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Tilburg University

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To my Family/献给我的家人

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Jie Zheng

Shenzhen, China, Fall 2012

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Chapter 1: Introduction

This doctoral thesis covers two topics that have gained considerable attention from policy makers, academics, and business representatives: export credit insurance and life expectancy. It consists of three essays. The first one (chapter 2), entitled "*Quantification of Longevity Risk of China*" and co-authored with Prof. Dr. Bertrand Melenberg, examines the effect of longevity risk on pension and annuities pricing and liabilities in the context of China. The second one (chapter 3), also a joint work with Prof. Dr. Bertrand Melenberg and entitled "*Health Expectancy of the Chinese Elderly: Current Trends and Future Projection*", estimates as well as projects health expectancy of Chinese elderly based on Sullivan's approach. The third one (chapter 4), sing-authored and entitled "*Export Credit Insurance and Trade Promotion*", theoretically and empirically studies the roles played by export credit insurance programs in mitigating non-payment risks and in promoting export levels.

Before discussing the contents of each essay, it is important and useful to understand the keywords, namely, longevity risk, health expectancy, and export credit insurance, in the three essays, respectively.

Longevity Risk

The population worldwide has experienced a rapid aging over the past half-century due to, along with lower fertility rates, dramatically increased life expectancy at old age. The trends in improving mortality among the elderly are significantly challenging public pension plans as well as private pension funds and life insurers. Though the views regarding the outlook for human longevity are still controversial (Antolin and Blommestein, 2007), the general opinion from the experts tends to be the presence of upward trends in longevity. However, there is a large degree of uncertainty concerning the improvement magnitude, especially at older ages. Therefore, the major challenge faced by policy-makers, pension/insurance institutions, and individuals is not the trend in longevity itself, but rather be the uncertainty around the trend in life expectancy in the future (De Waegenaere, Melenberg, and Stevens, 2010). When future life expectancy outcomes and mortality improvement turn out to be different from anticipated, longevity risk occurs. The significance of longevity risk is that increasing portfolio size can only mitigate but cannot eliminate this risk. Therefore, several innovative solutions to longevity risk through the financial system, namely, reinsurance (Richards and Jones, 2004), natural hedging (Cox and Lin, 2007), or securitization (Cowley and Cummins, 2005), are being discussed. But all these solutions require better understanding of future life expectancy.

Health Expectancy

With the extension of life expectancy, it is more recognized by the public that “increased longevity without quality of life is an empty prize” (WHO, 1997). Due to the mortality reduction at advanced ages, an increasing focus has been concentrated on the life quality of the rapidly aging population. The possibility that the population health deteriorates, even though mortality improves, is not only possible, but also likely under some circumstances. Since Sanders (1964) proposed the concept of health expectancy, interest in estimating it and in investigating its determinants has been increasingly becoming a new focus among policymakers and members of the academic community. Unlike life expectancy, health expectancy takes into account both mortality and morbidity, measuring the average time that individuals live in varying health statuses. More recently, the increasing recognition of the multidimensionality of health has focused attention of governments and academia on health expectancy when assessing the dynamics of population health, since a decline in mortality does not necessarily represent an improvement in other dimensions of health (Crimmins, 2004).

Export Credit Insurance

Export credit insurance, an insurance policy and a risk management product, is offered by private or public export credit agencies (ECAs) to businesses wishing to protect their overseas account receivable from loss due to commercial and/or political risks. As 80 to 90 percent of international trade relies on some form of export credit, export credit insurance, or guarantee (Auboin, 2007),[1] the declining availability of trade finance and its increasing costs are considered as the most important factors after demand causing the export collapse (Mora and Powers, 2009). In response, well-developed export credit insurance or guarantee

[1] The terms *insurance* and *guarantees* are often used interchangeably in literature, referring to the coverage against losses extended by a specialized institution to an exporter or financial institution.

programs are drawing more attention across industrialized countries as well as emerging economies. While roughly 10 percent of global trade is insured, it is not until the recent economic and financial crisis that export credit insurance comes to the attention of academic researchers.

In chapter 2, we use the Lee-Carter model to quantify longevity risk and to investigate the effect of longevity risk on pension and annuities pricing and liabilities in the context of China. By calculating the expected present value of life annuities and life expectancy for retirees that take into account stochastic mortality development, our estimation results reveal a significant impact of longevity risk on annuity pricing as well as longevity risk exposure faced by the state.

In chapter 3, using the Chinese Longitudinal Healthy Longevity Survey (CLHLS), we estimate health expectancy of the Chinese elderly based on different health measurements. Our estimations use Sullivan's method combining cohort life tables with (forecasted) prevalence rates. We also calculate the corresponding confidence intervals of life and health expectancy. We find that while the Chinese elderly of both gender groups experienced an improvement in life expectancy during the sample period, health expectancy shows a mixed result at both absolute as well as relative level, depending on health measurements. Our projections of health expectancy also show an inconclusive picture, with a negative trend in the healthy life expectancy (HLE), which is based on subjectively reported health, but a mixed one in the disability free life expectancy (DFLE), which is based on objective indicators.

In chapter 4, I present a theoretical model showing the competitiveness of OA terms in international trade, and the risk-reducing as well as export-enhancing role played by export credit insurance programs. Our theoretical analysis shows that, when exporters are risk averse, these programs are always effective without breaking the legal and financial obligations. Using Chinese export and insurance data, both static and dynamic models show a positive and statistically significant export-promoting effect of export credit insurance in China. The insurance effect across income groups also suggests the success of export credit insurance in diversifying export destinations.

Chapter 2: Quantification of Longevity Risk in China*

2.1 Introduction

Like in most of the western world, the population of China has experienced a rapid aging over the past half-century due to advances in public health, improved sanitation and personal hygiene, and general improvement in living standards (Lee, 2003; IMF, 2004). For example, the proportion of population aged 65 or older was only 4.41% in 1953 and 4.91% in 1982, respectively, but increased to 8.3% in 2008,[1] and by 2030 it will be more than doubled to 22% (James, 2002). Although age-specific death rates at all ages have declined exponentially at a constant rate in most developed countries (Tuljapurkar, Li, and Boe, 2000), it is the dramatically increased life expectancy at old age, along with lower fertility rates, that contributes to an increasing share of elderly people in the total population at a rapid rate in both OECD countries and emerging economies, most notably in China (Visco and d'Italia, 2006). In 1981, for example, a 60-year-old Chinese female individual had a life expectancy of 17.90 years, whereas in 2000 a 60-year-old female had a life expectancy of 19.62 years, representing an increase of 1.09 months per year (Zheng, 2005), i.e., more than five minutes per hour. The trends in improving mortality among the elderly are significantly challenging public pension plans as well as private pension funds and life insurers. In the U.K. and the U.S alone these institutions' exposure to longevity amounts to 400 billion USD in 2007 (Loeys, Panigirtzoglou, and Ribeiro, 2007). One more year of life expectancy at age 65 is estimated to add at least 3% to the present value of the pension liabilities in the U.K. (Biffis and Blake, 2009). In developing countries, including China, where pension systems are underdeveloped, these trends also significantly affect personal saving to fund retirement consumption. For example, consider a fairly-priced annuity with annual payoff ￥1 at the real interest rate of 3% in China. Then in 1981 the annuity price for a 60-year female should have been ￥14.11, but could have increased by 7% to ￥15.11 in 2000. Without other retirement income, this means that the 60-year-old females in 2000 should have saved 7% more to finance their retirement

* Co-authored with B. Melenberg. We are grateful to the participants of "British Academy: the UK-China Workshop" at Cambridge University, Chinese Economist Association Annual Conference at Oxford University, and the Erasmus Mundus Thematic Conference in Bordeaux, France, for very helpful comments.

[1] Data source: China Population and Employment Statistics Yearbook (2009).

consumption than in 1981.[1]

Though the views regarding the outlook for human longevity are still controversial (Antolin and Blommestein, 2007),[2] the general opinion from the experts tends to be the presence of upward trends in longevity. However, there is a large degree of uncertainty concerning the improvement magnitude, especially at older ages. From 1970 to 2000, the average increase in life expectancy of a 65-year-old male was 1.12 years/decade in the U.S. and 1.23 years/decade in the U.K., respectively, but the corresponding increase had only been 0.15 years over the previous decade in the U.S. and 0.17 years/decade over the previous century in the U.K. (Cocco and Gomes, 2008). China also experiences this uncertainty. According to Zhang (2005), in the 1980s the average increase in life expectancy of a 60-year-old Chinese male was 0.06 years per year, but increased to 0.09 years per year in the 1990s. Therefore, the major challenge faced by policy-makers, pension/insurance institutions, and individuals is not the trend in longevity itself, but rather be the uncertainty around the trend in life expectancy in the future (De Waegenaere, Melenberg, and Stevens, 2010). When future life expectancy outcomes and mortality improvement turn out to be different from anticipated, longevity risk occurs.

Cocco and Gomes (2008) find that, when individuals use official period life tables, -which do not allow for future life expectancy improvement-, to make their retirement finance decision, the effect of longevity improvement on individual welfare can be significant. Moreover, the importance of longevity risk for the liabilities of private pension funds and annuity providers is that increasing portfolio size can only mitigate but cannot eliminate this risk. Therefore, several innovative solutions to longevity risk through the financial system, namely, reinsurance (Richards and Jones, 2004), natural hedging (Cox and Lin, 2007), or securitization (Cowley and Cummins, 2005), are being discussed. But all these solutions require better understanding of future mortality development.

In this paper we use the Lee-Carter model to quantify longevity risk and to investigate the effect of longevity risk on pension and annuities pricing and liabilities in the context of China.

[1] The result is based on author's own calculation.

[2] For example, Olshansky et al. (2005) believe that there are natural limits to life expectancy, and suggest that the increase in life expectancy will slow down if not to stop; On the other hand, Oeppen and Vaupel (2002) argue that there are no limits to life expectancy and conclude from historical trends and age trajectories that longevity would keep increasing in the next decades.

By doing so, we contribute to existing literature in several ways. First, China, as the largest country in terms of population, has been experiencing a faster decline in mortality among the elderly since the 1964-82 periods than the now low-mortality countries at comparable levels of overall mortality (Banister and Hill, 2004). With China's increasing prosperity, these trends might be expected to continue. Moreover, the current public pension plans in China, unlike their counterparts in developed countries, are decentralized to the local governments.[1] The relative small portfolio of each public pension plan means that these plans might face both diversifiable *individual mortality risk* and non-diversifiable *longevity risk*. Both factors characterize the severity of longevity risk in China and aggravate Chinese pension plans' exposure to longevity risk. Nevertheless, the public and policy makers generally ignore the longevity risk in the current pension reforms and retirement-income product design. Since China has not achieved universal pension coverage to all citizens by far, the focus in China as a result is almost exclusively concentrated on the *accumulation stage,* namely, how to extend the pension coverage.[2] For example, in 2008 among its 302 million urban employees and 473 rural employees, only 55% and 12% were covered by the public pension system, respectively (Oksanen, 2010). However, the Chinese government has vowed universal pension coverage by 2013.[3] Thus, this paper attempts to quantify longevity risk, through which we highlight the significance of longevity risk exposure and increase the public's awareness and understanding of longevity risk. To the best of our knowledge, while prior research has extensively scrutinized longevity risk in developed countries, few have sought to understand it in the context of the developing world, partly due to data issues. Second, like in most developing countries, in China the mortality data is unavailable for older ages, which can result in inaccurate estimations. For example, Chinese mortality data are different in terms of the maximum age group available in each sample year, with most ending at age group 85 and over. In order to resolve the missing data issue, this paper applies two different approaches to quantify the longevity risk. On the one hand, we use the Kannisto model

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[1] It is reported by China Business News (15 August 2008) that the public pension plans in China now are organized by around 2,000 entities. Even though people are free to relocate, their pensions are not allowed to transfer freely, especially between provinces.

[2] On the contrary, the attention is more paid to the *distribution stage* in developed countries, namely, depending on pension laws, people at retirement age receive their pension benefit either as lump sum, programmed withdrawal, or as an annuity.

[3] http://www.china.org.cn/opinion/2011-06/22/content_22835444.htm

(Kannisto et al., 1994) to fit the available data to extrapolate the mortality rates at advanced ages and then the Lee-Carter model to project future mortality rates using the extended data set. Alternatively, we can use the Lee-Carter model to project future mortality rates using the unextended data and then the Kannisto model to extrapolate mortality at older ages based on the projection. Third, given the comparatively limited statistical data on mortality in China, the sampling inaccuracy might cause parameter risk, a special case of model risk arising due to the lack of knowledge regarding the true probability distribution of future mortality rates. Even though we might exactly know the true probability distribution of the future mortality rates, the process risk, namely the uncertainty in the mortality trends, still remains. This paper decomposes the longevity risk into parameter and process risk, quantifying each as well as their total impact on pension and annuities pricing. Finally, the urban-rural social-economic disparities exist in China, this paper also explore variations in longevity risk across residency groups

Our paper presents the following findings. First, the estimation of the Lee-Carter model using extended or unextended data sets show similar results. Second, our estimates of the Lee-Carter latent time processes show the existence of a unit root in level, but become stationary after first differencing, which is in line with prior studies. Nevertheless, unlike the previous finding that these latent time processes is an ARIMA (0, 1, 1) process (Yin, 2005), our results show that these processes follow a random walk for all population groups, except for the urban population. Finally, we find substantial longevity risk faced by China's state pension scheme and in the pension/annuities pricing. For example, without taking into account the mortality improvement in the future, the life expectancy of a 60-year old urban female in 2009 was 18.83 years, 3 percent underestimated compared with her cohort life expectancy allowing for the mortality improvement. At a 4 percent guaranteed investment return, her individual account can run out in 15.59 years according to the current payout policy, leaving the state bear longevity risk for at least 3 years. However, as the state usually guarantees investment returns only equaling to the one-year deposit rate, which was mostly less than 4 percent for the past decade, the real longevity risk exposure faced by the state should be more substantial. Furthermore, without including a longevity risk premium, the present value of life annuities for the same individual in 2009 is 10 percent under-priced with a 4 percent flat interest rate and 9 percent under-priced when using the term structure of Chinese government bonds. This implies that a fair valuation of pension and annuities might include a substantial longevity risk premium.

The remainder of this paper proceeds as follows. In section two, we introduce the source of longevity risk and its impact on annuity pricing. In section three, we present the data, the Lee-Carter model, and estimation results. Before quantifying the longevity risk, we briefly introduce China's pension system in section four. In section five, we show the impact of longevity risk, taking account of process risk and parameter risk. Finally, section six offers some concluding remarks.

2.2 Introduction to Longevity Risk

The uncertain mortality development may cause two kinds of risk, namely *longevity risk* and *individual mortality risk*.[1] According to Dahl (2004), *longevity risk* results from changes in the underlying mortality density, whereas *individual mortality risk* results from the random individual deaths with a fixed mortality density. For better understanding of the distinction between the two risks, see also De Waegenaere, Melenberg, and Stevens (2010), we first introduce some scientific notation and terminology.

2.2.1 Scientific Notations and Terminologies

The two basic building blocks of our projection of future life expectancy are the one-year death probabilities, denoted by $q_{x,t}^{(g)}$, and the central death rates, denoted by $m_{x,t}^{(g)}$. The one-year death probability, $q_{x,t}^{(g)}$, defines the probability that an x-year old person belonging to group g (female or male; rural or urban) will die within one year in year t. The central death rate is defined by

$$m_{x,t}^{(g)} = \frac{D_{(x,t}^{(g)}}{E_{x,t}^{(g)}}, \tag{2.1}$$

where $D_{x,t}^{(g)}$ denotes the death number of people belonging to group g at age x in year t, while

[1] The two kinds of risk are also named as systematic longevity risk and unsystematic longevity risk, respectively. In order to highlight the non-diversification of the former, following De Waegenaere, Melenberg, and Stevens (2010), we use *longevity risk* to indicate systematic longevity risk and *individual mortality risk* to unsystematic longevity risk.

$E_{x,t}^{(g)}$, also called exposure, denotes the number of person years in group g at age x in year t.

Since both $D_{x,t}^{(g)}$ and $E_{x,t}^{(g)}$ can be obtained from the national statistics, we could obtain the one-year death probability, $q_{x,t}^{(g)}$, from the central death rate, $m_{x,t}^{(g)}$ (McCutcheon and Nesbitt, 1973). In the general case, this relationship is complicated, but can be simplified with appropriate additional assumptions. For example, under the assumption that the central death rate equals to the force of mortality,[1] we could establish the following relationship

$$q_{x,t}^{(g)} = 1 - \exp(-m_{x,t}^{(g)}), \tag{2.2}$$

With the one-year death probability, we could also obtain the one-year survival probability, i.e., the probability that an x-year old individual belonging to group g survives at least another year in year t, by

$$p_{x,t}^{(g)} = 1 - q_{x,t}^{(g)}, \tag{2.3}$$

Under the assumption of *constant* time-independent mortality rates and one-year death probabilities over time, the one-year death (survival) probabilities would be independent of time and thus the subscript t can be suppressed. In this case, we could calculate the probability that a x-year old individual belonging to group g survives at least τ years, ${}_{\tau}p_x^{(g)}$, and the corresponding remaining life expectancy for this individual, $e_x^{(g)}$, as follows:

$${}_{\tau}p_x^{(g)} = \prod_{i=0}^{\tau-1} p_{x+i}^{(g)}, \tag{2.4}$$

$$e_x^{(g)} = \sum_{\tau \geq 1} {}_{\tau}p_x^{(g)}, \tag{2.5}$$

where ${}_1p_x = p_x$. From the time point of year t, this individual is expected to die in $e_x^{(g)} + t$ years at the age of $e_x^{(g)} + x$.

However, the results above, based on the assumption of *constant* one-year death probabilities and mortality rates over time, might not be correct: neither are they constant over time, nor do they change in the same direction and at the same magnitudes for different

[1] The force of mortality, often referred to as the hazard function in other fields such as in reliability theory, is defined as $\mu_x = \lim_{\Delta x \to 0} \frac{P(x < X \leq x + \Delta x \mid X > x)}{\Delta x}$ and specifies the instantaneous rate of death for x-year old people belonging to group g in year t, given that these individuals survive up to age x.

cohorts. Figure 2.1 presents the mortality rates of selected age groups for different time periods, normalized to one for the year 1981.

[***Insert Figure 2.1 here***]

At least over longer time horizon, both Chinese females and males in these selected age groups experience significant mortality improvement, reflecting the increase in longevity over time. On the one hand, these improvements are different in terms of gender, ages, and years. On the other hand, at least to some extent, these improvements seem to be random, reflecting the stochastic nature of the death probabilities. Since the death probabilities are not *constant* over time but rather *stochastic*, it is inappropriate to use (2.4) and (2.5) for calculating the remaining life expectancy of an x-year old individual belonging to group g in year *t*. With varying death probabilities, the survival probability of a x-year old individual belonging to group g for at least τ years in year t should follow

$$ {}_{\tau}p_x^{(g)} = \prod_{i=0}^{\tau-1} p_{x+i,t+i}^{(g)} , \tag{2.6} $$

The corresponding remaining life expectancy for this individual in year t should be calculated by

$$ e_x^{(g)} = \sum_{\tau \geq 1} {}_{\tau}p_{x,t}^{(g)} , \tag{2.7} $$

Both (2.6) and (2.7) need future death probabilities that are unobservable for the current period. Thus, when using current death probabilities rather than the projected ones, the expected life expectancy as well as the discounted value of pension liabilities might be underestimated. See, for example, Hari et al. (2008). Moreover, it is appropriate to assume the future death probabilities in a stochastic way instead of a deterministic way. With the assumption of stochastic future death probabilities, therefore, the *longevity risk* resulting from the long-term deviation from deterministic mortality improvement is unavoidable (De Waegenaere, Melenberg, and Stevens, 2010).

