RISK AND THE EVOLUTION OF INEQUALITY IN CHINA IN AN ERA OF GLOBALIZATION

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ABSTRACT. Recent increases in urban income inequality in China are mirrored in smaller increases in inequality in consumption expenditures. This connection between changes in the distribution of income and consumption expenditures could be entirely due to differences in preferences (in which case households’ intertemporal marginal rates of substitution would all be equated after every history), or could be due to imperfections in the markets for credit and insurance which would ordinarily serve to equate these intertemporal marginal rates of substitution. In this paper we presume that market imperfections drive changes in the distribution of expenditures, and use data on expenditures from repeated cross-sections of urban households in China to estimate a Markov transition function for shares of expenditures over the period 1985–2001. We then use this estimated function to compute the welfare losses due to risk over this period, and to predict the future trajectory of inequality from 2001 through 2025.

1. Introduction

The welfare loss due to risk faced by households at a point in time is intimately related to changes in inequality in expenditures. In particular, risk-averse households with time separable preferences will tend to prefer to smooth shocks to income over time, so that even entirely transitory shocks to income will tend to have a permanent effect on future consumption expenditures. Thus, the same shocks to income which makes next period’s consumption uncertain will also determine the household’s position in next period’s distribution of expenditures.

In this paper we exploit this link by using data on the evolution of expenditure inequality to estimate both household risk preferences and the welfare loss due to risk actually borne by urban Chinese households over the period 1985–2001, an era during which China’s economy has undergone dramatic reforms and experienced remarkable growth. Others have noted that increases in inequality imply that the rising tide of the aggregate Chinese economy has not lifted all boats equally.
RISK AND INEQUALITY IN CHINA (Kahn and Riskin, 2001). Here we note that because households may change their position in the wealth (and expenditure) distribution, merely looking at changes in inequality will understate the displacement and (ex ante) welfare loss experienced by risk-averse households facing dramatic economic change.

Though the chief contribution of this paper is the application of a method to infer household level idiosyncratic risk from aggregate data on the cross-sectional distribution of consumption, we also have something to say about changes in inequality in the absence of this risk. In particular, we see that although there has been a notable increase in inequality among urban households, this increase is dwarfed by the increase in inequality between rural and urban households. We’re also interested in documenting any relationship between globalization (as measured by changes in trade volume across sectors) and changes in urban inequality. In Section 3 we show that after controlling for any effects that globalization may have on aggregate urban consumption the trade shocks we measure can’t account for any of the observed changes in inequality observed within the urban population.

Models having complete markets à la Arrow-Debreu yield fully Pareto efficient outcomes; in such a model any changes in inequality must be preferred by all market participants, and so yield little in terms of interesting policy implications. Complete market models which feature Gorman aggregable preferences yield the very strong prediction that the distribution of consumption across households is invariant. More interesting are models in which some friction prevents allocations from being fully Pareto optimal, and which have enough dynamic structure to yield interesting predictions regarding the evolution of the distribution of consumption.

To estimate the importance of idiosyncratic risk we assume that all households have similar preferences, and that these preferences exhibit constant relative risk aversion (Arrow, 1964). We further assume that all households have access to credit markets on equal terms, and that households exploit these credit markets to smooth their consumption over time, à la the permanent income hypothesis. Beyond this, we make no notably restrictive assumptions. We allow quite arbitrary forms of technology and shocks, and avoid the problem of measuring asset returns. Though this framework is quite general in several dimensions, we will show that conditional on the distribution of production

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1For the reader who regards this assumption as unreasonable, we note that if some households are constrained so as to not have equal access to credit markets, then our estimates of risk for these households are likely to underestimate.
shocks the model yields rather sharp predictions regarding the evolution of the distribution of resources across households. In particular, the model gives us the law of motion governing the inverse Lorenz curves which describe inequality in the economy; the idiosyncratic risk borne by households can be shown to depend entirely on the distribution of “relative surprises” experienced by the household.

The law of motion for inverse Lorenz curves allows us to make predictions about the sequence of Lorenz curves we would expect to observe, conditional on household risk preferences, rates of aggregate economic growth, and on the distribution of unforecastable shocks facing households in different years, at different wealth levels, and in different occupations. By comparing realized and predicted Lorenz curves, we can estimate these preferences and distributions. This same procedure yields a Markov transition function mapping shares of consumption today into a probability distribution over possible shares tomorrow, and we use this object to calculate the risk borne by differently situated urban Chinese households in different years, and relate this risk to measures of globalization during this period.

The key to the empirical strategy of this paper involves exploiting the restrictions placed on data by Euler equations to make statements about the evolution of inequality. Related literature includes Deaton and Paxson (1994), who derive a martingale property from the consumption Euler equation and use several long panels of household level expenditure data to argue that within-cohort inequality in industrialized countries is increasing over time, and Storesletten et al. (2002) who use household panel data on expenditures from the U.S. and a more completely specified general equilibrium model to estimate a law of motion for the distribution of consumption. The central idea of those papers is to exploit intertemporal restrictions to estimate the law of motion for individual households’ consumption growth, and then in effect to integrate over households to infer what the law of motion is for the distribution of consumption across households. The present paper reverses these last two steps—we derive equations which impose intertemporal restrictions on individual households’ consumption growth, but then integrate over these equations to obtain restrictions on the law of motion for the distribution of consumption across households before taking these restrictions to the data. The cost of the procedure followed in this paper is that one can’t exploit all the information which would be available from the trajectories of consumption for many different individual households—the (closely related) benefit is that we can get by without panel data, using instead only a relatively limited set of data obtainable from repeated cross-sectional surveys of
household expenditures, of the sort that many countries conduct in order to, e.g., compute consumer price indices.

2. An Example of Risk and Inequality

The central idea of this paper is to use evidence on changes in the cross-sectional distribution of consumption to draw inferences about the welfare of households. In this section we’ll construct a simple example, meant to illustrate the connection between the evolution of inequality and household welfare, while Appendix A provides a more general treatment. As will be seen, the connection between household welfare and changes in inequality can be more complicated and interesting than one might suppose.

To set the stage for our example, consider an environment with many households, but only two types (each type comprising one half of the population), indexed by \( i = 1, 2 \). There are two periods, indexed by \( t = 1, 2 \). Households of both types derive momentary utility from consumption according to a logarithmic utility function

\[
u(c_{it}) = \log(c_{it})
\]

Both types of households also discount future utility using a common discount factor \( \beta \in (0, 1) \).

Critical to the example is that be some source of underlying uncertainty which may affect the second period distribution of consumption. Let \( \omega \in \Omega \) denote the realized state of the economy in this second period. Assuming \( \Omega \) finite, let \( \Pr(\omega) \) denote the probability of state \( \omega \) being realized.

Per capita consumption in period \( t \) is some exogenously determined (but possibly random) quantity \( \bar{c}_t \); we choose a normalization for consumption so that \( \bar{c}_1 = 1 \). The characteristic which distinguishes the two different types of households is is that each type begins with different shares of aggregate consumption. In particular, let the consumption of type one households in period one be \( c_{11} = 0.4 \), so that consumption of the second type is \( c_{21} = 0.6 \).

We now consider three different market structures, and ask how these influence the evolution of inequality.

2.1. Complete Markets. When there are complete markets, we can exploit the second welfare theorem to compute changes in inequality for our example economy. Accordingly, consider the planning problem of allocating consumption across representative households of each type,

\[
\max_{\{c_{11}, \{c_{12(\omega)}\}_{\omega \in \Omega}\}} \sigma u(c_{11}) + (1 - \sigma) u(c_{21}) + \beta \sum_{\omega \in \Omega} \Pr(\omega)[\sigma u(c_{11(\omega)}) + (1 - \sigma) u(c_{22(\omega)})]
\]
subject to resource constraints in each period,
\[ c_{11} + c_{21} \leq \tilde{c}_1, \]
and
\[ c_{12}(\omega) + c_{22}(\omega) \leq \tilde{c}_2(\omega). \]

Here the parameter \( \sigma \) is a ‘planning-weight’ which determines the weight of type one households relative to type two in the planner’s problem. With the form of utility function assumed above, it follows immediately from the first order conditions that
\[ c_{11} = \sigma \tilde{c}_1 \]
and
\[ c_{12} = \sigma \tilde{c}_2(\omega). \]

Note from this that the parameter \( \sigma \) corresponds to the share of aggregate consumption for type one households, and that this parameter doesn’t vary across either dates or states. As a consequence, any Pareto efficient outcome in this example will assign 40 per cent of aggregate consumption to households of type one in both periods, regardless of the realized value of \( \omega \).

This point generalizes. When households have identical utility functions featuring constant elasticities of substitution (of which logarithmic utility is a special case) and when markets are complete, then we should expect the distribution of consumption to be unchanging. Conversely, if the distribution of consumption is observed to change over time, then this is evidence that either our assumptions regarding household preferences are mistaken, or that markets are incomplete (Lucas, 1992).

2.2. Segmented Markets. Taking our cue from Section 2.1, we next imagine a particular sort of simple market incompleteness which can give rise to nontrivial changes in consumption inequality. In particular, suppose that while households of type \( i \) can engage in exchange with other households of the same type, circumstances contrive to make it impossible for households of type one to make exchanges with households of type two. Thus, a social planner must keep track of aggregate resources available to households of each type. Within the set of type \( i \) households there will be perfect insurance, so we can write
\[ c_{i2}(\omega) = \tilde{c}_2(\omega), \]
where \( \tilde{c}_2(\omega) \) is the per capita consumption available to households of type \( i \) in state \( \omega \).

