Intranational Risk Sharing and Its Determinants¹

Chun-Yu Ho²* Wai-Yip Alex Ho³ Dan Li⁴

First Version: November 23 2009

This Version: December 16, 2009

Abstract

This paper develops an empirical framework to examine the degree of consumption risk sharing across cities. Using a unique dataset on retail sales, output and other information of about 200 Chinese cities, we report that the aggregate component accounts only for 13-22% of fitted city consumption growth fluctuations and the welfare gain from eliminating idiosyncratic shocks is larger than that presented in the literatures. Moreover, we show that the degree of consumption risk sharing of a city depends on that of its residing province, which suggests that domestic borders affect risk sharing. A larger city size promotes risk sharing, but cities process higher volume of freight and produce more non-tradable goods are weaker in risk sharing.

Keywords: Consumption risk sharing, Border effect, City, China **JEL classifications**: E21, F15, R11

¹ We thank Qianying Chen, Cedric Tille, Shang-Jin Wei, Eric van Wincoop, seminar participants in Georgia Institute of Technology, Hong Kong University of Science and Technology for helpful comments and suggestions. The views and analysis expressed in this paper are those of the authors, and do not necessarily represent the views of the Hong Kong Monetary Authority.
² Georgia Institute of Technology. Email: <u>chunyu.ho@econ.gatech.edu</u>; URL: <u>http://www.prism.gatech.edu/ch033</u>;

³ Boston University and Hong Kong Monetary Authority. Email: <u>awyho@hkma.gov.hk</u>; Address: Market Research Division, 55/F, Two International Finance Centre, 8 Finance Street, Central, Hong Kong.

⁴ Fudan University. Email: <u>danli1981@fudan.edu.cn</u>; URL: <u>http://www.danli-fudan.cn</u>; Address: School of Economics, Fudan University, Shanghai, P.R.China.

1. Introduction

Although globalization attracts a wealth of discussion from academics and media, empirical researches consistently suggest that international risk sharing is still limited (Obstfeld 1994).⁵ Encouragingly, empirical literatures on intranational risk sharing report that, even though there is incomplete risk sharing within a country, the degree of risk sharing within a country is better than that across countries (Crucini, 1999). While the availability of provincial level data allow researchers to explore risk sharing within a country, data aggregation at provincial level masks the consumption fluctuations at city level or below.

In this paper, we develop and estimate a model of incomplete risk sharing at city level. Even though there is a vast literature on intranational risk sharing, those studies usually estimate the degree of risk sharing by using one lower sub-nation level data, i.e., province or state level data. Since most countries do not report figures on consumption or retail sales at city level, it prevents the literature advance to estimation of consumption risk sharing at city level to date. For example, while there is data on income at city level for the U.S. (Crihfield and Panggabean, 1995; Glaeser et al., 1995), figures on retail sales are only available at state level. China, on the other hand, provides a unique dataset at city level that overcomes this problem and allows us to explore risk sharing across cities.

The empirical analysis bases on a newly compiled dataset on retail sales, GDP and other information of about 200 Chinese cities for the period 1990-2006. We show that risk sharing is incomplete across Chinese cities. Variance decomposition indicates that the aggregate component only explain 13-22% of fitted city consumption growth fluctuations, which is lower than the corresponding figures (56-58%) derived from provincial level data. Thus, the welfare gain from eliminating idiosyncratic shocks (14%) is larger than that (2%) obtained

⁵ In this paper, we refer risk sharing to consumption risk sharing only.

from the provincial level data. Moreover, our results indicate that the degree of risk sharing of a city positively relates to that of its residing province, which suggests that provincial borders matter for risk sharing at city level. We also identify that a larger city size promotes risk sharing. On the other hand, cities process a higher volume of freight and produce more non-tradable goods have lower degree of risk sharing. Finally, we show that the empirical results are robust to outlier of sample, measurement errors and specification of income process.

We advance the literatures on intranational risk sharing in two dimensions. First, we extend the models of risk sharing developed in Crucini (1999) and Asdrubali and Kim (2008) to a model with multiple channels of risk sharing. Our structural model fits into the empirical analysis that dataset involves three aggregations levels, namely *aggregate*, *provincial* and *city* levels. Crucini (1999), Hess and Crucini (2000), Athanasoulis and van Wincoop (2001) and Asdrubali and Kim (2008) estimate the degree of intranational risk sharing. Boyreau-Debray and Wei (2005), Xu (2008) and Ho et al. (2009) suggest that experiences from industrialized economies indeed apply to China , a large developing economy. Our paper revisits this issue with city level data and finds that intranational risk sharing is actually worse than that shown with provincial/state level data. Furthermore, existing studies do not analyze the welfare implications of impediments for sharing consumption risks. We exploit the large cross-section of about 200 cities to identify determinants of risk sharing and quantify their welfare implications.

Our paper also contributes to identify a new dimension of the border effect at sub-national level. There is a vast literature on documenting the effect of national border as a trade barrier. Previous studies report the border effect exists in capital flows (Iwamoto and van Wincoop, 2000), prices (Engel and Rogers, 1996, 2001; Parsley and Wei, 1996, 2001), productivity (Vigfusson, 2008) and trade flows (McCallum, 1995; Helliwell, 1996; Anderson

and van Wincoop, 2003 between Canada and the U.S.; Nitch, 2009 for European Union countries; Wei, 1996 for OECD countries; Wolf, 2009 for Germany). In addition to the border effect across countries, recent studies also find sizable domestic border effects for prices across Canadian provinces (Ceglowski, 2003), and trade flows across Chinese provinces (Poncet, 2003, 2005) and across 48 contiguous U.S. states (Wolf, 2000; Hillberry and Hummels, 2003; Millimet and Osang, 2007).⁶ Strikingly, Coughlin and Novy (2009) suggest that domestic border effect is larger than national border effect. However, Wolf (2000) notes that it is difficult to derive welfare consequence for the domestic border effects on trade flows because it can arise from trade barriers or optimal location choice of production process. We add to the discussion by showing that the domestic border matters for risk sharing. Cities are more capable to share consumption risks and enjoy higher welfare if they locate in provinces with higher degrees of risk sharing.

This paper also sheds a new light on market integration in China. Young (2000), Naughton (2003) and Bai et al. (2004) argue that Chinese domestic markets become less integrated because production structure becomes less specialized after the economic reform. Furthermore, Poncet (2003, 2005) show that provincial borders matter for inter-provincial trade flows. We complement the literatures by suggesting markets for sharing consumption risks are also fragmented. The proportion of fitted consumption growth fluctuations across Chinese cities accounted by the common component is close to that across industrialized economies.

The rest of the paper is organized as follows. Section 2 first discusses the data and descriptive statistics. Section 3 outlines the model and empirical framework. Section 4 and 5 report the empirical model and results, respectively. Section 6 provides robustness checks. We conclude in section 7.

⁶ Our term domestic border is equivalent to state, provincial or intranational border used in the literatures.

2. Data and Descriptive Statistics

The data on Chinese cities are obtained from the Fifty Years of Cities in New China (year 1990-1998) and various issues (1999-2006) of China City Statistics Yearbooks, whereas the provincial level data are extracted from the China Data Center in the University of Michigan. Our dataset is derived from the national income account as in those used in Boyreau-Debray and Wei (2005) and Ho et al. (2009).⁷ The sample period is from 1990-2006 at annual frequency.

Similar to the literature on risk sharing (Crucini 1999; Crucini and Hess 2000), we use retail sales and GDP as proxies for consumption and income, respectively.⁸ City population is used to compute consumption and GDP per capita. Provincial consumer price index (CPI) is used to convert the consumption and GDP per capita to real Yuan terms at year 2000. The sample contains data for the Chinese aggregate, 24 provinces and 192 cities located in those provinces. We exclude two provinces, namely Hainan and Tibet, because we do not have complete data for any city in those in those provinces. We exclude four provincial level municipalities (Beijing, Chongqing, Shanghai and Tianjin). Even though these four cities are geographically defined as *city*, their governing and political structures are identical to a province, which is inappropriate for our analysis. Our sample of cities is representative as the total population across those cities is 49.2% and 61.5% of total population of China in year 1990 and 2006, respectively. The provincial distribution of city is shown in Appendix 1.

Turning to the descriptive statistics, we start with the average real consumption and GDP per capita (consumption and GDP hereafter) growths at city and provincial levels shown in

 $^{^{7}}$ Xu (2008) employs provincial level data from the surveys of urban and rural households to analyze consumption risk sharing across provinces, but that dataset do not have information at city level.

⁸ City GDP involves the output of multi-city firm that is generated in other cities which in turn shares part of the income risks.

Table 1.⁹ The average GDP growths at both levels are about 9%, which are close to that at aggregate level (10%). The corresponding figures for consumption growth are 7-8%, whereas the growth rate of consumption at aggregate level is 9%. Even though the average growth rates of our sample are slightly lower than that at aggregate level, it is not unexpected. Since we do not have small cities in our sample and since small cities may grow at a higher rate according to the convergence hypothesis, missing out small cities drags down average growth rate of our sample slightly as a result. The average of standard deviations of GDP and consumption growth at city level are 10%, which are higher than those (5%) at provincial level. It suggests that consumption and GDP growths are more volatile at city level, and parts of those fluctuations are cancelled out at provincial level due to data aggregation. Moreover, standard deviations of those measures (shown in brackets) across cities are higher than those across provinces, which indicate that the heterogeneity across cities is wider than that across provinces.

Although we use retail sales as a proxy for consumption, our estimates on standard deviation of consumption and consumption correlation (with aggregate consumption growth) corroborate with those in the literatures (Boyreau-Debray and Wei, 2005; Xu, 2008; Ho et al., 2009). For the standard deviation of consumption growth at provincial level, our result (5%) lies within the range (4-6%) reported in the literatures. Furthermore, the consumption correlation at provincial level (0.69) shown in Table 2 is comparable to those reported in Xu (2008, Table 1), but higher than those documented in the other two studies.¹⁰ It suggests that retail sales are reliable proxies for consumption in our sample.