2.2.2 Significance of Longevity risk

Assuming a finite number of scenarios for the evolution of future mortality probabilities, many studies (Olivieri, 2001; Coppola, Di Lorenzo, and Sibillo, 2000, 2003a, and 2003b) find that even when the size of a life insurance portfolio is increased, the *longevity risk* cannot be diversified and does not disappear, whereas the *individual mortality risk* is diversifiable (assuming that the individual lifes are independent). In most developing countries the pooling size of pensions is relatively small. Thus, unlike their counterpart in the developed world, the pension systems in developing countries typically might face both risks.

In order to demonstrate the non-diversifiable characteristics and significance of *longevity risk* and its distinction from *individual mortality risk*, we consider a pension plan composed of N x-year old immediate lifetime annuitants belonging to group g in year t. For simplicity, we assume that each annuitant gets one Chinese Yuan per year after retirement conditional on his/her survival, with a constant risk-free interest rate r. Thus, in year $t+\tau$ ($\tau \geq 1$) the present value of the future payment to annuitant i should equal

$$Y_i = \sum_{\tau \geq 1} 1_{i,t+\tau} \frac{1}{(1+r)^{\tau}}, \tag{2.8}$$

where $1_{i,t+\tau}$ denotes a dummy variable with value equal to one if annuitant i is still alive in year $t+\tau$.

We first only consider *individual mortality risk*, namely that the future mortality improvements are known with certainty. In year t, the expected present value of the future payment to annuitant i is thus given by

$$A_{x,t} = \sum_{\tau \geq 1} E(1_{i,t+\tau}) \frac{1}{(1+r)^{\tau}} = \sum_{\tau \geq 1} {}_{\tau}p_{x,t} \frac{1}{(1+r)^{\tau}}, \tag{2.9}$$

According to the pooling argument, $A_{x,t}$ should be the fair price of this annuity and the fair price of Y_i should be the same as the fair price of $\frac{1}{N}\sum_{i=1}^{N} Y_i$. Under the assumption of independent annuitants, the latter average has the following variance

$$Var\left(\frac{1}{N}\sum_{i=1}^{N} Y_i\right) = \frac{\sigma^2}{N}, \tag{2.10}$$

where we take $\sigma^2 = Var(Y_i)$ and $\mu = E(Y_i)$.

Obviously, with increasing pooling size, the variance of $\frac{1}{N}\sum_{i=1}^{N} Y_i$ approaches zero, i.e., it becomes risk free, so its fair price equals its expected present value, without a risk premium. With known future death probabilities, pension plans, and insurance companies only face *individual mortality risk* that can be eliminated by pooling.

When the future death probabilities are uncertain, however, *longevity risk* becomes dominant. We continue with the pension plan composed of N x-year old immediate lifetime annuitants belonging to group g in year t, given the set of future death rates in year t by $f_\infty = \{q_{x,t+\tau}^{(g)} \mid \tau \geq 1\}$. We follow the assumption of independent annuitants in *individual mortality risk* above but have different mean and variance both depending on f_∞, i.e. $\mu(f_\infty)$ and $\sigma^2(f_\infty)$. Thus, (10) should be replaced by

$$Var(\frac{1}{N}\sum_{i=1}^{N} Y_i) = E[Var(\frac{1}{N}\sum_{i=1}^{N} Y_i) \mid f_\infty] + Var[E(\frac{1}{N}\sum_{i=1}^{N} Y_i \mid f_\infty] = \frac{E[\sigma^2(f_\infty)]}{N} + Var[\mu(f_\infty)]. \tag{2.11}$$

With increasing pooling size, the first term on the most right hand side of (2.11) can still be eliminated, but the second term continues to exist, independently of N. With the existence of *longevity risk*, the pooling argument cannot eliminate mortality risk any more and a risk premium should be included into the pricing of financial products whose payoffs depend on the future mortality development.

In the context of China, the underdeveloped pension systems and low coverage might mean that both *individual mortality risk* and *longevity risk* exist. In addition, the incomplete market and non-diversifiable characteristics make the pricing of longevity risk and risk management even more difficult in China than in developed countries.

2.3 Lee-Carter Models and Data

In this paper, we only discuss extrapolative stochastic mortality models, without considering potential exogenous demographic or epidemiological factors, because this type of models seems to be developed well (see Booth and Tickle, 2008), and also because pension funds and annuity providers are much more interested in "all-cause" mortality (Hari, 2006).[1] Among

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[1] Next to stochastic models, there are also deterministic mortality models. Starting from De Moivre (1724)1, the deterministic approach (Gompertz, 1825; Makeham, 1860; Heligman and Pollard, 1980) typically only considers the age dimension, though recent models try to fit mortality rates in both of age and of time dimension. However, since this kind of

these stochastic models, the Lee-Carter model (1992) has become the “leading statistical model of mortality in the demographic literature” (Deaton and Paxson, 2004) and, along with its extensions, has been widely applied for many developed countries for its simplicity and robustness in the context of linear trends in age-specific death rates, for example, Japan (Wilmoth, 1993), G7 countries (Tuljapurkar, Li, and Boe, 2000), Australia (Booth, Maindonald, and Smith, 2002), England and Wales (Renshaw and Haberman, 2003), Belgium (Brouhns, Denuit, and Vermunt, 2002), and the Netherlands (Hari et al., 2008; De Waegenaere, Melenberg, and Stevens, 2010). However, the existing literature using the Lee-Carter model for developing countries, including China, is rather limited and incomplete, partly due to the unavailability of data. To our knowledge, Hou, Yu, and Chen (2000) are the first to apply the Lee-Carter model to the Chinese population. Using the mortality data on the rural males during 1988-1994,[1] they project the mortality movement for 1995-2000.The comparisons between the predicted mortality rates and the realized ones indicate that the Lee-Carter model has a significant prediction power. Yin (2005) estimates the Lee-Carter model with the mortality rates of Chinese males and females for 1986-2002. Zhu and Chen (2009) use the Brouhns et al. (2002) version of the Lee-Carter model and 1989-2006[2] mortality data to project the mortality dynamics of the urban population. Nevertheless, these researches allow for neither parameter risk not process risk (to be introduced in the next subsection). Furthermore, they only focus on a specific population group, for example, urban population or rural population, or a specific gender group.

2.3.1 Lee-Carter Model

According to Lee and Carter (1992), the log central death rate of the x-year-old persons in year t, $\ln(m_{x,t})$, is determined by a common time-dependent latent factor κ_t, with an age-specific level parameter, α_x, and an age-specific sensitivity parameter, β_x. Mathematically, the model can be expressed as follows:

$$\ln(m_{x,t}) = \alpha_x + \beta_x \kappa_t + \varepsilon_{x,t}, \tag{2.12}$$

approach usually does not take account of uncertainty and also the accurate in-sample fit is translated into only small prediction intervals, it does not seem to be very realistic in practice.

[1] The mortality data for 1991 are missing.

[2] The mortality data for 1987-1988, 1991-1993, and 2000 are missing.

where the white noise error terms, $\varepsilon_{x,t}$, with mean zero and variance σ_x^2, represent the transitory non-systematic shocks.

Obviously, the OLS method cannot be applied to the Lee-Carter model because none of the variables on the right hand of equation (2.12) is observable. In order for a unique solution, Lee and Carter first normalize the sum of β_x terms to unity and κ_t terms to zero, i.e., $\sum_x \beta_x = 1$ and $\sum_\kappa \kappa_t = 0$, and get the value of α_x since it becomes the average value of $\ln(m_{x,t})$ over time. Then they use a two-stage approach to solve this under-identification problem. The singular value decomposition (SVD) approach is used in the first stage for the matrix of $\ln(m_{x,t}) - \hat{\alpha}_x$ to get estimates of κ_t and β_x. Given the value of $\hat{\alpha}_x$ and $\hat{\beta}_x$, Lee and Carter (1992) re-estimate $\hat{\kappa}_t$ by iteration until the implied death number equals the actual death number such that

$$\sum_x D_{x,t} = \sum_x \left\lfloor E_{x,t} \exp(\hat{\alpha}_x + \hat{\beta}_x \hat{\kappa}_t) \right\rfloor, \tag{2.13}$$

Alternatively, a weighted singular value decomposition could also be used (Wilmoth, 1993). Moreover, Lee and Miller (2001) proposed using a matching on the basis of observed and modeled life expectancy rather than the matching according to (2.13). In addition, in order to avoid the violation of the assumption of constant α_x and β_x, Booth, Maindonald, and Smith (2002) suggest using statistical techniques to select an appropriate sample period.

In the second stage, a process for κ_t is postulated and estimated. Lee and Carter proposed to model κ_t as an ARIMA-process, and found an ARIMA(0,1,0)-process, i.e., κ_t satisfies a random walk with drift process, given by:

$$\kappa_t = \kappa_{t-1} + c + \xi_t, \tag{2.14}$$

where the white noise term, ξ_t, representing permanent shocks, is assumed to be independent of $\varepsilon_{x,t}$ and to follow a normal distribution with mean zero and variance of σ_ξ^2. With standard statistical or econometric time-series techniques, the parameters in (2.14) can be estimated. However, the ARIMA process of κ_t for other countries might be different from

(2.14). For example, Yin (2005) finds that the Chinese male process follows ARIMA (0,1,1), whereas the Chinese female process is a random walk. Thus, standard statistical procedures should be applied to find an appropriate ARIMA model for the time series of κ_t (Liu, 2008).

In this way, the systematic path of the central mortality rate of the x-year-old persons in year t satisfies:

$$\widehat{m}_{x,t} = \exp(\widehat{\alpha}_x + \widehat{\beta}_x \widehat{\kappa}_t)\,, \tag{2.15}$$

In order for the projection of future mortality, we firstly need to forecast the future values of $\widetilde{\kappa}_{T+\tau}$ (T is the final year of the sample) and then the systematic path of future central mortality rate by

$$\widehat{m}_{x,t+T} = \exp(\widehat{\alpha}_x + \widehat{\beta}_x \widetilde{\kappa}_{T+\tau})\,, \tag{2.16}$$

To avoid a jump-off bias, Lee and Miller (2001) alternatively propose using the observed (raw) central death rate of the final year in the sample as a jump-off value to predict the future central death rates such that

$$\widetilde{m}_{x,t+T} = m_{x,t} \exp(\widehat{\beta}_x (\widetilde{\kappa}_{T+\tau} - \widehat{\kappa}_T)).\,, \tag{2.17}$$

With the assumption that the force of mortality does not change during a year, i.e., $m_{x+s,t+s} = m_{x,t}\,(0 \le s < 1)$, the survival probability of one more year for one x-year-old person at time t is calculated by (2.2) and (2.3). From (2.6) and (2.7), we can obtain the projection of life expectancy at different ages.

There are several risks in our projection. First, since neither the true value of $\widetilde{\kappa}_{t+T}$ nor its distribution is known at time T, *process risk* might arise. This is the risk that originates from ξ_t in (2.14) to be random.[1] Second, limited sample size and measurement error might cause inaccurately estimated coefficients of α_x, β_x, σ_x^2, and σ_ξ^2, which generates *parameter risk*. In addition, there is the possibility that the Lee and Carter (1992)-model is misspecified, causing *model risk*, i.e., the risk of using a misspecified model. For methods quantifying these risks, see Koissi, Shapiro, and Hognas (2006) or Renshaw and Haberman

[1] Also the risk due to randomness of $\varepsilon_{x,t}$ in (2.12) could be considered as process risk.

(2008). In the sequel, we focus on process and parameter risk, ignoring model risk.

2.3.2 Data

Our data include 16 yearly observations of age-specific death and population counts across gender and residence groups during the period of 1994-2009,[1] from which we can use formula (2.1) to obtain the age-specific central death rates. Given disparities in social-economic levels between the urban and rural population, we make a distinction between the two population groups to explore variations in the longevity risk in China.[2] For example, the ratio of income earned by urbanites to that of rural residents is about 5.2. The gap between the urban and rural has lead to a massive immigration from rural areas to cities. Nevertheless, thanks to China's restrictive residence registration system (*Hukou* in Chinese), these rural immigrants hardly can obtain urban residence permit and hence cannot be entitled public services such as health, education and pension. As a result, it is appropriate to distinct the urban population from its rural counterpart when estimating life expectancy as well as quantifying longevity risk.

Before estimating, it should be mentioned that the statistical methods obtaining these count numbers are not consistent over all sample years. For example, the death and population counts in 2000 are based on national population census, while in other years on population sample survey or sample survey on population changes. Additionally, for each year the data are different in terms of the maximum age group available, with most ending at age group 85 and over. Since we are mainly concerned with the impact of longevity risk on pension and annuities, namely the impact of the uncertain life expectancy after retirement on pension and annuities, the missing mortality data at older ages might cause inaccurate estimation. Therefore, we need to use the available mortality data to estimate the central death rates at older ages.

In this paper we shall use the Kannisto model (Kannisto et al., 1994) to extrapolate the mortality rates to older ages.[3] This two-parameter logistic model is based on the empirical

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[1] We obtain the data from the China Population Statistical Yearbooks and the China Statistical Yearbooks compiled by the National Bureau of Statistics of China.

[2] The Chinese residence registration system (or Hukou in Chinese) makes it possible to monitor the residence status.

[3] The patterns of mortality at older ages have been well documented in many studies (Horiuchi and Wilmoth, 1998;

finding that

$$m_{x,t} = \frac{\alpha_t \cdot \exp(\beta_t x)}{1+\alpha_t \cdot \exp(\beta_t x)}, \quad (2.18)$$

fits the data well at older ages, where $m_{x,t}$ is the central death rate at age x in year t; α_t and β_t are the two parameters that need to be estimated. Given estimated values for the parameters in (2.18), one can use (2.18) to extrapolate the central death rate to older ages, not observed in-sample. Since the Kannisto model is not supposed to fit the mortality data on the whole age range, but only on (available) older ages, we first use the *life-table ageing rate* defined by Horiuchi and Cole (1990) to choose the starting value of our fitting age. This life-table ageing rate is given by

$$k_{x,t} = \frac{\ln(m_{(x,x+5),t}) - \ln(m_{(x-5,x),t})}{5}, \quad (2.19)$$

where $m_{(x,x+5),t}$ and $m_{(x-5,x),t}$ are central death rates for successive 5-year of age, with (approximated) corresponding standard errors given by

$$\sigma_{x,t} = \frac{1}{5}\sqrt{\frac{1}{D_{(x,x+5),t}} + \frac{1}{D_{(x-5,x),t}}}, \quad (2.20)$$

where $D_{(x,x+5),t}$ and $D_{(x-5,x),t}$ are the death counts in the age intervals between ages *x* and *x+5* and between ages *x*-5 and *x*, respectively.

[***Insert Table 2.1 Here***]

Table 2.1 presents the estimation results based on (2.19) and (2.20). For each gender group, the life table ageing rates and their corresponding standard errors from age 60 to 89 are reported for each sample year. Since the increase (decrease) in $k_{x,t}$ implies an acceleration (deceleration) in the age pattern of mortality (Horiuchi and Wilmoth, 1998), the lower age limit of our fitting range should be the one at which the estimate of life table aging rate falls off. Generally, the life-table aging rate begins to decrease at ages varying from 60 to 70 for males and from 65 to 75 for females, respectively. As a result, we use the Kannisto model to fit the mortality data from the age of 60 and 65 for males and females, respectively, to the maximum

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Thatcher, Kannisto, and Vaupel, 1998; Zeng and Vaupel, 2003). We use the Kannisto model, since it seems to work better than other models in fitting mortality pattern at old ages (Thatcher, Kannisto, and Vaupel, 1998), age available in each year and extrapolate the central death rates up to age 120 for each sample year during the period of 1994-2009. Following Roli (2008), we replace the observed death rates for all ages at or above $\bar{x}$, where $\bar{x}$ is the lowest age at which there are fewer death counts than 100 but should satisfy $80 \le \bar{x} \le 95$. In this way, we obtain an extended data covering age-specific mortality rates from age 0 to 120 for the period of 1994-2009.

An alternative approach is to firstly project the future mortality using our original (unextended) data and then to extrapolate mortality rates at older ages with projected estimates. For the purpose of comparison, we report the results using both data sets in the following sections.

Figure 2.2-2.4 shows the logarithm of the central death rates for the total population, urban population and rural population across gender groups for the sample period of 1994-2009, respectively. While mortality rates from age 0 to 84 are observed, those at and beyond age 85 are extrapolated using the Kannisto model. Like in most countries, the mortality pattern for each year in China firstly starts rather high for newborn infants and goes down at around age 15, then increasing again with the accident hump at around age 20-25.

[***Insert Figure 2.2, 2.3 and 2.4 Here***]

2.3.3 Estimation Results

Using the singular value decomposition (SVD) approach, we firstly estimate the values of α_x , β_x , and κ_t in the Lee-Carter model, respectively. Figure 2.5, 2.6 and 2.7 plot the estimated α_x , β_x , and κ_t for the total, urban and rural population, respectively. The results estimated based on the extended and unextended data sets show basically overlapping patterns.

[***Insert Figure 2.5, 2.6, and 2.7 Here***]

Since α_x is the average value of $\ln(m_{x,t})$ over time, it can be interpreted as the mean age profile of mortality. The estimated α_x shows a similar mortality pattern across population and gender groups. Nevertheless, for most age groups the mean of log force of mortality for females, regardless of residency status, is smaller than or equal to that for males, explaining the fact that females, on average, face longer life expectancy than males.

The loading factor, β_x, measures the age-specific response to the changes in the latent factor, κ_t. For example, a low (high) value of β_x represents a slowly (rapidly) decrease of mortality at specific age if κ_t declines over time. The estimation results of β_x, after being smoothed, show different patterns, depending on sex groups and residency status. Generally speaking, the estimates of β_x for both gender groups go down from age 0 and then begin to jump up at around age 10. For females regardless of their residency, β_x shows an overall declining sensitivity to the mortality movement again after age 20, indicating a diminishing increase in life expectancy. On the contrary, while the estimates of β_x for males also show the same pattern after age 20, they rebound at around age 40 and exceed their female counterparts at around age 60. As a result, Chinese males aged beyond 40 are more sensitive than their sex counterparts to the mortality improvement. In terms of residency effect, the estimates of β_x for the urban population are generally larger than those for the rural population, showing the urban-rural disparities in China.

The estimates of κ_t show decreasing trends over time. In order to determine the appropriate ARIMA model for the time series of κ_t, we use the Augmented Dickey-Fuller test and the Phillips-Perron Test to check stationarity. Table 2.2-2.4 present the results for total, urban, and rural population, respectively. Though there exist unit roots for the κ_t processes in level, they become stationary after first differencing. Thus, the κ_t processes for both gender groups need to be integrated of order one. Moreover, from panel B and C of each table we conclude that these κ_t processes follow a random walk except for the urban population.[1] Our results differ from previous findings. For example, Yin (2005) finds that the male process is an ARIMA (0, 1, 1) process.