To be concrete, suppose that the share of type one households happens to fall from 0.4 in the first period to 0.3 in the second, but that total consumption across both groups remains constant. Then the \( ex \)
post welfare outcome for each household type relative to the complete markets case is the same in the first period, but in the second the difference is given by

\[
\log(0.3) - \log(0.4) \approx -0.288 \\
\log(0.7) - \log(0.6) \approx 0.154.
\]

Though very contrived, this accounting seems to capture the usual idea behind analyses of changes in inequality—in this case, poor households (type one) are hurt by an increase in inequality, while wealthy households (type two) fare better. The chief point missed by this idea is that in the face of uninsured shocks individual households are likely to change their position in the consumption distribution.

2.3. Credit Markets. We next eliminate the supposition of segmented markets, and suppose that households of both types can exchange debt in competitive credit markets. However, for whatever reason, we also suppose that households can’t perfectly insure their future consumption, as they did in Section 2.1. We then derive intertemporal restrictions on the evolution of each household’s share of aggregate consumption. The key assumptions we exploit here (and later in our empirical work) are that households all have similar preferences featuring constant relative risk aversion, and that all households have access to credit on the same terms. Note that this latter assumption is weaker than assuming that credit markets are perfect—in particular, it may be the case that at the interest rates faced by households for some reason credit markets fail to clear.

At date one, households of each type can exchange claims to consumption at date two with other households at a price $\bar{\psi}$, solving the problem

\[
\max_{b_{it}} u(c_{i1} - b_{i}\beta) + \beta E u(c_{i2} + b_{i})
\]

where $E$ denotes the expectations operator conditional on information available at time one, $b_{i}$ denotes the debt issued by a household of type $i$ in the first period and $c_{it}$ denotes the household’s time $t$ consumption expenditures.

We modify our notation slightly to let the index $i$ refer to individual households $i = 1, \ldots, n$, while maintaining our assumption that all of these households are of one of two distinct types. The modification is necessary because we want to consider the possibility that households of the same type may face different shocks, even though the distribution of these shocks will be the same for all households of the same type ex ante.
The first order conditions associated with the household’s problem of debt-issuance indicate that the household will consume \( c_{it} \) at \( t \) if the usual Euler equation
\[
 u'(c_{it}) = \mathbb{E} u'(c_{i,t+1})
\]
is satisfied.

Exploiting our assumption of logarithmic utility, (5) implies that
\[
 1 = \mathbb{E} \left( \frac{c_{i1}}{c_{i2}} \right)
\]
for \( i = 1, 2, \ldots, n \).

Let
\[
 \epsilon_i = \left( \frac{c_{i1}}{c_{i2}} \right) - 1
\]
denote household \( i \)'s time one “forecast error.” Note from the properties of (6) that \( \mathbb{E} \epsilon_i = 0 \), as is usual when evaluating forecast errors from Euler equations. Note also from (5) and Jensen’s inequality we have \( c_{i1}/\mathbb{E}c_{i2} \leq 1 \), so that
\[
 \mathbb{E}c_{i2} \geq c_{i1};
\]
that is, expected consumption is increasing for both types of households.

2.3.1. Risk. The risk facing any individual household with consumption \( c_{it} \) at time \( t \) which may reduce its utility at time \( t + 1 \) depends on the distribution on the forecast error \( \epsilon_i \).

Let \( \sigma_{it} \) denote household \( i \)'s consumption share at date \( t \). Define the idiosyncratic risk borne by the household at time one to be the \textit{ex ante} loss in expected utility due solely to variation in the purely idiosyncratic shock \( \epsilon_i \), or
\[
 R_i = u(\hat{c}_2 \sigma_{i1}) - \mathbb{E}[u_i(c_{i2})]
\]
Here the first term is the utility the household would obtain in period two if the household’s share of expenditures was unchanged (as would be the case if no household faced any idiosyncratic risk) and if the household knew in advance what aggregate consumption would be in period two. The second term is the expected utility of the household given that it remained ignorant of the idiosyncratic shocks it would experience.

As demonstrated above, in a world with complete markets and the assumed logarithmic preferences we work with here, it’s easy to establish that each households’ share of aggregate consumption will remain constant, eliminating all idiosyncratic risk. Thus, we can interpret the
first term of (7) as the utility the household would obtain if no households bore any idiosyncratic risk less the expected utility of consumption when the household does bear this risk. It’s trivial to establish that this cardinal measure of risk is uniquely consistent (up to an linear transformation of $u$) with the notion of increasing risk defined by Rothschild and Stiglitz (1970). Because our measure of idiosyncratic risk is denominated in utils, it’s straightforward to construct a variety of useful measures of the welfare loss associated with this risk.

Again, for the sake of concreteness, let us assume that $\log(1 + \varepsilon_i)$ is distributed $N(-v_i^2/2, v_i)$, with the consequence that $E\varepsilon_i = 0$, as is required by our definition of the forecast error above, with $v_i$ a parameter equal to the standard deviation of $\log(1 + \varepsilon_i)$ for household $i$. With this assumption it follows that household $i$’s idiosyncratic risk (that is, holding aggregate consumption constant) is given by

$$R_i = v_i^2/2$$

Thus the ex ante welfare loss due to the uninsurability of idiosyncratic shocks is simply equal to one half the variance of $\log(1 + \varepsilon_i)$.

2.3.2. Distribution. Now, how is this risk related to the evolution of inequality? Let $\Psi(\sigma_{i2}|\sigma_{i1})$ denote the Markov transition function for the household’s share $\sigma$ between periods one and two. Then the expression for household $i$’s time $t$ idiosyncratic risk, as defined above, may be written

$$R_i = u(\bar{c}_2\sigma_{i1}) - \int u(\bar{c}_2\sigma')d\Psi(\sigma'|\sigma_{i1}).$$

We’ve already seen that we can compute risk $R_i$ from knowledge of the distribution of $i$’s forecast errors $\varepsilon_i$, so this equation allows us to relate the transition function $\Psi$ to the parameters of this distribution.

The Markov transition function $\Psi$ which is critical for calculating average risk in the population is also critical for understanding how the distribution of resources changes over time. In particular, the distribution of consumption shares (inverse Lorenz curves) $\{\Gamma_1\}$ will satisfy a law of motion

$$\Gamma_2(\sigma) = \int_{\{\sigma' < \sigma\}} d\Psi(\sigma'|\sigma)d\Gamma_1(\sigma).$$

Accordingly, knowledge of the transition function $\Psi$ suffices to characterize both average risk as well as the evolution of inequality in the population.

Let us now discuss how knowledge of the cross-sectional distribution of consumption can be used to draw inferences about household-level
risk. Recall that an individual household’s risk depends only on forecast errors $\epsilon_i$. In particular, we can use (6) to express $\Psi$ in terms of the distribution of forecast errors in the population. Let $\epsilon_i$ have the cumulative probability distribution $F(\epsilon|\sigma_i)$. Then (6) implies

$$c_i = c_i (1 + \epsilon_{it+1})^{-1},$$

so that, conditioning on consumption growth $g = \bar{c}_2/\bar{c}_1$

$$\Psi(\sigma'|\sigma) = \int_{\{\epsilon > (\sigma/\sigma')^{-1}/g\}} dF(\epsilon|\sigma).$$

Now, let us suppose that the change in the distribution of consumption is as above in Section 2.2. In particular, the share of the bottom 50 per cent of households falls from 40 per cent in the first period to 30 per cent in the second. We maintain our assumption that (one plus) forecast errors are distributed log normal and that these forecast errors have mean zero. We also maintain our assumption that the two different types of households are *ex ante* identical, and use the change in the distribution of consumption to infer the parameters $v_i$ which govern the distribution of forecast errors and risk borne by the households.

Using (8) and (10) it’s straightforward to compute (see Appendix B) the values of $v_i$ implied by this change in distribution. In particular, households of type one will have $v_i$ 0.267, while households of type two will have $v_i$ of 0.55. As an immediate consequence the risk borne by poor households will be equal to 0.0385, while the risk borne by wealthy households will be equal to 0.1540 (bear in mind that these risk figures are denominated in utils).

The quite surprising result is that the apparent increase in wealthy households’ share of consumption from 60 to 70 per cent on average *hurts* the households which were wealthy *ex ante*. The cross-sectional distribution of consumption can’t change unless at least some households face some idiosyncratic risk, and the only way to get the share of *ex post* wealthy households to increase is to expose all *ex ante* wealthy (type two) households to a great deal of risk. As a consequence, even though *expected* consumption is increasing for all households, for type two households the probability of having a big drop in consumption offsets the expected consumption increase. Figure 1 shows the distribution of period two log consumption for each of the two household types. Note that though the mean of the type two distribution is still greater than the mean of the type one distribution, the much greater variance in outcomes for the initially wealthier households means that some of these households will be at the very bottom of the consumption distribution in period two.
This apparently perverse result depends less on the details of our quite special example than one might suppose. So long as preferences exhibit decreasing absolute risk aversion, it will be initially wealthy households which will choose to take larger risks. Thus big falls in the share of the bottom consumption quantile are likely to be due to some previously wealthy households having very bad luck, while a larger share of previously poor households will move into higher quantiles. In the example just presented, the matrix governing the transition between the bottom 50 per cent and the top 50 per cent turns out to be

\[
\begin{pmatrix}
0.88 & 0.12 \\
0.06 & 0.94
\end{pmatrix}
\]

Accordingly, we can see that 12 per cent of type one households move up into the top quantile, while 6 per cent of type two households fall down into the bottom quantile. The basic flavor of the result seems to depend only on decreasing absolute risk aversion and common access to credit markets. With these two ingredients apparent increases
in inequality may actually imply that \textit{ex ante} wealthy households are bearing large amounts of risk which often cast them far down the consumption distribution.