Furthermore, following Obstfeld (1994), Crucini and Hess (2000) and other previous studies, we compute the unconditional tests for risk sharing. When a city/province engages in

 $^{^{9}}$ The term "average" of a variable X in this paragraph refers to the cross-section average of the time-series average (or standard deviation or correlation with aggregate) for each city and province in our sample.

¹⁰ Our data for consumption are different from total consumption in Boyreau-Debray and Wei (2005) and household consumption in Ho et al. (2009).

perfect risk sharing, its consumption growth should perfectly correlate with that of the aggregate. We measure the degree of risk sharing as the correlation between consumption growths of city *j* and the aggregate, which is denoted by ρ_j . Similarly, we compute the correlation between consumption growths of province *p* and the aggregate, which is denoted by ρ_p , to measure the extent of risk sharing of province *p*.

Table 2A reports the average correlation of consumption growth between a city/province with that of the aggregate. The consumption correlation is less than unity, which suggests incomplete risk sharing. Importantly, the correlation at city level is lower than that at provincial level, which is also shown in Figure 1 and 2. It is consistent with the pattern of standard deviations shown in Table 1 and provides another evidence for showing that part of the idiosyncratic consumption fluctuation at city level is cancelled out in the provincial figures due to data aggregation.

3. A Model of Risk Sharing

In this section, we outline a framework of incomplete consumption risk sharing a la Crucini (1999). We assume that there are J identical cities in each province p = 1, ..., P. There is a representative household in each city j = 1,...,J. City j owns a stochastic endowment of income, Y_{jt} , in each period t. We assume that there are two channels of risk-sharing, one is pooling incomes at the national level and the other is pooling incomes at the provincial level (i.e. sharing with households in the *same* province). According to the theory of incomplete risk sharing, risk-averse households want to pool all of their income at the aggregate level, which can minimize her income fluctuations. However, the presence of transaction costs prevents households from sharing the income at the aggregate level and makes them share part of the income at the provincial level to lower the income fluctuations. The transaction costs also

keep households from allocating all the income at the provincial level. There are several explanations behind these costs: Trade barrier for inter-provincial trade, missing market for trading asset claims of other provinces and home bias in buying local assets and consumption goods. We will explore the determinants of risk sharing in the later sections.

Accordingly, we assume that household *j* sells a fraction of its income stream λ^a for a claim to the pooled income streams of all JP cites (aggregate pool, hereafter). Household *j* also sells a fraction of its income stream λ^p for a claim to the pool income streams of all *J* cities in the same province only (provincial pool, hereafter).¹¹ According to this rule of allocation, we have the flow of disposable income after sharing for each household as follows

$$\widetilde{Y}_{jt} = \lambda^a Y_t^a + \lambda^p Y_t^p + (1 - \lambda^a - \lambda^p) Y_{jt}$$

where

$$Y_t^a \equiv \frac{1}{JP} \sum_{p=1}^P \sum_{j=1}^J Y_{jt} \quad \text{and} \quad Y_t^p \equiv \frac{1}{J} \sum_{j=1}^J Y_{jt}$$

The disposal income of each household can be decomposed into three terms: The first term is the income claim from the aggregate pool, the second term is the claim from the provincial pool where the city locates and the last term is the current income of the city.

Suppose further that those households can smooth their consumptions by borrowing and lending freely at a fixed exogenous real interest rate, the change in level of household consumption is given by

$$\Delta C_{jt} = (1 - \beta) \sum_{h=0}^{\infty} \beta^h \Big[E_t \widetilde{Y}_{jt+h} - E_{t-1} \widetilde{Y}_{jt+h} \Big].$$

The definition of national aggregate consumption per capita gives

$$C_t^a \equiv \frac{1}{JP} \sum_{p=1}^P \sum_{j=1}^J C_{jt}$$

¹¹ We also follow Crucini (1999) and assume that households are *ex ante* identical and choose the same sharing parameters for the national pool and provincial pool.

$$\begin{split} \Delta C_{t}^{a} &= \frac{1}{JP} \sum_{p=1}^{P} \sum_{j=1}^{J} \Delta C_{jt} \\ &= \frac{1}{JP} \sum_{p=1}^{P} \sum_{j=1}^{J} (1-\beta) \sum_{h=0}^{\infty} \beta^{h} \Big[E_{t} \widetilde{Y}_{jt+h} - E_{t-1} \widetilde{Y}_{jt+h} \Big] \\ &= \frac{1}{JP} \sum_{p=1}^{P} \sum_{j=1}^{J} (1-\beta) \sum_{h=0}^{\infty} \beta^{h} [E_{t} [\lambda^{a} Y_{t+h}^{a} + \lambda^{p} Y_{t+h}^{p} + (1-\lambda^{a} - \lambda^{p}) Y_{jt+h}] \\ &- \frac{1}{JP} \sum_{p=1}^{P} \sum_{j=1}^{J} (1-\beta) \sum_{h=0}^{\infty} \beta^{h} E_{t-1} [\lambda^{a} Y_{t+h}^{a} + \lambda^{p} Y_{t+h}^{p} + (1-\lambda^{a} - \lambda^{p}) Y_{jt+h}] \Big] \\ &= (1-\beta) \sum_{h=0}^{\infty} \beta^{h} \Big[E_{t} Y_{t+h}^{a} - E_{t-1} Y_{t+h}^{a} \Big] \end{split}$$

Consequently, the level change of consumption process of household is given by

$$\Delta C_{jt} = \lambda^{a} \Delta C_{t}^{a} + \lambda^{p} (1 - \beta) \sum_{h=0}^{\infty} \beta^{h} \Big[E_{t} Y_{t+h}^{p} - E_{t-1} Y_{t+h}^{p} \Big] + (1 - \lambda^{a} - \lambda^{p}) (1 - \beta) \sum_{h=0}^{\infty} \beta^{h} \Big[E_{t} Y_{jt+h} - E_{t-1} Y_{jt+h} \Big]$$
(1)

Equation (1) implies that the individual consumption change responses not only to its own permanent income innovations, but also to the permanent income innovations to the province that the city locates. Since the provincial level of consumption per capita is defined as

$$C_t^p \equiv \frac{1}{J} \sum_{j=1}^J C_{jt} ,$$

which implies that the derived change of consumption per capita at provincial level is

$$\Delta C_{t}^{p} = \lambda^{a} \Delta C_{t}^{a} + (1 - \lambda^{a})(1 - \beta) \sum_{h=0}^{\infty} \beta^{h} \left[E_{t} Y_{t+h}^{p} - E_{t-1} Y_{t+h}^{p} \right]$$
(2)

which returns to the incomplete risk-sharing model with single aggregation level as in Crucini (1999).

4. Empirical Model

We utilize the structural model outlined in the previous section to quantify the economic significance of our results. Following Obstfeld (1994) and Crucini (1999), we log-linearize

structural equations of the model to obtain the empirical model:

$$\Delta \log C_{jt} = \varphi_j^0 + \varphi_j^a \Delta \log C_t^a + \varphi_j^p \Delta \log Y P_t^p + \varphi_j^c \Delta \log Y P_{jt} + u_{jt}$$
(3)

where $\Delta logYP_{jt}$ is the log-linear approximated expected infinite sum of permanent income innovations of city *j* in period *t*, $\Delta logYP^{p}_{t}$ is the log-linear approximated expected infinite sum of permanent income innovations of province *p* (where city *j* locates) in period t and u_{jt} an independently and identically distributed (i.i.d.) measurement error (or taste shock as interpreted in Mace (1991)). Parameter φ^{a}_{j} characterizes the degree of risk sharing at national level achieved by city *j*, whereas parameter φ^{p}_{j} and φ^{c}_{j} inform impacts of provincial and local resource constraint at provincial and city levels on risk of consumption, respectively. Under complete risk sharing at the national level, the parameter φ^{a}_{j} takes the value one and φ^{p}_{j} and φ^{c}_{j} equal to zero. We estimate equation (3) in for each city by Ordinary Least Square (OLS) Method to obtain city specific estimates of risk-sharing.

In addition to the measures at city level, we estimate similar measures at provincial level using equation (2) as follows

$$\Delta \log C_t^p = \omega_p^0 + \omega_p^a \Delta \log C_t^a + \omega_p^p \Delta \log Y P_t^p + u_{pt}$$
⁽⁴⁾

where u_{pt} is an i.i.d. measurement error. We estimate this equation with OLS method for each province as we did for equation (3) for each city. This model is used to contrast the degree of risk sharing obtained from datasets at alternative aggregation levels. Without aggregation bias, the coefficient on aggregate consumption growth from equation (3) should be close to that from equation (4). According to our model, we impose the restrictions of (1) $\varphi_j^a + \varphi_j^p + \varphi_j^c = 1$ and (2) $\omega_p^a + \omega_p^p = 1$.

Since there is no consensus on the parametric form of income growth, we employ three different specifications to estimate city and province income process, which include specification of unit root, persistent growth and VAR with aggregate and provincial income growth. The results obtained from assuming unit root city income growth and province income growth are first discussed as main result in section 5. Results from the other two specifications are discussed in robustness check in section 6.

The large number of cities in our sample provides an opportunity for identifying the determinants for risk sharing which usually cannot be done with provincial level data or can only be done with imprecision. We utilize this large sample size advantage to investigate determinants of risk-sharing in the last subsection in section 5.

5. Empirical Results

We first discuss parameter estimates of empirical models (3) and (4) under the assumption of unit root income for province and city in this section. Then, we compare the variance decompositions of those two models to understand how well intranational risk sharing is. We close this section by investigating the determinants of risk sharing.

5.1 Parameter Estimates

We report the descriptive statistics of estimates on $\{\varphi_{j}^{0}, \varphi_{j}^{a}, \varphi_{j}^{p}, \varphi_{j}^{c}\}$ of equation (3) and $\{\omega_{p}^{0}, \omega_{p}^{a}, \omega_{p}^{p}\}$ of equation (4) in Table 3A and 3B. Recall that φ_{j}^{a} and ω_{p}^{a} represent the degree of risk sharing with nation at city and provincial levels, respectively. The average degree of risk sharing at provincial level is 0.72, which is higher than that at city level (0.60). Moreover, our estimate from provincial level data is close to that (0.76) reported in Xu (2008) for Chinese provinces during 1990-2004.