[***Insert Table 2.2, 2.3, and 2.4 Here***]

Based on the results above, we can use project future values of $\widetilde{\kappa}_{t+T}$ with (2.18) and

[1] For the urban male population, using the unextended data, we find that this process follows an ARIMA (2, 1, 6) process. For the extended data, we find an ARIMA (2, 1, 5) process.

(2.19) for males and females, respectively, and then calculate projected one-year death probabilities and life expectancies at different ages according to the relevant equations above.

We now show the longevity risk resulting from *process risk* and *parameter risk* through predicting the logarithm of the central death rate beginning from 2010, the first year after our sample period. Parameter risk can be seen as a special case of model risk arising due to the lack of knowledge regarding the true probability distribution of future mortality rates. Even though we might exactly know the true probability distribution of the future mortality rates, the uncertainty in the mortality trends can still cause process risk. We use the Girosi and King (2006)-variant of the Lee-Carter model to illustrate these risks (see appendix for the Girosi and King (2006)-variant) because the asymptotic characteristics of the estimator based on this variant imply that making predictions as well as quantifying the longevity risk becomes a standard exercise in statistics or econometrics (De Waegenaere, Melenberg, and Stevens, 2010).

[***Insert Figure 2.8, 2.9, and 2.10 here***]

We show the observed and 20-year ahead prediction of the logarithm of the central death rate for 60-year old Chinese with parameter risk and process risk in figure 2.8-2.10 for total, urban, and rural population, respectively. The prediction begins from 2010, the first year after our sample period. In each figure, three cases, i.e., parameter risk, process risk and both risks, are taken into account, reported using 95% confidence intervals. We draw two conclusions from these projections: on the one hand, all these figure show same projection results, no matter what data set is used. Take urban male population for example, the projected log mortality rate of a 60-year old male in 2029 using the extended or unextended data is –5.4986, with the corresponding 95% confidence interval of both process and parameter risks being (-10.98, -0.02). Therefore, quantifying the longevity risk with either unextended data or extended data should obtain same or highly similar results. On the other hand, all figures show clearly the downward trends not only in-sample but also out-of-sample, predicting mortality improvements in the future. However, these figures also show the high uncertainty about future mortality movement in terms of direction and magnitude.

2.4 China's Pension System

Before quantifying the impact of longevity risk on the pension system, in this section we briefly introduce China's pension system. In line with advices by the World Bank, the current Chinese pension system consists of multiple pillars.

The National Social Security Fund (NSSF), established as the zero pillar by China's central government in 2000, is a strategic reserve fund in a response to the rapidly ageing population and the expected looming fiscal pressure in the coming decades. As of 2011 the asset under management of NSSF was RMB 869 billion.[1]

The state pension scheme, the first pillar of China's pension system, is characterized by a fragmentation, depending on employment and/or residency status. China has one scheme for urban workers, one for non-workers, another for public sector employees, and a fourth for rural folk, each administered by separate provincial, city, or county governments. Civil servants and employees in public service sectors (for example, education) in China are covered by an unfounded Pay-As-You-Go (PAYG) scheme with contributions solely from the state budget. As a standalone and generous scheme, this Defined-Benefit (DB) plan promises a replacement rate of up to 90 percent. The first pillar scheme for employed urban residents comprises two mandatory parts: a social pooling account and an individual account. The social pooling account is a PAYG and DB scheme solely contributed by employers. With contributions being 20 percent of the total employees' wages, this re-distributive scheme pays a fixed percentage of average citywide earning for each year of coverage and targets a 35 percent replacement rate after 35-year contributions. On the other hand, the individual account is a funded and Defined-Contribution (DC) scheme, which is financed solely by employee contributions of 8% of his or her wages. Nevertheless, this DC scheme also has DB elements regarding minimum investment returns and pension guarantees. For example, after retirement at 60,[2] from this scheme retirees receive an equal pension benefit calculated by dividing the accumulated amount plus investment returns by a parameter being 139.[3] Even if individual accounts are depleted, all benefits are continuously paid out of the pension

[1] http://www.ssf.gov.cn/cwsj/ndbg/201206/t20120618_5601.html

[2] Retirement ages are currently set at 55 for women and 60 for men.

[3] Assuming that retirees have a life expectancy of 10 years at the age of 60, the Chinese government initially set the parameter to be 120 to calculate the monthly individual account benefit. Nevertheless, this parameter soon has been increased to 139 in accordance to the improved life expectancy.

insurance fund. Given 15 years of contributions, the target replacement rate from this scheme is maximized at 24 percent.

While the state pension scheme mainly covers public sector and employed urban residents, a pilot program for rural residents was launched in 2009, and in 2011 for unemployed urban dwellers, both of which are voluntary. The New Rural Pension Scheme, firstly experimented in selected localities in the 1990s, also consists of two components, for example, a social pooling account and an individual account. The former, operated on a PAYG basis, is contributed by the government budget and pays a flat-rate benefit of minimum RMB 55 per month. The individual account is fully funded with contributions from individuals, local governments, and collectives. The benefit is the account balance divided by 139. For unemployed urban residents, the central government launched a similar scheme in 2011. By far more than 50 million people are slated to benefit from scheme.

The second pillar of China's pension system is the voluntary Enterprise Annuity (EA), which is similar to defined contribution plans such as 401k plans in the US. Both employers and employees can contribute to the fund, but only employers are required to do so. Contribution by the employer can be treated as costs for a maximum of 4% (or more, depending on the city) of the total payroll. The balance is payable as a lump sum or annuity. So far, EA has been mainly established by the large state owned enterprises.

The third pillar refers to the voluntary individual saving/pension schemes, and is designed to meet the needs of the population who wants to receive higher income after retirement.

Nevertheless, given that the second as well as third pillar are highly underdeveloped, it is the first pillar – the state pension scheme - that dominates China' pension system. As the first pillar is essentially based on a DB scheme, the continuous declining trends in mortality make the Chinese governments at various levels bear the increasing longevity risk. This may push governments to change their pension plans from DB to DC. As a result, in the end, individuals rather than the state are exposed to the longevity risk.

2.5 Pricing of Longevity Risk

In this section we investigate the impact of longevity risk on public pension plans as well as private pension funds and life insurers by calculating the expected present value of a life annuity in different scenarios through simulation.

[***Insert Table 2.5 Here***]

Table 2.5 presents period as well as cohort life expectancies for selected ages, and numbers of years that an individual account runs out in different scenarios. Panel A and B report the cohort and period life expectancies using the extended and unextended data, respectively. Except for the minor discrepancies at age 65, both panels present same results. As a result, either data set can be used in quantifying the impact of longevity risk. Both panels show that, without taking into account the future mortality improvement, the period life expectancy is underestimated compared with the cohort one. For a 60-year old urban female in 2009, for example, the period life expectancy is 19.83 years, representing a 3 percent underestimation. Moreover, there exists a gap in life expectancy between males and females as well as between urban and rural areas. Generally, the urban population has a longer (cohort and period) life expectancy than its rural counterpart; and females live longer than males.

As the state guarantees a minimum investment return on individual accounts as well as pension payouts even after the individual account runs out, by comparing panel A/B with C, we find out that the state is facing substantial exposures to longevity risk. Take a 60-year old urban female for example.[1] The period and cohort life expectancy of a 60-year old urban female is 18.83 and 19.43 years, respectively. In order to prevent the individual account running out before death, the investment return of individual accounts should be no less than 5%. However, as the assets of individual accounts are only allowed to invest in deposit products or government bonds, the guaranteed investment returns of individual accounts are usually set to be equal to one-year deposit interests, which is less than 4% for the past decade. Under the assumption of a 4% investment return, individual accounts of people retiring at age 60 would run out in 15.59 years and the state has to bear the payout obligation for at least 3 years. More badly, the period life expectancies, without taking into account the future mortality improvement, are all underestimated compared with their cohort counterparts, which makes the state face more exposure to longevity risk.

[1] For simplicity, we don’t take into account inflation in our calculations in this paper.

We continue to explore the impact of longevity risk on pension/annuity pricing. We assume that each annuitant gets one Chinese yuan per year after retirement, conditional on his/her survival, with a constant risk-free interest rate r or under term structure of interest rate of government bond. Thus, in year $t+\tau$ ($\tau \geq 1$) the present value of the future payment should follow (2.8). In order to highlight the impact of scholastic death probabilities on the annuity price, we also calculate the expected present value of a life annuity under the assumption of constant one-year death probabilities based on (2.4) and (2.5).

[***Insert Table 2.6 Here***]

Table 2.6 presents the simulation results for the annuity price in different scenarios with corresponding 95% confidence intervals in parenthesis. These standard errors are estimated, following the bootstrap approach by Koissi, Shapiro, and Hognas (2006). For the purpose of comparison, table 2.6 also reports the annuity prices based on a period life table. Without taking into account the mortality improvement in the future, these annuity prices calculated with a period life table are significantly under-priced compared with those allowing for the future mortality improvement. For example, with interest rate of 3%, the life annuity price for 60-year old urban female in 2009 was 17.88 based on the period life table. Nevertheless, when the mortality improvement is allowed for, the fair valuation for the same individual should be 20, representing a 12 percent increase for the same annuity product. Moreover, the confidence intervals reported in table 2.6 also reflect the uncertain trends in mortality improvement in the future. Therefore, without taking into account longevity risk and its randomness when designing pension systems or products, the impact of longevity risk on risk management would be substantial. Our result is also relevant to the current rural pension reform in China. Unlike in developed countries, in China there are still significant disparities between rural and urban areas. Compared with those for the urban population, the fair annuity valuations of rural residents are much smaller. Consequently, in order to encourage rural residents' voluntary participation in the state pension plan, the contribution policy should be flexible rather than universal.

2.6 Conclusions

In this paper we use the Lee-Carter model to quantify longevity risk and to investigate the effect of longevity risk on pension and insurance pricing and liabilities in the context of China.

Due to the unavailable mortality data at older ages in China, we use two approaches to resolve this issue and find both approaches equally acceptable. Unlike the previous findings, our results show that the latent factor process follows a random walk for all population groups except for the urban population. In addition to *process risk,* resulting from the unknown distribution of the latent factor in the future, we also take into account the impact of *parameter risk* on our projection of future mortality development. Though the future mortality development shows a strong downward trend, it also presents substantial uncertainties when *process risk* and *parameter risk* are involved. In order to investigate the impact of longevity risk on pension plans, we simulate the expected present value of life annuity for 60-year old Chinese males and female beginning from 2009. As comparison, we also calculate the corresponding annuity price with a period life table. Our simulated results show that, without taking into account the stochastic mortality development in the future, the pricing of life annuity products would be underestimated, significantly challenging public pension plans as well as private pension funds and life insurers. For example, without taking into account the mortality improvement in the future, the life expectancy of a 60-year old urban female in 2009 was 18.83 years, 3 percent underestimated compared with her cohort life expectancy allowing for the mortality improvement. At a 4 percent guaranteed investment return, her individual account can run out in 15.59 years according to the current payout policy, leaving the state bearing longevity risk for at least 3 years. However, as the state usually guarantees investment returns only equaling to the one-year deposit rate, which was mostly less than 4 percent for the past decade, the real longevity risk exposure faced by the state should be more substantial. Furthermore, without including a longevity risk premium, the present value of life annuities for the same individual in 2009 is 10 percent under-priced with a 4 percent flat rate and 9 percent under-priced with the term structure of Chinese government bonds. This implies that a fair valuation of pension and annuities should include a substantial longevity risk premium.

As the world's largest country in terms of population, China has experienced a rapid aging over the past half-century and thus the Chinese government is reforming its pubic pension system to meet the urgent challenges of an ageing society. Compared with other developed economies, China still has not achieved the universal pension coverage by far. As a result, much attention in China now is almost exclusively paid to increasing coverage, with the longevity risk generally ignored by the public and policy makers. However, this paper reveals the significant impact of longevity risk on risk management and pension/annuity pricing. Thus, increasing awareness and understanding of longevity risk by the public, especially the policy makers, would contribute to the current public pension reforms and product design in China.

2.7 References

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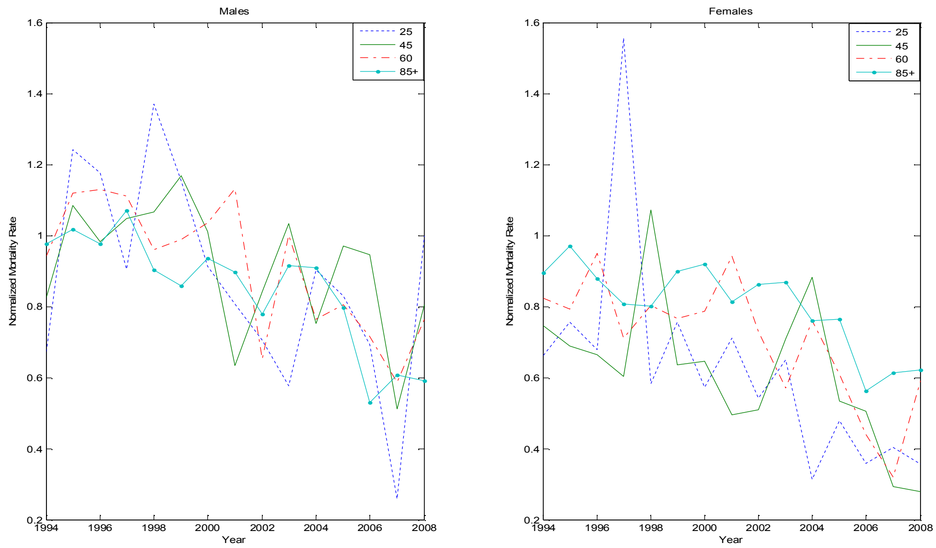
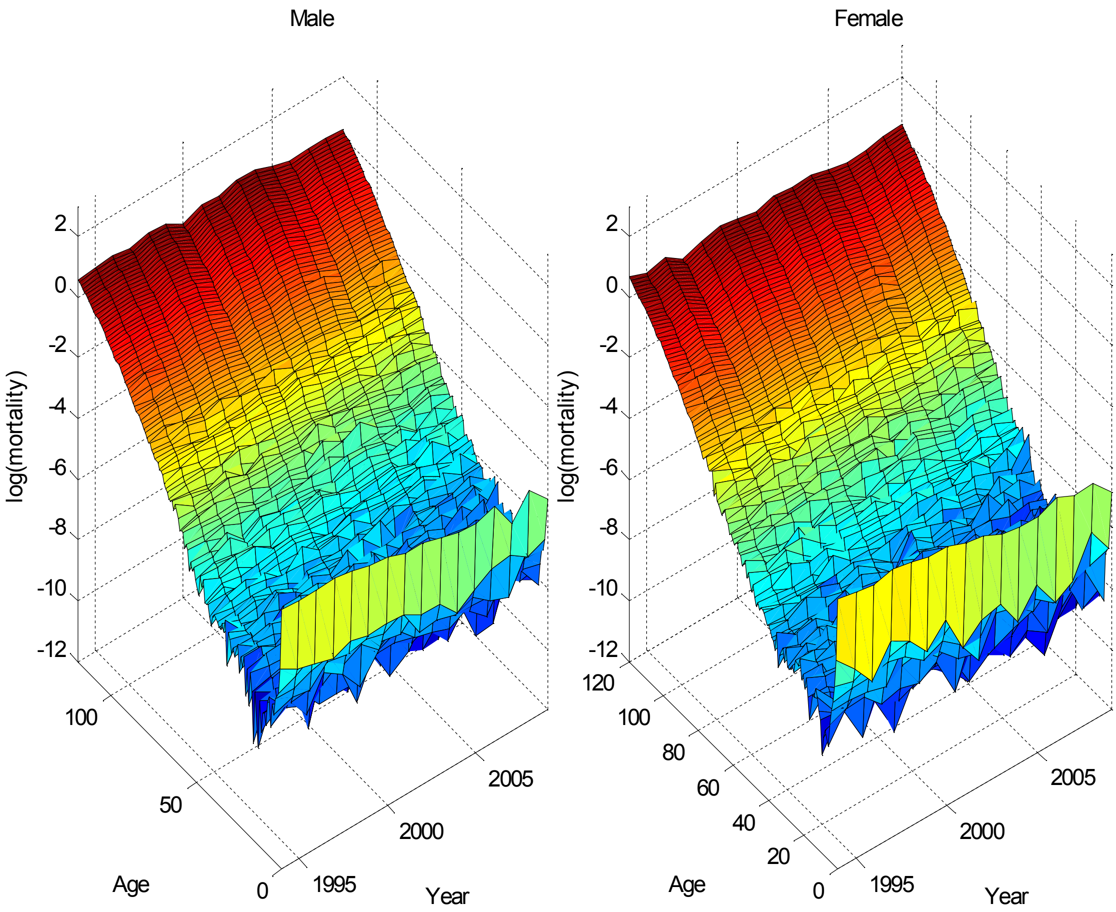
Figure 2.1: Normalized Death Rate for Selected Age Groups



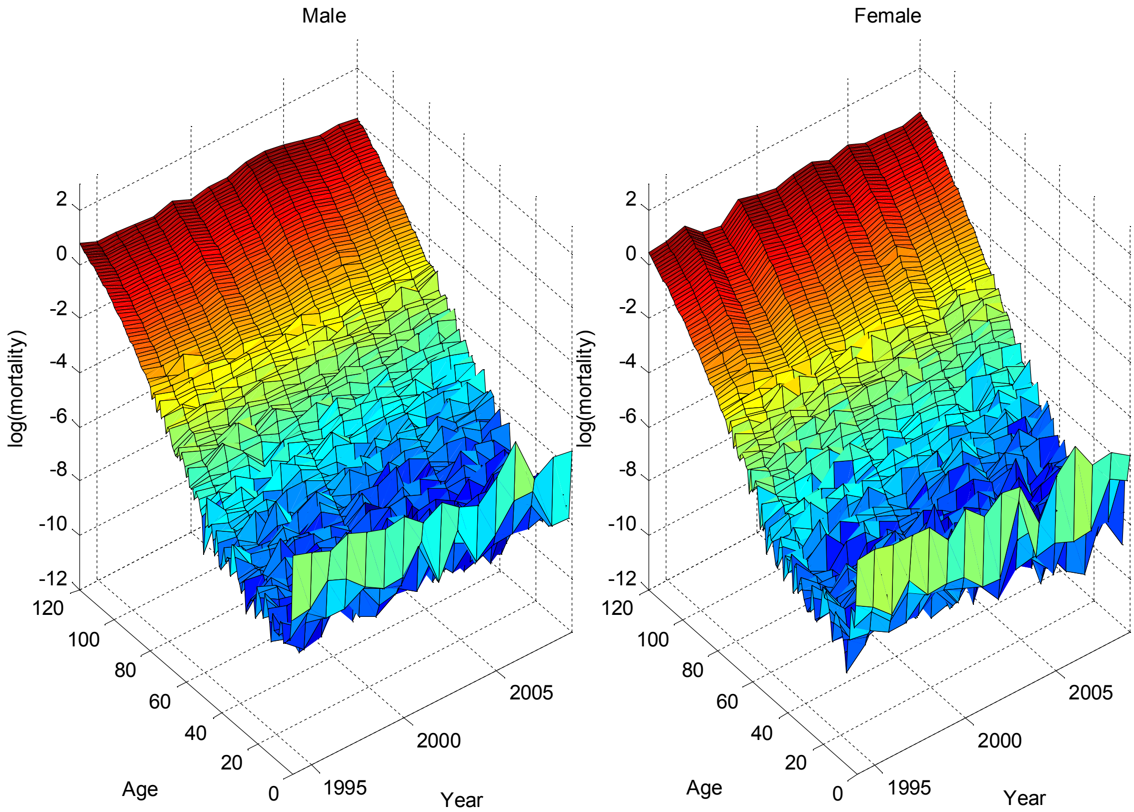
This figure plots the observed death rates for Chinese males (left) and Chinese females (right), for selected age groups and for different time periods, normalized to one for year 1981. The data originates from the China Population Statistical Yearbooks and the China Statistical Yearbook compiled by the National Bureau of Statistics of China.