3. The Data

We next turn to an application of some of the ideas developed in the preceding example, and make an effort to draw inferences regarding the risk borne by households in China from data from the sequence of Lorenz curves describing the evolution of consumption inequality in China over the period 1985–2001.

In this section we document a few basic facts about Chinese inequality, and then assume a structure similar to that of Section 2.2, so that households within a population quantile stay within that quantile, sharing the variable consumption which accrues to the quantile. In a later section we instead assume equal access to credit markets, and then use variation in Lorenz curves to draw inferences about idiosyncratic risk.

3.1. Chinese Inequality. Numerous authors have documented notable increases in inequality within China over the last two decades, though over the same period there’s been a dramatic increase in aggregate consumption.

There are two observations about changes in Chinese inequality that seem to qualify as stylized facts. The first is that there have been large increases in the difference between rural and urban incomes over the last twenty years, while the second is that there’s been increasing inequality in income across regions (especially between the coastal and interior areas).

In support of the first observation Kahn and Riskin (2001) document notable increases in income inequality between rural and urban households over the period 1988–1995. Ravallion (2004) and Chen and Ravallion (2004) explain part of this increase in urban-rural inequality by computing the effects of WTO accession on rural and urban poverty, finding that on average rural households tend to lose due to decreases in the price of their mostly agricultural output, while urban consumers gain.

In support of the second observation, a number of authors have documented notable increases in regional inequality. Yang (1997) documents large shifts in the resources transferred between coastal and interior regions, and argues that such shifts entail increased regional inequality as a consequence. While using data on outcomes, Yao and
Zhang (2001) document increases in inter-provincial inequality, and argue the existence of “clubs” of provinces with incomes diverging from the incomes of other clubs.

Of course, even if both these observations are true, it may be the case that one observation is a consequence of the other. In particular, since there’s wide variation in the proportion of rural households across provinces, it may well be the case that the observed increase in inequality across regions is simply a consequence of increased rural-urban inequality. Bhalla et al. (2003) and Kanbur and Zhang (2003) use data on province-level incomes to argue that most inequality is due to rural-urban differences, rather than to provincial-level differences; however, both papers still find a large role for provincial differences even after accounting for differences in rural-urban composition.

The general connection between trade and inequality (or poverty) discussed by Chen and Ravallion (2004) can also be found using much more aggregate provincial-level data. Kanbur and Zhang (2003) find that increases in interprovincial income inequality over time are associated with differences in openness, while Zhang and Zhang (2003) decompose a Theil measure of inequality, and find that 20 per cent of differences in per capita GDP across provinces in 1995 can be attributed to measures of trade (Milanovic (2004) shows that it’s critical to weight provinces by population to obtain this result). However, as Ravallion (2004) cautions, this kind of association between two endogenous aggregates (inequality and trade) doesn’t allow us to draw any inference about cause.

In an important reminder that inequality isn’t mostly about aggregates, Benjamin et al. (2004) examine a large panel of rural Chinese households, and find evidence of larger increases in inequality within small geographical regions than across them.

3.2. Urban Inequality. Against this background of rapid increases in overall Chinese inequality, how should we assess changes in urban inequality? The way in which inequality changes over time matters greatly for evaluating household welfare. If all the increase in inequality is due to increases in equality between different groups, then the idiosyncratic risk due to this increasing inequality will be small. For example, one of the key features of Chinese reform has to do with the fact that reform began in the countryside, with the establishment of the household responsibility system in the late 1970s and corresponding introduction of market prices (at the margin) for agricultural goods. These reforms ushered in a decade of rapid rural economic growth. The nineties brought an important change. A decade of rural growth
was followed by an extended period of urban growth and relative rural stagnation. Yang (1997) argues convincingly that this shift was due to quite conscious and quite visible policy choices made by the central government, which exploited its control of non-agricultural prices to implicitly tax the interior of the country, and to use the proceeds of these implicit taxes to finance investment in coastal urban areas. To the extent that one could predict that urban households would benefit from these policies at the expense of rural households, neither urban nor rural households would face any risk subsequent to this policy shift, but simply different expected growth trajectories.

Since the focus of this paper is on urban households, let us henceforth set aside changes in overall inequality due to the well documented divergence in the consumption expenditures of rural and urban China. Instead, let us ask what can our data tell us about the evolution of inequality among urban Chinese households.

Figure 2. Changes in Consumption Lorenz Curves for Registered Urban Households
At beginning of the period for which we have data, inequality in China was remarkably low. While one still doesn’t observe gross inequities in the distribution of consumption in China, over the course of 1985–2001 one does observe an increase in urban inequality. This point is made most clearly by Figure 2. This figure shows the change in Lorenz curves for urban consumption over the period 1985–2001. Individual changes are shown year by year. It’s apparent from these that inequality isn’t always increasing— from year to year one sees increases in equality with almost the same frequency as decreases. However, the average decrease in equality is larger than the average increase, with the consequence that when we aggregate all these changes, we see that the total change in Lorenz curves is considerable, with the bottom sixty per cent of the distribution seeing a fall in their aggregate share of consumption of about four per cent. The bottom ten per cent of the distribution sees a much larger (proportional) drop, with their share falling from about 8 per cent in 1985 to about 6.5 per cent in 2001, or a nearly 20 per cent fall. Of course, as we’ve seen in Table 1 this same bottom 10 per cent has seen large increases in total consumption, so this fall in share has been much more than offset by increases in aggregate consumption.

We tackle the measurement of changes in urban inequality in two stages. First, we use aggregate data on the distribution of consumption expenditures to characterize changes in welfare and inequality across consumption quartiles. Subsequently we turn our attention to the problem of inferring the distribution of possible consumption outcomes for individual households at different points in the cross-sectional consumption distribution. We’ll use the inferences so drawn to quantify the idiosyncratic risk borne by these households.

We begin by trying to understand consumption growth by population quantile. Table 1 reports the average rate of consumption growth for each of eight quantiles over the period 1986–2001. The results of this exercise show that, when averaged over this entire period, that there’s remarkably little difference in the average rate of consumption growth for different quantiles. All of the eight quantiles have consumption growth which averages about 12 per cent per year, and no quantile has a rate of growth significantly greater than that of any other quantile.

Of course, the fact that different quantiles all have roughly the same rate of consumption growth over a long period doesn’t imply that there aren’t differences over shorter periods. Accordingly, we next ask about how much of the variation in individual quantiles’ consumption can be explained by country-level shocks. We begin by asking what proportion of quantiles’ consumption growth is attributable to aggregate
Table 1. Increasing Inequality? Average growth rates of consumption expenditures for different quantiles of the consumption distribution appear in the first row of the table, with \( t \) statistics for these point estimates immediately below. The lower panel of the table presents \( t \)-tests of differences among the growth rates of different quantiles.

<table>
<thead>
<tr>
<th>Quartile</th>
<th>5%</th>
<th>10%</th>
<th>20%</th>
<th>40%</th>
<th>60%</th>
<th>80%</th>
<th>90%</th>
<th>100%</th>
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<tr>
<td>Growth Rate</td>
<td>0.123</td>
<td>0.117</td>
<td>0.112</td>
<td>0.117</td>
<td>0.110</td>
<td>0.128</td>
<td>0.133</td>
<td>0.113</td>
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<td>( t )-stat.</td>
<td>5.064</td>
<td>4.786</td>
<td>4.593</td>
<td>4.816</td>
<td>4.531</td>
<td>5.272</td>
<td>5.440</td>
<td>4.629</td>
</tr>
<tr>
<td>5%</td>
<td>0.000</td>
<td>0.197</td>
<td>0.333</td>
<td>0.176</td>
<td>0.377</td>
<td>-0.146</td>
<td>-0.266</td>
<td>0.308</td>
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<tr>
<td>10%</td>
<td>-0.197</td>
<td>0.000</td>
<td>0.136</td>
<td>-0.021</td>
<td>0.180</td>
<td>-0.344</td>
<td>-0.463</td>
<td>0.111</td>
</tr>
<tr>
<td>20%</td>
<td>-0.333</td>
<td>-0.136</td>
<td>0.000</td>
<td>-0.157</td>
<td>0.044</td>
<td>-0.480</td>
<td>-0.599</td>
<td>-0.025</td>
</tr>
<tr>
<td>40%</td>
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<td>0.021</td>
<td>0.157</td>
<td>0.000</td>
<td>0.201</td>
<td>-0.322</td>
<td>-0.442</td>
<td>0.132</td>
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<tr>
<td>60%</td>
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<td>-0.180</td>
<td>-0.044</td>
<td>-0.201</td>
<td>0.000</td>
<td>-0.523</td>
<td>-0.643</td>
<td>-0.069</td>
</tr>
<tr>
<td>80%</td>
<td>0.146</td>
<td>0.344</td>
<td>0.480</td>
<td>0.322</td>
<td>0.523</td>
<td>0.000</td>
<td>-0.119</td>
<td>0.454</td>
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<tr>
<td>90%</td>
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<td>0.463</td>
<td>0.599</td>
<td>0.442</td>
<td>0.643</td>
<td>0.119</td>
<td>0.000</td>
<td>0.574</td>
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<td>100%</td>
<td>-0.308</td>
<td>-0.111</td>
<td>0.025</td>
<td>-0.132</td>
<td>0.069</td>
<td>-0.454</td>
<td>-0.574</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Table 2. Analysis of Variance of Consumption Growth

<table>
<thead>
<tr>
<th>Variables</th>
<th>Individual Contribution ( (R^2) )</th>
<th>Cumulative Contribution ( (R^2) )</th>
<th>( p )-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quantile</td>
<td>0.008</td>
<td>0.008</td>
<td>0.998</td>
</tr>
<tr>
<td>Country Shocks</td>
<td>0.893</td>
<td>0.901</td>
<td>0.000</td>
</tr>
<tr>
<td>Import Shocks</td>
<td>0.496</td>
<td>0.963</td>
<td>0.998</td>
</tr>
</tbody>
</table>

growth. These results are reported in the first row of Table 2. We see from this that nearly 90 per cent of variation in quantile consumption is due to entirely aggregate variation.