The coefficients on φ_{j}^{p} and φ_{j}^{c} are about zero and 0.4, respectively. The provincial resources do not impose a tight constraint on the city consumption growth fluctuations. It is because the fraction of income allocated to the provincial pool is insignificant (φ_{j}^{p} =0). We

suggest that the (regulated) low return on deposit discourages household's incentive in allocating resources to the provincial pool. The coefficient on ω^{p}_{p} is about 0.28, which suggests that the local resources constraint is binding at the provincial level but the extent is less than that at the city level.

5.2 How Well Is Intranational Risk Sharing?

Since there is incomplete risk sharing as shown, another way to characterize the degree of risk sharing is doing variance decomposition to the consumption growth. We employ equation (3) to decompose the variance of fitted city consumption growth into six terms as follow

$$Var(\Delta \log \hat{C}_{jt}) = \hat{\varphi}_{j}^{a^{2}} Var(\Delta \log C_{at}) + \hat{\varphi}_{j}^{p^{2}} Var(\Delta \log Y_{pt}) + \hat{\varphi}_{j}^{c^{2}} Var(\Delta \log Y_{jt}) + 2\hat{\varphi}_{j}^{a} \hat{\varphi}_{j}^{p} Cov(\Delta \log C_{at}, \Delta \log Y_{pt}) + 2\hat{\varphi}_{j}^{a} \hat{\varphi}_{j}^{c} Cov(\Delta \log C_{at}, \Delta \log Y_{jt}) + 2\hat{\varphi}_{j}^{p} \hat{\varphi}_{j}^{c} Cov(\Delta \log Y_{pt}, \Delta \log Y_{jt})$$

(6)

This specification provides further insight than those of Crucini (1999) and Xu (2008) because we can decompose the variance of fitted consumption growth into aggregate (1st term), provincial (2nd, 4th and half of the 6th terms) and city (3rd, 5th and half of the 6th terms) components.¹² Table 4A presents the results of such variance decomposition at the average coefficients on { ϕ^a_j , ϕ^p_j , ϕ^c_j } of equation (3). The aggregate component accounts for only 13% of the variance of fitted consumption growth, while the rest is mainly driven by the city component. The provincial component only accounts for a trivial fraction of consumption growth fluctuations.

Similarly, we use equation (4) to decompose the variance of the fitted provincial

¹² We assign the contribution of last term into provincial and city components equally. Since this term is small, the rule of division does not affect our results significantly.

consumption growth into three terms as follow

$$Var(\Delta \log \hat{C}_{pt}) = \hat{\omega}_p^{a^2} Var(\Delta \log C_{at}) + \hat{\omega}_p^{p^2} Var(\Delta \log Y_{pt}) + 2\hat{\omega}_p^{a} \hat{\omega}_p^{p} Cov(\Delta \log C_{at}, \Delta \log Y_{pt})$$

This specification is close to those of Crucini (1999) and Xu (2008) but we group the provincial and covariance terms into one group for our discussion. Table 4B presents the results of such variance decomposition at the average coefficients on $\{\omega_{p}^{a}, \omega_{p}^{p}\}$ of equation (4). Most of the variance of the fitted consumption growth (58%) is explained by the aggregate component, while the rest (42%) is determined by the provincial component. Our results at the provincial level are consistent with those in Xu (2008) in which the aggregate component accounts for 52-74% of the fitted consumption growth fluctuations across Chinese provinces.

Our results on the variance decomposition exercise with city level data indicate that consumption growth is less driven by the aggregate factor than those estimated with provincial/state level data for Canada (68-72%), China (52-74%) and the U.S. (78-92%). The results are close to those of G-7 countries report in Crucini (1999), in which about 14-34% of the national consumption growth is accounted by the aggregate component. Consistent with our findings, Poncet (2003, 2005) argue that the trade barriers due to borders among Chinese provinces are higher than those within the US and those within Canada, but similar to the national borders among countries in EU, and between Canada and the US. We suggest that the degree of risk sharing within China (intranationally, at city level) is actually similar to those across countries at international dimension, and the market for sharing consumption risks is fragmented in China.

Moreover, we gauge the welfare gain from eliminating city-specific and idiosyncratic consumption growth fluctuations. van Wincoop (1994) shows that, if consumption growth follows a random walk and households have constant relative risk aversion (CRRA) utility, the welfare gain from a reduction in consumption growth volatility is

$$\frac{-\frac{1}{2}\gamma d\sigma_{\Delta\log C}^2}{r-\overline{\mu}}$$
(7)

We denote μ as the expected consumption growth rate and $\sigma_{\Delta \log C}^2$ as the variance of consumption growth. The parameters $\overline{\mu} = \mu - (0.5\gamma \sigma_{\Delta \log C}^2)$ and $r = (1/\beta - 1) + \gamma \overline{\mu}$ represent the risk-adjusted growth rate and the risk-free rate, respectively. We follow Crucini and Hess (2000) and Xu (2008) to set the coefficient of relative risk aversion γ =4 and the discount rate β =0.99, and calibrate μ =0.07 and $\sigma_{\Delta \log C}$ =0.11 according to Table 1. The risk-free rate, r, is calibrated to 19.3%. Since the interest rate is regulated in China, the market interest rate cannot reflect the cost of capital. According to Bai et al. (2006), the average marginal product of capital (MPK) between 1993 and 2005 is 21%, which is slightly higher than our estimate. Since their estimates are estimated with firm-level data, thus the return on capital is higher than that provided by the hypothetical risk-free bond.

Table 4B reports households are willing to pay 3% of their consumptions to eliminate the province-specific and idiosyncratic consumption growth fluctuations. Our provincial result on the welfare gain is smaller than that (7.6%) reported in Xu (2008) because we calibrate the interest rate to 19.3% instead of 7% as in Xu (2008). More importantly, our city result in Table 4A indicates that households are willing to pay 17% of their consumptions to eliminate the city-specific and idiosyncratic consumption growth fluctuations. Our estimate on the welfare gain is also larger those reported in Crucini and Hess (2000) for the Canadian, Japanese and U.S. households.

5.3 What Affect(s) Risk Sharing?

Since the degree of risk sharing depends on the set of coefficients { ϕ^a_j , ϕ^p_j , ϕ^c_j } of the structural model. We postulate that those three coefficients are functions of city-specific factors. Specifically, we estimate three semi-log models in the following form for k = a, p and

$$\varphi_{j}^{k} = \ln X_{j} \theta_{k} + \varepsilon_{j} \tag{5}$$

The number of observations is equal to the number of cities. We assume ε_j is an i.i.d. error and estimate those three equations with OLS.

The dependent variable in equation (5) is each of those three estimated risk-sharing parameters obtained from equation (3). The explanatory variables include the degree of risk sharing of its residing province and a set of city-specific variables in year 1990. The degree of risk sharing of a province is measured by the unconditional time-series correlation between consumption growth of a province and that of aggregate, ρ_p . We use a set of city-specific variables in year 1990 to explore the determinants of risk sharing across cities. Following the empirical economic growth literatures, we use the initial year of conditioning variables to avoid the potential endogeneity bias. The set of variables includes: (1) GDP per capita to measure the economic development; (2) Population to measure the market size; (3) Ratio of investment to GDP (I/Y) and (4) Ratio of government expenditures to GDP (G/Y) to characterize the composition of GDP; (5) Ratio of saving deposit to GDP (SD/Y) to measure the development of financial market; (6) Average wage to measure the human capital; (7) Percentage of GDP contributed by secondary and (8) Percentage of GDP contributed by tertiary industry to characterize the industrial structure; (9) Number of passengers carried through highway and (10) tons of goods carried through highway to measure the mobility of population and goods, respectively; (11) Minimum distance to either Shanghai or Shenzhen to measure transaction costs to reach capital and coastal markets;¹³ (12) A dummy variable of

¹³ The distance of each city to Shanghai (in miles) is calculated based on the latitude and longitude of cities level using the formula: SQRT $(69.1^2*(Lat_2-Lat_1)^2+53^2(Long_2-Long_1)^2)$, where SQRT denotes square-root operator, the subscript 1 and 2 represent the beginning and end points of distance under calculation. Similarly, we compute the distances between each city and Shenzhen.

Special Economic Zone (SEZ) for 5 special economic zones (designated by policy) and 14 open coastal cities to capture effects of preferential development policies and proximity to engage in international trade.¹⁴ Appendix 2 presents the descriptive statistics of those variables.

Table 5 reports parameter estimates of equation (5). It shows that coefficients of the structural model (equation (3)) are functions of part of city attributes. Based on estimation results of equation (5), we perform counterfactual experiments with variables that are significant at 10% level or higher as follow. We increase each of those significant variables by 1% and examine its impact on those three risk sharing coefficients. The original and counterfactual sets of coefficients are reported in Table 6. To analyze the impact of those hypothetic changes, we contrast results from variance decomposition with original and counterfactual coefficients using equation (6) and reports them in Table 7.

The coefficient on provincial risk sharing is positive and significant in the regression equation for φ^{p}_{j} but negative and significant in the equation for φ^{c}_{j} . However, it is not significant in the regression equation for φ^{a}_{j} . It informs that the degree of risk sharing of city *j* at national level is independent from its residing province but the degree of risk sharing of city *j* at provincial level is affected by the ability of its residing province in doing sharing with other provinces. We argue that it is a sign of existence of border effect. Even though the provincial border does not affect the city's ability to share risk at the national level, it does affect the city's ability to share risk at the provincial level. In particular, a positive coefficient here indicates that if a province has better risk sharing arrangements with other provinces, it benefits the cities within its provincial boundary through inducing cities within boundary to share risks. Table 7 reports that a rise in provincial risk sharing results in a higher aggregate and provincial components in the variance of fitted consumption growth.

