frac{[\int c_{it} dF_i(c)]^{1-\eta}}{1 - \eta}, \quad (3.9)$$

where β is the discount factor and $F_i(c)$ is the distribution of household i ’s consumption.

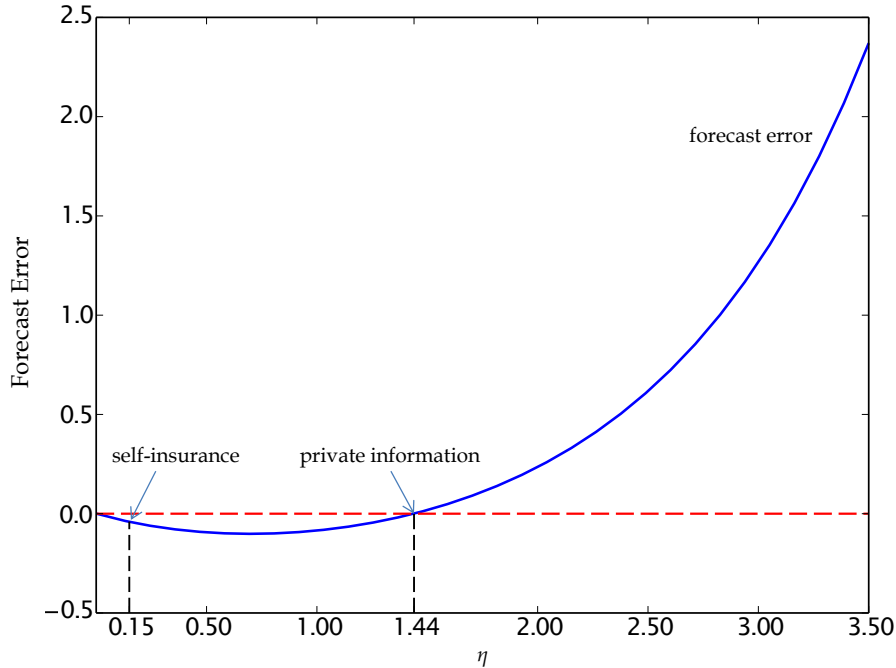


Figure 3.1: Coefficients of Risk Aversion Under Alternative Regimes

Notes: The forecast error is defined by equations 3.8. Under the private information regime, $\xi(\eta) = 0$, and under limited enforcement, $\xi(\eta) \geq 0$. Under self-insurance, the empirical estimate is $\eta = 0.15$.

The welfare loss from risk can be decomposed into an aggregate and an idiosyncratic parts. My decomposition approach extends the decomposition proposed by Ligon and Schechter (2003) to a dynamic setting. I first decompose consumption as

$$\ln c_{it} = \delta_{it} + \tau_t + \epsilon_{it},$$

where τ_t is time fixed effects that represent aggregate risk, δ_{it} is explained idiosyncratic risk, and ϵ_{it} is remaining idiosyncratic risk which includes risk unexplained by observable characteristics of the household and potential measurement error in consumption, with distributions: $\delta_{it} \sim F_i(\delta)$, $\tau_t \sim F(\tau)$, $\epsilon_{it} \sim F_i(\epsilon)$. Suppose the distributions of aggregate and idiosyncratic risk are independent from each other. I can compute the equivalent variation for aggregate and idiosyncratic sources of risk separately. Let λ_i^{agg} and λ_i^{idio} denote the

equivalent variation for aggregate risk and idiosyncratic risk, respectively. By definition,

$$\begin{aligned} & \int \beta^t \left\{ \frac{[(1 + \lambda_i^{agg}) (\int \delta_{it} dF_i(\delta) + \int \epsilon_{it} dF_i(\epsilon) + \tau_t)]^{1-\eta}}{1 - \eta} \right\} dF(\tau) \\ &= \beta^t \frac{[\int (\int \delta_{it} dF_i(\delta) + \int \epsilon_{it} dF_i(\epsilon) + \tau_t) dF(\tau)]^{1-\eta}}{1 - \eta}, \end{aligned} \quad (3.10)$$

and

$$\int \beta^t \left\{ \frac{[(1 + \lambda_i^{idio}) (\delta_{it} + \int \tau_t F(\tau) + \epsilon_{it})]^{1-\eta}}{1 - \eta} \right\} dF_i(\epsilon) = \beta^t \frac{[\int (\int \delta_{it} + \int \tau_t F(\tau) + \epsilon_{it}) dF_i(\epsilon)]^{1-\eta}}{1 - \eta}. \quad (3.11)$$

To operationalize the procedure, I project the explained idiosyncratic risk onto the subspace of observable household characteristics, $\mathbb{E}[\delta_{it}] = X_i' \gamma$, where X_i' is the time-invariant household characteristics (or the averages of time-varying characteristics). In addition, I project aggregate shock onto rainfall and time dummies. This suggests that I can decompose consumption with a linear model,

$$\ln c_{ivt} = X_{ivt}' \gamma_1 + R_{vt} \gamma_2 + \tau_t + \epsilon_{ivt},$$

which will provide estimates of empirical distributions of aggregate and idiosyncratic shocks: $\widehat{F}_i(\delta)$, $\widehat{F}(\tau)$, and $\widehat{F}_i(\epsilon)$. The second column of table 3.6 shows the regression results. The economic and statistical significance of rainfall and most of the time dummies suggest that aggregate risk in consumption is important. Moreover, households headed by more educated people tend to enjoy a higher level of consumption (in per adult-equivalent terms).

To estimate the equivalent variation for overall risk, aggregate risk, and idiosyncratic risk, I replace the distributions in equations (3.9), (3.10), and (3.11) with their empirical counterparts and construct a consumption path for each household by re-sampling (with replacement) from the empirical distributions of aggregate and idiosyncratic shocks.¹² This approach of calculating welfare loss takes into account the risk sharing arrangement that currently exists in the economy. Through re-sampling, I construct a consumption series of 10,000 periods for each household to compute the expectation terms in the expressions that define the equivalent variation.¹³

Table 3.7 shows statistics of the distribution of equivalent variation with different CRRA coefficients. A few patterns stand out. First, even accounting for existing mutual insurance, there is still about 40% of risk coming from idiosyncratic sources. About 60% of risk originates from aggregate sources, and this significance of aggregate risk is broadly consistent with the finding in Ligon and Schechter (2003) who estimate vulnerability of rural households

¹²A similar re-sampling approach is used by Kühl (2003) to estimate vulnerability of rural households in Ethiopia.

¹³Note that in the steady state, β does not affect the equivalent variation. In my calculations, I use $\beta = 0.95$.