After controlling for entirely aggregate variation in urban consumption growth, we next ask whether or not changes in trade shocks can help account for quantile-specific variation. We use data on imports in various sectors interacted with a complete set of quantile dummies.\(^2\) The idea is that trade shocks to a particular sector may have unequal effects on households situated in different parts of the consumption distribution. This builds on the idea (Lundberg and Squire, 2003) that globalization may have effects both on the distribution of resources

\(^2\)See the discussion of the trade data used in Section 4, infra.
The evidence from Table 2 is that the effect of the trade shocks we’re able to measure has entirely to do with aggregate outcomes—these trade variables have no power to explain changes in urban inequality within China at all (though trade shocks explain 6.2 per cent more variation than country shocks alone, this increment in explanatory power isn’t significant). This last finding may be contrasted with the findings of Ligon (2004). Using a very similar methodology, it’s shown in that paper that for a sample of mostly low-income countries entirely global factors explain a significant portion of changes in within country inequality after controlling (as here) for country-level shocks.

Finally, Table 3 displays estimates of the welfare loss for households due to aggregate sources of risk (risk shared by all households in the country, quantile-level risk related to trade shocks, and residual quantile-level risk). All measures are denominated in utils, and are computed in a manner analogous to the approach taken by Ligon and Schechter (2003). Note, however, that these measures of risk completely neglect idiosyncratic factors. Inferring this idiosyncratic component is the chief task of the remainder of this paper.

### Table 3. Decomposition of Risk Across Quantiles.

<table>
<thead>
<tr>
<th>Risk</th>
<th>Country</th>
<th>Trade</th>
<th>Quantile Risk</th>
</tr>
</thead>
<tbody>
<tr>
<td>5%</td>
<td>0.249</td>
<td>0.323</td>
<td>1.664</td>
</tr>
<tr>
<td>10%</td>
<td>0.003</td>
<td>0.196</td>
<td>2.703</td>
</tr>
<tr>
<td>20%</td>
<td>0.139</td>
<td>0.101</td>
<td>1.894</td>
</tr>
<tr>
<td>40%</td>
<td>0.117</td>
<td>-0.070</td>
<td>1.969</td>
</tr>
<tr>
<td>60%</td>
<td>0.002</td>
<td>-0.030</td>
<td>2.372</td>
</tr>
<tr>
<td>80%</td>
<td>0.171</td>
<td>-0.062</td>
<td>1.548</td>
</tr>
<tr>
<td>90%</td>
<td>0.069</td>
<td>-0.111</td>
<td>2.080</td>
</tr>
<tr>
<td>100%</td>
<td>0.057</td>
<td>-0.182</td>
<td>1.779</td>
</tr>
</tbody>
</table>

Note that these figures do not include estimates of the risk due to idiosyncratic shocks.

### 4. Measuring the Effects of Globalization in China

When households have identical CES utility functions, any changes in the distribution of consumption is evidence of risk borne by these households. More particularly, if households have access to credit markets on equal terms, then changes in the distribution of consumption...
must be due to “relative surprises” experienced by individual households.\textsuperscript{3} We have not, however, said anything about the source of these surprises. In this section we describe a simple way to relate variation in consumption volatility across the distribution to simple measures of “globalization.”

Of course, it’s not at all obvious how one ought to go about measuring “globalization,” but certainly globalization has something to do with trade. Further, for workers in a particular sector the uncertainty induced by globalization seems to be plausibly related to changes in the volume of imports of goods or services which they might otherwise provide, and the occupational distribution of workers is related to the distribution of consumption.

We proceed as follows. Suppose that both workers and imports can be assigned to one of \( K \) different sectors. Let \( y_t \) be a \( K \)-vector of the value of imports into China for each of these \( K \) sectors in year \( t \). Imports are, of course endogenous. To model imports we turn to the literature on the “gravity-model” of trade. Let countries be indexed by \( i = 1, \ldots, M \). A typical application of the gravity model (e.g. Anderson, 1979; Deardorff, 1998) which typically models exports by

\[
 y_{ij}^{kt} = \beta_{0k}^{ij} + \beta_{1k}^{ij} x_{jt} + \beta_{2k}^{ij} x_{it} + \beta_{3k}^{ij} d_{ij}^{it} + \varepsilon_{ij}^{kt},
\]

where \( y_{ij}^{kt} \) denotes the logarithm exports from country \( i \) to country \( j \) in sector \( k \) at \( t \), and \( x_{it} \) is the logarithm of country \( i \)'s GDP at \( t \), and \( d_{ij}^{it} \) is a measure of the distance between countries \( i \) and \( j \) at time \( t \). Ideally this last measure should reflect the costs of transporting goods and services between countries \( i \) and \( j \) at time \( t \), including the costs of surmounting trade barriers including both tariffs and non-tariff barriers.

Now, let country \( j \) be China, and omit this superscript henceforth. Then summing over \( i \), we obtain an expression for imports to China for sector \( k \) at time \( t \),

\[
 y_{kt} = \beta_{0k} + \beta_{1k} x_{jt} + \beta_{2k} \sum_{i=1}^{M} x_{it} + \xi_{kt}
\]

where \( \beta_{0k} = \sum_{i=1}^{M} \beta_{0k}^{ij} \) and \( \xi_{kt} = \sum_{i=1}^{M} (\beta_{3k} d_{ij}^{it} + \varepsilon_{ij}^{kt}) \). Now, the term \( \xi_{kt} \) captures changes in trade conditions which we might think of as being

\textsuperscript{3}Appendix A outlines in detail the kind of structure placed on the evolution of inequality in expenditures by credit markets, and shows that changes in the distribution of expenditures over time depend entirely on the “relative surprises” faced by individual households.
related to ‘globalization,’ including the reduction of trade barriers and decreases in transport costs.

<table>
<thead>
<tr>
<th>Sector</th>
<th>NBS Occ. Description</th>
<th>WDI Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture</td>
<td>1</td>
<td>Agricultural Raw Materials</td>
</tr>
<tr>
<td>Food</td>
<td>8</td>
<td>Food</td>
</tr>
<tr>
<td>Fuel</td>
<td>4</td>
<td>Fuel</td>
</tr>
<tr>
<td>Manufactures</td>
<td>3</td>
<td>Manufactures</td>
</tr>
<tr>
<td>Ores &amp; Metals</td>
<td>2,6</td>
<td>Ores &amp; Metals</td>
</tr>
<tr>
<td>Transport &amp; Communications</td>
<td>7</td>
<td>Computer, communications &amp; Other Services; Transport Services; Travel Services</td>
</tr>
<tr>
<td>Finance &amp; Insurance</td>
<td>9</td>
<td>Insurance &amp; Financial Services</td>
</tr>
<tr>
<td>Nontradable Services</td>
<td>5, 10–16</td>
<td>—</td>
</tr>
</tbody>
</table>

Table 4. Definition of Sectors, and Relation to NBS Occupational Codes and WDI Trade Data.

The household survey used to measure household expenditures for urban households classifies household members’ occupations into one of sixteen sectors. There’s a fairly close (but not one-to-one, see Table 4) correspondence between these sixteen occupational categories and the categories of goods and services for which the World Development Institute reports imports and exports. Matching occupational categories with categories of traded goods and services yields a set of seven categories matching occupation with trade data (and an eighth consisting of non-tradable services). Use of this classification scheme yields data on \( y_{kt} \). We use the Penn World Tables (Summers and Heston, 1991) to compile data on GDP.