Figure 2.2: Logarithm of Central Mortality Rates for Total Population



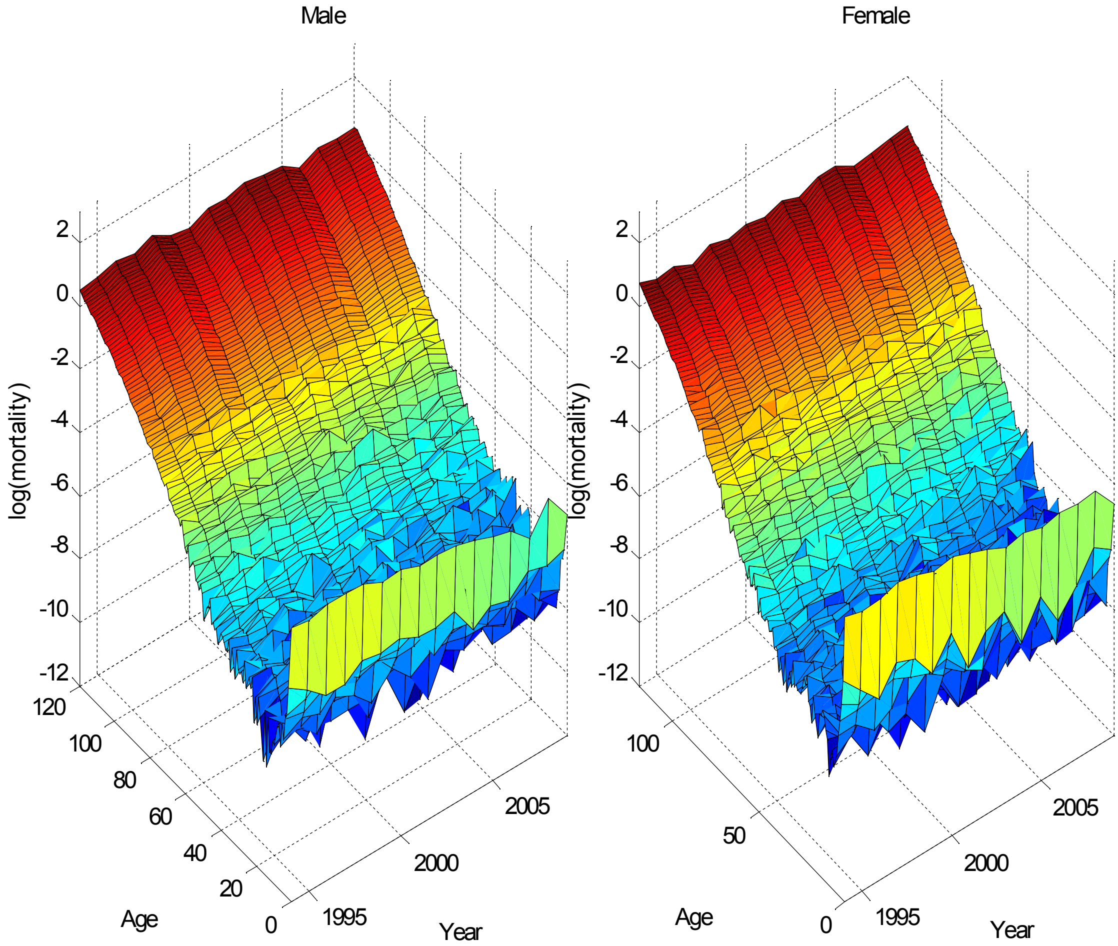
This figure plots the logarithm of central death rates for total population during the period of 1994-2009. Mortality rates from age 0 to 84 are observed, and beyond age 85 are extrapolated using the Kannisto model.

Figure 2.3: Logarithm of Central Mortality Rates for Urban Population



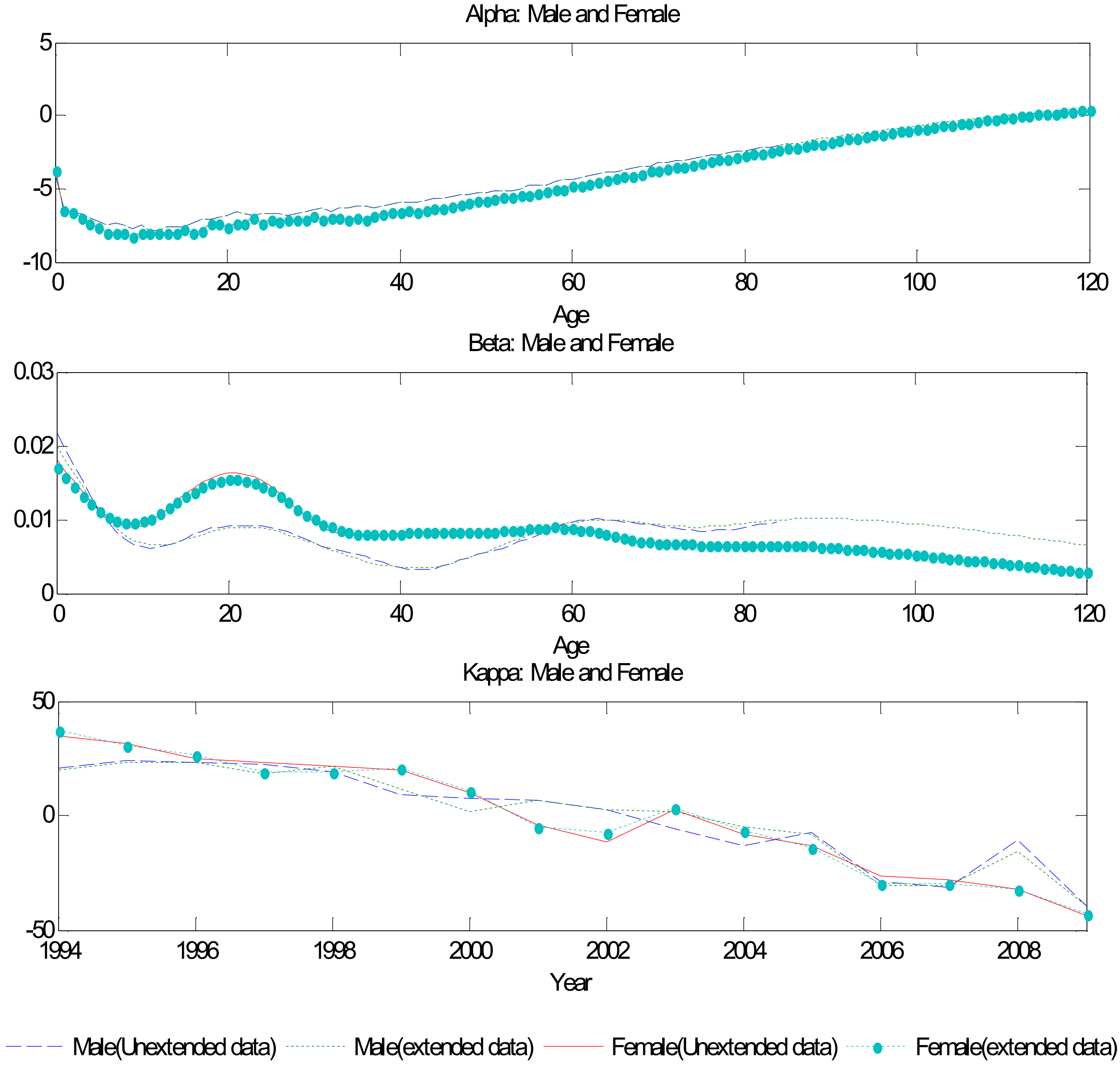
This figure plots the logarithm of central death rates for urban population during the period of 1994-2009. Mortality rates from age 0 to 84 are observed, and beyond age 85 are extrapolated using the Kannisto model.

Figure 2.4: Logarithm of Central Mortality Rates for Rural Population



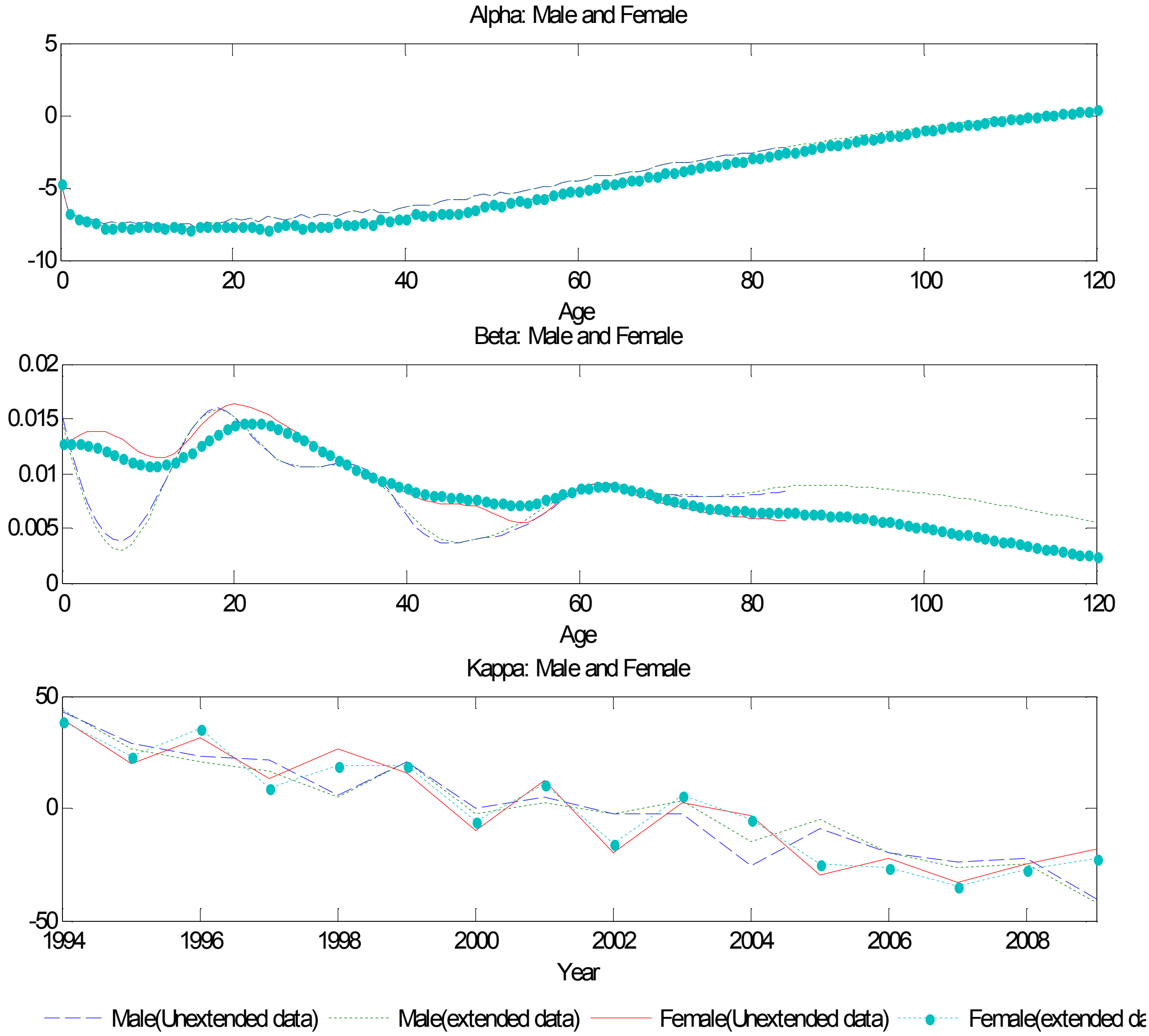
This figure plots the logarithm of central death rates for rural population during the period of 1994-2009. Mortality rates from age 0 to 84 are observed, and beyond age 85 are extrapolated using the Kannisto model.

Figure 2.5: Lee-Carter Model Estimation Results for Total Population



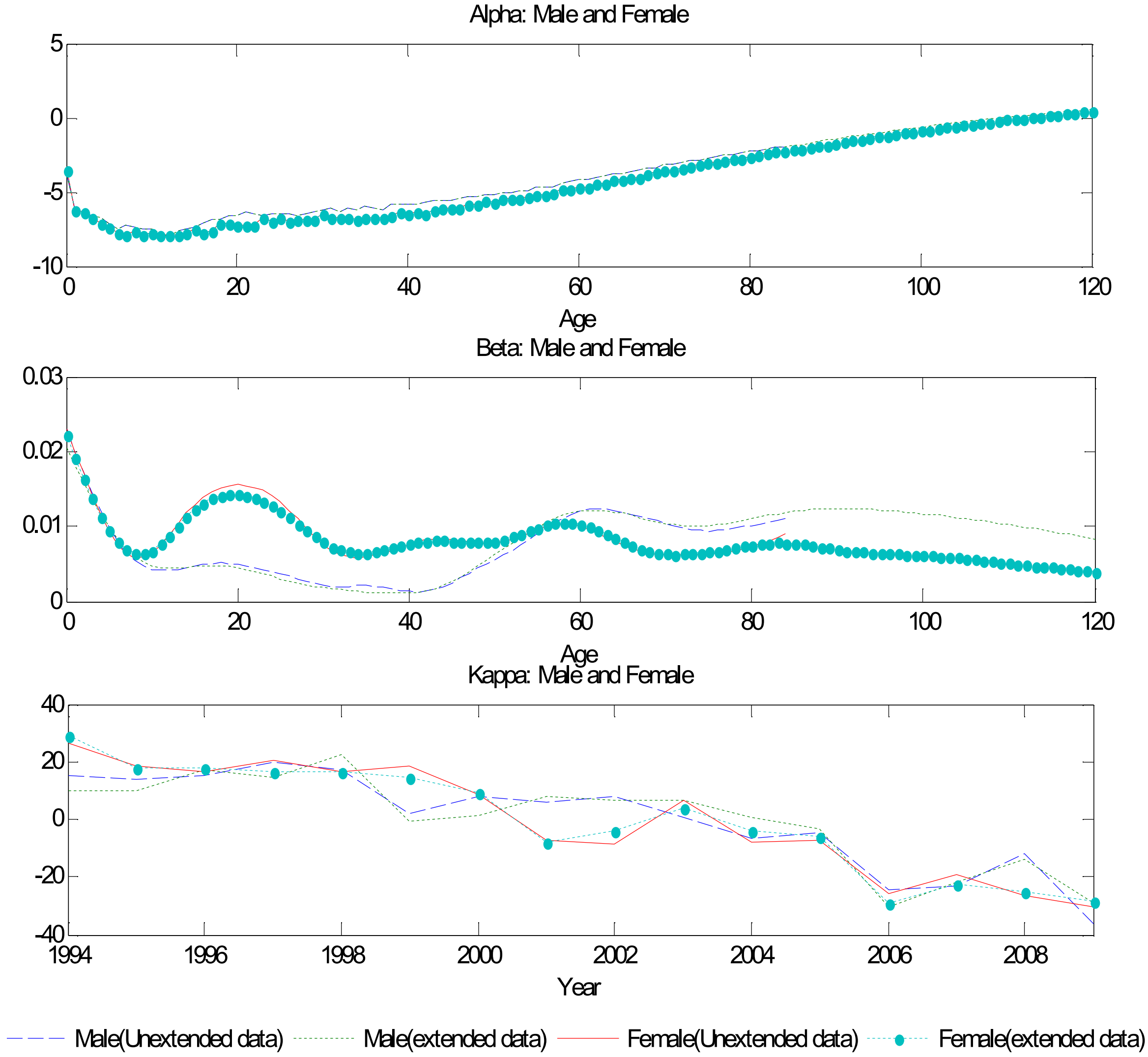
This figure plots the Lee-Carter Model estimation results for the total population across gender groups. Both extended and unextended data are using for the purpose of comparison. Beta is smoothed using cubic B-splines.

Figure 2.6: Lee-Carter Model Estimation Results for Urban Population



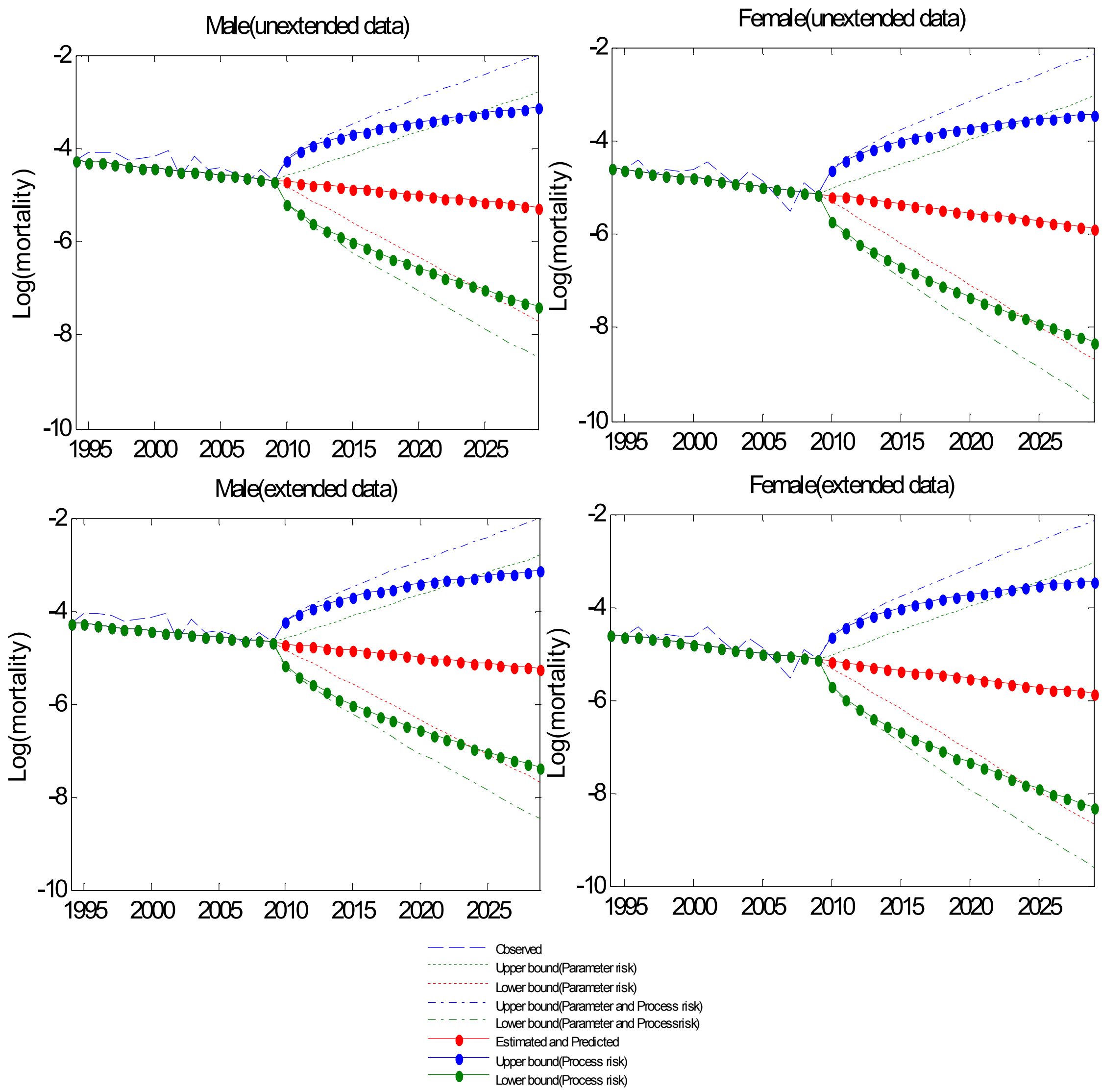
This figure plots the Lee-Carter Model estimation results for the urban population across gender groups. Both extended and unextended data are using for the purpose of comparison. Beta is smoothed using cubic B-splines.