Table 3.6: Correlates of Consumption Risk and Equivalent Variation

	$\ln c_t$	EV ($\eta=0.15$)	EV ($\eta=1.44$)	EV ($\eta=2.68$)
HH head had schooling	0.2399*** (0.0508)	-0.2723* (0.1656)	-3.073 (2.062)	-5.168 (3.626)
HH head is female	0.0521 (0.0447)	0.4706*** (0.1596)	5.440** (2.159)	8.589** (3.962)
HH head age	-0.00080 (0.00089)	0.0086** (0.0042)	0.105** (0.053)	0.1984** (0.0965)
Days HH head is sick	0.00055 (0.00059)	0.0075* (0.0045)	0.0932 (0.0580)	0.1867* (0.1110)
Rainfall	0.0527* (0.0302)	-0.0300 (0.1414)	0.1186 (1.943)	0.9841 (3.546)
Rainfall dispersion		0.5625 (0.9359)	4.646 (12.23)	5.065 (21.81)
Time dummy 1	0.9378** (0.0392)			
Time dummy 2	0.0710** (2.007)			
Time dummy 3	0.0236 (0.0247)			
Constant	11.40*** (0.0846)	1.820*** (0.4194)	20.18*** (5.489)	36.09*** (9.724)
R^2	0.3199	0.0293	0.0187	0.0157
N	3008	752	752	752

Note 1: Standard errors (in parenthesis) in column 1 are clustered at the village level. Those in columns 2-4 are Eicker-White standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Note 2: Consumption is expressed in per adult equivalent annualized terms, with the conversion rule specified in the notes under table 3.2. The rainfall variable is standardized using the regional time series (1980-2004) averages of the two rain seasons (March-May and October-December). It is matched to villages based on the nearest weather station. Rainfall dispersion is defined to be the ratio of the time series standard deviation to the mean at the village level.

Note 3: The regressions of equivalent variation on household characteristics, as shown in the last four columns, are estimated using only data from the first wave (because household characteristics did not change much over the survey periods).

in Bulgaria. Second, there is substantial variations across households in their vulnerability to overall consumption risk. Third, if one mis-classifies the information regime of the village economy, the welfare loss from risk may be grossly underestimated. For example, if a researcher incorrectly concluded that the village economy operates under the self-insurance

regime by using $\eta = 0.15$ in the welfare analysis, he would estimate an EV of only 2.3%, much lower than the estimate of 26% using $\eta = 1.44$ under the private information model. This suggests that an incorrect inference on the insurance regime could underestimate the welfare loss from risk by as much as ten times.

Table 3.7: Statistics of the Distribution of Equivalent Variation

	10 th	25 th	50 th	75 th	90 th	Mean	Std. dev.
Overall risk							
$\eta = 0.15$	0.494	0.961	1.692	2.963	5.147	2.319	2.015
$\eta = 1.44$	4.796	9.528	17.46	32.15	58.04	26.13	29.39
Aggregate risk							
$\eta = 0.15$	1.372	1.472	1.559	1.654	1.654	1.535	0.113
$\eta = 1.44$	11.95	12.83	13.62	14.46	14.46	13.41	1.009
Idiosyncratic risk							
$\eta = 0.15$	0.157	0.331	0.696	1.311	2.163	0.984	0.941
$\eta = 1.44$	1.544	3.209	7.290	14.11	25.33	10.76	11.99

Note: The EVs are represented as % of consumption each year that each household has to be compensated so as to be indifferent between a consumption path that is fluctuating and an alternative smooth path with the same expected consumption level.

It is also informative to look at the correlation between the EV estimates and household characteristics, as shown in the last two columns of table 3.6. Overall, households headed by people with formal schooling have lower EV and hence less vulnerable to consumption risk. Households with female or older heads, however, tend to be more vulnerable. Such relative vulnerability of households in which the head is female and less educated is also found by Ligon and Schechter (2003). While as expected households living in villages that experience more variant rainfall are more vulnerable, the sample does not seem to have enough power to deliver a statistically significant coefficient. Finally, the health status of the household head as measured by the number of days of being sick does not appear to affect vulnerability much (although the coefficient is statistically significant at the 10% level in two cases). This occurs possibly because households tend to be better insured against small health shocks (Townsend, 1995). However, it is also possible that this measure is poorly measured as survey respondents may have different interpretations of questions regarding this measure. Indeed, when a more reliable index of health status is used, Gertler and Gruber (2002) find that people in Indonesian villages suffer large economic costs associated with major illness.

3.6 Conclusion

In this paper, I develop a unified approach to distinguish between alternative insurance regimes of full insurance, self-insurance, and private information. Unlike the existing approaches in the literature, the proposed testing approach accounts for aggregate shocks and

does not require data on interest rates, which is an important advantage for studying risk sharing in rural economies. Applying the testing approach to a longitudinal dataset from rural household surveys in Tanzanian villages, I reject regimes of full insurance and private information, and but not self-insurance.

Using estimated coefficients of risk aversion under alternative regimes, I calculate welfare costs of consumption risk facing rural households and decompose it into aggregate and idiosyncratic sources. I find that even accounting for existing risk sharing mechanism there is still about 40% of risk coming from idiosyncratic sources, and that there is substantial variation across households in their vulnerability to risk. Finally, a comparison of welfare estimates under alternative regimes suggests that an incorrect inference on the insurance regime could underestimate the welfare loss from risk by as much as ten times.

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Appendix A

The “China Shock” on China: Trade, Structural Transformation, and Real Exchange Rate Dynamics

A.1 Migration Share

Lifetime Expected Utility

This section derives the lifetime expected utility in equation 1.1 and the migration shares in equation 1.2. The derivation follows Caliendo et al. (2015) closely and is presented here for reference. With an abuse of notation, I abstract away from the conditioning on asset level $a_{h,t}$ in the proof below.¹ Workers seek to maximize their utility:

$$V_{ns,t} = U(C_{ns,t}) + \max_{\{n',s'\}_{n'=0,s'=0}^{N,S}} \{ \beta \mathbb{E}_t[V_{n',s',t+1}] - \kappa_{n',s',ns,t} + v \epsilon_{n',s',t} \},$$

Let $\bar{V}_{ns,t} \equiv \mathbb{E}_t[V_{ns,t}]$ be the expected lifetime utility over future preference shocks. The idiosyncratic preference shocks ϵ are assumed to be i.i.d. over time and distributed Type-I Extreme Value with zero mean. In particular, the cumulative distribution function is $F(\epsilon) = \exp(-\exp(-\epsilon - \bar{\gamma}))$, with a density function $f(\epsilon) = \frac{\partial F}{\partial \epsilon} = \exp(-\exp(-\epsilon - \bar{\gamma})) \exp(-\epsilon - \bar{\gamma})$.

Let $\Phi_{ns} \equiv \mathbb{E}_t \left(\max_{\{n',s'\}_{n'=0,s'=0}^{N,S}} \{ \beta \mathbb{E}_t[V_{n',s',t+1}] - \kappa_{n',s',ns,t} + v \epsilon_{n',s',t} \} \right)$. It suffices to show

$$\Phi_{ns,t} = v \log \left[\sum_{n'=0}^N \sum_{s'=0}^S \exp \left(\frac{\beta \bar{V}_{n',s',t+1} - \kappa_{n',s',ns,t}}{v} \right) \right].$$

¹Adding the conditioning on asset levels will not change the proof.