Estimates of the parameters of (12) are presented in Table 5 for each of seven sectors. Chinese GDP is much the most important variable for explaining the volume of imports, both in terms of statistical significance and in terms of the magnitude of the estimated coefficient—the coefficient associated with the sum of log GDP across the world is consistently negative, but never statistically significant. Neither are the estimated intercepts significant. Notable results by sector include manufactures, transport and communications, and finance and insurance—for each of these three sectors the estimated coefficient associated with the logarithm of Chinese GDP is significant, and the estimated elasticity greater than one in magnitude. Particularly notable are the very large income elasticities for the presumably ‘high tech’ services associated with transport, communication, finance, and insurance.
### Imports

<table>
<thead>
<tr>
<th>Sector</th>
<th>Intercept</th>
<th>World GDP</th>
<th>China GDP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture</td>
<td>12.753</td>
<td>-0.001</td>
<td>1.000</td>
</tr>
<tr>
<td></td>
<td>(9.784)</td>
<td>(0.001)</td>
<td>(0.786)</td>
</tr>
<tr>
<td>Manufactures</td>
<td>8.468</td>
<td>-0.001</td>
<td>1.428*</td>
</tr>
<tr>
<td></td>
<td>(6.646)</td>
<td>(0.001)</td>
<td>(0.534)</td>
</tr>
<tr>
<td>Ores &amp; Metals</td>
<td>-4.986</td>
<td>-0.001</td>
<td>2.134*</td>
</tr>
<tr>
<td></td>
<td>(12.794)</td>
<td>(0.002)</td>
<td>(1.027)</td>
</tr>
<tr>
<td>Transport &amp; Comms.</td>
<td>-11.544</td>
<td>-0.000</td>
<td>2.548*</td>
</tr>
<tr>
<td></td>
<td>(11.735)</td>
<td>(0.002)</td>
<td>(0.942)</td>
</tr>
<tr>
<td>Finance &amp; Insurance</td>
<td>-40.778</td>
<td>-0.005</td>
<td>4.884*</td>
</tr>
<tr>
<td></td>
<td>(21.659)</td>
<td>(0.003)</td>
<td>(1.739)</td>
</tr>
</tbody>
</table>

### Exports

<table>
<thead>
<tr>
<th>Sector</th>
<th>Intercept</th>
<th>World GDP</th>
<th>China GDP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture</td>
<td>28.736*</td>
<td>-0.000</td>
<td>-0.130</td>
</tr>
<tr>
<td></td>
<td>(7.351)</td>
<td>(0.001)</td>
<td>(0.590)</td>
</tr>
<tr>
<td>Manufactures</td>
<td>3.810</td>
<td>-0.001</td>
<td>1.735*</td>
</tr>
<tr>
<td></td>
<td>(7.655)</td>
<td>(0.001)</td>
<td>(0.615)</td>
</tr>
<tr>
<td>Ores &amp; Metals</td>
<td>7.203</td>
<td>-0.001</td>
<td>1.348</td>
</tr>
<tr>
<td></td>
<td>(10.677)</td>
<td>(0.002)</td>
<td>(0.857)</td>
</tr>
<tr>
<td>Transport &amp; Comms.</td>
<td>-13.373</td>
<td>-0.001</td>
<td>2.684*</td>
</tr>
<tr>
<td></td>
<td>(11.856)</td>
<td>(0.002)</td>
<td>(0.952)</td>
</tr>
<tr>
<td>Finance &amp; Insurance</td>
<td>6.524</td>
<td>-0.001</td>
<td>1.309</td>
</tr>
<tr>
<td></td>
<td>(32.769)</td>
<td>(0.005)</td>
<td>(2.631)</td>
</tr>
</tbody>
</table>

Table 5. Estimates from ‘gravity’ model for Chinese imports and exports. Figures in parentheses are estimated standard errors; asterisks indicate significance at a 95 per cent level of confidence.

The second panel of Table 5 reports coefficient estimates when \( y_{kt} \) reports the logarithm of exports, rather than of imports. Broadly interpreted, results are similar to those for imports—coefficients associated with the world GDP variable are typically negative (with one exception) but insignificant. Coefficients associated with China’s GDP, in contrast, are positive (again with one exception) and significant for manufactures and transport and communications.

Though the results reported in Table 5 may have some slight independent interest, recall that the point of estimating this version of the gravity model was to isolate—in the estimated residuals—the effects of ‘globalization’ on imports and exports, independent of changes since
Figure 3. Residuals from estimation of (11) for log imports (top panel) and log exports (bottom panel).
Figure 4. Growth rate necessary to compensate for risk, by quantiles. Each line indicates the minimum rate of growth necessary to compensate for the risk faced by the average household at the consumption share quantile indicated at the far right. For example, the line labelled ‘5’ gives the rate of growth in each year necessary to compensate the average household ex ante at the 5 per cent quantile for the risk borne by that household.

In this section we use the logic developed in the example of Section 2 to draw inferences about the level of idiosyncratic risk from a sequence of Lorenz curves. We relax many of the most restrictive assumptions of the example, developing a more general framework for inference in 1985 which might have influenced trade via GDP. Reflecting our interest in these residuals, Figure 3 show scatterplots of residuals for both imports and exports over time.

5. IDIOSYNCRATIC RISK

In this section we use the logic developed in the example of Section 2 to draw inferences about the level of idiosyncratic risk from a sequence of Lorenz curves. We relax many of the most restrictive assumptions of the example, developing a more general framework for inference in
Appendix A and Appendix B. One useful generalization involves giving a parametric form for the variance (or scale) which governs risk, permitting this variance to depend on a variety of observable variables. The general form for this scale parameter is given by (24).

5.1. Error Components Structure. We begin with (adapting some language from Amemiya, 1984) a simple ‘error components’ structure, permitting the log of the variance of the relative forecast error to depend on the sum of a year-specific constant and a quantile-specific constant, so that

\[
\log v_{it} = \alpha_i + \nu_t.
\]

Here \(v_{it}\) is the standard error of the relative forecast shock for a household in the \(i\)th quantile of the consumption share distribution in year \(y\); in practice we divide this distribution into 17 different quantiles, but for the sake of identifying these parameters we constrain the top quantile to have \(\alpha_{17} = 0\).
Table 6 presents the fitted parameters given this ‘error components’ variance structure. The leftmost panel of the table shows parameters which vary across years. Estimates of the normalizing constants \{\eta_t\} appear in the first column of this panel, while the “year effects” part of the variance structure, \{\nu_t\} appears in the second column. Recall from our earlier discussion the interpretation of \eta_t as a measure of the aggregate uncertainty at time \(t\)—this specification gives us a simple way to check the model, since \nu_t provides a direct measure of aggregate uncertainty. In this case, the correlation between the two measures is 0.47, consistent with our expectations.

The primary virtue of this ‘error components’ specification of the structure of the variance of relative forecast errors has to do with the simplicity of interpreting estimates of \(\alpha_i\) and \nu_t. In particular, for years in which \nu_t is relatively large, the entire population faces greater risk than usual. At the same time the specification allows for variation in uncertainty by wealth (consumption share); the average households in a quantile for which \(\alpha_i\) is negative faces less uncertainty in an average year than do the very wealthiest households, while the average household in a quantile with \(\alpha_i\) greater than zero faces more.
Turning our attention to differences in the uncertainty faced by households across the distribution, consider the second panel of Table 6. Here we see that the households in the bottom quantile who collectively consume 1.4 per cent of the aggregate face the least uncertainty, with a quantile “fixed effect” of -3.59. However, households in the 5–8 per cent quantile face the most, with an estimated quantile fixed effect of 3.84. Eight of the consumption share quantiles bear more uncertainty than does the topmost quantile, while seven bear less.

At this point let us pause a moment to be careful about what is meant by “uncertainty” above. Differences in the parameters \( \nu_t \) across time or \( \alpha_i \) across quantiles are really just related to the standard deviation of the relative forecast errors \( \hat{\epsilon}_{it} \). These relative forecast errors have numerous desirable properties, but don’t have a straight-forward interpretation either in terms of the welfare costs of uncertainty or in terms of variation in quantities which might be observable. In particular, the distribution of \( \hat{\epsilon}_{it} \) depends both on household risk-preferences (here \( \gamma \)) and on the distribution of consumption growth, making it critical to estimate \( \gamma \) and the variance structure of the forecast errors simultaneously. In the present case, the estimated value of the coefficient of relative risk aversion is 0.723. This is on the low end of the range of estimates of this parameter in the micro-econometric literature, but doesn’t seem obviously wrong.

To get a sense of the magnitude of the risk facing individual households, we use the parameters reported in Table 6 to estimate the risk facing the average household at selected consumption-share quantiles in Figure 4. To construct this figure we’ve started with estimates of the measure of risk given by (19), but rather than reporting the welfare loss due to uncertainty in utils (which may be difficult to interpret), we’ve computed the growth rate of aggregate consumption expenditures which would be just enough to compensate households for the risk they bear.

In the present case, because we assume CES utility functions future aggregate consumption \( \tilde{c}_{t+1} \) cancels out of this calculation. By substituting in our estimates of the parameters \( \eta_t \) and of the marginal Markov transition function a simple line-search algorithm can be used to find the compensating growth rates.

These compensating growth-rates are shown for selected consumption-share quantiles in Figure 4. Note first that the growth we’re referring to is the rate of growth in aggregate consumption expenditures for urban households—this quantity grew at an average annual rate of 12 per cent over the period 1985–2001. Using the quantity \( g_t(\sigma) \) as our measure of the welfare loss of uncertainty, the poorest (displayed) quantile of
households is much the worst off—from 1985 to 1986 these households would have needed urban expenditures to have grown by nearly 14 per cent before they would have preferred the status quo to stagnation and an “iron rice bowl.” Setting the poorest households aside, risk does increase in a monotone way, with households at the 92 per cent quantile requiring compensation which never exceeds five per cent. Thus, were we to graph it, this measure of risk would display a “U” pattern, with the poorest households bearing a great deal of risk, low income households bearing the least, and risk gradually increasing with consumption shares throughout the rest of the distribution.

We now turn our attention from risk to inequality. Recall that we’re now able to construct estimates of the Markov transition functions. If these functions were invariant across time, it would be a trivial matter to calculate the future evolution of the distribution of consumption for as many periods as we choose, simply by using an estimate of some initial distribution $\Gamma_0$, and then applying (20) iteratively to trace out future distributions.