¹⁴ Five special economic zones are Shantou, Shenzhen, Zhuhai, Xiamen and the Hainan province. 14 open coastal cities include Beihai, Dalian, Fuzhou, Guangzhou, Qinhuangdao, Qingdao, Lianyungang, Nantong, Ningbo, Shanghai, Tianjin, Wenzhou, Yantai and Zhanjiang.

An increase in population size leads to a smaller coefficient on φ^c_{j} . The market infrastructure of a larger city is more conducive to risk sharing which dampens city-specific shocks. Our results complement findings in Au and Henderson (2006) who find that undersized cities have limited productivity growth due to slower agglomeration. We further show that lowering the size of a city can reduce its capability of engaging in risk sharing. An increase in population size leads to a higher aggregate and provincial components in the variance of fitted consumption growth.

The coefficients on $\phi^a{}_j$ and $\phi^p{}_j$ become higher and smaller when more goods are transported through highway, respectively. Households are more likely to share risks across provinces rather than within provinces when the transaction cost for inter-provincial trade decreases. Cities with more freight per capita have larger aggregate components at the expense of provincial components. On the other hand, we show that a larger portion of city GDP contributed by tertiary sector results in a higher coefficient on φ^{c}_{i} . It indicates that cities with a higher share of tertiary industry, which will produce a higher share of non-tradable goods (e.g. services), leads to weaker risk sharing. This is consistent with theories on market completeness. Under the complete market hypothesis, if markets are complete, the share of non-tradable goods does not matter for consumption risk as there are enough independent assets that enable cities to fully insure their consumption risk. However, if markets are incomplete, then the share of non-tradable goods matters for consumption risk. Since cities with higher share of non-tradable goods generally face higher income risk as markets are incomplete and there are some states of nature that cannot be covered by markets. It makes those cities cannot fully insure away the idiosyncratic risk. Therefore, higher the share of non-tradable goods induces a lower degree of risk sharing. Consequently, a larger share of tertiary sector in GDP composition increases the city component and hence the variance of fitted consumption growth is subject to city-specific shocks only.

Since there are multiple effects of each counterfactual change, the welfare implications of the hypothetical changes are complex. For example, aggregate and city components can rise in tandem in response to a change in city attribute. To provide an evaluation of each hypothetical change, we examine the welfare change due to the net change in variance of fitted consumption growth according to equation (7). The results are reported in Table 7 under the column Δ Welfare.

When there is a 1% increase in the degree of risk sharing of a province, it improves the welfare of its cities by 2%. To put our results into perspective, let's consider two cities which are identical but located in two adjacent provinces (Anhui and Zhejiang; both of them are adjacent to Shanghai), which have different degrees of risk sharing, ρ_p . The degree of risk sharing of Anhui and Zhejiang are 0.57 and 0.59, respectively. As a result, the city located in Zhejiang enjoys a higher welfare by 7.4 consumption units than that located in Anhui.

Interestingly, our results echo the literature on market integration in China. The literature on risk sharing and literature on market integration are interrelated because risk sharing can be achieved by trading in credit and goods markets. High trade cost impedes households to participate in credit and good markets to share their consumption risks. Young (2000), Naughton (2003) and Bai et al. (2004) suggest that local protectionism impedes inter-provincial trade after the reform, which increases the frictions in goods markets and hence prevents households from pooling their consumption risks. Protecting local employment and extracting fiscal revenue are two main reasons behind the local protectionism. Our results suggest that protectionism among provinces hinder risk sharing across cities, which reduces households' welfare.

A city experiences a 1% welfare improvement when its population size rises by 1%. A city with larger population can have better infrastructure for sharing consumption risks. It provides another mechanism of welfare gain in addition to the agglomeration effect on output

suggested in Au and Henderson (2006). Our results suggest that migration restrictions reduce risk sharing across cities and households' welfare.

On the other hand, cities with more freight per capita enjoy lower welfare gain. A 1% increase in the ton of goods carried through highways per capita leads to a reduction of 0.5 units of welfare. Even though outputs can be more efficiently transported to other cities when there is a positive productivity shock hits a city, it also allows this city to import more inputs to increase production and hence consumption. Consequently, better logistics system makes the consumption path of a city more pro-cyclical because the effect of city component dominates that of aggregate component. Similarly, there is a substantial welfare loss of 18% for 1% increases in the proportion of GDP produced by tertiary sector. High trading cost of the products produced by tertiary industries imposes high risks on the city. However, the appropriate tradeoff of higher consumption risks should involve a higher growth potential provided by tertiary sector and logistic system.

6. Robustness Checks

We examine the robustness of our result to the outliers in the data by looking into the median estimates. Then, we look into the effects of measurement error and income process on our results.

6.1 Median Estimates

To circumvent the outliers in the panel of cities, we analyze our results with the median estimates instead of the mean estimates. We also estimate the parameters of equation (5) with median regression. Since the regression is based on the conditional median, it reduces the outlier problem of OLS which utilizes the conditional mean in the estimation. In this section,

we report the parameter estimates at the median for equation (3) and (4). We then discuss the results of equation (5) from the median regression and the corresponding results of counterfactual experiment.

The consumption correlation is higher than the output correlation at both levels, which is consistent with the theory of risk sharing. However, the standard deviations of those measures are large relative to the averages. It is hard to conclude that the consumption correlation is higher than the output correlation in a statistical sense. Therefore, we argue that the quantity anomaly (the correlation of consumption growth is lower than that of the output growth) does not complete absent in China at city and provincial levels in our sample period, but the extent is less than those revealed in cross-country (Obstfeld, 1994) and U.S. state level (Hess and Shin, 1998) studies.¹⁵

We report the median, minimum and maximum of the consumption and output correlations in Table 2. The median figures of unconditional test indicate the risk sharing is incomplete at city and provincial levels. Table 3 shows the median degrees of risk sharing at city and provincial levels for the structural model, respectively. The median estimates are close to the mean estimates. Table 4 reports the variance decomposition based on the median coefficients. The city component is still the most important driver (78%) of the variance of fitted consumption growth, whereas the aggregate component accounts for the remaining portion. For the provincial data, the aggregate component accounts for 56% of the variance of fitted consumption growth and the rest is explained by the provincial component. It suggests that our results are robust to outlier observations.

Turning to the determinants of risk sharing, encouragingly, the coefficients on provincial risk sharing, population size, ton of freight per capita and GDP share of tertiary industry of equation (5) are robust to the estimation method. However, the magnitudes of those

¹⁵ Hess and Shin (1998) argue that measurement errors and preference shocks account part of the anomaly, and Ho et al. (2009) discuss the potential effects of measurement errors with a focus on the Chinese data at provincial level.

coefficients are smaller than those from the OLS estimation as indicated in Table 5. Moreover, there are more variables showing results at 10% significant level or below. A city with higher GDP per capita has a smaller coefficient on φ^{p}_{j} , which suggests that more prosperous cities provide better infrastructure and opportunity to share consumption risks, but it also experiences larger city-specific productivity shocks. A city with higher average wage results in a larger coefficient on φ^{p}_{j} and, to a less extent, φ^{a}_{j} . Households with higher human capital are more capable to exploit risk sharing opportunity at either aggregate or provincial levels. Korniotis and Kumar (2008) suggest that risk sharing levels are higher in U.S. states in which investors have higher cognitive abilities or education.

A larger number of passengers travelled through highway increases the coefficient on φ^{p}_{j} and φ^{c}_{j} . More mobile population exacerbates productivity shocks which lower city-specific risk sharing. When there is a positive shock hits a city, it attracts workers from nearby cities to look for employment, which makes the consumption paths of cities become more pro-cyclical. Furthermore, cities are further away from Shanghai or Shenzhen rely more on mechanism provided by its province to share consumption risk, i.e. a higher φ^{p}_{j} . A longer distance to those two cities may impose higher transaction cost for accessing coastal markets and investing in capital markets (Coval and Moskowitz 1999, 2001; Huberman, 2001), which hinders households to trade abroad and hold asset claims in other provinces.

We follow the aforementioned procedure to compute variance decompositions for each hypothetical change and its welfare implication. We reported those results in Table 6 and 7 under the columns Median Regression. Looking into results on welfare change due to those counterfactual experiments, they are different from those obtained from the OLS estimation. The welfare change due to changes in provincial risk sharing, population size, ton of freight and GDP share of tertiary industry become more modest, the welfare changes are 0.2%, 0.7%, -0.4 and -7%, respectively. An increase in the minimum distance to Shanghai or Shenzhen

produces a welfare gain because the city component is reduced. Finally, the counterfactual changes on GDP per capita and passengers carried through highway result in welfare losses because the provincial or city component becomes larger in those cases. However, we suggest that the welfare evaluations with the median estimates are less reliable because the median coefficients of the structural model do not add up to unity in most cases. For instance, the sum of resulting coefficients of hypothetic change on average wage is about 1.5, which increases the variance of fitted consumption growth.

6.2 Measurement Error

We use retail sales to proxy consumption for our empirical analysis, it is expected that measurement error in retail sales may affect our results as in the studies employing U.S. retail sales such as Crucini (1999) and Crucini and Hess (2000). Let C* be the actual consumption, v be the preference shock, and e be the measurement error, the observed consumption growth can be expressed as $\Delta \log C_{jt} = \Delta \log C_{jt}^* + v_{jt} + e_{jt}$. Let Y* be the actual output and χ be the measurement error. The observed income growth can be expressed as $\Delta \log Y_{jt} = \Delta \log Y_{jt}^* + \chi_{jt}$. Hess and Shin (1998) argue that measurement error and preference shock are reasons behind the quantity anomaly shown with U.S. data, i.e. the correlation of consumption growth is lower than that of the output growth. They show that the ratio of correlation of consumption growth to income growth is bounded below by a constant

$$\frac{Corr(\Delta \log C_{jt}, \Delta \log C_{-jt})}{Corr(\Delta \log Y_{jt}, \Delta \log Y_{-jt})} > \frac{1 - \frac{\sigma_v^2 + \sigma_e^2}{\sigma_{\Delta \log C}^2}}{1 - \frac{\sigma_\chi^2}{\sigma_{\Delta \log Y}^2}}$$
(8)

We denote σ_v , σ_e and σ_{χ} as the standard deviations of preference shock, measurement error of consumption growth and measurement error of income growth, respectively. If there is no measurement error in income growth (χ =0), the estimated ratio can be less than one even if

the true value of the ratio is larger than unity.