Let $\widehat{\epsilon}^{n's',n''s''} = \frac{\beta(\overline{V}_{n's',t+1} - \overline{V}_{n''s'',t+1}) - (\kappa_{ns,n's',t} - \kappa_{ns,n''s'',t})}{v}$. Then

$$\begin{aligned} \Phi_{ns,t} &= \sum_{n'=0}^N \sum_{s'=0}^S \int_{-\infty}^{\infty} (\beta \overline{V}_{ns,t+1} - \kappa_{n's',ns,t} + v \epsilon_{n's',t}) f(\epsilon_{n's',t}) \times \\ &\quad \prod_{n's' \neq n''s''} F\left(\widehat{\epsilon}^{n's',n''s''} + \epsilon_{n's',t}\right) d\epsilon_{n's',t}. \end{aligned}$$

Let $\gamma = \int_{-\infty}^{\infty} x \exp(-x - \exp(-x)) dx$ be Euler's constant. Then

$$\begin{aligned} \Phi_{ns,t} &= \sum_{n'=0}^N \sum_{s'=0}^S \int_{-\infty}^{\infty} (\beta \overline{V}_{ns,t+1} - \kappa_{n's',ns,t} + v \epsilon_{n's',t}) \times \\ &\quad e^{-\epsilon_{n's',t} - \gamma} e^{-e^{-\epsilon_{n's',t} - \gamma} \sum_{n''=1}^N \sum_{s''=0}^S e^{-\widehat{\epsilon}^{n's',n''s''}}} d\epsilon_{n's',t}. \end{aligned}$$

Let $\lambda_t = \log \sum_{n''=0}^N \sum_{s''=0}^S \exp(-\widehat{\epsilon}^{n's',n''s''})$. Consider a change of variables $\zeta_t = \epsilon_{n's',t} + \gamma$.

$$\Phi_{ns,t} = \sum_{n'=0}^N \sum_{s'=0}^S \int_{-\infty}^{\infty} (\beta \overline{V}_{ns,t+1} - \kappa_{n's',ns,t} + v(\zeta_t - \gamma)) \exp(-\zeta_t - \exp(-(\zeta_t - \lambda_t))) d\zeta_t.$$

Consider an additional change of variables $\eta_t = \zeta_t - \gamma$.

$$\begin{aligned} \Phi_{ns,t} &= \sum_{n'=0}^N \sum_{s'=0}^S \exp(-\lambda_t) \times \\ &\quad \left[(\beta \overline{V}_{ns,t+1} - \kappa_{n's',ns,t} + v(\zeta_t - \gamma)) + v \int_{-\infty}^{\infty} \eta_t \exp(-\eta_t - \exp(-\eta_t)) d\eta_t \right]. \end{aligned}$$

Using the definition of γ ,

$$\Phi_{ns,t} = \sum_{n'=0}^N \sum_{s'=0}^S \exp(-\lambda_t) (\beta \overline{V}_{ns,t+1} - \kappa_{n's',ns,t} + v \lambda_t).$$

Replacing the definition of λ_t ,

$$\begin{aligned} \Phi_{ns,t} &= \sum_{n'=0}^N \sum_{s'=0}^S \exp\left(-\log \sum_{n''=0}^N \sum_{s''=0}^S \exp(-\widehat{\epsilon}^{n's',n''s''})\right) \times \\ &\quad \left(\beta \overline{V}_{ns,t+1} - \kappa_{n's',ns,t} + v \log \sum_{n''=0}^N \sum_{s''=0}^S \exp(-\widehat{\epsilon}^{n's',n''s''}) \right). \end{aligned}$$

Replacing the definition of $\widehat{\epsilon}^{n's',n''s''}$,

$$\begin{aligned}
 \Phi_{ns,t} &= \sum_{n'=0}^N \sum_{s'=0}^S \exp \left(-\log \sum_{n''=0}^N \sum_{s''=0}^S \exp \left(-\frac{\beta(\overline{V}_{n's',t+1} - \overline{V}_{n''s'',t+1}) - (\kappa_{ns,n's',t} - \kappa_{ns,n''s'',t})}{v} \right) \right) \times \\
 &\quad [\beta \overline{V}_{ns,t+1} - \kappa_{n's',ns,t} + \\
 &\quad v \log \sum_{n''=0}^N \sum_{s''=0}^S \exp \left(-\frac{\beta(\overline{V}_{n's',t+1} - \overline{V}_{n''s'',t+1}) - (\kappa_{ns,n's',t} - \kappa_{ns,n''s'',t})}{v} \right)] \\
 &= v \log \sum_{n'=0}^N \sum_{s'=0}^S \exp \left(\frac{\beta \overline{V}_{ns,t+1} - \kappa_{n's',ns,t}}{v} \right) \frac{\sum_{n''=0}^N \sum_{s''=0}^S \exp \left(\frac{\beta \overline{V}_{ns,t+1} - \kappa_{n's',ns,t}}{v} \right)}{\sum_{n''=0}^N \sum_{s''=0}^S \exp \left(\frac{\beta \overline{V}_{ns,t+1} - \kappa_{n''s'',ns,t}}{v} \right)} \\
 &= v \log \sum_{n'=0}^N \sum_{s'=0}^S \exp \left(\frac{\beta \overline{V}_{ns,t+1} - \kappa_{n's',ns,t}}{v} \right).
 \end{aligned}$$

Therefore,

$$\overline{V}_{ns,t} = U(C_{ns,t}) + v \log \left[\sum_{n'=0}^N \sum_{s'=0}^S \exp \left(\frac{\beta \overline{V}_{n's',t+1} - \kappa_{n's',ns,t}}{v} \right) \right]. \quad (\text{A.1})$$

Migration Share

Define $\mu_{n's',ns,t}$ as the fraction of workers that reallocation from market ns to $n's'$. This fraction is equal to the probability that market $n's'$ offers the highest expected utility among all labor markets. Formally

$$\begin{aligned}
 \mu_{n's',ns,t} &= \Pr \left(\frac{\beta \overline{V}_{n's',t+1} - \kappa_{n's',ns,t}}{v} + \epsilon_{n's',t} \geq \max_{n''s'' \neq n's'} \left\{ \frac{\beta \overline{V}_{n''s'',t+1} - \kappa_{n''s'',ns,t}}{v} + \epsilon_{n''s'',t} \right\} \right) \\
 &= \int_{-\infty}^{\infty} f(\epsilon_{n's',t}) \times \\
 &\quad \prod_{n''s'' \neq n's'} F \left(\frac{\beta(\overline{V}_{n's',t+1} - \overline{V}_{n''s'',t+1}) - (\kappa_{ns,n's',t} - \kappa_{ns,n''s'',t})}{v} + \epsilon_{n's',t} \right) d\epsilon_{n's',t} \\
 &= \int_{-\infty}^{\infty} \exp(-\epsilon_{n's',t} - \gamma) \exp \left[-\exp(-\epsilon_{n's',t} - \gamma) \sum_{n''=0}^N \sum_{s''=0}^S \exp \left(-\widehat{\epsilon}^{n's',n''s''} \right) \right] d\epsilon_{n's',t}.
 \end{aligned}$$