Of course, matters are not quite so simple. Instead, we have estimates of the transition function for 16 different values of $t$, from 1985–2001, and while it’s a simple matter to trace out the predicted trajectory over the course of this sample period, this tells us little about future inequality. We adopt the following simple strategy. Given our collection of 16 different estimated transition functions, we simply assume that these functions are representative of the kinds of transition functions which may be realized in the future. Thus, to estimate the evolution of the distribution of consumption over $\tau$ periods we simply make $\tau$ random draws (with replacement) from the collection of transition functions $\{\Psi_t\}$. Starting with the actual distribution of consumption shares in 2001, we substitute these draws sequentially into (20); inverting the resulting function $\Gamma_t$ yields an estimate of the Lorenz curve $L_t$. Then we use these $\tau$ equations to calculate one possible sample trajectory of the Lorenz curves, which we denote by $\{\hat{L}_t\}_{t=1}^\tau$. We repeat this procedure many times, so that we have a bootstrapped sample of $m$ possible trajectories for the Lorenz curve over time, or $\mathcal{L} = \{\{\hat{L}_t\}_{t=1}^\tau\}_{i=1}^m$.

Now, for any population quantile $x$ we can compute a “mean” trajectory by computing

$$\hat{L}_t(x) = \frac{1}{m} \sum_{i=1}^m L_i^t(x),$$
or characterize the distribution of possible trajectories by simply working with the bootstrap sample \( \mathcal{L} \).

Figure 5 shows values of \( L_t(x) \) for selected values of \( x^4 \) (the solid lines) along with 80 per cent confidence intervals, for predicted trajectories beginning in 2001 and running through 2025. The figure has several notable features. First, note that the confidence intervals are very tight, relative to the variation across population quantiles. This is a reflection of a fact already noted above—differences across households are much more pronounced than differences across time. The very small variation in our estimated “time effects” \( \{ \nu_t \} \) and normalizing constants \( \{ \eta_t \} \) mean that in fact our estimated transition functions don’t change very much over time at all; as a consequence it doesn’t matter very much what actual sequence of transition functions we draw in our bootstrap exercise.

Thus emboldened, we henceforth refer to the evolution of \( L_t \). Our estimated model predicts that inequality will continue to increase in China through 2025, but at a relatively slow rate. However, the bottom ten per cent of the population will, by then, consume a much smaller share in 2025 (2 per cent) than at present (6.5 per cent). Neglecting the welfare costs of risk discussed above, to keep the level of consumption constant for this poorest 10 per cent of the population, aggregate urban consumption must grow at an average rate of about five per cent to compensate this part of the population whose share is sharply declining. To compensate for risk, of course, much higher growth rates would have to be sustained.

5.2. The Effects of Trade on Inequality. We next abandon our ‘error-components’ structure for the scale parameters \( v_{it} \), and seek to relate the risk borne by households in different initial quantiles to changes in the volume of imports. The idea is that we want to relate changes in ‘globalization’ to the volatility of shocks experienced by Chinese workers by their position in the distribution of consumption. Accordingly, let \( y_t \) denote a vector of imports by sector, as described in Section 4. Now, let \( v_t(\sigma) \) be the standard deviation of the relative forecast error for the average household with consumption share \( \sigma \). Parameterizing this let

\[
\log v_t(\sigma) = \nu_t + \mu(\sigma)'\Delta y_t
\]

so that the variance of relative forecast errors for households with consumption share \( \sigma \) depends on an “aggregate” time-varying variance \( \nu_t \).

\footnote{These are those available in the China Statistical Yearbooks, and are equal to (0.05, 0.1, 0.2, 0.4, 0.6, 0.80, 0.9)}
RISK AND INEQUALITY IN CHINA

and on changes in imports in different sectors. These trade shocks are permitted to have an independent effect on different quantiles, governed by the parameters $\mu(\sigma)$.

<table>
<thead>
<tr>
<th>Year</th>
<th>$\gamma$</th>
<th>$\eta_t$</th>
<th>$\nu_t$</th>
<th>Quantile Agr.</th>
<th>Manuf.</th>
<th>Mining</th>
<th>Transport</th>
<th>Finance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1988</td>
<td>1.3102</td>
<td>-1.5406</td>
<td>0.0136</td>
<td>-0.0004</td>
<td>-2.0304</td>
<td>0.0000</td>
<td>1.5396</td>
<td>12.3230</td>
</tr>
<tr>
<td>1989</td>
<td>1.2353</td>
<td>-0.0170</td>
<td>0.0273</td>
<td>-0.0007</td>
<td>-2.2672</td>
<td>0.0000</td>
<td>-4.3855</td>
<td>12.8280</td>
</tr>
<tr>
<td>1990</td>
<td>1.4337</td>
<td>2.5841</td>
<td>0.0531</td>
<td>4.5349</td>
<td>-2.1832</td>
<td>1.3506</td>
<td>-0.0000</td>
<td>-0.0000</td>
</tr>
<tr>
<td>1991</td>
<td>1.2300</td>
<td>2.2895</td>
<td>0.0790</td>
<td>-0.0000</td>
<td>-2.4558</td>
<td>0.0000</td>
<td>6.5110</td>
<td>4.0127</td>
</tr>
<tr>
<td>1992</td>
<td>1.3537</td>
<td>0.0000</td>
<td>0.1129</td>
<td>0.0000</td>
<td>-0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>-8.5340</td>
</tr>
<tr>
<td>1993</td>
<td>1.6218</td>
<td>0.0000</td>
<td>0.1468</td>
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<td>-0.0000</td>
<td>0.0000</td>
<td>-3.6058</td>
<td>-9.6880</td>
</tr>
<tr>
<td>1994</td>
<td>1.7864</td>
<td>1.1665</td>
<td>0.2259</td>
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<td>-2.6470</td>
<td>0.0000</td>
<td>-0.0000</td>
<td>-0.0000</td>
</tr>
<tr>
<td>1995</td>
<td>1.1746</td>
<td>0.5833</td>
<td>0.3050</td>
<td>0.0000</td>
<td>-0.3680</td>
<td>0.0000</td>
<td>0.0000</td>
<td>12.5413</td>
</tr>
<tr>
<td>1996</td>
<td>1.3131</td>
<td>-0.9937</td>
<td>0.3981</td>
<td>4.7465</td>
<td>-5.5254</td>
<td>0.0000</td>
<td>-15.4754</td>
<td>-0.0000</td>
</tr>
<tr>
<td>1997</td>
<td>1.1368</td>
<td>0.0000</td>
<td>0.4912</td>
<td>0.0001</td>
<td>4.8948</td>
<td>0.0000</td>
<td>0.0000</td>
<td>-0.0001</td>
</tr>
<tr>
<td>1998</td>
<td>1.3334</td>
<td>-0.0000</td>
<td>0.6005</td>
<td>-0.0000</td>
<td>6.3471</td>
<td>0.0000</td>
<td>0.0000</td>
<td>-15.8008</td>
</tr>
<tr>
<td>1999</td>
<td>1.3031</td>
<td>0.0000</td>
<td>0.7098</td>
<td>-0.0295</td>
<td>0.0000</td>
<td>-3.8934</td>
<td>18.4582</td>
<td>0.0000</td>
</tr>
<tr>
<td>2000</td>
<td>1.2135</td>
<td>0.0640</td>
<td>0.7739</td>
<td>-0.0000</td>
<td>0.0000</td>
<td>-0.0000</td>
<td>0.0000</td>
<td>-0.0000</td>
</tr>
</tbody>
</table>

$\hat{\gamma} = 1.0808$

| $\hat{\gamma}$ | 1.0000 | -0.0001 | 0.0000 | -0.0002 | 0.0000 | -0.0000 |

Table 7. Parameter Estimates assuming log-normal relative forecast errors and relating variance to imports.

Estimates of parameters for this specification are given in Table 7. Note first that estimates of the risk aversion parameter $\gamma$ are slightly greater than one, implying that utility is close to logarithmic. As before, variation in the year effects $\nu_t$ is substantial, implying considerable changes in risk across years. The right-hand panel of the table gives the remaining parameters of our specification, relating quantile-specific scale parameters to changes in imports across five different sectors. It’s difficult to draw any general conclusion here about the connection between risk and trade, particularly in the absence of any standard errors of our estimates of the parameters $\mu(\sigma)$.

However, turning our attention to estimates of the level of idiosyncratic risk given this collection of estimates in Table 8 some useful patterns emerge. The left-most column gives different quantiles, so that the first row reports levels of risk for households in the poorest quantile which consumes 1.36% of the aggregate. The second and third columns give estimates of (100 times the) country and quantile
risk derived (via interpolation, and with $\gamma = 1.08$ to match the estimate given in Table 7) from the figures presented in Table 3. The final column adds our estimates of (100 times) idiosyncratic risk. Since the idiosyncratic risk is calculated independently of quantile risk this isn’t a quite a decomposition, as the figures in Table 3 were; rather the idea is to allow us to make some broad statements about relative magnitude and comparisons across quantiles.

As before, it’s notable that country-risk is more important for poor households; indeed, this source of variation seems to provide some slight insurance to better-off households, though in the absence of any kind of confidence intervals for these figures we should be governed by caution. Quantile risk is quantitatively much more important than country-level risk, and seems not to vary systematically across quantiles. This is in contrast to idiosyncratic risk (which encompasses quantile risk). Though the magnitudes of idiosyncratic and quantile risk are similar, idiosyncratic risk seems to generally decrease as households’ wealth increases.