Table 2 reports that the consumption correlation is higher than the output correlation at both levels, which is consistent with the theory of risk sharing. However, the standard deviations of those measures are large relative to the averages. It is hard to conclude that the consumption correlation is higher than the output correlation in a statistical sense. We argue that the quantity anomaly does not complete absent in China at city and provincial levels in our sample period, but the extent is less than those revealed in cross-country (Obstfeld, 1994) and U.S. state level (Hess and Shin, 1998) studies.¹⁶ Therefore, the problem of measurement error does not hinder our analysis on risk sharing severely.

Furthermore, the city level regression employs the growth rates of retail sales and GDP, which may subject to measurement error and preference shock. If those error and shock (for example, goods and services purchased by households in nearby cities) are not independent of each other, the coefficient on city-specific GDP growth is biased. To reduce the idiosyncrasies of city-specific variables, we aggregate those variables at city level to provincial level as follows

$$C_{rp} = \frac{\sum_{j \in p} C_j}{\sum_{j \in p} POP_j} \qquad Y_{rp} = \frac{\sum_{j \in p} Y_j}{\sum_{j \in p} POP_j}$$

We call those constructed provincial consumption and income as restricted provincial consumption and income. The restricted provincial variables only contain information for the cities in our sample, which are more developed than the remaining cities of the province. The descriptive statistics of restricted provincial consumption and income growths are reported in Table 1C and 2C. Analogously, restricted aggregate consumption and income growths are constructed by summing the data across all cities in our sample.

¹⁶ Hess and Shin (1998) argue that measurement errors and preference shocks account part of the anomaly, and Ho et al. (2009) discuss the potential effects of measurement errors with a focus on the Chinese data at provincial level.

$$C_{ra} = \frac{\sum_{j} C_{j}}{\sum_{j} POP_{j}} \qquad Y_{ra} = \frac{\sum_{j} Y_{j}}{\sum_{j} POP_{j}}$$

If our results on the low degree of risk sharing are driven by the correlated measurement errors and preference shocks of retail sales and GDP growths at city level, the degree of risk sharing in equation (10) will be higher than that in equation (4). On the other hand, the provincial variables aggregate information from cities, which eliminate part of the city-specific and idiosyncratic shocks. If the degree of risk sharing is still low in equation (10), where the restricted aggregate and provincial variables are used, it suggests that the aggregation biases across all sub-provincial units in the provincial variables produce the high degree of risk sharing in Table 3B.

Table 8 reports the descriptive statistics of coefficients for the following equations at restricted city and provincial levels

$$\Delta \log C_{jt} = \varphi_{rj}^{0} + \varphi_{rj}^{a} \Delta \log C_{t}^{ra} + \varphi_{rj}^{p} \Delta \log Y P_{t}^{rp} + \varphi_{rj}^{c} \Delta \log Y P_{jt} + u_{rjt}$$
(9)
$$\Delta \log C_{t}^{rp} = \omega_{rp}^{0} + \omega_{rp}^{a} \Delta \log C_{t}^{ra} + \omega_{rp}^{p} \Delta \log Y P_{t}^{rp} + u_{rpt}$$
(10)

The mean and median of coefficients on aggregate consumption growth for equation (9) and (10) are close to each other, thus the measurement errors and preference shocks do not affect our results on risk sharing substantially. Table 8C and 8D report that the aggregate component is still only account for about 18% and 27% of variances of fitted consumption growth at restricted city and restricted provincial level regressions. The degree of risk sharing of the provincial level regression is slightly higher than that of the city level regression, which indicates that provincial variables smooth out a small part of the idiosyncratic shocks at city level and mask the poor risk sharing at the sub-provincial level. On the other hand, the degree of risk sharing estimated from equation (10) is much lower than that from equation (4). We infer that the aggregate biases across sub-provincial units in the provincial variables attribute

to the high degree of risk sharing obtained in equation (4).¹⁷

6.3 Income Process

In previous sections, we assume the income processes at city and provincial levels are random walks. To check whether our results are robust to more general income processes, we assume the city and provincial incomes follow first-order autoregressive (AR1) processes and construct the time series of innovations to permanent income for each city and province with the AR1 income processes. The income process for each city is specified as follows

$$\Delta \log Y_{it} = \rho_{0i} + \rho_{1i} \Delta \log Y_{it-1} + v_{it} \tag{11}$$

Similarly, we specific the income process for each province as follows

$$\Delta \log Y_{pt} = \rho_{0p} + \rho_{1p} \Delta \log Y_{pt-1} + v_{pt}$$
(12)

We estimate the parameter ρ_{0j} and ρ_{1j} of the income process for each city with OLS and then use the residuals to construct the city-specific innovation to permanent income. The innovation to permanent income at provincial level is constructed in an analogous way. Then, we report the estimated parameters of equation (3) and (4) with those alternative time series of innovations to permanent income.

Table 9 reports the coefficients of equation (11) and (12) and their corresponding results on risk sharing. Intercepts of income processes are usually positive and significant, which capture the positive income growth. However, the coefficient on lagged income growth are less significant of which less than half of those coefficients are significant at the 5% confidence level. Their mean and median *t*-statistics are also lower than the critical value of 5% confidence level. It suggests that the assumption of random walk income process is not rejected for most cities and provinces.

¹⁷ We note that equation (9) and (10) produce lower estimates on aggregate consumption growth because there is a measurement error in restricted aggregate consumption growth for measuring actual aggregate consumption growth. Nonetheless, the results on equation (3) and (9) are close to each other, which suggest that this measurement error does not affect our results substantially.

Since the income process is more persistent at the provincial level (see Table 9B for the results on parameter ρ_{1p}), current income growth captures not only current innovations to permanent income, but also past innovations. The coefficient on innovation to permanent income is biased upward because it captures household's response to the whole history of innovations to permanent income instead of the current innovation. Therefore, the coefficients on aggregate consumption growth in Table 9 are higher than those in Table 3.

Furthermore, we allow the interactions among income processes at aggregate, provincial and city levels by estimating the following VAR system

$$\begin{bmatrix} \Delta \log Y_{at} \\ \Delta \log Y_{pt} \\ \Delta \log Y_{jt} \end{bmatrix} = \begin{bmatrix} \rho_{0a} \\ \rho_{0p} \\ \rho_{0j} \end{bmatrix} + \begin{bmatrix} \rho_{1a} & \rho_{2a} & \rho_{3a} \\ \rho_{1p} & \rho_{2p} & \rho_{3p} \\ \rho_{1j} & \rho_{2j} & \rho_{3j} \end{bmatrix} \begin{bmatrix} \Delta \log Y_{at-1} \\ \Delta \log Y_{pt-1} \\ \Delta \log Y_{jt-1} \end{bmatrix} + \begin{bmatrix} v_{at} \\ v_{pt} \\ v_{jt} \end{bmatrix}$$

We estimate the parameters of the income process for each city with three stage least square and then use the residuals to construct the city-specific innovation to permanent income. The innovation to permanent income at provincial is constructed by taking the population weighted average across cities within a province. We then use those variables to estimate equation (3) and (4) and report the results in Table 10.

Owing to the small sample of each city, the coefficients are not estimated precisely. Consequently, there is no further gain from using the VAR income processes than the AR income processes. The results in Table 10 are close to the corresponding results in Table 9.¹⁸

7. Conclusion

Risk sharing improves the well-being of people by stabilizing consumption path. China has

¹⁸ We also estimate equation (12) with restricted provincial income growth to construct its corresponding innovation to permanent income. Similarly, we estimate the VAR system with restricted aggregate income growth, restricted provincial income growth and city income growth and then construct the innovation to permanent income at city and restricted provincial levels. The results of equation (3) and (4) from using the sets of variables computed from those AR and VAR income processes are reported in Appendix 3 and 4, respectively.

strong economic growth since 1978, but researches show that consumption fluctuations are subject to aggregate and idiosyncratic shocks. This paper estimates the degree of risk sharing at city level and examines its determinants. Our results suggest that the market for sharing consumption risks across cities is fragmented. There is a significant welfare gain from eliminating city-specific and idiosyncratic consumption fluctuations.

We identify factors that affecting city risk sharing. Cities reside in a province with better risk sharing and with larger population size are more capable to share consumption risks, but a better logistics system and a higher share of GDP contributed by tertiary sector reduces risk sharing. Government can reduce barriers for inter-provincial trades to improve provincial risk sharing and facilitate inter-provincial migration to increase city size. City government also plays a role to reduce income shocks by sharing productivity shocks and diversifying industrial structure.

References

- Anderson, James E., and Eric van Wincoop, 2003. Gravity with gravitas: a solution to the border puzzle. *American Economic Review*, 93, 170–92
- Asdrubali, P. and Kim, S., 2008. Incomplete risk sharing and incomplete intertemporal consumption smoothing. *Journal of Money, Credit and Banking*, 40:7, 1521-31.
- Athanasouli, S. and van Wincoop, E., 2001. Risksharing within the United States: What have Financial Markets and Fiscal Federalism Accomplished? *Review of Economics and Statistics*, 83:4, 688-698.
- Au, C-C and Henderson, J. V., 2006. How migration restrictions limit agglomeration and productivity in China, *Journal of Development Economics*, 80, 350-388.
- Bai, C., Du, Y.J., Tao, Z.G. and Tong, S.Y., 2004. Local protectionism and regional specialization: evidence from China's industries. *Journal of International Economics*, 63, 397-417.
- Boyreau-Debray, G., Wei, S. 2005. Pitfalls of a state-dominated financial system: The case of China. NBER Working Paper 11214.
- Ceglowski, Janet, 2000. The law of one price: intranational evidence for Canada. *Canadian Journal of Economics*, 36, 373-400.
- Coval, J. D. and Moskowitz, T. J., 1999. Home Bias at Home: Local Equity Preference in Domestic Portfolios. *Journal of Finance*, 54:6, 2045–2074.
- Coval, J. D. and Moskowitz, T. J., 2001. The geography of investment: Informed trading and asset prices. *Journal of Political Economy*, 109, 811-841.
- Crihfield J B, Panggabean M P H, 1995. Growth and convergence in US cities. *Journal* of *Urban Economics*, 38 138 165
- Crucini, M., 1999. On International and National Dimensions of Risk Sharing. *Review of Economics and Statistics*, 81: 1, 73-84.
- Crucini, M. and Hess, G., 2000. Intranational and International Risk Sharing. in Gregory D. Hess and Eric van Wincoop, eds., *Intranational Macroeconomics*, Cambridge University Press.