From the derivations in the previous section, I get

$$\mu_{n's',ns,t} = \exp(-\lambda_t) \int_{-\infty}^{\infty} \exp(-\eta_t - \exp(-\eta_t)) d\eta_t,$$

and upon solving this integration, I obtain

$$\mu_{n's',ns,t} = \frac{\exp\left(\frac{\beta \bar{V}_{n's',t+1} - \kappa_{n's',ns,t}}{v}\right)}{\sum_{n'=0}^N \sum_{s'=0}^S \exp\left(\frac{\beta \bar{V}_{n's',t+1} - \kappa_{n's',ns,t}}{v}\right)}.$$

A.2 Independence of Past Savings

Proposition: Suppose asset returns $R_{n,t}$ are indexed to the local basket of goods such that $R_{n,t} = P_{n,t}R_t$. Then the value function of workers can be decomposed as

$$V_{ns,t}(a_{h,t}) = V_{ns,t} + f(a_{h,t}),$$

where $V_{ns,t}$ does not depend on workers' asset levels and $f(a_{h,t})$ is some function that does. Therefore, workers' migration decisions are independent of their asset levels:

$$\mu_{n's',ns,t}(a_{h,t}) = \mu_{n's',ns,t}(a_{h',t}) \quad \forall a_{h,t} \neq a_{h',t}.$$

Proof: Consider workers currently residing in market ns and contemplating migration to other markets. I can rewrite workers' value function as

$$\begin{aligned} V_{ns,t}(a_{h,t}) &= \sum_{t=1}^{\infty} \beta^{t-1} \max_{\{n',s'\}_{n'=0,s'=0}^{N,S}} \{ \mathbb{E}_t[U(C_{hns,t}) - \kappa_{n's',ns,t} + v\epsilon_{n's',t}] \} \\ &= \sum_{t=1}^{\infty} \beta^{t-1} \max_{\{n',s'\}_{n'=0,s'=0}^{N,S}} \left\{ \mathbb{E}_t \left[(1-\lambda) \frac{w_{ns,t}}{P_{n,t}} + (1-\lambda) R_t a_{h,t} - \kappa_{n's',ns,t} + v\epsilon_{n's',t} \right] \right\} \\ &= \sum_{t=1}^{\infty} \beta^{t-1} \max_{\{n',s'\}_{n'=0,s'=0}^{N,S}} \left\{ \mathbb{E}_t \left[(1-\lambda) \frac{w_{ns,t}}{P_{n,t}} - \kappa_{n's',ns,t} + v\epsilon_{n's',t} \right] \right\} + \\ &\quad \sum_{t=1}^{\infty} (1-\lambda) \beta^{t-1} R_t a_{h,t}. \end{aligned}$$

Next, I show that the second term can be decomposed into two components: one that is invariant to workers' asset levels and another that depends on the current asset level $a_{h,t}$. To see this, I iterate forward to obtain future asset levels as

$$\begin{aligned} a_{h,t+J} &= \lambda w_{n,t+J} + \lambda R_{t+J-1} P_{n,t+J-1} a_{h,t+J-1} \\ &= \lambda w_{n,t+J} + \lambda R_{t+J-1} P_{n,t+J-1} (\lambda w_{n,t+J-1} + \lambda R_{t+J-2} P_{n,t+J-2} a_{h,t+J-2}) \\ &= \dots \\ &= \sum_{i=0}^{J-1} \left(\prod_{j=i}^{J-1} R_{t+j} P_{n,t+j} \right) \lambda^{J-i} w_{n,t+i} + \prod_{j=0}^{J-1} \lambda R_{t+j} P_{n,t+j} a_{h,t}, \end{aligned}$$

where the first term is common for all workers regardless of their current asset levels. The value function is thus separable from asset levels:

$$V_{ns,t}(a_{h,t}) = V_{ns,t} + f(a_{h,t}),$$

where $V_{ns,t}$ does not depend on workers’ asset levels and $f(a_{h,t})$ is some function that does. So the expected value function:

$$\bar{V}_{ns,t}(a_{h,t}) = \bar{V}_{ns,t} + f(a_{h,t}).$$

To prove migration decisions are independent of asset levels, it suffices to show that the expected value in any two locations $\bar{V}_{ns,t}(a_{h,t}) - \bar{V}_{n's',t}(a_{h,t})$ does not depend on $a_{h,t}$, which is indeed the case because

$$\bar{V}_{ns,t}(a_{h,t}) - \bar{V}_{n's',t}(a_{h,t}) = \bar{V}_{ns,t} - \bar{V}_{n's',t}.$$

A.3 Capital Allocation Share

I derive the capital allocation share in equation 1.4. Mutual fund managers maximize

$$V_t^K = \max_{\{n,s\}_{n=0,s=0}^{N,S}} (r_{ns,t} + v^K \epsilon_{n's',t}^K),$$

where I use superscript K to denote variables related to the capital allocation problem. Similar to the worker’s problem, I assume that the idiosyncratic frictions (“amenity shocks”) ϵ^K are i.i.d. over time, have zero mean, and follow a Type-I Extreme Value distribution. Then using a similar procedure as the proof for the migration shares, I can show that the probability of capital allocation to market ns is

$$\begin{aligned} \mu_{ns,t}^K &= \Pr \left(\frac{r_{ns,t}}{v^K} + \epsilon_{ns,t}^K \geq \max_{n's' \neq ns} \left\{ \frac{r_{n's',t}}{v^K} + \epsilon_{n's',t}^K \right\} \right) \\ &= \int_{-\infty}^{\infty} f(\epsilon_{ns,t}^K) \prod_{n's' \neq ns} F \left(\frac{r_{ns,t} - r_{n's',t}}{v^K} + \epsilon_{n's',t}^K \right) d\epsilon_{ns,t}^K \\ &= \frac{\exp \left(\frac{r_{ns,t}}{v^K} \right)}{\sum_{n=0}^N \sum_{s=0}^S \exp \left(\frac{r_{ns,t}}{v^K} \right)}. \end{aligned}$$

Returns to Savings

I derive the return to savings:

$$R_{t+1} = \left(\sum_{n=0}^N \sum_{s=1}^S r_{ns,t+1} \mu_{ns,t+1}^K \right) \frac{\sum_{n=0}^N \sum_{s=1}^S a_{ns,t+1} L_{ns,t}}{\sum_{n'=0}^N \sum_{s'=1}^S P_{n',t+1} \sum_{n=0}^N \sum_{s=1}^S \mu_{n's',ns,t} a_{ns,t+1} L_{ns,t}}.$$

This return ensures that workers’ earn an indexed return to their savings in terms of the local basket of goods in the location to which they reallocate. Note that the nominal value between what the mutual fund pays workers and what it collects from firms by renting out capital has to be equal:

$$\sum_{n=0}^N \sum_{s=1}^S r_{ns,t+1} K_{ns,t+1} = R_{t+1} \sum_{n'=0}^N \sum_{s'=1}^S P_{n't+1} \sum_{n=0}^N \sum_{s=1}^S \mu_{n's',ns,t} a_{ns,t+1} L_{ns,t}.$$

Substitute into the above equation

$$K_{ns,t+1} = \mu_{ns,t+1}^K K_{t+1}$$

and

$$K_{t+1} = I_t = \sum_{n=0}^N \sum_{s=1}^S a_{ns,t+1} L_{ns,t}.$$

Rearrange to obtain the desired result.