Figure 2.7: Lee-Carter Model Estimation Results for Rural Population



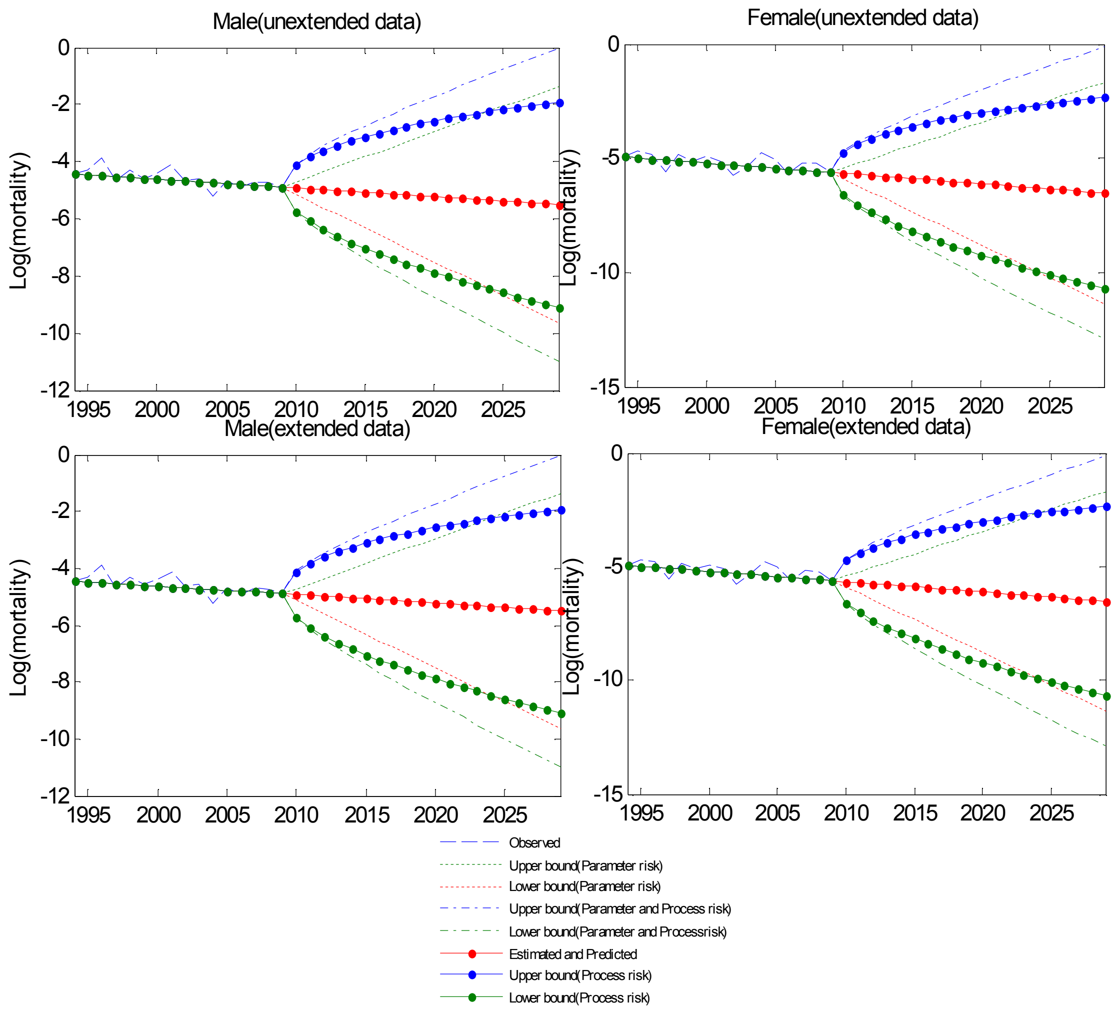
This figure plots the Lee-Carter Model estimation results for the rural population across gender groups. Both extended and unextended data are using for the purpose of comparison. Beta is smoothed using cubic B-splines.

Figure 2.8: Prediction of Log Mortality Rate at 60, Total Population



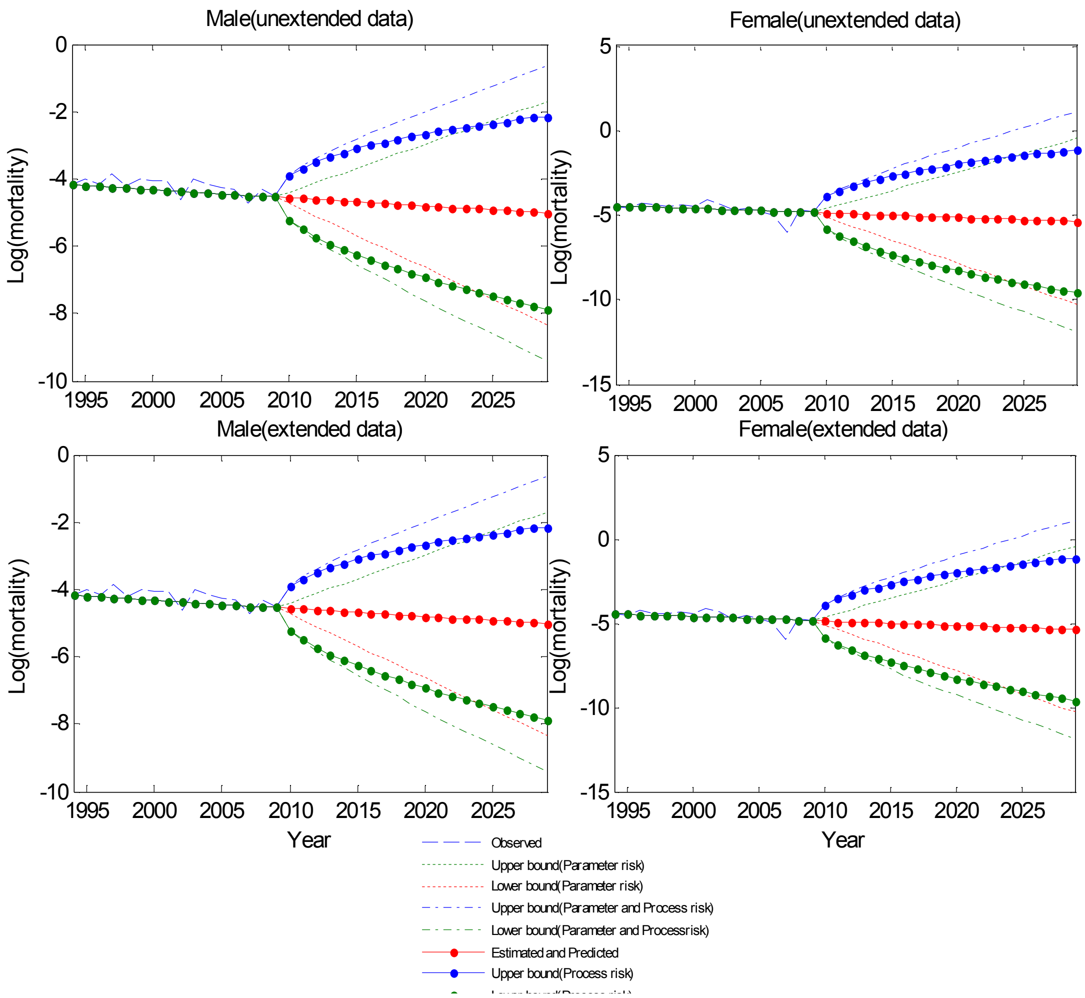
This figure shows the (observed and predicated) logarithm of central death rates at the age of 60 for total population, taking into account parameter risk, process risk, and both within 95% confidence intervals. The upper part is based on the unextended data, while the lower part on the extended data.

Figure 2.9: Prediction of Log Mortality Rate at 60, Urban Population



This figure shows the (observed and predicated) logarithm of central death rates at the age of 60 for urban population, taking into account parameter risk, process risk, and both within 95% confidence intervals. The upper part is based on the unextended data, while the lower part on the extended data.

Figure 2.10: Prediction of Log Mortality Rate at 60, Rural Population



This figure shows the (observed and predicated) logarithm of central death rates at the age of 60 for rural population, taking into account parameter risk, process risk, and both within 95% confidence intervals. The upper part is based on the unextended data, while the lower part on the extended data.

Table 2.1: Estimates of Life-Table Ageing Rate ($k_{x,t}$), 1994-2009

Panel A: Total Population

	Male				Female			
	1994	1999	2004	2009	1994	1999	2004	2009
60	0.127 (0.019)	0.136 (0.016)	0.078 (0.015)	0.040 (0.015)	0.085 (0.025)	0.083 (0.020)	0.099 (0.020)	0.044 (0.020)
65	0.074 (0.016)	0.083 (0.013)	0.078 (0.014)	0.044 (0.013)	0.089 (0.021)	0.117 (0.017)	0.089 (0.018)	0.058 (0.018)
70	0.108 (0.016)	0.096 (0.012)	0.114 (0.012)	0.045 (0.012)	0.140 (0.019)	0.096 (0.015)	0.118 (0.015)	0.046 (0.015)
75	0.086 (0.016)	0.098 (0.012)	0.086 (0.012)	0.041 (0.011)	0.087 (0.017)	0.079 (0.014)	0.108 (0.013)	0.044 (0.013)
80	0.082 (0.019)	0.105 (0.014)	0.107 (0.013)	0.036 (0.012)	0.118 (0.017)	0.133 (0.014)	0.096 (0.014)	0.042 (0.013)
85	0.083 (0.026)	0.056 (0.018)	0.096 (0.017)	0.022 (0.016)	0.057 (0.021)	0.084 (0.016)	0.085 (0.016)	0.036 (0.015)

Panel B: Urban Population

	Male				Female			
	1994	1999	2004	2009	1994	1999	2004	2009
60	0.119 (0.034)	0.150 (0.026)	0.058 (0.025)	0.065 (0.024)	0.092 (0.043)	0.137 (0.032)	0.109 (0.031)	0.105 (0.035)
65	0.060 (0.031)	0.088 (0.020)	0.132 (0.022)	0.136 (0.022)	0.107 (0.038)	0.062 (0.026)	0.068 (0.027)	0.144 (0.031)
70	0.129 (0.030)	0.073 (0.019)	0.085 (0.018)	0.089 (0.019)	0.096 (0.034)	0.114 (0.024)	0.142 (0.023)	0.125 (0.025)
75	0.092 (0.030)	0.093 (0.020)	0.072 (0.019)	0.111 (0.017)	0.092 (0.034)	0.079 (0.024)	0.110 (0.021)	0.092 (0.021)
80	0.094 (0.034)	0.102 (0.024)	0.134 (0.021)	0.050 (0.019)	0.106 (0.034)	0.147 (0.025)	0.057 (0.023)	0.087 (0.022)
85	0.144 (0.041)	0.117 (0.028)	0.140 (0.024)	0.079 (0.023)	0.119 (0.035)	0.103 (0.025)	0.157 (0.024)	0.145 (0.022)

Panel C: Rural Population

	Male				Female			
	1994	1999	2004	2009	1994	1999	2004	2009
60	0.132 (0.020)	0.105 (0.017)	0.090 (0.017)	0.105 (0.018)	0.097 (0.025)	0.077 (0.021)	0.096 (0.022)	0.104 (0.024)
65	0.087 (0.017)	0.110 (0.015)	0.072 (0.015)	0.083 (0.017)	0.089 (0.022)	0.097 (0.018)	0.098 (0.019)	0.124 (0.021)
70	0.093 (0.016)	0.084 (0.013)	0.117 (0.013)	0.116 (0.016)	0.130 (0.019)	0.114 (0.015)	0.102 (0.016)	0.097 (0.019)
75	0.078 (0.016)	0.099 (0.013)	0.092 (0.013)	0.083 (0.014)	0.088 (0.017)	0.072 (0.014)	0.107 (0.014)	0.107 (0.016)
80	0.075 (0.020)	0.097 (0.015)	0.100 (0.014)	0.105 (0.015)	0.114 (0.018)	0.110 (0.015)	0.103 (0.014)	0.099 (0.016)
85	0.075 (0.027)	0.031 (0.020)	0.088 (0.018)	0.066 (0.019)	0.062 (0.020)	0.103 (0.016)	0.088 (0.016)	0.100 (0.016)

Note: the corresponding standard errors are reported in the parentheses.

Table 2.2: Unit Root Test and Model Selection for κ_t, Total Population

Panel A: Unit Root Test in Level and first Difference

	Male		Female	
t-Statistics	Unextended Data	Extended Data	Unextended Data	Extended data
ADF Test in Level	1.194	0.989	0.105	1.697
	(0.996)	(0.993)	(0.955)	(0.999)
PP Test in Level	0.702	1.297	1.628	0.976
	(0.988)	(0.997)	(0.999)	(0.994)
ADF Test first Difference	-6.900	-4.703	-4.005	-4.094
	(0.000)	(0.003)	(0.010)	(0.011)
PP Test in first Difference	-9.951	-6.592	-5.785	-5.028
	(0.000)	(0.000)	(0.001)	(0.002)

Panel B: Autocorrelation and Partial Correlation of First Difference, Unextended Data

	Male				Female			
	AC	PAC	Q-Stat	Prob.	AC	PAC	Q-Stat	Prob.
1	-0.086	-0.086	0.135	0.713	-0.157	-0.157	0.452	0.502
2	0.001	-0.007	0.135	0.935	-0.213	-0.244	1.344	0.511
3	0.029	0.029	0.153	0.985	-0.364	-0.484	4.161	0.245
4	0.006	0.011	0.154	0.997	0.091	-0.245	4.352	0.360
5	0.027	0.029	0.173	0.999	0.063	-0.318	4.454	0.486

Panel C: Autocorrelation and Partial Correlation of First Difference, Extended Data

	Male				Female			
	AC	PAC	Q-Stat	Prob.	AC	PAC	Q-Stat	Prob.
1	-0.039	-0.039	0.028	0.867	-0.010	-0.010	0.002	0.965
2	0.012	0.010	0.031	0.985	-0.441	-0.442	3.823	0.148
3	0.000	0.001	0.031	0.999	-0.357	-0.457	6.527	0.089
4	-0.055	-0.055	0.101	0.999	0.259	-0.033	8.077	0.089
5	0.020	0.016	0.111	1.000	0.078	-0.365	8.233	0.144

Note: ADF test- Augmented Dickey-Fuller Test; PP test- Phillips-Perron Test in Level; the corresponding probabilities are reported in the parentheses.

Table 2.3: Unit Root Test and Model Selection for κ_t, Urban Population

Panel A: Unit Root Test in Level and first Difference

	Male		Female	
t-Statistics	Unextended Data	Extended Data	Unextended Data	Extended data
ADF Test in Level	-0.582	0.446	-1.055	-0.938
	(0.843)	(0.977)	(0.699)	(0.744)
PP Test in Level	-0.828	-0.778	-1.983	-1.624
	(0.782)	(0.796)	(0.290)	(0.447)
ADF Test first Difference	-5.481	-4.703	-4.718	-4.542
	(0.001)	(0.003)	(0.005)	(0.006)
PP Test in first Difference	-24.615	-4.729	-12.226	-12.358
	(0.000)	(0.000)	(0.000)	(0.002)

Panel B: Autocorrelation and Partial Correlation of First Difference, Unextended Data

	Male				Female			
	AC	PAC	Q-Stat	Prob.	AC	PAC	Q-Stat	Prob.
1	-0.654	-0.654	7.794	0.005	-0.681	-0.681	8.451	0.004
2	0.368	-0.104	10.453	0.005	0.198	-0.497	9.218	0.010
3	-0.206	-0.014	11.351	0.010	0.202	0.161	10.083	0.018
4	0.236	0.213	12.643	0.013	-0.400	-0.089	13.791	0.008
5	-0.151	0.164	13.224	0.021	0.351	-0.055	16.938	0.005

Panel C: Autocorrelation and Partial Correlation of First Difference, Extended Data

	Male				Female			
	AC	PAC	Q-Stat	Prob.	AC	PAC	Q-Stat	Prob.
1	-0.566	-0.566	5.831	0.016	-0.678	-0.678	8.369	0.004
2	0.314	-0.009	7.768	0.021	0.258	-0.372	9.676	0.008
3	-0.157	0.026	8.289	0.040	0.085	0.157	9.831	0.020
4	0.128	0.076	8.670	0.070	-0.333	-0.207	12.407	0.015
5	-0.117	-0.032	9.021	0.108	0.386	-0.010	16.212	0.006

Note: ADF test- Augmented Dickey-Fuller Test; PP test- Phillips-Perron Test in Level; the corresponding probabilities are reported in the parentheses.

Table 2.4: Unit Root Test and Model Selection for κ_t, Rural Population

Panel A: Unit Root Test in Level and first Difference

	Male		Female	
t-Statistics	Unextended Data	Extended Data	Unextended Data	Extended data
ADF Test in Level	1.100	-0.777	-0.735	-0.927
	(0.995)	(0.796)	(0.808)	(0.750)
PP Test in Level	1.183	-0.351	-0.479	-0.609
	(0.996)	(0.895)	(0.870)	(0.841)
ADF Test first Difference	-4.531	-5.029	-5.266	-4.051
	(0.005)	(0.002)	(0.001)	(0.013)
PP Test in first Difference	-6.290	-6.093	-7.859	-8.767
	(0.000)	(0.000)	(0.000)	(0.000)

Panel B: Autocorrelation and Partial Correlation of First Difference, Unextended Data

	Male				Female			
	AC	PAC	Q-Stat	Prob.	AC	PAC	Q-Stat	Prob.
1	-0.155	-0.155	0.436	0.509	-0.387	-0.387	2.725	0.099
2	0.030	0.007	0.454	0.797	-0.044	-0.227	2.763	0.251
3	0.015	0.021	0.458	0.928	-0.226	-0.415	3.845	0.279
4	0.026	0.031	0.474	0.976	-0.019	-0.488	3.853	0.426
5	0.074	0.084	0.614	0.987	-0.037	-0.812	3.888	0.566

Panel C: Autocorrelation and Partial Correlation of First Difference, Extended Data

	Male				Female			
	AC	PAC	Q-Stat	Prob.	AC	PAC	Q-Stat	Prob.
1	-0.293	-0.293	1.569	0.210	-0.310	-0.310	1.745	0.187
2	0.142	0.061	1.965	0.374	-0.110	-0.227	1.981	0.371
3	-0.115	-0.063	2.245	0.523	-0.196	-0.359	2.798	0.424
4	-0.022	-0.086	2.257	0.689	-0.022	-0.353	2.810	0.590
5	0.086	0.080	2.445	0.785	-0.011	-0.439	2.813	0.729

Note: ADF test- Augmented Dickey-Fuller Test; PP test- Phillips-Perron Test in Level; the corresponding probabilities are reported in the parentheses.