- Engel, Charles, and John Rogers, 1996. How Wide Is the Border? American Economic Review, 86, 1112–25.
- Engel, Charles, and John Rogers, 2001. Violating the Law of One Price: Should We Make a Federal Case Out of It? *Journal of Money, Credit, and Banking*, 33, 1–15
- Glaeser, E.L., Scheinkman, J.A. and Shleifer, A. (1995) Economic Growth in a Cross- section of Cities, *Journal of Monetary Economics*, 36(1), pp.117-143.
- Hess, G. D. and Shin, K, 1998. Intranational Business Cycles in the United States. *Journal of International Economics*, 44, 289-314.
- Helliwell, John F., 1996. Do national borders matter for Quebec's trade? *Canadian Journal of Economics*, 29, 507–22.
- Ho, Chun-Yu, Wai-Yip Alex Ho and Dan Li, 2009. Consumption Fluctuations and Welfare: Evidence from China. mimeo, Georgia Institute of Technology.
- Huberman, Gur, 2001. Familiarity breeds investment. *Review of Financial Studies*, 14, 659-680.
- Iwamoto, Y. and Eric van Wincoop, 2000. Do Border Matter? Evidence from Japanese International Capital Flows. *International Economics Review*, 41:1, 241-69.
- Kose, A., E. Prasad, and M. Terrones, 2009. How Does Financial Globalization Affect International Risk Sharing: Patterns and Channels. *Journal of Development Economics*, 89:2, 258-270.
- Korniotis, George M. and Alok Kumar, 2008. Do Behavioral, Biases Adversely Affect the Macro-Economy? Federal Reserve Board FEDS series 2008-49.
- McCallum, John, 1995. National borders matter: Canada-U.S. regional trade patterns. *American Economic Review*, 85, 615–23.
- Naughton, B. 2003, How much can regional integration do to unify China's markets? In N. Hope, D. Yang, & Mu Yang Li (Eds.), *How far across the river? Chinese policy reform at the millennium*, Stanford University Press, 204-232.
- National Bureau of Statistics, 1999. New China's Cities Fifty Years (Xin Zhongguo cheng shi 50 nian), Xinhua Press Beijing, People's Republic of China.
- National Bureau of Statistics, various years. China City Statistics Yearbooks, China Statistical Press, Beijing, People's Republic of China.

- Obstfeld, M., 1994. Are industrial-country consumption risks globally diversified? In L. Leiderman & A. Razin (Eds.), *Capital mobility: The impact on consumption, investment and growth.* Cambridge, U.K.: Cambridge University Press, 13-47.
- Parsley, David, and Shang-Jin Wei, 1996. Convergence to the Law of One Price Without Trade Barriers or Currency Fluctuations. *Quarterly Journal of Economics*, 111, 1211–36
- Parsley, David, and Shang-Jin Wei, 2001. Explaining the Border Effect: the Role of Exchange Rate Variability, Shipping Costs, and Geography. *Journal of International Economics*, 55, 87–105
- Poncet, S., 2003. Measuring Chinese domestic and international integration. *China Economic Review*, 14:1, 1–21.
- Poncet, S. 2005. A Fragmented China: Measure and Determinants of Chinese Domestic Market Disintegration. *Review of International Economics*, 13:3, 409-30.
- Tochkov, K., 2007. Interregional transfers and the smoothing of provincial expenditure in China. *China Economic Review*, 18:1, 54-65.
- Vigfusson, R., 2008. How Does the Border Affect Productivity? Evidence from American and Canadian Manufacturing Industries. *Review of Economics and Statistics*, 90:1, 49-64.
- Wei, S., 1996. Intra-National Versus International Trade: How Stubborn are Nations in Global Integration? NBER Working Paper #5531.
- Wolf, Holger, 2000. Intranational Home Bias in Trade. *Review of Economics and Statistics*, 82, 555–63.
- Wolf, Nikolaus, 2009. Was Germany Ever United? Evidence from Intra- and International Trade 1885-1933. *Journal of Economic History* 69, 846-881.
- Xu, X. 2008. Consumption risk sharing in China. Economica, 75:2, 326-341.
- Young, A. 2000. The razor's edge: Distortions and incremental reform in the People's Republic of China. *Quarterly Journal of Economics*, 115:4, 1091-1135.



Figure 1: Consumption Correlation against Output Correlation across provinces

Note: ρ_p is the consumption correlation between consumption growths of province and aggregate; ρ_{py} is the output correlation between output growths of province and aggregate



Figure 2: Consumption Correlation against Output Correlation across cities

Note: ρ_c is the consumption correlation between consumption growths of city and aggregate; ρ_{cv} is the output correlation between output growths of city and aggregate

1991-2006	City	1991-2006	City
Mean(dlnRS _c)	0.07	Mean(dlnY _c)	0.09
	[0.03]		[0.03]
SD(dlnRS _c)	0.11	$SD(dlnY_c)$	0.10
	[0.13]		[0.08]
Observation	192	Observation	192

Table 1A: Mean and Standard Deviation (City)

Table 1B: Mean and Standard Deviation (Province)

1991-200	6 Province	1991-2006	Province
Mean(dlnR	S_{p}) 0.08	$Mean(dlnY_p)$	0.09
	[0.02]		[0.02]
SD(dlnRS	p) 0.05	$SD(dlnY_p)$	0.05
	[0.02]		[0.02]
Observatio	on 24	Observation	24

Table 1C: Mean and Standard Deviation (Restricted Province)

1991-2006	RProvince	1991-2006	RProvince
Mean(dlnRS _{rp})	0.08	$Mean(dlnY_{rp})$	0.09
	[0.03]		[0.02]
$SD(dlnRS_{rp})$	0.08	$SD(dlnY_{rp})$	0.07
	[0.04]		[0.03]
Observation	24	Observation	24

Index c = City; p = Province; rp = restricted province; Top panel: First, we compute the statistics (MEAN & SD) for each city; then we compute the cross-sectional MEAN (or SD for the figures in the bracket) of those city-specific statistics; Same calculation in the lower panels with provincial and restricted provincial data.

Sources for city data: New China's Cities Fifty Years; China City Statistics Yearbook; Sources for provincial data: China Data Centre

1991-2006	Mean	1991-2006	Median
Corr(dlnRS _c ,dlnRS _a)	0.36	Corr(dlnRS _p ,dlnRS _a)	0.37
	[0.31]		[-0.80,0.93]
Corr(dlnY _c ,dlnY _a)	0.33	Corr(dlnY _p ,dlnY _a)	0.36
	[0.33]		[-0.47,0.89]

Table 2A: Correlations (City)

Table 2B: Correlations (Province)

1991-2006	Mean	1991-2006	Median
Corr(dlnRS _c ,dlnRS _a)	0.69	Corr(dlnRS _p ,dlnRS _a)	0.75
	[0.19]		[0.17,0.92]
$Corr(dlnY_c, dlnY_a)$	0.64	$Corr(dlnY_p, dlnY_a)$	0.68
	[0.23]		[0.04,0.88]

Table 2C: Correlations (Restricted Province)

1991-2006	Mean	1991-2006	Median
Corr(dlnRS _c ,dlnRS _a)	0.54	Corr(dlnRS _p ,dlnRS _a)	0.52
	[0.22]		[0.10,0.89]
Corr(dlnY _c ,dlnY _a)	0.44	$Corr(dlnY_p, dlnY_a)$	0.51
	[0.29]		[-0.09,0.77]

Index c = City; p = Province; rp = restricted province; a = Aggregate; Top left panel: First, we compute the correlation for each city, then we compute the cross-sectional MEAN (or SD for the figures in the bracket) of those city-specific correlations; Top right panel: Compute the correlation for each city; Compute the cross-sectional MEDIAN of those city-specific (or province) correlations; The figures in the bracket is the cross-sectional MIN & MAX of those correlations; Same calculation in the lower panels with provincial and restricted provincial data.

Coefficient	ϕ^0_{j}	$\phi^{a}{}_{j}$	$\phi^{p}{}_{j}$	φ^{c}_{j}		
Mean	-0.01	0.60	-0.06	0.46		
Median	-0.01	0.63	0.01	0.34		
[SD]	[0.04]	[0.66]	[0.95]	[0.73]		
t-statistic						
Mean	-0.67	1.95	0.04	2.83		
Median	-0.63	1.82	0.03	1.48		
N-5%	36	93	36	81		
Model: $\Delta \log C_{jt} = \varphi_j^0 + \varphi_j^a \Delta \log C_t^a + \varphi_j^p \Delta \log Y P_t^p + \varphi_j^c \Delta \log Y P_{jt} + u_{jt}$						

Table 3A: Descriptive Statistics on Risk Sharing Coefficients (City)

Table 3B: Descriptive Statistics on Risk Sharing Coefficients (Province)

Coefficient	ω_{p}^{0}	ω^{a}_{p}	ω^{p}_{p}
Mean	-0.01	0.72	0.28
Median	-0.01	0.71	0.29
[SD]	[0.01]	[0.26]	[0.26]
t-statistic			
Mean	-0.99	3.73	1.78
Median	-0.72	4.13	1.34
N-5%	4	21	7

Model: $\Delta \log C_t^p = \omega_p^0 + \omega_p^a \Delta \log C_t^a + \omega_p^p \Delta \log YP_t^p + u_{pt}$

No. of observation: 192 for city panel and 24 for provincial panel.