A.4 Imputation of Migration Matrix

Suppose that migration costs take a fairly general additive structure and that migration costs to home region-sector are normalized to be one:

$$\begin{aligned} \kappa_{n's',ns,t} &= \kappa_{n',n,t} + \kappa_{s,t} + \kappa_{s',t}, \text{ if } s \neq s' \\ \kappa_{n',n,t} &= \kappa_{n,n',t}, \kappa_{n,n,t} = 0, \kappa_{ns,ns,t} = 0. \end{aligned}$$

I want to show that

$$\mu_{n's',ns,t} = \left(\sum_{s'=0}^S \mu_{n's',ns,t} \right) \times \left(\frac{\sum_{n=0}^N \sum_{s=0}^S \mu_{n's',ns,t} L_{n,t}}{\sum_{s'=0}^S \sum_{n=0}^N \sum_{s=0}^S \mu_{n's',ns,t} L_{n,t}} \right). \quad (\text{A.2})$$

Proof: Let $\chi_{n's',ns,t} \equiv \exp\left(\frac{-\kappa_{n's',ns,t}}{v}\right)$, $\chi_{n',n,t} \equiv \exp\left(\frac{-\kappa_{n',n,t}}{v}\right)$, $\chi_{s,t} \equiv \exp\left(\frac{-\kappa_{s,t}}{v}\right)$, and $W_{ns,t} \equiv \exp\left(\frac{\beta V_{ns,t}}{v}\right)$. Note that $\chi_{n's',ns,t} = \chi_{n',n,t} \chi_{s,t} \chi_{s',t}$. Then $\mu_{n's',ns,t} = \chi_{n',n,t} \chi_{s,t} \chi_{s',t} W_{n's',t}$. The right hand side of equation A.2 is

$$\begin{aligned} RHS &= \left(\sum_{s'=0}^S \chi_{n',n,t} \chi_{s,t} \chi_{s',t} W_{n's',t} \right) \times \left(\frac{\sum_{n=0}^N \sum_{s=0}^S \chi_{n',n,t} \chi_{s,t} \chi_{s',t} W_{n's',t} L_{n,t}}{\sum_{s'=0}^S \sum_{n=0}^N \sum_{s=0}^S \chi_{n',n,t} \chi_{s,t} \chi_{s',t} W_{n's',t} L_{n,t}} \right) \\ &= \left(\chi_{n',n,t} \chi_{s,t} \sum_{s'=0}^S \chi_{s',t} W_{n's',t} \right) \times \left(\frac{\chi_{s',t} W_{n's',t} \sum_{n=0}^N \sum_{s=0}^S \chi_{n',n,t} \chi_{s,t} L_{n,t}}{\sum_{s'=0}^S \sum_{n=0}^N \sum_{s=0}^S \chi_{n',n,t} \chi_{s,t} \chi_{s',t} W_{n's',t} L_{n,t}} \right) \\ &= \chi_{n',n,t} \chi_{s,t} \chi_{s',t} W_{n's',t} \frac{\sum_{s'=0}^S \chi_{s',t} W_{n's',t} \sum_{n=0}^N \sum_{s=0}^S \chi_{n',n,t} \chi_{s,t} L_{n,t}}{\sum_{s'=0}^S \sum_{n=0}^N \sum_{s=0}^S \chi_{n',n,t} \chi_{s,t} \chi_{s',t} W_{n's',t} L_{n,t}} \\ &= \chi_{n',n,t} \chi_{s,t} \chi_{s',t} W_{n's',t} \frac{\sum_{s'=0}^S \sum_{n=0}^N \sum_{s=0}^S \chi_{n',n,t} \chi_{s,t} \chi_{s',t} W_{n's',t} L_{n,t}}{\sum_{s'=0}^S \sum_{n=0}^N \sum_{s=0}^S \chi_{n',n,t} \chi_{s,t} \chi_{s',t} W_{n's',t} L_{n,t}} \\ &= \chi_{n',n,t} \chi_{s,t} \chi_{s',t} W_{n's',t} \\ &= \mu_{n's',ns,t}. \end{aligned}$$

A.5 Inference of Migration Costs

Proposition: *Inference of Migration Costs* Assume migration costs take on an additive structure and normalization as shown in equations 1.11 and 1.12. Then bilateral migration costs across regions and sectors can be inferred with the following expression:

$$\kappa_{n's',ns,t} = \frac{1}{2}v \left[\log \left(\frac{\mu_{n's',n's,t}\mu_{ns,ns',t}}{\mu_{ns,n's',t}\mu_{n's',ns,t}} \right) + \log \left(\frac{\mu_{n's,n's,t}\mu_{n's',n's',t}}{\mu_{n's',n's,t}\mu_{n's,n's',t}} \right) \right] \quad (\text{A.3})$$

Proof: It suffices to show that

$$\log \left(\frac{\mu_{n's',n's,t}\mu_{ns,ns',t}}{\mu_{ns,n's',t}\mu_{n's',ns,t}} \right) = \frac{2}{v}\kappa_{n',n,t}$$

and

$$\log \left(\frac{\mu_{n's,n's,t}\mu_{n's',n's',t}}{\mu_{n's',n's,t}\mu_{n's,n's',t}} \right) = \frac{2}{v}(\kappa_{s,t} + \kappa_{s',t}).$$

For the first part, note that

$$\begin{aligned} \log \left(\frac{\mu_{n's',n's,t}\mu_{ns,ns',t}}{\mu_{ns,n's',t}\mu_{n's',ns,t}} \right) &= \log \left(\frac{\exp \left(\frac{\beta\bar{V}_{n's',t+1} - \kappa_{n's',n's,t}}{v} \right) \exp \left(\frac{\beta\bar{V}_{ns,t+1} - \kappa_{ns,ns',t}}{v} \right)}{\exp \left(\frac{\beta\bar{V}_{ns,t+1} - \kappa_{ns,n's',t}}{v} \right) \exp \left(\frac{\beta\bar{V}_{n's',t+1} - \kappa_{n's',ns,t}}{v} \right)} \right) \\ &= \log \left[\frac{\exp \left(\frac{-\kappa_{n's',ns,t}}{v} \right) \exp \left(\frac{-\kappa_{ns,ns',t}}{v} \right)}{\exp \left(\frac{-\kappa_{ns,n's',t}}{v} \right) \exp \left(\frac{-\kappa_{n's',ns,t}}{v} \right)} \right] \\ &= \frac{1}{v} (\kappa_{ns,n's',t} + \kappa_{n's',ns,t} - \kappa_{n's',n's,t} - \kappa_{ns,ns',t}) \\ &= \frac{1}{v} [\kappa_{n',n,t} + \kappa_{s',t} + \kappa_{s,t} + \kappa_{n,n',t} + \kappa_{s,t} + \kappa_{s',t} \\ &\quad - (\kappa_{s,t} + \kappa_{s',t}) - (\kappa_{s',t} + \kappa_{s,t})] \\ &= \frac{1}{v} (2\kappa_{n',n,t} + 2\kappa_{s,t} + 2\kappa_{s',t} - 2\kappa_{s,t} - 2\kappa_{s',t}) \\ &= \frac{2}{v}\kappa_{n',n,t}. \end{aligned}$$

The proof is similar for the second part.