Table 2.5: The Impact of Life Expectancy on Individual Account, 2009

Panel A: Extended Data

Male	Period			Cohort			Female	Period			Cohort		
Age	Total	Urban	Rural	Total	Urban	Rural	Age	Total	Urban	Rural	Total	Urban	Rural
55	18.35	18.66	18.11	19.05	19.12	18.83	55	19.30	19.76	18.90	19.75	20.16	19.30
60	16.96	17.41	16.60	17.95	18.13	17.58	60	18.15	18.83	17.58	18.84	19.43	18.18
65	15.07	15.55	14.66	16.33	16.68	15.82	65	16.44	17.37	15.67	17.44	18.23	16.56

Panel B: Unextended Data

Male	Period			Cohort			Female	Period			Cohort		
Age	Total	Urban	Rural	Total	Urban	Rural	Age	Total	Urban	Rural	Total	Urban	Rural
55	18.35	18.66	18.11	19.05	19.12	18.83	55	19.30	19.76	18.90	19.75	20.16	19.30
60	16.96	17.41	16.60	17.94	18.13	17.58	60	18.15	18.83	17.59	18.84	19.43	18.18
65	15.03	15.49	14.65	16.29	16.59	15.81	65	16.43	17.35	15.70	17.43	18.18	16.63

Panel C: Individual Account

Age	Payout factor	1%	2%	3%	4%	5%	6%	7%
55	170	15.28	16.67	18.41	20.94	24.69	31.70	68.59
60	139	12.32	13.19	14.25	15.59	17.35	19.84	23.86
65	101	8.80	9.22	9.71	10.28	10.95	11.75	12.75

This table presents life expectancies at selected ages using the extended data (panel A) and unextended data (panel B). Period life expectancies are calculated for the purpose of comparison. Cohort life expectancies are calculated with 20-year mortality projections. For highlighting the impact of longevity risk, panel C presents numbers of years that an individual account runs out under different interest rates. According to China’s current pension policy, retirees who retire at 55, 60, and 65 receive an equal monthly pension benefit from their individual accounts, which is calculated by dividing the accumulated amount at retirement by 170, 139, and 101, respectively.

Table 2.6: Life Annuity Price, 60-year Male and Female in 2009

Panel A: Extended Data

	Male (Total Population)						Female (Total Population)				
r	Period Life Table	Cohort Life Table	Parameter Risk	Process Risk	Parameter & Process Risk	r	Period Life Table	Cohort Life Table	Parameter Risk	Process Risk	Parameter & Process Risk
0.02	17.01	21.28	(14.99, 30.67)	(14.99, 29.49)	(12.85, 32.14)	0.02	18.91	22.40	(14.99, 32.14)	(14.99, 30.67)	(12.11, 33.17)
0.03	15.42	18.76	(13.75, 25.27)	(13.75, 24.52)	(11.94, 26.17)	0.03	16.94	19.60	(13.75, 26.17)	(13.75, 25.27)	(11.30, 26.77)
0.04	14.03	16.66	(12.66, 21.20)	(12.66, 20.72)	(11.12, 21.75)	0.04	15.25	17.29	(12.66, 21.75)	(12.66, 21.20)	(10.56, 22.11)
0.05	12.82	14.90	(11.69, 18.08)	(11.69, 17.77)	(10.38, 18.42)	0.05	13.80	15.37	(11.69, 18.42)	(11.69, 18.08)	(9.90, 18.63)
0.06	11.76	13.41	(10.83, 15.65)	(10.83, 15.46)	(9.71, 15.86)	0.06	12.55	13.76	(10.83, 15.86)	(10.83, 15.65)	(9.30, 15.99)
Term	14.70	17.31	(13.31, 21.61)	(13.31, 21.17)	(11.71, 21.86)	Term	15.92	17.93	(13.31, 21.86)	(13.31, 21.61)	(11.13, 21.86)

	Male (Urban Population)						Female (Urban Population)				
r	Period Life Table	Cohort Life Table	Parameter Risk	Process Risk	Parameter & Process Risk	r	Period Life Table	Cohort Life Table	Parameter Risk	Process Risk	Parameter & Process Risk
0.02	17.66	25.00	(12.85, 32.50)	(12.11, 32.14)	(9.79, 33.50)	0.02	20.12	22.94	(12.85, 33.83)	(12.11, 33.17)	(9.79, 34.46)
0.03	15.94	21.49	(11.94, 26.38)	(11.30, 26.17)	(9.25, 26.97)	0.03	17.88	20.00	(11.94, 27.15)	(11.30, 26.77)	(9.25, 27.51)
0.04	14.45	18.66	(11.12, 21.87)	(10.56, 21.75)	(8.76, 22.22)	0.04	15.98	17.59	(11.12, 22.33)	(10.56, 22.11)	(8.76, 22.53)
0.05	13.16	16.37	(10.38, 18.49)	(9.90, 18.42)	(8.31, 18.70)	0.05	14.38	15.59	(10.38, 18.76)	(9.90, 18.63)	(8.31,18.88)
0.06	12.04	14.50	(9.71, 15.91)	(9.30, 15.86)	(7.89, 16.03)	0.06	13.00	13.93	(9.71, 16.06)	(9.30, 15.99)	(7.89, 16.13)
Term	15.13	19.25	(11.71, 21.86)	(11.13, 21.86)	(9.20, 21.86)	Term	16.64	18.21	(11.71, 21.86)	(11.13, 21.86)	(9.20, 21.86)

	Male (Rural Population)						Female (Urban Population)				
r	Period Life Table	Cohort Life Table	Parameter Risk	Process Risk	Parameter & Process Risk	r	Period Life Table	Cohort Life Table	Parameter Risk	Process Risk	Parameter & Process Risk
0.02	16.35	18.91	(12.85, 31.42)	(12.11, 29.89)	(10.58, 32.84)	0.02	17.66	20.71	(12.11, 32.50)	(11.35, 31.42)	(9.79, 33.50)
0.03	14.88	16.94	(11.94, 25.73)	(11.30, 24.78)	(9.95, 26.58)	0.03	15.94	18.33	(11.30, 26.38)	(10.64, 25.73)	(9.25, 26.97)
0.04	13.59	15.25	(11.12, 21.48)	(10.56, 20.88)	(9.39, 21.99)	0.04	14.45	16.33	(10.56, 21.87)	(9.99, 21.48)	(8.76, 22.22)
0.05	12.46	13.80	(10.38, 18.26)	(9.90, 17.88)	(8.86, 18.57)	0.05	13.16	14.64	(9.90, 18.49)	(9.39, 18.26)	(8.31, 18.70)

0.06	11.47	12.55	(9.71, 15.76)	(9.30, 15.52)	(8.38, 15.95)	0.06	12.04	13.21	(9.30, 15.91)	(8.85, 15.76)	(7.89, 16.03)
Term	14.26	15.92	(11.71, 21.86)	(11.13, 21.33)	(9.87, 21.86)	Term	15.13	16.98	(11.13, 21.86)	(10.51, 21.86)	(9.20, 21.86)

Panel B: Unextended Data

	Male (Total Population)						Female (Total Population)				
r	Period Life Table	Cohort Life Table	Parameter Risk	Process Risk	Parameter & Process Risk	r	Period Life Table	Cohort Life Table	Parameter Risk	Process Risk	Parameter & Process Risk
0.02	17.01	20.71	(14.99, 25.00)	(14.99, 24.50)	(12.85, 25.97)	0.02	18.91	22.40	(14.99, 27.80)	(14.99, 27.36)	(12.11, 29.08)
0.03	15.42	18.33	(13.75, 21.49)	(13.75, 21.13)	(11.94, 22.17)	0.03	16.94	19.60	(13.75, 23.41)	(13.75, 23.11)	(11.30, 24.25)
0.04	14.03	16.33	(12.66, 18.66)	(12.66, 18.41)	(11.12, 19.14)	0.04	15.25	17.29	(12.66, 19.99)	(12.66, 19.79)	(10.56, 20.55)
0.05	12.82	14.64	(11.69, 16.37)	(11.69, 16.19)	(10.38, 16.71)	0.05	13.80	15.37	(11.69, 17.29)	(11.69, 17.16)	(9.90, 17.66)
0.06	11.76	13.21	(10.83, 14.50)	(10.83, 14.37)	(9.71, 14.74)	0.06	12.55	13.76	(10.83, 15.14)	(10.83, 15.05)	(9.30, 15.38)
Term	14.70	16.98	(13.31, 19.25)	(13.31, 19.00)	(11.71, 19.70)	Term	15.92	17.93	(13.31, 20.50)	(13.31, 20.31)	(11.13, 21.02)

	Male (Urban Population)						Female (Urban Population)				
r	Period Life Table	Cohort Life Table	Parameter Risk	Process Risk	Parameter & Process Risk	r	Period Life Table	Cohort Life Table	Parameter Risk	Process Risk	Parameter & Process Risk
0.02	17.66	22.40	(12.85, 26.44)	(12.11, 26.44)	(9.79, 27.36)	0.02	19.52	22.40	(12.11, 27.80)	(12.11, 27.36)	(9.79, 28.23)
0.03	15.94	19.60	(11.94, 22.49)	(11.30, 22.49)	(9.25, 23.11)	0.03	17.41	19.60	(11.30, 23.41)	(11.30, 23.11)	(9.25, 23.70)
0.04	14.45	17.29	(11.12, 19.37)	(10.56, 19.37)	(8.76, 19.79)	0.04	15.62	17.29	(10.56, 19.99)	(10.56, 19.79)	(8.76, 20.19)
0.05	13.16	15.37	(10.38, 16.87)	(9.90, 16.87)	(8.31, 17.16)	0.05	14.09	15.37	(9.90, 17.29)	(9.90, 17.16)	(8.31, 17.42)
0.06	12.04	13.76	(9.71, 14.85)	(9.30, 14.85)	(7.89, 15.05)	0.06	12.78	13.76	(9.30, 15.14)	(9.30, 15.05)	(7.89, 15.22)
Term	15.13	17.93	(11.71, 19.91)	(11.13, 19.91)	(9.20, 20.31)	Term	16.29	17.93	(11.13, 20.50)	(11.13, 20.31)	(9.20, 20.68)

	Male (Rural Population)						Female (Rural Population)				
r	Period Life Table	Cohort Life Table	Parameter Risk	Process Risk	Parameter & Process Risk	r	Period Life Table	Cohort Life Table	Parameter Risk	Process Risk	Parameter & Process Risk
0.02	16.35	18.91	(12.85, 25.00)	(12.11, 24.50)	(10.58, 26.44)	0.02	17.66	22.40	(12.11, 33.17)	(11.35, 32.84)	(9.79, 33.83)
0.03	14.88	16.94	(11.94, 21.49)	(11.30, 21.13)	(9.95, 22.49)	0.03	15.94	19.60	(11.30, 26.77)	(10.64, 26.58)	(9.25, 27.15)
0.04	13.59	15.25	(11.12, 18.66)	(10.56, 18.41)	(9.39, 19.37)	0.04	14.45	17.29	(10.56, 22.11)	(9.99, 21.99)	(8.76, 22.33)

0.05	12.46	13.80	(10.38, 16.37)	(9.90, 16.19)	(8.86, 16.87)	0.05	13.16	15.37	(9.90, 18.63)	(9.39, 18.57)	(8.31, 18.76)
0.06	11.47	12.55	(9.71, 14.50)	(9.30, 14.37)	(8.38, 14.85)	0.06	12.04	13.76	(9.30, 15.99)	(8.85, 15.95)	(7.89, 16.06)
Term	14.26	15.92	(11.71, 19.25)	(11.13, 19.00)	(9.87, 19.91)	Term	15.13	17.93	(11.13, 21.86)	(10.51, 21.86)	(9.20, 21.86)

This figure table presents the annuity price for 60-year old Chinese males and females in 2009 under different scenarios. Panel A is based on the extended data, and panel B on unextended data. The cohort life table is calculated with 60-year mortality projections. The term structure of China's government bond 28th June 2012 is obtained from http://yield.chinabond.com.cn/icbweb/index.htm?lx=yc.

Appendix: The Girosi and King (2006)-variant of the Lee-Carter model

First of all, let

$$l_t = \begin{pmatrix} \ln(m_{1,t}) \\ \vdots \\ \ln(m_{ma,t}) \end{pmatrix},$$

where ma stands for the maximum age.

Then, let

$$\alpha = \begin{pmatrix} \alpha_1 \\ \vdots \\ \alpha_{ma} \end{pmatrix}, \quad \beta = \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_{ma} \end{pmatrix}, \text{ and } \varepsilon_t = \begin{pmatrix} \varepsilon_{1,t} \\ \vdots \\ \varepsilon_{ma,t} \end{pmatrix}.$$

Now, from

$$l_t = \alpha + \beta\kappa_t + \varepsilon_t \quad \text{and} \quad \varepsilon_t = \mu + \varepsilon_{t-1} + \delta_t,$$

the Lee-Carter model can be rewritten as

$$l_t = \theta + l_{t-1} + \zeta_t,$$

where $\theta = \beta\mu$ and $\zeta_t = \beta\delta_t + \varepsilon_t - \varepsilon_{t-1}$

Now, we can easily estimate the model, make prediction, and quantify the longevity risk.

In our application, we assume that ζ_t is *i.i.d.* (thus, ignoring possible autocorrelation as implied by the original Lee and Carter-formulation).

Chapter 3: Health Expectancy of the Chinese Elderly: Current Trends and Future Projection*

3.1 Introduction

It is well known that life expectancy in China has increased substantially and more rapidly than that in the developed countries over the past five decades. For example, in China the life expectancy at birth was only about 35 years at the beginning of the 1950s (Jiang, Zhang, and Zhu, 1984), which was very low because of the prolonged and large-scale wars before the establishment of the People's Republic of China in 1949. However, the life expectancy has been extended to 71 years by 2000 (Banister and Hill, 2004), representing an increase of 8.64 months per year. In the US, the increase is from 68 years in 1949 to 75.40 years in 1990 (Lai, Lee, and Lee, 2000), representing an increase of only 2.17 months per year. Not surprisingly, with the extension of longevity, it is more recognized by the public that "increased longevity without quality of life is an empty prize" (WHO, 1997). Due to the mortality reduction at advanced ages, an increasing focus has been concentrated on the life quality of the rapidly growing older and oldest-old population.[1] Nevertheless, whether increases in life expectancy or declines in mortality have been accompanied by a decrease in morbidity and disability is controversial worldwide (Fries, 1980; Freedman, Martin, and Schoeni, 2002). The possibility that the population health deteriorates, even though mortality improves, is not only possible, but also likely under some circumstances. For instance, several studies find that, despite of increased life expectancy in the 1960s and 1970s, mild disability increased in this period in the U.S. (Crimmins, Satio, and Ingegneri, 1997), Canada (Wilkins and Adams, 1983), Japan (Riley, 1990), and Australia (Mathers, 1990).[2] Furthermore, it has been documented that health improvements among the elderly are not universal and that the change patterns are partly attributable to the stage of the epidemiological transition in a given country (Robine and Michel, 2004). The disabilities and impairments suffered by the older population decrease their quality of life, change the household consumption

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[1] Older and oldest old population is defined as people aged 60 and over and aged 80 and over, respectively. The population of centenarians in Western Europe, Japan, and China has been doubling every decade in recent decades (Vaupel and Jeune, 1995).

[2] It should be mentioned that the disability trends, defined and measured in different ways, are rather complicated.

behavior,[1] and affect the national public health policies.[2]

There are several competing theories regarding the past and possible future trends in mortality and morbidity. Fries (1989) argued for a *compression of morbidity*. Under the assumptions of delayed onset of the chronic diseases and a relatively constant life span, this theory states that morbidity will be compressed into a shorter period of time before death, which increases not only the absolute value of the average time spent in an active state, but also its proportion of total life expectancy. On the other hand, *expansion of morbidity* expressed by Olshansky et al. (1991), suggests an increasing prevalence of morbidity and disability and an extension of life with chronic conditions. According to this theory, therefore, the elderly spend a larger proportion of their lives in poor health. Manton (1982) proposed the *dynamic equilibrium*, which falls somewhere between these two theories. With the hypothesis that mortality and morbidity are correlated and that the same factors improving mortality also reduce the severity and rate of progression of chronic diseases, this theory indicates that the dynamics of both longevity and morbidity depend on how these factors affect the disease incidence and severity as well as the impacts of disease on disability. Given that each theory has its own explaining power, which one is more appropriate in describing the trends in mortality and morbidity finally becomes an empirical issue (Imai and Soneji, 2007).

Since Sanders (1964) proposed the concept of health expectancy,[3] interest in estimating it and in investigating its determinants has been increasingly becoming a new focus among policymakers and members of the academic community. Unlike life expectancy, health expectancy takes into account both mortality and morbidity, measuring the average time that individuals live in varying health statuses. Even though life expectancy still has been widely used as an important indicator of population health, the increasing recognition of the multidimensionality of health has focused attention of governments and academia on health expectancy when assessing the dynamics of population health, since a decline in mortality does not necessarily represent an improvement in other dimensions of health (Crimmins, 2004). For conceptual studies of

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[1] For example, in China the proportion of household expenditure on health care and medical services to total household expenditure per capita in urban areas increased from 0.75% in 1985 to 7.14% in 2006 (China Urban Living and Price Statistical Yearbook, 2007). The population ageing, along with medical reforms and decreasing fertility, is anecdotally reported to contribute to China's increasing household saving rates.

[2] For example, it is reported by the Wall Street Journal that the population aged 65 and older in the US consumes roughly a third of all of the medical spending (*"In Medicare's Data Trove, Clues to Curing Cost Crisis"*, 25th October, 2010). In China, around a fourth of all of the retirees accounts for 60% of the pooling account of the public medical insurance (*"老龄化吞噬医保基金" (ageing engulfs medical fund* in English), the 21st Century Business Herald, 19th August, 2010).

[3] The terms *health expectancy* and *healthy life expectancy* are often used interchangeably in the literature.

health expectancy, see Robine, Michel, and Branch (1992).

However, the literature on health expectancy by far is still unsatisfactory and incomplete. First, with few exceptions addressing this topic in developing countries or regions,[1] most prior studies have focused on the developed world.[2] Given that the developing world accounts for the bulk of the world population, identifying the trends in health expectancy in developing countries is therefore important for the world population health. Second, the measures of health status used for estimating the health expectancy often differ across studies. As a result, the evidence demonstrating the trend in one dimension of health may not accurately reflect the changes in other dimensions of health (Crimmins, 2004), both within and across nations. Moreover, due to the differences in sampling, survey methods, questionnaire wording, and analytic strategies, even studies using data of the same country also get different results (Freedman et al., 2004). Third, most of these studies only report health expectancy for single time points, without examining the differences over time. Few studies take into account the trends into the future. Finally, Sullivan's (1971) method, given its primary methodological importance in the exploration of morbidity, has been extensively used to estimate the health expectancy. Under stationarity assumptions, Imai and Soneji (2007) show that this method combining the period life table with the disability prevalence yields a consistent estimator of health expectancy. In reality, however, stationarity assumptions might not be appropriate. For example, age-specific death rates at all ages have declined exponentially at a constant rate in most developed countries. Therefore, an alternative method estimating health expectancy without the stationarity assumptions might be of interest. Imai and Soneji (2007) demonstrate that, by combining a cohort life table with the disability prevalence (from a longitudinal survey or consecutive cross-sectional surveys), Sullivan's method can be extended to estimate the health expectancy without stationarity assumptions. As a result, we apply their method in this paper.