Mean	Aggregate	Provincial	City	Idiosyncratic
% Contribution	13%	-3%	89%	N/A
Welfare Gain	N/A	0%	3%	14%
% Welfare Gain	N/A	-1%	20%	81%
Median	Aggregate	Provincial	City	Idiosyncratic
% Contribution	22%	1%	78%	N/A
Welfare Gain	N/A	0%	2%	15%
% Welfare Gain	N/A	0%	12%	88%

 Table 4A: Variance Decomposition & Welfare Gain (City)

Table 4B: Variance Decomposition & Welfare Gain (Province)

Mean	Aggregate	Provincial	Idiosyncratic
% Contribution	58%	42%	N/A
Welfare Gain	N/A	1%	2%
% Welfare Gain	N/A	21%	79%
Median	Aggregate	Provincial	Idiosyncratic
% Contribution	56%	44%	N/A
Welfare Gain	N/A	1%	2%
% Welfare Gain	N/A	22%	78%

Unit for welfare gain: % of steady state consumption. They do not add up to 100% because of rounding errors.

	OLS Regression			Mec	Median Regression			
VARIABLES	ϕ^{a}_{j}	φ^{p}_{j}	φ^{c}_{j}	ϕ^{a}_{j}	$\phi^{p}{}_{j}$	φ^{c}_{j}		
Provincial RS	-0.149	0.469***	-0.320***	-0.00832	0.148*	-0.0561		
	[0.146]	[0.149]	[0.106]	[0.140]	[0.0867]	[0.153]		
GDP per capita	0.0869	-0.0388	-0.0481	0.135	-0.274**	0.248		
	[0.244]	[0.353]	[0.261]	[0.202]	[0.132]	[0.230]		
Population	0.0264	0.151	-0.177***	0.0374	0.0787*	-0.102		
	[0.0605]	[0.0937]	[0.0625]	[0.0667]	[0.0437]	[0.0742]		
Investment/GDP	-0.0107	-0.125	0.136	-0.0646	0.0353	0.00527		
	[0.0988]	[0.141]	[0.130]	[0.101]	[0.0690]	[0.113]		
Government								
Expenditure/GDP	-0.0289	0.312	-0.284	-0.0166	0.0705	-0.132		
	[0.219]	[0.287]	[0.194]	[0.171]	[0.117]	[0.197]		
Saving Deposit/GDP	-0.128	-0.0221	0.151	-0.0455	-0.0619	0.169		
	[0.221]	[0.297]	[0.240]	[0.162]	[0.107]	[0.182]		
Average wage	0.503	0.0649	-0.568	0.107	0.816***	-0.437		
	[0.347]	[0.628]	[0.532]	[0.389]	[0.248]	[0.451]		
%GDP in 3rd industries	-0.111	-0.686*	0.797***	0.131	-0.401***	0.453*		
	[0.200]	[0.372]	[0.283]	[0.210]	[0.138]	[0.237]		
%GDP in 2nd industries	-0.420	0.263	0.157	-0.233	0.0998	-0.114		
	[0.267]	[0.373]	[0.340]	[0.260]	[0.178]	[0.297]		
Goods carried through								
highway per capita	0.123*	-0.167**	0.0438	0.104	-0.136***	0.0382		
	[0.0617]	[0.0691]	[0.0530]	[0.0644]	[0.0419]	[0.0711]		
Passengers carried through								
highway per capita	-0.204	0.225	-0.0206	-0.254***	0.198***	0.0546		
	[0.150]	[0.159]	[0.0805]	[0.0799]	[0.0519]	[0.0903]		
Distance to Shanghai or								
Shenzhen	-0.0429	0.168	-0.125	-0.0446	0.206***	-0.0803		
	[0.118]	[0.188]	[0.127]	[0.0893]	[0.0587]	[0.100]		
SEZ	-0.178	0.110	0.0681	-0.254	-0.0607	0.106		
	[0.165]	[0.178]	[0.129]	[0.207]	[0.135]	[0.227]		
Constant	-1.599	-0.106	2.706	-1.328	-4.193**	1.249		
	[3.191]	[4.446]	[3.043]	[3.204]	[2.092]	[3.726]		
Observations	192	192	192	192	192	192		
R-squared	0.118	0.149	0.230	0.074	0.087	0.128		

Table 5: Empirical Results

*** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in brackets

	OL	OLS Regression		Med	ian Regres	ssion
Model	ϕ^{a}_{j}	$\phi^{p}{}_{j}$	φ ^c _j	ϕ^{a}_{j}	ϕ^{p}_{j}	ϕ^{c}_{j}
Original	0.60	-0.06	0.46	0.63	0.01	0.34
Provincial RS	0.45	0.41	0.14	0.62	0.16	0.29
GDP per capita	0.69	-0.10	0.41	0.76	-0.27	0.59
Population	0.63	0.09	0.29	0.66	0.09	0.24
Investment/GDP	0.59	-0.19	0.60	0.56	0.04	0.35
Government Expenditure/GDP	0.57	0.25	0.18	0.61	0.08	0.21
Saving Deposit/GDP	0.47	-0.08	0.61	0.58	-0.05	0.51
Average wage	1.10	0.00	-0.10	0.73	0.82	-0.09
%GDP in 3rd industries	0.49	-0.75	1.26	0.76	-0.39	0.80
%GDP in 2nd industries	0.18	0.20	0.62	0.39	0.11	0.23
Goods carried through highway						
per capita	0.72	-0.23	0.51	0.73	-0.13	0.38
Passengers carried through						
highway per capita	0.39	0.16	0.44	0.37	0.21	0.40
Distance to Shanghai or Shenzhen	0.56	0.11	0.34	0.58	0.21	0.26
SEZ	0.42	0.05	0.53	0.37	-0.05	0.45

Table 6: Original and Counterfactual Risk Sharing Coefficients

	OLS Regression			Median Regression				
Model	Aggregate	Province	City	∆Welfare	Aggregate	Province	City	∆Welfare
Original	13.4%	-2.8%	89.4%		21.9%	0.5%	77.5%	
Provincial RS	17.0%	53.3%	29.7%	2.1%	23.0%	13.4%	63.6%	0.2%
GDP per capita	20.5%	-5.1%	84.6%	0.5%	14.6%	-7.7%	93.1%	-3.1%
Population	25.5%	7.5%	67.0%	1.6%	33.7%	8.3%	58.0%	0.7%
Investment/GDP	8.8%	-5.5%	96.7%	-1.8%	17.6%	2.9%	79.5%	0.0%
Government Expenditure/GDP	27.9%	30.5%	41.7%	2.1%	35.4%	8.5%	56.2%	1.1%
Saving Deposit/GDP	5.4%	-2.5%	97.2%	-2.1%	10.7%	-2.2%	91.5%	-2.0%
Average wage	98.9%	0.3%	0.8%	2.0%	22.3%	81.3%	-3.6%	-0.9%
%GDP in 3rd industries	1.6%	-4.3%	102.7%	-17.5%	8.7%	-7.1%	98.4%	-6.9%
%GDP in 2nd industries	0.7%	6.8%	92.5%	-2.7%	17.0%	11.7%	71.3%	1.3%
Goods carried through highway per capita	17.1%	-8.0%	90.9%	-0.5%	26.2%	-6.9%	80.7%	-0.4%
Passengers carried through highway per capita	5.9%	8.9%	85.3%	0.0%	6.1%	12.8%	81.1%	-0.7%
Distance to Shanghai or Shenzhen	16.8%	7.7%	75.4%	1.2%	21.6%	20.0%	58.5%	0.3%
SEZ	5.3%	1.9%	92.8%	-1.0%	6.2%	-2.3%	96.1%	-0.7%

 Table 7: Variance Decompositions under the Original and Counterfactual Risk Sharing Coefficients & Welfare Change

Coefficient	ϕ^0_{j}	$\phi^{a}{}_{j}$	$\phi^{p}{}_{j}$	φ^{c}_{j}
Mean	-0.01	0.57	-0.08	0.51
Median	-0.01	0.62	0.02	0.39
[SD]	[0.04]	[0.54]	[0.86]	[0.73]
t-statistic				
Mean	-0.59	2.66	-0.09	2.50
Median	-0.54	2.57	0.09	1.40
N-5%	32	121	38	72

Table 8A: Descriptive Statistics on Risk Sharing Coefficients (Restricted City)

Model: $\Delta \log C_{jt} = \varphi_j^0 + \varphi_j^a \Delta \log C_t^a + \varphi_j^p \Delta \log Y P_t^p + \varphi_j^c \Delta \log Y P_{jt} + u_{jt}$

Table 8B: Descriptive Statistics on Risk Sharing Coefficients (Restricted Province)

Coefficient	ω^{0}_{rp}	ω^{a}_{rp}	ω^{p}_{rp}
Mean	-0.01	0.54	0.46
Median	-0.01	0.58	0.42
[SD]	[0.02]	[0.25]	[0.25]
t-statistic			
Mean	-0.65	3.69	3.01
Median	-0.85	3.52	3.11
N-5%	2	18	16

Model: $\Delta \log C_t^p = \omega_p^0 + \omega_p^a \Delta \log C_t^a + \omega_p^p \Delta \log Y P_t^p + u_{pt}$

No. of observation: 191 for city panel and 23 for restricted provincial panel. Qinghai is dropped because there is only one city in this province.