<table>
<thead>
<tr>
<th>Risk (%)</th>
<th>Country +</th>
<th>Quantile +</th>
<th>Idio. Risk</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.36%</td>
<td>1.384</td>
<td>9.435</td>
<td>10.497</td>
</tr>
<tr>
<td>2.73%</td>
<td>1.224</td>
<td>10.856</td>
<td>11.803</td>
</tr>
<tr>
<td>5.31%</td>
<td>0.934</td>
<td>13.028</td>
<td>12.977</td>
</tr>
<tr>
<td>7.90%</td>
<td>0.737</td>
<td>11.416</td>
<td>13.352</td>
</tr>
<tr>
<td>11.29%</td>
<td>0.452</td>
<td>10.172</td>
<td>12.682</td>
</tr>
<tr>
<td>14.68%</td>
<td>0.126</td>
<td>10.351</td>
<td>11.714</td>
</tr>
<tr>
<td>22.59%</td>
<td>-0.358</td>
<td>11.045</td>
<td>9.860</td>
</tr>
<tr>
<td>30.50%</td>
<td>-0.274</td>
<td>12.300</td>
<td>7.729</td>
</tr>
<tr>
<td>39.81%</td>
<td>-0.176</td>
<td>13.780</td>
<td>6.697</td>
</tr>
<tr>
<td>49.12%</td>
<td>-0.279</td>
<td>11.718</td>
<td>6.536</td>
</tr>
<tr>
<td>60.05%</td>
<td>-0.405</td>
<td>9.232</td>
<td>6.272</td>
</tr>
<tr>
<td>70.98%</td>
<td>-0.567</td>
<td>10.828</td>
<td>6.396</td>
</tr>
<tr>
<td>77.39%</td>
<td>-0.662</td>
<td>11.764</td>
<td>6.563</td>
</tr>
<tr>
<td>83.80%</td>
<td>-0.899</td>
<td>11.754</td>
<td>6.911</td>
</tr>
<tr>
<td>91.90%</td>
<td>-1.223</td>
<td>11.116</td>
<td>7.314</td>
</tr>
<tr>
<td>100.00%</td>
<td>-1.223</td>
<td>11.116</td>
<td>7.379</td>
</tr>
</tbody>
</table>

Table 8. Idiosyncratic risk compared with other sources. All figures are denominated in 100 times util-denominated risk.
6. Conclusion

China’s economy has changed dramatically over the last two decades, but household level data to understand the effects of China’s growth and opening to the outside world are very difficult to come by—data from China’s National Bureau of Statistics either have very limited coverage or are very aggregated.

In this paper we make a silk purse of a sow’s ear by using aggregate data on the distribution of consumption expenditures across (registered) urban households to construct a sequence of Lorenz curves, and then use intertemporal restrictions on individual households’ consumption expenditures implied by optimizing behavior by risk-averse households to derive the restrictions on the evolution of these Lorenz curves implied by theory. The evolution of the Lorenz curve turns out to depend on just two kinds of objects: household utility functions, and the distribution of “relative forecast errors” for intertemporally optimizing households.

To pin down household utility, we assume that household preferences exhibit constant relative risk aversion. To pin down the distribution of relative forecast errors we choose a three-parameter log-normal specification, based on an examination of data from a small subset of urban households for which we construct the empirical probability distribution for these relative forecast errors.

For any estimate of the coefficient of relative risk aversion and parameters governing the distribution of relative forecast errors, we are able to predict a sequence of future Lorenz distributions. We compare this predicted trajectory with the actual sequence of distributions realized between 1986–2001, choosing our preference and distributional parameters so as to minimize a measure of the distance between these sequences of Lorenz curves.

We present two major empirical findings. First, the risk \(\text{(ex ante welfare loss due to variation in future consumption)}\) borne by households depends much more on households’ resources than it does on the year—even though there are enormous changes in China’s aggregate economy over this period, idiosyncratic risk is much more important than any aggregate shock in determining household welfare and in determining evolution of inequality over time.

Second, our estimates of the law of motion governing the Lorenz curves for urban China allow us to make predictions about future consumption inequality. Looking at the entire distribution, we predict that most of the increase in inequality between 1985 and 2025 has already
occurred; however, we also predict that the share of consumption accruing to the poorest decile of these households will continue to fall at a relatively rapid rate, lowering the share of consumption for these households from 6.5 per cent in 2001 to only two per cent in 2025.

**Appendix A. A Model with Idiosyncratic Risk**

In this section we describe a model in which households can exchange debt in competitive credit markets, and derive restrictions on the evolution of each household’s share of aggregate consumption. The key assumptions we’ll exploit are that households all have similar preferences featuring constant relative risk aversion, and that all households have access to credit on the same terms. Note that this latter assumption is weaker than assuming that credit markets are perfect—in particular, it may be the case that at the interest rates faced by households for some reason credit markets fail to clear.

Consider, then, an environment with $n$ infinitely lived households. We index these households by $i = 1, 2, \ldots, n$. Time is discrete, and is indexed by $t$. Household $i$ derives momentary utility from consumption according to some function $u_i : \mathbb{R} \to \mathbb{R}$, and discounts future utility at a common rate $\beta \in (0, 1)$.

**A.1. Intertemporal Restrictions.** At any date $t$, household $i$ can exchange claims to consumption at $t + 1$ with other households at a price $1/\rho_t$, solving the problem

$$
\max_{b_{it}} u_i(c_{it} - b_{it}/\rho_t) + \beta E_t \left\{ u_i(c_{it+1} + b_{it}) + \sum_{j=2}^{\infty} \beta^{j-1} u_i(c_{it+j}) \right\}
$$

where $E_t$ denotes the expectations operator conditional on information available at time $t$, $b_{it}$ denotes the debt issued by the household at time $t$, and $c_{it}$ denotes the households time $t$ consumption expenditures.

The first order conditions associated with the household’s problem of debt-issuance at time $t$ indicate that the household will consume $c_{it}$ at $t$ if the usual Euler equation

$$
u'_i(c_{it}) = \beta \rho_t E_t u'_i(c_{it+1})$$

is satisfied.

It’s convenient to restrict our attention to the case in which utility functions exhibit constant relative risk aversion, so that

$$u_i(c_{it}) = \frac{c_{it}^{1-\gamma} - 1}{1 - \gamma}$$
where $\gamma$ is the coefficient of relative risk aversion. In this case, (15) implies that

$$[\beta \rho_t]^{-1} = E_t \left( \frac{c_{it+1}}{c_{it}} \right)^{-\gamma}$$

for all $i = 1, \ldots, n$ and all $t$. As a consequence, we have

$$E_t \left( \frac{c_{it+1}}{c_{it}} \right)^{-\gamma} = \frac{1}{n} \sum_{j=1}^{n} E_t \left( \frac{c_{jt+1}}{c_{jt}} \right)^{-\gamma}. \tag{17}$$

We can interpret this as a prediction that with the ability to freely exchange debt all households will have the same expected growth in their marginal utilities of consumption.

Because we want to understand the links between intertemporal restrictions on consumption such as (17) and the evolution of inequality, we'll translate (17) into a statement about shares of consumption expenditures. Let $\bar{c}_t = \sum_{i=1}^{n} c_{it}$ denote aggregate consumption expenditures at $t$, and $\sigma_{it} = c_{it}/\bar{c}_t$ denote $i$'s share of expenditures at $t$. Then

$$E_t \left\{ \left[ \left( \frac{\sigma_{it+1}}{\sigma_{it}} \right)^{-\gamma} - \frac{1}{n} \sum_{j=1}^{n} \left( \frac{\sigma_{jt+1}}{\sigma_{jt}} \right)^{-\gamma} \right] \left( \frac{\bar{c}_{t+1}}{\bar{c}_t} \right)^{-\gamma} \right\} = 0.$$

Let

$$\epsilon_{it+1} \equiv \left[ \left( \frac{\sigma_{it+1}}{\sigma_{it}} \right)^{-\gamma} - \frac{1}{n} \sum_{j=1}^{n} \left( \frac{\sigma_{jt+1}}{\sigma_{jt}} \right)^{-\gamma} \right] \left( \frac{\bar{c}_{t+1}}{\bar{c}_t} \right)^{-\gamma} \tag{18}$$

denote household $i$'s time $t$ “forecast error” relative to the average forecast error. Note from the properties of (18) that $E_t \epsilon_{it+1} = 0$, as is usual when evaluating forecast errors from Euler equations. However, as Chamberlain (1984) points out, in the usual analysis there may be an aggregate shock which induces correlation across households’ forecast errors in the cross-section, so that there’s no guarantee that realized forecast errors at $t + 1$ will in fact average to zero. We’ve avoided this problem here by eliminating $\rho_t$; for us $\frac{1}{n} \sum_{j=1}^{n} \epsilon_{jt} = 0$ by construction.

**A.2. Risk.** The uncertainty facing any individual household with consumption share $\sigma_{it}$ at time $t$ which may reduce its utility at time $t + 1$, then, can be summarized by three random variables. First of these just has to do with variation in the growth of aggregate consumption, $\gamma_{t+1} \equiv \bar{c}_{t+1}/\bar{c}_t$. Second are household-specific surprises which may change the household’s share of aggregate expenditures, $\epsilon_{it}$. Third and finally, the aggregate of surprises facing all other households may change the distribution of resources, $\eta_{t+1} \equiv \frac{1}{n} \sum_{j=1}^{n} \left( \frac{\sigma_{jt+1}}{\sigma_{jt}} \right)^{-\gamma}$. 

Deﬁne the idiosyncratic risk borne by the household at time \( t \) to be the \textit{ex ante} loss in expected utility at \( t + 1 \) due solely to variation in the purely idiosyncratic shock \( \epsilon_{it+1} \), or

\begin{equation}
R_{it} \equiv u_i(\bar{c}_{t+1}\sigma_{it}) - E[u_i(c_{it+1})|I_t, \eta_{t+1}, g_{t+1}]
\end{equation}

where \( I_t \) denotes the information set at time \( t \). Here the ﬁrst term is the utility the household would obtain at \( t + 1 \) if the household’s share of expenditures was unchanged (as would be the case if no household faced any idiosyncratic risk) and the household knew in advance what aggregate consumption would be in \( t + 1 \). The second term is the utility the household would expect if it somehow knew in advance what the realization of all the relevant aggregate random variables would be, so that it remained ignorant only of the idiosyncratic shocks it would experience in the ﬁrst period.