A.6 Proof of Proposition for Solution Method

This section presents the proof of the proposition for the solution method. Let $\hat{x}_{t+1} = \frac{x_{t+1}}{x_t}$ denote the change of a variable in relative time differences, let $\Delta x_{t+1} \equiv (x_{t+1} - x_t)$ denote the first time difference of a variable, and let $\Omega(L_t, \Theta_t)$ denote the temporary equilibrium

allocation consistent with labor distribution L_t and fundamentals Θ_t , i.e., the set of trade shares, value added, and gross output.

Proposition: *Equilibrium under Shocks to Fundamentals* Consider a sequence of unanticipated changes in fundamentals, $\hat{\Theta} = \{\hat{\Theta}_t\}_{t=1}^{\infty}$. Conditional on the initial allocation of the economy, $(L_0, K_0, \mu_0, \mu_0^K, \Omega(L_0, K_0, \Theta_0))$, and the baseline sequential competitive equilibrium in time differences at $t = 0$, $(\hat{V}_{ns,1}, \mu_0, \mu_0^K)$, the solution to the sequential equilibrium in relative time differences given $\hat{\Theta}$ does not require information on the level of fundamentals Θ , and solves the following system of nonlinear equations:

$$\hat{\mu}_{n's',ns,t+1}(\hat{\Theta}) = \frac{\exp\left[\frac{1}{v}\left(\beta\Delta V_{n's',t+2}(\hat{\Theta}) - \Delta\kappa_{n's',ns,t+1}\right)\right]}{\sum_{n'=0}^N \sum_{s'=0}^S \mu_{n's',ns,t}(\hat{\Theta}) \exp\left[\frac{1}{v}\left(\beta\Delta V_{n's',t+2}(\hat{\Theta}) - \Delta\kappa_{n's',ns,t+1}\right)\right]},$$

$$\exp\left(\frac{1}{v}\hat{V}_{ns,t+1}(\hat{\Theta})\right) = \exp\left(\frac{1-\lambda}{v}\Delta\left(\frac{w_{ns,t+1}}{P_{n,t+1}}\right)\right) \times \sum_{n'=0}^N \sum_{s'=0}^S \mu_{n's',ns,t}(\hat{\Theta}) \exp\left[\frac{1}{v}\left(\beta\hat{V}_{n's',t+2}(\hat{\Theta}) - \Delta\kappa_{n's',ns,t+1}\right)\right],$$

$$L_{ns,t+1} = \sum_{n'=0}^N \sum_{s'=0}^J \mu_{ns,n's',t} L_{n's',t},$$

$$\hat{\mu}_{ns,t}^K = \frac{\exp\left(\frac{1}{v^K}\Delta r_{ns,t}(\hat{\Theta})\right)}{\sum_{n=0}^N \sum_{s=1}^S \mu_{ns,t}^K \exp\left(\frac{1}{v^K}\Delta r_{ns,t}(\hat{\Theta})\right)},$$

$$K_{ns,t+1} = \mu_{ns,t+1}^K \sum_{n=0}^N \sum_{s=1}^S a_{ns,t+1} L_{ns,t}.$$

Proof: Consider the fraction of workers who reallocate from market $n's'$ to ns at $t + 1$:

$$\mu_{n's',ns,t+1} = \frac{\exp\left(\frac{\beta\bar{V}_{n's',t+2} - \kappa_{n's',ns,t+1}}{v}\right)}{\sum_{n'=0}^N \sum_{s'=0}^S \exp\left(\frac{\beta\bar{V}_{n's',t+2} - \kappa_{n's',ns,t+1}}{v}\right)}.$$

Take the relative time differences of this equation:

$$\begin{aligned}
 \frac{\mu_{n's',ns,t+1}}{\mu_{n's',ns,t}} &= \frac{\exp\left(\frac{\beta\bar{V}_{n's',t+2}-\kappa_{n's',ns,t+1}}{v}\right)}{\sum_{n'=0}^N \sum_{s'=0}^S \exp\left(\frac{\beta\bar{V}_{n's',t+2}-\kappa_{n's',ns,t+1}}{v}\right)} \\
 &= \frac{\exp\left(\frac{\beta\bar{V}_{n's',t+1}-\kappa_{n's',ns,t}}{v}\right)}{\sum_{n'=0}^N \sum_{s'=0}^S \exp\left(\frac{\beta\bar{V}_{n's',t+1}-\kappa_{n's',ns,t}}{v}\right)} \\
 &= \frac{\exp\left(\frac{\beta(\bar{V}_{n's',t+2}-\bar{V}_{n's',t+1})}{v}\right) \frac{1}{\exp\left(\frac{\kappa_{n's',ns,t+1}-\kappa_{n's',ns,t}}{v}\right)}}{\sum_{n'=0}^N \sum_{s'=0}^S \frac{\exp\left(\frac{\beta\bar{V}_{n's',t+2}-\kappa_{n's',ns,t+1}}{v}\right)}{\sum_{n'=0}^N \sum_{s'=0}^S \exp\left(\frac{\beta\bar{V}_{n's',t+1}-\kappa_{n's',ns,t}}{v}\right)}} \\
 &= \frac{\exp\left(\frac{\beta(\bar{V}_{n's',t+2}-\bar{V}_{n's',t+1})}{v}\right) \frac{1}{\exp\left(\frac{\kappa_{n's',ns,t+1}-\kappa_{n's',ns,t}}{v}\right)}}{\sum_{n'=0}^N \sum_{s'=0}^S \frac{\exp\left(\frac{\beta\bar{V}_{n's',t+2}-\kappa_{n's',ns,t+1}}{v}\right) \frac{\exp\left(\frac{\beta\bar{V}_{n's',t+1}-\kappa_{n's',ns,t}}{v}\right)}{\exp\left(\frac{\beta\bar{V}_{n's',t+1}-\kappa_{n's',ns,t}}{v}\right)}}{\sum_{n'=0}^N \sum_{s'=0}^S \exp\left(\frac{\beta\bar{V}_{n's',t+1}-\kappa_{n's',ns,t}}{v}\right)}} \\
 &= \frac{\exp\left(\frac{\beta(\bar{V}_{n's',t+2}-\bar{V}_{n's',t+1})}{v}\right) \frac{1}{\exp\left(\frac{\kappa_{n's',ns,t+1}-\kappa_{n's',ns,t}}{v}\right)}}{\sum_{n'=0}^N \sum_{s'=0}^S \frac{\exp\left(\frac{\beta\bar{V}_{n's',t+1}-\kappa_{n's',ns,t}}{v}\right) \frac{\exp\left(\frac{\beta\bar{V}_{n's',t+2}-\kappa_{n's',ns,t+1}}{v}\right)}{\exp\left(\frac{\beta\bar{V}_{n's',t+1}-\kappa_{n's',ns,t}}{v}\right)}}{\sum_{n'=0}^N \sum_{s'=0}^S \exp\left(\frac{\beta\bar{V}_{n's',t+1}-\kappa_{n's',ns,t}}{v}\right)}} \\
 &= \frac{\exp\left(\frac{\beta(\bar{V}_{n's',t+2}-\bar{V}_{n's',t+1})}{v}\right) \frac{1}{\exp\left(\frac{\kappa_{n's',ns,t+1}-\kappa_{n's',ns,t}}{v}\right)}}{\sum_{n'=0}^N \sum_{s'=0}^S \mu_{n's',ns,t} \exp\left(\frac{\beta(\bar{V}_{n's',t+2}-\bar{V}_{n's',t+1})}{v}\right) \frac{1}{\exp\left(\frac{\kappa_{n's',ns,t+1}-\kappa_{n's',ns,t}}{v}\right)}} \\
 &= \frac{\exp\left[\frac{1}{v}(\beta\Delta V_{n's',t+2} - \Delta\kappa_{n's',ns,t+1})\right]}{\sum_{n'=0}^N \sum_{s'=0}^S \mu_{n's',ns,t} \exp\left[\frac{1}{v}(\beta\Delta V_{n's',t+2} - \Delta\kappa_{n's',ns,t+1})\right]}.
 \end{aligned}$$