Aggregate	Provincial	City	Idiosyncratic
15%	-6%	91%	N/A
N/A	0%	4%	13%
N/A	-1%	23%	78%
Aggregate	Provincial	City	Idiosyncratic
23%	2%	75%	N/A
N/A	0%	3%	14%
NT/A	001	1501	0.4.07
	Aggregate 15% N/A N/A Aggregate 23% N/A N/A	Aggregate Provincial 15% -6% N/A 0% N/A -1% Aggregate Provincial 23% 2% N/A 0%	Aggregate Provincial City 15% -6% 91% N/A 0% 4% N/A -1% 23% Aggregate Provincial City 23% 2% 75% N/A 0% 3%

 Table 8C: Variance Decomposition & Welfare Gain (Restricted City)

Table 8D: Variance Decomposition & Welfare Gain (Restricted Province)

Mean	Aggregate	Provincial	Idiosyncratic
% Contribution	24%	76%	N/A
Welfare Gain	N/A	2%	5%
% Welfare Gain	N/A	27%	73%
Median	Aggregate	Provincial	Idiosyncratic
% Contribution	29%	71%	N/A
Welfare Gain	N/A	2%	5%
% Welfare Gain	N/A	23%	77%

Unit for welfare gain: % of steady state consumption. They do not add up to 100% because of rounding errors.

				-		
Coefficient	ρ _{0j}	ρ_{1j}	$\phi^{0}{}_{j}$	$\phi^{a}{}_{j}$	$\phi^{p}{}_{j}$	ϕ^{c}_{j}
Mean	0.07	0.14	0.01	0.68	-0.18	0.51
Median	0.07	0.15	0.01	0.68	-0.07	0.36
[SD]	[0.03]	[0.30]	[0.05]	[0.54]	[0.59]	[0.30]
t-statistic						
Mean	2.39	0.60	0.48	1.98	-0.13	2.65
Median	2.27	0.55	0.38	1.79	-0.23	1.37
N-5%	115	32	40	87	42	75

Table 9A: Descriptive Statistics on persistence Income growth process coefficients and

associated risk sharing estimates (City)

Table 9B: Descriptive Statistics on persistence Income growth process coefficients and

Coefficient	$ ho_{0p}$	ρ_{1p}	ω_{p}^{0}	ω^{a}_{p}	ω^{p}_{p}
Mean	0.06	0.37	0.01	0.86	0.14
Median	0.06	0.36	0.01	0.81	0.19
[SD]	[0.03]	[0.35]	[0.02]	[0.25]	[0.25]
t-statistic					
Mean	2.46	1.63	0.60	3.96	0.99
Median	2.35	1.35	0.30	4.01	0.86
N-5%	13	10	5	22	4

associated risk sharing estimates (Province)

No. of observation: 192 for city panel and 24 for provincial panel.

Coefficient	ροj	ρ_{1j}	ρ_{2j}	ρ_{3j}	ϕ^0_{j}	$\phi^{a}{}_{j}$	$\phi^{p}{}_{j}$	ϕ^{c}_{j}
Mean	0.02	0.38	0.38	-0.03	0.01	0.68	-0.17	0.50
Median	0.02	0.35	0.30	-0.02	0.02	0.66	-0.01	0.32
[SD]	[0.12]	[1.65]	[1.51]	[0.35]	[0.08]	[0.82]	[1.10]	[0.91]
t-statistic								
Mean	0.43	0.60	0.55	-0.13	0.51	1.87	-0.02	1.79
Median	0.45	-0.00	-0.26	-0.00	0.46	1.65	-0.02	1.17
N-5%	25	34	33	26	43	80	43	63

Table 10A: Descriptive Statistics on VAR Income process coefficients and associated risk

sharing estimates (City)

Table 10B: Descriptive Statistics on VAR Income process coefficients and associated risk

Coefficient	ρ_{0p}	ρ_{1p}	ρ_{2p}	ρ_{3p}	ω^{0}_{p}	ω^{a}_{p}	ω^{p}_{p}
Mean	0.04	0.53	0.06	0.00	-0.00	0.90	0.10
Median	0.03	0.46	0.01	-0.01	0.00	0.89	0.11
[SD]	[0.04]	[0.53]	[0.49]	[0.25]	[0.06]	[0.45]	[0.45]
t-statistic							
Mean	1.45	1.39	0.18	0.04	0.52	2.50	0.77
Median	0.87	1.37	-0.78	0.13	-0.01	2.01	0.46
N-5%	53	47	47	33	4	12	5

sharing estimates (Province)

Table 10C: Descriptive Statistics on VAR Income process coefficients (Aggregate)

Coefficient	ρ_{0a}	ρ_{1a}	ρ_{2a}	ρ_{3a}
Mean	0.03	0.63	0.11	-0.00
Median	0.03	0.68	-0.01	0.00
[SD]	[0.02]	[0.28]	[0.37]	[0.15]
t-statistic				
Mean	1.43	2.52	0.43	0.10
Median	1.36	3.40	-0.04	-0.07
N-5%	40	126	41	38

No. of observation: 192 for city panel and 24 for provincial panel.

Region: Province	Number of City		
Eastern			
Fujian	8		
Guangdong	14		
Heilongjiang	10		
Jiangsu	9		
Jiangxi	6		
Jilin	6		
Liaoning	14		
Shandong	13		
Zhejiang	9		
Central			
Anhui	11		
Hebei	10		
Henan	14		
Hubei	10		
Hunan	11		
Western			
Gansu	4		
Guangxi	6		
Guizhou	3		
Inner Monogolia	4		
Ningxia	2		
Qinghai	1		
Shaanxi	7		
Shanxi	6		
Sichuan	12		
Yunnan	2		
Total	192		
Eastern	89		
Central	56		
Western	47		

Appendix 1: Provincial Distribution of City

Variable	Mean	Std.Dev.
GDP per capita (Yuan)	2012.42	1022.77
Population (1,000)	2926.91	2241.52
Investment/GDP	0.21	0.23
Government Expenditure/GDP	0.09	0.03
Saving Deposit/GDP	0.44	0.15
Average wage (Yuan)	2105.40	370.89
%GDP of 3rd industries	25.9	7.16
%GDP of 2nd industries	47.5	13.4
Passengers carried through highway per capita (People)	0.01	0.01
Goods carried through highway per capita (Tons)	0.01	0.02
Distance to Shanghai or Shenzhen (Miles)	500.68	297.34
SEZ (Dummy variable)	0.08	0.27

Appendix 2: Descriptive Statistics of City Level Data

Observation = 192

Sources: New China's Cities Fifty Years; China City Statistics Yearbook

Coefficient	ρ _{0j}	$ ho_{1j}$	$\phi^0_{\ j}$	$\phi^{a}{}_{j}$	$\phi^{p}{}_{j}$	$\phi^{c}{}_{j}$
Mean	0.07	0.14	0.03	0.53	-0.00	0.47
Median	0.07	0.15	0.03	0.58	0.05	0.38
[SD]	[0.03]	[0.30]	[0.06]	[0.63]	[0.99]	[0.77]
t-statistic						
Mean	2.39	0.60	1.04	2.29	0.03	2.19
Median	2.27	0.55	1.03	2.14	0.16	1.19
N-5%	115	32	56	106	42	69

Appendix 3A: Descriptive Statistics on persistence Income growth process coefficients

and associated risk sharing estimates (Restricted City)

Appendix 3B: Descriptive Statistics on persistence Income growth process coefficients

Coefficient	ρ_{0rp}	ρ_{1rp}	ω^{0}_{rp}	ω^{a}_{rp}	ω^{p}_{rp}
Mean	0.08	0.14	0.04	0.51	0.49
Median	0.08	0.21	0.03	0.59	0.41
[SD]	[0.03]	[0.35]	[0.03]	[0.38]	[0.38]
t-statistic					
Mean	2.96	0.56	1.92	3.07	2.59
Median	2.69	0.81	1.44	2.76	2.57
N-5%	15	5	9	18	15

and associated risk sharing estimates (Restricted Province)

No. of observation: 191 for city panel and 23 for restricted provincial panel. Qinghai is dropped because there is only one city in this province.

Coefficient	ροj	ρ_{1j}	ρ_{2j}	ρ_{3j}	ϕ^0_{j}	ϕ^{a}_{j}	$\phi^{p}{}_{j}$	ϕ^{c}_{j}
Mean	0.05	0.52	-0.14	0.07	0.02	0.51	0.10	0.39
Median	0.04	0.44	-0.10	0.01	0.02	0.63	0.10	0.26
[SD]	[0.12]	[1.55]	[1.21]	[0.57]	[0.07]	[0.75]	[1.09]	[0.85]
t-statistic								
Mean	0.96	0.87	-0.26	0.11	0.79	1.98	0.31	1.40
Median	0.88	0.85	-0.31	0.07	0.71	2.02	0.27	1.00
N-5%	48	58	46	36	45	98	36	57

Appendix 4A: Descriptive Statistics on VAR Income process coefficients and associated

risk sharing estimates (Restricted City)

Appendix 4B: Descriptive Statistics on VAR Income process coefficients and associated

Coefficient	ρ_{0rp}	ρ_{1rp}	ρ_{2rp}	ρ_{3rp}	ω^{0}_{rp}	ω^{a}_{rp}	ω^{p}_{rp}
Mean	0.05	0.51	-0.10	0.02	0.03	0.56	0.44
Median	0.05	0.42	-0.19	0.04	0.02	0.64	0.36
[SD]	[0.07]	[0.78]	[0.62]	[0.47]	[0.04]	[0.37]	[0.37]
t-statistic							
Mean	1.54	1.09	-0.53	0.17	1.62	2.88	1.94
Median	1.34	0.92	-0.70	0.34	1.08	2.77	1.82
N-5%	78	71	58	44	10	14	11

risk sharing estimates (Restricted Province)

Appendix 4C: Descriptive Statistics on VAR Income process coefficients (Restricted

Aggregate)

Coefficient ρ_{0a} ρ_{1a} ρ_{2a} ρ_{3a} Mean 0.06 0.44 -0.00 -0.01 0.06 0.01 Median 0.43 -0.01 [SD] [0.02] [0.26] [0.30] [0.25] t-statistic Mean 2.68 1.80 -0.15 -0.00 Median 2.72 1.83 -0.04 0.11 N-5% 81 39 43 161

No. of observation: 191 for city panel and 23 for restricted provincial panel. Qinghai is dropped because there is only one city in this province.