Using the Chinese Longitudinal Healthy Longevity Survey (CLHLS), the purpose of this paper is to fill in the gap in the existing literature by estimating and extrapolating the trends in health expectancy of the elderly in China. China provides an interesting setting for a number of reasons. Firstly, as the largest country in terms of population with more

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[1] For example, ASEAN countries (Chen and Jones, 1989), Asian countries (Lamb, 1999), and Latin American countries (Ham-Chande, 2003).

[2] For example, the United States (Cai and Lubitz, 2007), the United Kingdom (Breakwell and Bajekal, 2006), the Netherlands (Nusselder and Looman, 2004), Germany (Shkolnikov et al., 2007), France (Cambois, Robine, and Hayward, 2001), Canada (Belanger et al., 2002), Japan (Schoeni et al., 2005), Belgium (Bossuyt et al., 2004), Austria (Doblhammer and Krtir, 2001), and Denmark (Bronnum-Hansen, Davidsen, and Kjoller, 2003).

than 20 percent of the world's inhabitants, China has over 21 percent and 16 percent of the world's older and oldest old population in 2000, respectively (Poston and Zeng, 2008), and is a significant factor in the development of the world population health. To our knowledge, few studies have focused on the oldest-old, particularly in developing countries, due to a lack of data. Secondly, as a transition economy, China is experiencing more unique factors making it complicated to understand the trends in health expectancy. On the one hand, for example, the rapid economic growth and epidemiological transition might result in comparable trends in health improvement in China as in the developed world, since the younger cohorts with better conditions at their early life and healthier lifestyles are replacing the older generations (Zhu and Xie, 2007). On the other hand, however, health care reforms, implemented in the mid 1980s, caused Chinese, especially those living in rural areas, difficulty in accessing their limited health insurance established in the 1960s and 1970s (Lai, 2009). The changing family structure resulting from the family planning policy initiated from the late 1970s also makes it difficult for the younger generation to undertake the traditional duties of family care (Li, 2005). It is documented that the Chinese elders who receive respect from family members are reported to have better rated mental and physical health than those not having a sense of filial piety from their children (Yu et al., 1997). These social and institutional changes might result in negative effects on the Chinese population health. Therefore, estimating health expectancy, especially its future trends, is of high importance for providing the relevant demographic background for appropriate socio-economic policy decisions. Finally, with indications of changing trends in morbidity and mortality[1] and new data available, it is reasonable to estimate the health expectancy in China.

The contributions of this paper are threefold. First of all, using updated data we examine the latest trends in health expectancy based on different measures for the Chinese elderly. Secondly, we use Sullivan's approach, combining the cohort life table derived from the Lee-Carter model rather than the period life table with the disability prevalence, to estimate the healthy expectancy. In this way, we can use Sullivan's method without stationarity and other assumptions. Thirdly, by constructing a bad health index, we attempt to predict the future trends in health status using a logit model in Lee-Carter format, taking into account uncertainties in the health improvement. We hence project the health expectancy by combining the cohort life table with the projected health

[1] For example, over the 20th century, mortality rate for the oldest ages have declined. Furthermore, the prevalence of activities of daily living (ADL) disability for the Chinese elderly declines around 1% annually between 1992 and 2002 (Gu and Zeng, 2006).

status trends.

Our paper presents several main findings: first, while the Chinese elderly of both sex groups experienced an improvement in life expectancy for all ages during the sample period, health expectancy shows a mixed result. On the one hand, the Healthy Life Expectancy (HLE), based on self-evaluated health, and regardless of the widely or the narrowly defined healthy status, followed an Increase-Decrease-Increase pattern across age as well as sex groups. On the other, the trends in the Disability-Free Life Expectancy (DFLE) were mixed, depending on health measurements and age as well as sex groups. However, both the HLE and DFLE were better off in 2005 than in 1998. At the relative level, the HLE shows the increasing proportion of lives in poor health over time, whereas the DFLE presents a mixed result again. Second, though females generally could expect to live longer than males in terms of life as well as health expectancy, it is males who could expect to live a larger of their remaining lifetime in good health. Finally, in terms of future trends, while the HLEs, either based on a period health index or a cohort one, are smaller in selected future years than in 2005, the DFLEs are larger. Nevertheless, the widening confidence intervals of both HLE and DFLE over time also reflect increasing uncertainties associated with our projections.

The remainder of this paper is organized as follows. In the second section, we introduce the data on mortality and health status, health expectancy measurements, and definitions of health/disability. Section three introduces how to construct cohort life tables using the Lee-Carter model as well as Sullivan's method combining cohort life tables with the prevalence of morbidity, and reports estimations results. In section four, we predict health status trends and estimate the future health expectancy taking into account uncertainties in the health as well as mortality improvement. Finally, section five offers some concluding remarks.

3.2 Data and Health Measures

In this section we introduce the data on health status and mortality, both of which we need to estimate the health expectancy. Additionally, we describe the definitions of health status used in this paper and the corresponding measurements of health expectancy based on these definitions.

3.2.1 Mortality Data

Our data include 16 yearly age-specific observations of death and population counts by sex groups from age 0 to 84 inclusive during the period of 1994-2009.[1] Using these death and population counts, we can obtain raw age-specific central mortality rates. Nevertheless, as the mortality data at older ages are missing, we need to use the available data to extrapolate death rates at older ages for accurate estimations of life expectancy as well as health expectancy.

Similar to Zhend and Melenberg (2012), we use the Kannisto model to fit the mortality data from the age of 60 and 65 for males and females, respectively, to the maximum age available in each year and extrapolate the central death rates up to age 120 for each sample year during the period of 1994-2009. Following Roli (2008), we replace the observed death rates for all ages at or above $\bar{x}$, where $\bar{x}$ is the lowest age at which there are fewer death counts than 100 but should satisfy $80 \le \bar{x} \le 95$. In this way, we obtain an extended data covering age-specific mortality rates from age 0 to 120 for the period of 1994-2009. With this extended data, we use the Lee-Carter model to project future mortality rates, by which cohort life tables can be constructed. An alternative approach to construct the cohort life table is to firstly project future mortality rates with the Lee-Carter model using the raw unextended data (namely only from age 0 to 84) and hence to extrapolate mortality rates at older ages with these projected results. In Melenberg and Zheng (2012), cohort life tables constructed by both approaches yield similar results.

3.2.2 Health Data

We draw the data on health status from the first four waves of the Chinese Longitudinal Healthy Longevity Survey (hereafter CLHLS). The CLHLS was conducted in 631 randomly selected counties and cities in 22 of China's 31 provinces, which account for about 85 percent of the total Chinese population. Moreover, the CLHLS was the first large nationally representative and longitudinal survey on health and longevity for extremely old (i.e., 100 years and older) and oldest old population in China (Zeng et al., 2001).[2] The first wave including 8,959 respondents aged 80 years and older was conducted in 1998 as a baseline, with the follow-up surveys conducted in 2000, 2002, and 2005. Since the CLHLS contains detailed information regarding demographic and health characteristics,

[1] These data are obtained from the China Population Statistics Yearbook and China Statistical Yearbook, respectively, which are compiled by the National Bureau of Statistics of China (NBSC).

[2] To our knowledge, three other national surveys on the population aged 60 and older in China were conducted in 1987, 1992, and 2000, respectively, namely, The Aged Population over 60 Years Sampling Survey (1987), The Survey on Old Age Support System (1992), and The Survey on Urban and Rural Elderly in China (2000). But none of these surveys are longitudinal.

for example, self-rated health status and Activities of Daily Living (ADLs), this makes it possible to obtain the prevalence data among people at the oldest ages. Table 3.1 provides the (percentage) sample distribution by sex and age of the CLHLS. In each sample year, respondents aged 80 and over account for, on average, 80 percent of total respondents. This makes it possible for us to better understand the health status of the oldest-old Chinese population. For the detailed description of the sampling design and data quality, see Zeng et al. (2001).

[Insert Table 3.1 here]

In response to the question on quality of life, several measurements of health expectancy have been reported, including the Disability-Free Life Expectancy (hereafter DFLE), the Healthy Life Expectancy (hereafter HLE), and the (Specific) Diseases-Free Life Expectancy (hereafter SDFLE). For example, 23 OECD member states firstly reported their estimations on health expectancy in 1997; the World Health Organization (WHO) reported the 1999 health expectancy for 191 countries worldwide in 2000.

The DFLE[1] is an objective measurement and the most commonly used form of health expectancy (Lièvre, Alley, and Crimmins, 2008). Since 1985, the DFLE has been used as one of the indicators measuring the achievement of regional 'Health for All' objectives in Europe. Based on limitations in Activities of Daily Living (hereafter ADLs) or in Instrumental Activities of Daily Living (hereafter IADLs), the DFLE is the average number of years an individual is expected to live free of disability if current patterns of mortality and disability continue to apply. On the other hand, the HLE is more or less a subjective measurement of health expectancy. Based on the subjective self-rated health[2] questions, the HLE is the average number of years that an individual is expected to live in a given health status if current patterns of mortality and health states continue to apply.

Both measures have their advantages and disadvantages. For example, when examining the social-economic status gradient in health, the HLE might not be a good indicator, given that different standards may be used in evaluating health among social classes (Thorslund and Lundberg, 1994). Albeit being a subjective indicator of health, the self-rated health is a good predictor of disability (Ferraro and Su, 2000) and of mortality

[1] It is also called healthy life years (HLY) or active life expectancy (ALE) in literature. The differences between them are not clear since many studies do not distinguish between these concepts (Crimmins and Saito, 2001). According to Verbrugge and Jette (1994), this confusion might result from the definitions and usage of terms, for example, handicap, functional limitations, or disability. Nevertheless, since they are usually computed using the prevalence of activities of daily living (ADL) limitations, they are essentially a disability life expectancy corresponding to the life expectancy without ADL limitations.

[2] Self-rated health and other terms are often interchangeably used. For example, self-assessed health, self-rating of health, perceived health, and global health status (Liu and Zhang, 2004).

(Schwarze, Andersen, and Anger, 2000). For example, it is reported that the risk of early and late mortality for individuals with poor self-rated health is 2.92 and 2.77 times that of those with excellent self-rated health, respectively, controlling for objective physical conditons and sociodemographic factors (Mossey and Shapiro, 1982). On the other hand, the HLE is a much better indicator due to the aging population, taking into account both the changes in living with a disability and in mortality that are responsible for the increase in life expectancy. In China, for example, the proportion of disabled increased from 4.9% in 1987 to 6.4% in 2006 with the population ageing (Qiao, 2009). Due to its correlation with the physician- rated health, the self-rated health as a proxy indicator of the objective health status is therefore commonly accepted. Moreover, it might be an appropriate indicator in the context of China. During the rapid transition from the agricultural society to the industrial society and from a planned economy to a market economy, it is anecdotally reported that the Chinese are more mentally unhealthy, even though they are physically disability free. Therefore, self-rated health might be better for calculating the health expectancy. In this paper, both the HLE and the DFLE are estimated, since showing several health expectancy indicators together can help to clarify the situation in a country and improve understanding of the trends over time.

3.2.3 Definitions of Health Status

In this paper, we estimate the HLE according to the self-rated health status based on the answer to the following question: "How do you rate your health at present?" The answer to this question is coded on a 1-6 scale, with 1 being "very good", 2 as "good", 3 as "so-so", 4 as "poor", 5 as "very poor", and 6 as "not able to answer"[1]. In order for a consistent comparison with other studies, we define individuals as bad health using a narrow and wide definition, respectively. In the wide definition, bad health consists of self-rated ratings "so-so", "poor", and "very poor", whereas in the narrow one bad health consists only of "poor" and "very poor". Table 3.2 provides the descriptive information about the prevalence rates of self-rated bad health by sex and age groups. In each sample year, no matter what definition of bad health is used, the prevalence rates across age groups follow somewhat inverted-U patterns, though variations among age groups are minor. Nevertheless, the prevalence rates at each age group increase over time for both gender groups, indicating the self-rated health deterioration across sample years.

[1] The proportion of respondents with "not able to answer" is small. For example, in 1998 only about 3 percent of males chose this answer.

For example, in terms of the narrow definition of bad health, about 7 percent of males and 9 percent of females self-reported bad health in 1998; in 2005, the same indicator increased to 13.76 percent for males and 16.16 percent for females, respectively. Additionally, table 3.3 shows that females are more subjectively pessimistic about their health status than males.

[Insert Table 3.2 here]

We also estimate the DFLE according to the ADLs disability, which is defined as the self-reported limitations in performing any ADLs items, namely bathing, dressing, eating, indoor transferring, toileting, and continence. Furthermore, we categorize the individuals with no ADLs limitations as ADLs active, with one or two limitations as mild disability, and with three or more limitations as severe disability. Table 3.3 shows the prevalence rates of ADLs limitation among the Chinese elderly by sex in sample years. Though the functional limitations in ADLs also increase with advancing age in each year, especially after age 85, Chinese elderly generally experienced an improvement in terms of functional limitations over time. Take the ADLs active as an example: the overall prevalence rates of ADLs active, namely with no ADLs limitations, increased from about 72 percent in 1998 to about 82 percent for males and from about 56 percent in 1998 to about 70 percent in 2005 for females. Moreover, females are generally worse than males regarding the ADLs status at all age groups, no matter what measurements are used.

[Insert Table 3.3 here]

Table 3.2 and 3.3 shows the health differentials resulting from different definitions of health status. This quantitatively confirms our hypothesis that, even though the Chinese elderly may actually experience an improvement in physical health based on ADLs, they are more mentally unhealthy according to the self-rated health status.

3.3. Estimation of the Health Expectancy

In this section, we use Sullivan's method based on cohort life tables to estimate the health expectancy of the Chinese elderly. Before doing so, we introduce the Lee-Carter model (1992), through which we project the age-specific mortality rates and thus construct cohort life tables.

3.3.1 Sullivan's Method

Sullivan's Method (1971) combines mortality data with cross sectional health status data to generate estimates of expected years of life in various health states. Given a (period) life table and starting with *n* people (at a particular age) one can calculate how many people will survive x years, for x=0,1,2,…, from which one can calculate the life expectancy (for the given age). From the cross sectional health status data, one can calculate for each age the fraction of people in a particular health status. Combining this with the survival data, one can calculate for every year how many people will survive in that particular health status. This allows one to calculate the health expectancy (for each age). Details are provided by Imai and Soneji (2007). In our calculations, we shall follow closely EHEMU’s (2007) technical guide.

Sullivan’s Method has been one of the most widely used methods for estimating health expectancy over the past four decades. It has been proved to be a useful instrument, especially when longitudinal data on transition between functional statuses and differences in mortality among people with different functional statuses are unavailable (Zeng, Gu, and Land, 2004). Moreover, under stationarity assumptions of the period life table[1] and the age-specific disability prevalence, Imai and Soneji (2007) prove that Sullivan’s estimator of health expectancy is “unbiased and consistent”. For a review on the quality of Sullivan’s method, see Mathers and Robine (1997).

In reality, however, the stationarity assumptions might not be appropriate. Take the age-specific death rates as an example: neither are they constant over time, nor do they change in the same direction and in the same magnitudes across cohorts. Figure 3.1 presents the mortality rates of selected age groups for several time periods, normalized to one for the year 1981. Obviously, figure 3.1 shows the non-stationary dynamics of the age-specific death rates.

[Insert Figure 3.1 here]

An alternative method for estimating health expectancy without stationarity assumptions is the multi-state method, a life table method based on a division of the population by age and sex into any a number of health states and taking into account transition rates between these health states. For example, Majer (2011) applies a multi-state life table model to the Dutch population aged 55 and older and estimates health expectancies between 1989 and 2030. Not only does he show the life expectancy and the proportion of the original birth cohorts still alive at different ages, but also the remaining life expectancy and proportion of people alive in a given state. Therefore, the multi-state life table, providing valuable information about transitions among different states, allows researchers to conduct a richer analysis of mortality and morbidity than

[1] A period life table relies on the following stationarity assumptions of the population: 1) the age-specific hazard rate is constant over time; 2) the birth rate is constant over time; 3) the net migration rates are 0 at all ages (Preston, Heuveline, and Guillot, 2001).

Sullivan's method. However, this method also requires a number of assumptions about transition probabilities and the functional form of the hazard functions, none of which is necessary for Sullivan's method. Furthermore, the multi-state method requires a large-scale longitudinal data, which usually is unavailable, especially in developing countries.

In this paper we follow Imai and Soneji (2007) to estimate the health expectancy of the Chinese elderly by Sullivan's method based on cohort life tables, which has several advantages over the methods mentioned above. On the one hand, with cohort life tables available, Sullivan's method can be extended to estimate the health expectancy without stationarity assumptions. On the other hand, even if the consecutive cross-sectional health surveys are used, this method can be applied to get an unbiased estimation of the health expectancy. This is particularly an attractive advantage, because the cross-sectional surveys are usually easier to obtain than longitudinal data. For a detailed description of Sullivan's method based on a cohort life table, see Imai and Soneji (2007).

3.3.2 Cohort Life Table and the Lee-Carter Model

In order to use Sullivan's method based on cohort life tables, we need to construct cohort life tables, which describe the mortality experience of a real cohort of individuals from birth of the first to the death of the last member of this group. In this paper, we use the Lee-Carter model (1992) to fulfill this projection, because it has become the "leading statistical model of mortality in the demographic literature" (Deaton and Paxson, 2004) and, along with its extensions, has been widely applied for many countries for its simplicity and robustness in the context of linear trends in age-specific death rates.

According to Lee and Carter (1992), $\ln(m_{x,t})$, the log central death rate of the x-year-old persons in year t, is determined by a common latent factor κ_t, with an age-specific level parameter, α_x, and an age-specific sensitivity parameter, β_x.

Mathematically, the model can be expressed as follows:

$$\ln(m_{x,t}) = \alpha_x + \beta_x \kappa_t + \varepsilon_{x,t}, \quad \sum_x \beta_x = 1 \text{ and } \sum_\kappa \kappa_t = 0 \tag{3.1}$$

where the white noise error terms, $\varepsilon_{x,t}$, represent the transitory non-systematic shocks.

Here κ_t is assumed to be an ARIMA process. Lee and Carter (1992) originally find that, for the mortality data of the US, κ_t satisfies a random walk with drift process as:

$$\kappa_t = \kappa_{t-1} + c + \xi_t, \tag{3.2}$$

where the white noise terms, ξ_t, representing permanent shocks, are assumed to be independent of $\varepsilon_{x,t}$ and to follow a (normal) distribution with mean zero and variance of σ_ζ^2.

With standard statistical or econometric time-series techniques, the parameters in (3.1) and (3.2) can be estimated. However, the resulting ARIMA process of κ_t for other countries rather than the USA might be different from a random walk with drift. Thus, standard statistical procedures should be applied to find an appropriate ARIMA model for the time series of κ_t (Liu, 2008).