Next,

$$\begin{aligned}
 \widehat{V}_{ns,t+1} &= U(C_{ns,t+1}) - U(C_{ns,t}) + v \log \left[\frac{\sum_{n'=0}^N \sum_{s'=0}^S \exp\left(\frac{\beta \bar{V}_{n's',t+2} - \kappa_{n's',ns,t+1}}{v}\right)}{\sum_{n'=0}^N \sum_{s'=0}^S \exp\left(\frac{\beta \bar{V}_{n's',t+1} - \kappa_{n's',ns,t}}{v}\right)} \right] \\
 &= U(C_{ns,t+1}) - U(C_{ns,t}) + \\
 &\quad v \log \left[\frac{\sum_{n'=0}^N \sum_{s'=0}^S \mu_{n's',ns,t} \exp\left(\frac{\beta (\bar{V}_{n's',t+2} - \bar{V}_{n's',t+1})}{v}\right) \frac{1}{\exp\left(\frac{\kappa_{n's',ns,t+1} - \kappa_{n's',ns,t}}{v}\right)}}{\sum_{n'=0}^N \sum_{s'=0}^S \mu_{n's',ns,t} \exp\left[\frac{1}{v} (\beta \widehat{V}_{n's',t+2} - \widehat{\kappa}_{n's',ns,t+1})\right]} \right] \\
 &= (1 - \lambda) \Delta \left(\frac{w_{ns,t+1}}{P_{n,t+1}} \right) + v \log \sum_{n'=0}^N \sum_{s'=0}^S \mu_{n's',ns,t} \exp \left[\frac{1}{v} (\beta \widehat{V}_{n's',t+2} - \widehat{\kappa}_{n's',ns,t+1}) \right].
 \end{aligned}$$

So

$$\begin{aligned}
 \exp\left(\frac{1}{v} \widehat{V}_{ns,t+1}\right) &= \exp\left(\frac{1 - \lambda}{v} \Delta \left(\frac{w_{ns,t+1}}{P_{n,t+1}} \right)\right) \times \\
 &\quad \sum_{n'=0}^N \sum_{s'=0}^S \mu_{n's',ns,t} \exp \left[\frac{1}{v} (\beta \widehat{V}_{n's',t+2} - \Delta \kappa_{n's',ns,t+1}) \right]
 \end{aligned}$$

Similarly,

$$\begin{aligned}
 \widehat{\mu}_{ns,t+1}^K &= \frac{\frac{\exp\left(\frac{r_{ns,t+1}}{vK}\right)}{\sum_{n=0}^N \sum_{s=0}^S \exp\left(\frac{r_{ns,t+1}}{vK}\right)}}{\frac{\exp\left(\frac{r_{ns,t}}{vK}\right)}{\sum_{n=0}^N \sum_{s=0}^S \exp\left(\frac{r_{ns,t}}{vK}\right)}} \\
 &= \frac{\exp\left(\frac{r_{ns,t+1} - r_{ns,t}}{vK}\right)}{\sum_{n=0}^N \sum_{s=0}^S \frac{\exp\left(\frac{r_{ns,t+1}}{vK}\right)}{\sum_{n=0}^N \sum_{s=0}^S \exp\left(\frac{r_{ns,t}}{vK}\right)}} \\
 &= \frac{\exp\left(\frac{r_{ns,t+1} - r_{ns,t}}{vK}\right)}{\sum_{n=0}^N \sum_{s=0}^S \frac{\exp\left(\frac{r_{ns,t}}{vK}\right) \frac{\exp\left(\frac{r_{ns,t+1}}{vK}\right)}{\exp\left(\frac{r_{ns,t}}{vK}\right)}}{\sum_{n=0}^N \sum_{s=0}^S \exp\left(\frac{r_{ns,t}}{vK}\right)}} \\
 &= \frac{\exp\left(\frac{r_{ns,t+1} - r_{ns,t}}{vK}\right)}{\sum_{n=0}^N \sum_{s=0}^S \left(\frac{\exp\left(\frac{r_{ns,t}}{vK}\right)}{\sum_{n=0}^N \sum_{s=0}^S \exp\left(\frac{r_{ns,t}}{vK}\right)} \right) \frac{\exp\left(\frac{r_{ns,t+1}}{vK}\right)}{\exp\left(\frac{r_{ns,t}}{vK}\right)}} \\
 &= \frac{\exp\left(\frac{r_{ns,t+1} - r_{ns,t}}{vK}\right)}{\sum_{n=0}^N \sum_{s=0}^S \mu_{ns,t}^K \exp\left(\frac{r_{ns,t+1} - r_{ns,t}}{vK}\right)} \\
 &= \frac{\exp\left(\frac{1}{vK} \Delta r_{n's',t}\right)}{\sum_{n=0}^N \sum_{s=1}^S \mu_{ns,t}^K \exp\left(\frac{1}{vK} \Delta r_{ns,t}\right)}.
 \end{aligned}$$

Equilibrium Conditions in Time Differences

This section presents a set of equilibrium conditions in time differences to be used in the solution algorithm. Let $\hat{x}_t = \frac{x_{t+1}}{x_t}$ denote the change of a variable in relative time differences, let $\Delta x_t \equiv (x_{t+1} - x_t)$ denote the first time difference of a variable.