In a world with complete markets and the assumed CES preferences we work with here, it’s easy to establish that each households’ share of aggregate consumption will remain constant, eliminating all idiosyncratic risk. Thus, we can interpret the ﬁrst term of (19) as the utility the household would obtain if no households bore any idiosyncratic risk less the expected utility of consumption when the household does bear this idiosyncratic component of risk. It’s trivial to establish that this \textit{cardinal} measure of risk is uniquely consistent (up to a linear transformation of \( u_i \)) with the notion of increasing risk deﬁned by Rothschild and Stiglitz (1970). Because our measure of idiosyncratic risk is denominated in utils, it’s straightforward to construct a variety of useful measures of the welfare loss associated with this risk.

Let \( \Psi_t(\sigma_{it+1}|\sigma_{it}, x_{it}, g_{t+1}, \eta_{t+1}) \) denote the time \( t \) Markov transition function for the household’s share \( \sigma \) given household characteristics \( x_{it} \) and knowledge of the aggregate quantities \( g_{t+1} \) and \( \eta_{t+1} \). Then the expression for household \( i \)’s time \( t \) idiosyncratic risk, as deﬁned above, may be written

\begin{equation}
R_{it} = u_i(\bar{c}_{t+1}\sigma_{it}) - \int u_i(\bar{c}_{t+1}\sigma')d\Psi_t(\sigma'|\sigma_{it}, x_{it}, g_{t+1}, \eta_{t+1}).
\end{equation}

Note that idiosyncratic risk can depend on both household characteristics \( x_{it} \) as well as on the household’s current position in the consumption distribution, \( \sigma_{it} \). Let the distribution of characteristics \( x \) of households having a share \( \sigma \) of aggregate consumption time \( t \) be given by \( G_t(x|\sigma) \). Then to calculate average idiosyncratic risk of households with share \( \sigma \) we integrate out the characteristics \( x \), obtaining the marginal Markov transition function \( \tilde{\Psi}_t(\sigma'|\sigma, g_{t+1}, \eta_{t+1}) = \int d\Psi_t(\sigma'|\sigma_{it}, x_{it}, g_{t+1}, \eta_{t+1}) \).
Let the distribution of \( \sigma \) at \( t \) be given by \( \Gamma_t(\sigma) \) (this is the inverse of the Lorenz curve). Average idiosyncratic risk is then given by

\[
R_t = \int u_i(\tilde{c}_{t+1}\sigma) d\Gamma_t(\sigma) - \int u_i(\tilde{c}_{t+1}\sigma') d\tilde{\Psi}_t(\sigma'|\sigma, g_{t+1}, \eta_{t+1}) d\Gamma_t(\sigma).
\]

A.3. Distribution. The Markov transition function \( \tilde{\Psi} \) which is critical for calculating average risk in the population is also critical for understanding how the distribution of resources changes over time. In particular, the inverse Lorenz curves \( \{\Gamma_t\} \) satisfy a law of motion

\[
\Gamma_{t+1}(\tilde{\sigma}) = \int_{\{\sigma' < \tilde{\sigma}\}} d\tilde{\Psi}_t(\sigma'|\sigma, g_{t+1}, \eta_{t+1}) d\Gamma_t(\sigma).
\]

Accordingly, knowledge of the transition functions \( \tilde{\Psi}_t \) suffices to characterize both average risk as well as the evolution of inequality in the population.

A.4. Forecast Errors and Markov Transitions. Recall that an individual household’s uncertainty depends only on relative forecast errors \( \epsilon_{it+1}, \eta_{it+1} \), and on \( g_{it+1} \). In particular, we can use (18) to express \( \tilde{\Psi}_t \) in terms of the distribution of relative forecast errors in the population. Let \( \epsilon_{it+1} \) have the cumulative probability distribution \( F_t(\epsilon|\sigma_{it}, x_{it}) \). Then note from (18) that we have

\[
\sigma_{it+1} = \sigma_{it} \left( g_{it+1}^{\gamma} \epsilon_{it+1} + \eta_{it+1} \right)^{-1/\gamma},
\]

so that

\[
\tilde{\Psi}_t(\sigma'|\sigma, g_{it+1}, \eta_{it+1}) = \int \int \left\{ \epsilon > \frac{(\sigma/\sigma')^{\gamma} - \eta_{it+1}}{g_{it+1}} \right\} dF_t(\epsilon|\sigma, x) dG_t(x|\sigma).
\]

Let \( \tilde{F}_t(\epsilon|\sigma) = \int dF_t(\epsilon|\sigma, x) dG_t(x|\sigma) \) denote the marginal distribution of relative forecast errors \( \epsilon \) for households having consumption share \( \sigma \). Then, because time \( t + 1 \) shares must integrate to one, we have the adding up restriction

\[
\int \sigma[\eta_{t+1} + \epsilon g_{t+1}^{\gamma}]^{-1/\gamma} d\tilde{F}_t(\epsilon|\sigma) d\Gamma_t(\sigma) = 1,
\]

which pins down the value of the \( \{\eta_t\} \) in terms of the remaining objects in (23). Accordingly, given knowledge of the distributions \( \{(F_t, G_t)\} \), the sequence of realized aggregate consumptions to pin down \( \{g_t\} \), and the risk aversion parameter \( \gamma \), we can completely describe the evolution of inequality and the distribution of risk in the population.
APPENDIX B. Estimating Idiosyncratic Risk

How can we go about using data on the evolution of Lorenz curves to estimate the risk borne by differently situated households? Given our maintained assumption of equal access to credit markets and some initial distribution of consumption shares $\Gamma_0$, (20) allows us to trace out changes in the distribution over time given knowledge of the Markov transition functions $\{\Psi_t\}$ and of the sequence $\{g_t, \eta_t\}$. However, each $\{\Psi_t\}$ must be consistent with the law of motion for shares (21), while the unknown sequence $\{\eta_t\}$ is determined by the adding-up restriction (23). As a consequence, the extent of our ignorance regarding $\{\Psi_t\}$ amounts to ignorance regarding the risk-aversion parameter $\gamma$, and the marginal distributions of relative forecast errors in each period, $\{\tilde{F}_t\}$.

Though we don’t begin with knowledge of the distributions of errors $\{\tilde{F}_t\}$, the first moment of each $\tilde{F}_t$ must be equal to zero by (15), while the support of the distribution at $t$ must be a subset of $[\eta_{t+1}/\hat{g}_{t+1}, \infty)$. After examining the empirical distribution of estimated relative forecast errors for a small panel of urban Chinese households, it appears that this empirical distribution at $t$ is adequately represented by what Johnson and Kotz (1970) call the “three-parameter log-normal distribution,” with $\log(\epsilon + \theta_{t+1})$ distributed $N(\mu_t(\sigma), \nu_t^2(\sigma))$. Of the three parameters $(\theta_t, \mu_t(\sigma), \nu_t(\sigma))$ only two are free, with $\theta_t = \eta_t/\hat{g}_t^\gamma$ (since shares must all lie in the $(0, 1)$ interval) and $\mu_t = \log(\theta_t) - \nu_t^2(\sigma)/2$ (since the expected value of $\epsilon$ must be zero).

With these restrictions on the distribution of relative forecast errors, the only things which remain for us to infer from data are the coefficient of relative risk aversion $\gamma$ and the scale parameters $\{\nu_t(\sigma)\}$. In practice, we only work with a finite number (say $n$) of share values, and have only a finite number of periods ($T$) of data on the distribution of consumption. We impose a log-linear structure on these scale parameters, assuming that for every year $t = 1, \ldots, T$ and share $\sigma \in \{\sigma_1, \ldots, \sigma_n\}$ there exists an $\ell$-vector of observable variables $x_{it}$ which determines the scale parameters via

$$
(24) \quad \log \nu_t(\sigma_i) = \delta' x_{it}.
$$

for some $\ell$-vector $\delta$. This assumption allows us to estimate a set of $\ell$ parameters which may be presumed to be smaller than $Tn$, and guarantees that estimated values of $\nu_t(\sigma)$ will be positive, as they must be to be interpretable as the standard deviation of a normally distributed variable.

As a consequence of the foregoing, we’re left with the problem of estimating $\ell + 1$ parameters $b_0 = (\gamma, \delta')$. We have data on the share of
consumption expenditures for population quantiles \((x_1, x_2, \ldots, x_m)\) for each of \(T + 1\) years. We use these data on consumption expenditures to approximate the Lorenz curves \(\{L_t(x)\}_{t=0}^{T}\) of expenditure shares. We fix an initial guess of our parameters \(b\). Noting that \(L_t = \Gamma_t^{-1}\), conditional on this guess we use the law of motion (20) (along with the adding-up restriction (23), and (24)) to predict a sequence of Lorenz curves \(\{L_t(x|b)\}_{t=1}^{T}\). We compute a simple measure of distance between the predicted and actual Lorenz curves

\[
d(b) = \sum_{t=1}^{T} \sum_{i=1}^{m} \left( L_t(x_i) - \hat{L}_t(x_i|b) \right)^2,
\]

and then use a simplex minimization routine to find the value \(\hat{b} = \arg\min_b d(b)\).

### References


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