The unit cost of an input bundle:

$$\hat{\chi}_{ns,t+1} = \left[(\hat{r}_{ns,t+1})^{\xi_n} (\hat{w}_{ns,t+1})^{1-\xi_n} \right]^{\gamma_{ns}} \prod_{s'=1}^S \left[\hat{P}_{ns',t+1} \right]^{\gamma_{ns,s'}}. \quad (\text{A.4})$$

Price index:

$$\hat{P}_{ns',t+1} = \left[\sum_{n'=0}^N \pi_{ns',n',t} (\hat{\chi}_{n's,t+1} \hat{\tau}_{ns',n',t+1})^{-\theta} \left(\hat{A}_{n's,t+1} \right)^{\theta \gamma_{n's}} \right]^{-1/\theta}. \quad (\text{A.5})$$

Trade shares:

$$\hat{\pi}_{ns',n',t+1} = \left(\frac{\hat{\chi}_{n's,t+1} \hat{\tau}_{ns',n',t+1}}{\hat{P}_{ns',t+1}} \right)^{-\theta} \left(\hat{A}_{n's,t+1} \right)^{\theta \gamma_{n's}} \quad (\text{A.6})$$

Market clearing in final goods

$$X_{ns,t+1} = \sum_{s'=1}^S \gamma_{ns',s} \sum_{n'=0}^N \pi_{n's',n,t+1} X_{n's',t+1} + \alpha_s (1 - \lambda) \sum_{s'=1}^S y_{ns',t+1} L_{ns',t+1}, \quad (\text{A.7})$$

where

$$y_{ns,t+1} = w_{ns,t+1} + P_{n,t+1} R_{t+1} a_{ns,t+1}, \quad (\text{A.8})$$

and

$$a_{ns,t+1} = \frac{\sum_{n'=0}^N \sum_{s'=0}^S \mu_{ns',n',t} \lambda \left(\frac{w_{n's',t}}{P_{n',t}} + R_t a_{n's',t} \right) L_{n's',t}}{\sum_{n'=0}^N \sum_{s'=0}^S \mu_{ns',n',t} L_{n's',t}}, \quad (\text{A.9})$$

$$R_{t+1} = \left(\sum_{n=0}^N \sum_{s=1}^S r_{ns,t+1} \mu_{ns,t+1}^K \right) \frac{\sum_{n=0}^N \sum_{s=1}^S a_{ns,t+1} L_{ns,t}}{\sum_{n'=0}^N \sum_{s'=1}^S P_{n',t+1} \sum_{n=1}^N \sum_{s=1}^S \mu_{n's',ns,t} a_{ns,t+1} L_{ns,t}}. \quad (\text{A.10})$$

Migration share:

$$\hat{\mu}_{n's',ns,t+1} = \frac{\exp \left[\frac{1}{v} (\beta \Delta V_{n's',t+2} - \Delta \kappa_{n's',ns,t+1}) \right]}{\sum_{n'=0}^N \sum_{s'=0}^S \mu_{n's',ns,t} \exp \left[\frac{1}{v} (\beta \Delta V_{n's',t+2} - \Delta \kappa_{n's',ns,t+1}) \right]}, \quad (\text{A.11})$$

where the value function is defined in the following expression:

$$\exp \left(\frac{1}{v} \Delta V_{ns,t+1} \right) = \exp \left(\frac{1-\lambda}{v} \Delta \left(\frac{w_{ns,t+1}}{P_{n,t+1}} \right) \right) \sum_{n'=0}^N \sum_{s'=0}^S \mu_{n's',ns,t} \exp \left(\frac{\beta}{v} \Delta V_{n's',t+2} \right). \quad (\text{A.12})$$

Labor allocation dynamics

$$L_{ns,t+1} = \sum_{n'=0}^N \sum_{s'=0}^S \mu_{ns,n's',t} L_{n's',t}. \quad (\text{A.13})$$

Capital share:

$$\hat{\mu}_{nst+1}^K = \frac{\exp\left(\frac{1}{v^K} \Delta r_{ns,t}\right)}{\sum_{n=0}^N \sum_{s=1}^S \mu_{ns,t}^K \exp\left(\frac{1}{v^K} \Delta r_{ns,t}\right)}. \quad (\text{A.14})$$

Capital allocation dynamics:

$$K_{ns,t+1} = \mu_{ns,t+1}^K \sum_{n=0}^N \sum_{s=1}^S a_{ns,t+1} L_{n,t}. \quad (\text{A.15})$$

Finally, labor market clearing condition

$$\hat{w}_{ns,t+1} \hat{L}_{ns,t+1} w_{ns,t} L_{ns,t} = \gamma_{ns} (1 - \xi_n) \sum_{n'=0}^N \pi_{n's,n,t+1} X_{n's,t+1} \quad (\text{A.16})$$

and

$$\hat{r}_{ns,t+1} \hat{K}_{ns,t+1} r_{ns,t} K_{ns,t} = \gamma_{ns} \xi_n \sum_{n'=0}^N \pi_{n's,n,t+1} X_{n's,t+1}. \quad (\text{A.17})$$

A.7 Solution Algorithm

Part I: Solving for the baseline equilibrium

The baseline equilibrium corresponds to the situation where, given initial allocation, there are no policy changes in the economy from period 0 onward. The algorithm proceeds as follows:

0. Take as given v and v^K .
1. Initiate the algorithm at $t = 0$ with a guess for the path of $\{\Delta V_{ns,t+1}^{(0)}\}$, where the superscript (0) denotes it is an initial guess. The path should converge to 0 for sufficiently large T . Take as given the initial allocation in the economy.
2. Solve for the path of $\{\mu_{n's',ns,t+1}\}$ using equation A.11.
3. Solve for the path $L_{ns,t+1}$ using equation A.13.
4. Guess a sequence $\{R_t^{(0)}\}$.
5. Based on the labor path and initial capital allocation, solve for the temporary equilibrium:
 - a) For each $t \geq 0$, given $\hat{L}_{ns,t+1}$ and aggregate savings $\sum_{n=0}^N \sum_{s=1}^S \lambda_n y_{ns,t} L_{ns,t}$, guess a value for $\hat{w}_{ns,t+1}$ and $\hat{r}_{ns,t+1}$.
 - b) Obtain $\hat{\chi}_{ns,t+1}$, $\hat{P}_{ns',t+1}$, $\hat{\pi}_{ns,n',t+1}$ using equations A.4, A.5, and A.6.

- c) Solve for $\widehat{\mu}_{ns,t+1}^K$ from A.14.
- d) Solve for $a_{ns,t}$ from A.9 and $a_{ns,0}$.
- e) Solve for $K_{ns,t+1}$ from A.15. This determines capital allocation for the next period.
- f) Obtain $y_{ns,t+1}$ and $X_{ns,t+1}$ from equation A.8 and A.7.
- g) Check if the labor and capital market is in equilibrium in equations A.16 and A.17. If not, go back to step a) and adjust the initial guesses until the factor markets clear.
- h) Repeat steps a) through e) for each period.
- 6) Solve for a new path $\{R_t^{(1)}\}$ from equation A.10.
- 7) Check if $\{R_t^{(1)}\} \simeq \{R_t^{(0)}\}$. If not, go back to step 4 and update the initial guess with $\{R_t^{(1)}\}$.
- 8) Solve backwards for a new path $\{\widehat{V}_{ns,t+1}^{(1)}\}$ using equation A.12, where the superscript (1) denotes an updated path.
- 9) Check if $\{\Delta V_{ns,t+1}^{(1)}\} \simeq \{\Delta V_{ns,t+1}^{(0)}\}$. If not, go back to step 1 and update the initial guess with $\{\Delta V_{ns,t+1}^{(1)}\}$.

Part II: Solving for the counterfactual equilibrium

Similar to Part I, except that I need to input the estimated changes in fundamentals first.