The systematic path of the central mortality rate of the x-year-old persons in year t satisfies:

$$m_{x,t} = \exp(\alpha_x + \beta_x \kappa_t), \tag{3.3}$$

In order for the projection of future mortality, we firstly need to forecast the future values of $\widetilde{\kappa}_{T+\tau}$ (T is the final year of the sample) and then the systematic path of future central mortality rate by

$$m_{x,t+T} = \exp(\alpha_x + \beta_x \widetilde{\kappa}_{T+\tau}), \tag{3.4}$$

Melenberg and Zheng (2012) estimate the Lee-Carter model using the same mortality data and find that the κ_t processes for both Chinese males and females follow a random walk. They also project the future age-specific mortality rates. We directly use their projection results to construct the cohort life table.

3.3 Estimation Results

In this section we follow EHEMU's (2007) technical guide to calculate the health expectancy and present estimation results. While age-specific mortality rates in the period life table are assumed to be time-independent, they are time-dependent in the cohort life table. Therefore, in addition to observed age-specific mortality rates, projected ones are also needed to construct the cohort life table. As far as the prevalence rates of morbidity are concerned, in this section we assume that they are time-independent. Therefore, we can obtain the period prevalence rates of morbidity directly from each sample year. For example, in order to estimate the health expectancy in 1998, we only need age-specific prevalence rates of morbidity from the 1998 CLHLS data. In the next section, we relax this assumption and allow for dynamic health improvements, namely prevalence rates of morbidity, like mortality rates, are also time-dependent. In order to take into account estimation uncertainties of life as well as health expectancy, we report a 95 percent confidence interval for each estimate using the bootstrap. Koissi, Shapiro, and Högnäs (2006) apply the bootstrap technique to the Lee-Carter model to construct confidence intervals for projected life expectancies. By doing so, their confidence intervals take into account uncertainties resulting from the variability from all parameters in the model. For the purpose of comparison, we also calculate the health expectancy using Sullivan's method based on period life tables and report results in appendix 1.

[Insert Table 3.4a and 3.4b]

Table 3.4a and 3.4b show the healthy life expectancy and disability free life expectancy based on Sullivan's method combining cohort life tables with period health data, for the four years for which health data is available (1998, 200, 2002, and 2005). First, both Chinese males and females experienced a strictly positive trend in life expectancy for all age groups during the sample period. For example, the cohort life expectancy of an 80-year old Chinese elderly increased from 6.89 years in 1998 to 8.48 years in 2005 for males, and from 8.46 years in 1998 to 9.66 years in 2005 for females, respectively. Second, health expectancies, regardless of health measurements, were better off in 2005 than in 1998 across age and sex groups. For example, an 80-year old male was expected to live 0.08 years more in 2005 than in 1998 based on the widely defined HLE, and 1.34 years more in 2005 than in 1998 based on the DFLE with ADLs active, which represent a 2 and 24 percent increase, respectively. Nevertheless, during the sample period the trends in health expectancy did not follow consistently increasing patterns but show substantial volatilities. For the HLE, regardless of the widely or narrowly defined healthy status, almost all age groups across sex followed an Increase-Decrease-Increase pattern. On the contrary, the DFLE showed mixed patterns, depending on health measurements and sex as well as age groups. For example, while males experienced a consistently positive trend in both the DFLE2 (without mild disability) and DFLE3 (without severe disability), females faced the same pattern only in the DFLE3 but an Increase-Decrease-Increase one in the DFLE1 (no disability) and DFLE2. Given that ADLs limitations and self-reported health are usually correlated (for example, no ADLs limitations resulting in good self-reported health), a decrease in the DFLE may cause the decline of HLE, like the case of Chinese females. As a result, the disparities in health expectancy trends across the HLE and DFLE for males might arise from their more pessimistic assessments of health status. Nevertheless, it seems that Chinese elderly are generally pessimistic towards their health status. For example, the objective health expectancies under the most rigorous definition (for example, with no ADLs limitation) are larger than their subjective counterparts that are also rigorously defined (for example, the "so-so" is included into the definition of bad health) for most age groups. Third, there exist sex differentials in the life as well as health expectancy. In our sample years, Chinese females performed better in both life expectancy and health expectancy than their sex counterparts for most age groups, which is in line with prior studies. Finally, without taking into account the future mortality improvement, the life expectancy in the period life table (see appendix 1) for all selected ages are consistently underestimated compared with those reported in table 3.4a and 3.4b.

[Insert Figure 3.2 and 3.3 here]

As both the life expectancy and health expectancy of the Chinese elderly experienced an absolute improvement from 1998 to 2005, we now use the health ratio, the ratio of health expectancy to life expectancy, to measure the relative trends in health status. Figure 3.2 and 3.3 demonstrate the trends in health ratio for the HLE and the DFLE, respectively. In each sample year, figure 3.2 shows that ratios of HLE to life expectancy are relatively stable or do even increase with advancing ages, whereas figure 3.3 shows the proportion of life lived in a healthy state, which, regardless of health definitions, decreases with advancing ages. In order to find out which theory regarding the past and possible future trends in mortality and morbidity is appropriate for Chinese elderly, we now turn to the trends in the health ratio over time. In terms of the HLE, health ratios in 2005 were generally smaller than those in 1998, indicating the deterioration in the relative health expectancy. With a larger proportion of lives in poor health, the health expectancy measured by the HLE can be explained by *expansion of morbidity*. However, figure 3.3 presents mixed results, depending on health measurements. Finally, sex differentials still exist in the health ratio. Though females live longer than males in terms of life expectancy and health expectancy, both figures show that males could expect to live a larger of their remaining lifetime in good health.

3.4 Health Expectancy with Future Health Trend

Though understanding the future trends in health expectancy is of high importance for providing the relevant demographic background for appropriate socio-economic policy decisions, to our knowledge, few of the relevant work has involved such a projection. In this section, we attempt to fill in this gap by projecting health expectancy under different health measurements. More specifically, we combine a logit model with the Lee-Carter approach to first project prevalence rates of morbidity and then combine them with projected mortality rates to estimate the health expectancy. There are several reasons regarding our model choice: on the one hand, the logit model is appropriate in terms of the prevalence rate of morbidity, given its values between 0 and 1; on the other hand, the logit model in Lee-Carter format can account for uncertainties of health improvements. Mathematically, this logit model is expressed as the following:[1]

$$\text{logit}(I_{x,t}) = \ln(\frac{I_{x,t}}{1-I_{x,t}}) = \alpha_x^I + \beta_x^I \kappa_t^I + \varepsilon_{x,t}^I, \quad \sum_x \beta_x^I = 1 \text{ and} \sum_\kappa \kappa_t^I = 0 \tag{3.5}$$

where $I_{x,t}$ is the bad health index representing the prevalence rate of morbidity at the age *x* in year *t,* κ_t^I is a common latent factor, α_x^I is an age-specific level parameter, β_x^I is an age-specific sensitivity parameter, and $\varepsilon_{x,t}^I$ is the white noise error terms.

Like in the original Lee and Carter (1992)-model, κ_t^I is postulated to follow an ARIMA process. Due to the relatively short period of health data and for simplicity, we shall assume that κ_t^I follows a random walk with drift as:

$$\kappa_t^I = \kappa_{t-1}^I + c^I + \xi_t^I, \tag{3.6}$$

[Insert Figure 3.4 and 3.5 here]

Figure 3.4 and 3.5 plot the observed and projected bad health index across age and sex groups. We project the bad health index for 30 years, namely from 2006 to 2035. The trends in the bad health index show different patterns between the HLE and DFLE. In terms of the HLE, the projected bad health indexes for all age groups across sex generally show an increasing trend, indicating that the Chinese elderly are projected to have a higher proportion of bad self-reported health status in the future. On the other hand, the projected bad health indexes based on the DFLE are mixed, depending on health measurements and age groups. For example, the bad health indexes of females based on the DFLE without disability (ADL active), follow an increasing pattern for age groups between 95 and 100, but a somewhat decreasing one between 90 and 95. Moreover, as we do not know the true probability distribution of the bad health index, the

[1] Many factors also affect health status. However, in this paper, we only discus the extrapolative stochastic health model, without considering potential exogenous demographic or epidemiological factors. First, this type of models seems to be developed well (see Booth and Tickle, 2008); second, policy makers and businesses are much more interested in “all-cause” health status.

estimates of α_x^I and β_x^I can cause parameter risk, and even though we might exactly know its true probability distribution, the uncertainty in the health trends arising from ξ_t^I can still cause process risk. Both risks can cause substantial uncertainties of our bad health index projections. For example, take an 80-year old male. The 95 percent confidence interval of the bad health index based on the widely defined HLE is (0.4423, 0.7369) in 2006, the first year of our projection. The same indicator then widens to (0.3590, 0.9987) in 2015 and (0.3291, 0.9999) in 2020, respectively, indicating increasing uncertainties of health status in the future.

[Insert Table 3.5a and 3.5b]

[Insert Figure 3.6 and 3.7 here]

Like in section 3, we assume that projected patterns of morbidity continue to apply and relax this assumption later. With these projected morbidity, we now combine them with the derived cohort-life table to estimate the health expectancy from 2006 to 2035. We report the projection results for 2010, 2015, and 2020. Due to the short period of health data, projection results beyond 2020 might be inaccurate. Table 3.5a and 3.5b present the projected HLE and DFLE through Sullivan's method combining cohort life tables with period prevalence rates of morbidity, just like Tables 3.4a and 3.4b (to make a comparison possible), but now with the predicted period health status of the years 2010, 2015, and 2020. We obtain several findings from the projections: first, while both males and females for all age groups are expected to live longer in out-sample years than in 2005, the projected health expectancy shows a mixed picture. The Chinese elderly are expected to live shorter in selected years than in 2005 in terms of the HLE, but longer in terms of the DFLE. For example, the projected (widely defined) HLE of an 80-year old male decreases from 4.48 years in 2005 to 3.34 years in 2020, whereas the projected DFLE with ADLs active increases from 6.95 years in 2005 to 8.84 years in 2020. These disparities result from the declining trends in self-reported good health status as well as increasing trends in ADLs limitations in the sample period. Second, no matter how health is measured, females are projected to live longer than their sex counterparts in terms of both life and health expectancy. In order for the relative trends in health expectancy, we again use the health ratio plotted in figure 3.6 and 3.7, respectively. In terms of the HLE, health ratios in each selected years follow an increasing pattern with advancing ages, suggesting that the Chinese elderly at older ages spend a larger proportion of their lives in good health. This is an interesting finding, implying that the older Chinese elderly, the more the subjective satisfaction with their health. Nevertheless, over time, Chinese elderly spend less time lived in good health, indicating the relative deterioration of the self-reported health status. On the other hand, the projected health ratios of the DFLE in figure 3.7 are complicated, without a consistent pattern. For example, while the DFLE with ADLs active for males follows a U-shaped pattern in 2020, it shows a decreasing one in 2010 and 2015. These inconsistent results also reflect the uncertainties of future health developments.

So far, we have assumed that observed and projected patterns of morbidity continue to apply, namely using the period prevalence rates of morbidity in our estimations. As health might also be time-dependent, we now use the cohort prevalence rates of morbidity to re-estimate health expectancy for the same selected years.

[Insert Table 3.6a and 3.6b]

[Insert Figure 3.8 and 3.9 here]

Table 3.6a and 3.6b present the projected HLE and DFLE, respectively, through Sullivan's method combining the cohort life table with the cohort prevalence rates of morbidity. Figure 3.8 and 3.9 plot the corresponding health ratio for the HLE and DFLE, respectively. Compared with those based on the period health index in table 3.5a and 3.5b, new estimations in table 3.6a and 3.6b are generally smaller as they take into account further health developments. Nevertheless, the new estimated HLE and DFLE basically follow same patterns as those based on the period health index: the Chinese elderly are expected to live shorter in selected years than in 2005 in terms of the HLE, but longer in terms of the DFLE. In terms of health ratios, figure 3.8 and 3.9 present similar results.

3.5 Conclusions

In this paper, we use the Chinese Longitudinal Healthy Longevity Survey (CLHLS) to estimate the health expectancy for the Chinese elderly. Unlike the previous studies ignoring the stationarity assumptions, we use Sullivan's method combining cohort life tables rather than period life tables with the prevalence rates of morbidity, taking into account the non-stationary data.

We find that the Chinese elderly of both sex groups experienced an improvement in life expectancy for all age groups during the sample period. While health expectancies, regardless of health measurements, were better off in 2005 than in 1998 across sex and age groups, during the sample period the trends in health expectancy show substantial volatilities, without following consistently increasing patterns. There exist sex differentials in life as well as health expectancy, with females showing a better “performance”. In terms of the health ratio, however, the Chinese elderly experienced a declining trend over time, indicating the deterioration of older population health. On the contrary, the health ratio of DFLE shows a mixed picture.

By constructing a health index, we use the logit model combined with the Lee-Carter approach to project the prevalence rates into the future and then estimate the future health expectancy. In addition to the period health index, we also allow for the cohort one in our projections. While the health expectancies using the cohort health index are smaller than those using the period one, we find that projected health expectancies in both scenarios follow similar patterns.

The mixed estimation results of DFLE in both in-sample as well as out-sample years to some extent reflect uncertainties of health developments. Moreover, the disparities between the HLE and the DFLE should be highlighted to policy makers and the academic community. With the economic transition and family policy, the family size and family structure in China has dramatically changed over the past three decades. Traditionally, it is the family members that undertake the role of taking care of the elderly, but the family role is declining, with more Chinese elderly living alone. This might affect the attitudes of the Chinese elderly towards their health status, though their functional limitations have improved greatly.

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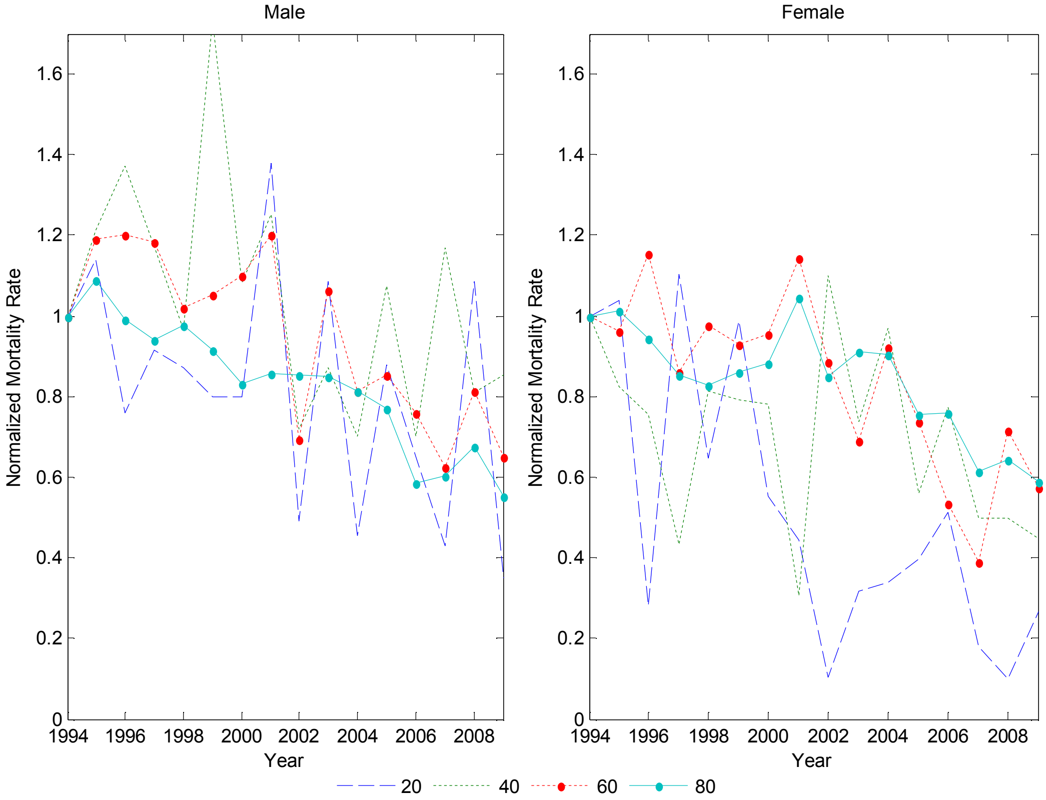
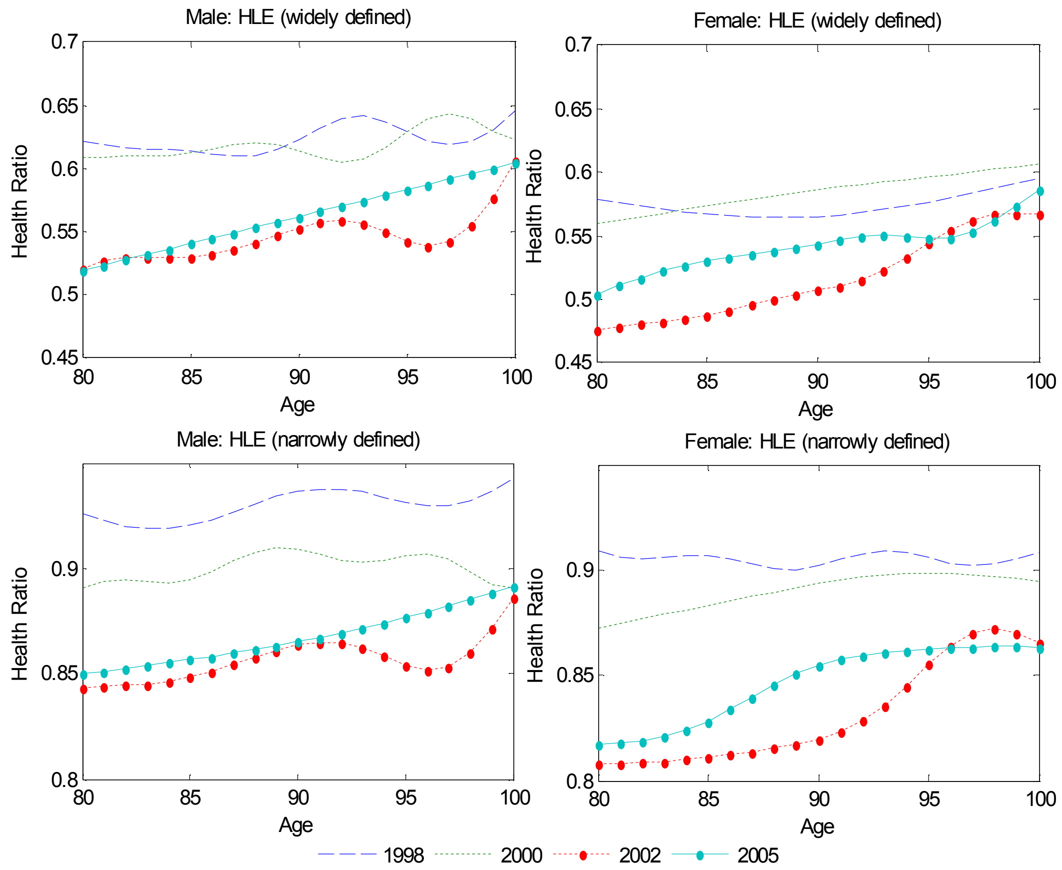
Figure 3.1: Normalized Mortality Rates for Selected Age Groups



This figure plots the observed mortality rates of Chinese males (left) and females (right) for selected age groups during the period of 1994-2009, normalized to one for year 1994. The data originates from the China Population Statistical Yearbook and the China Statistical Yearbook compiled by the National Bureau of Statistics of China (NBSC).

Figure 3.2: The Ratio of Healthy Life Expectancy to Life Expectancy

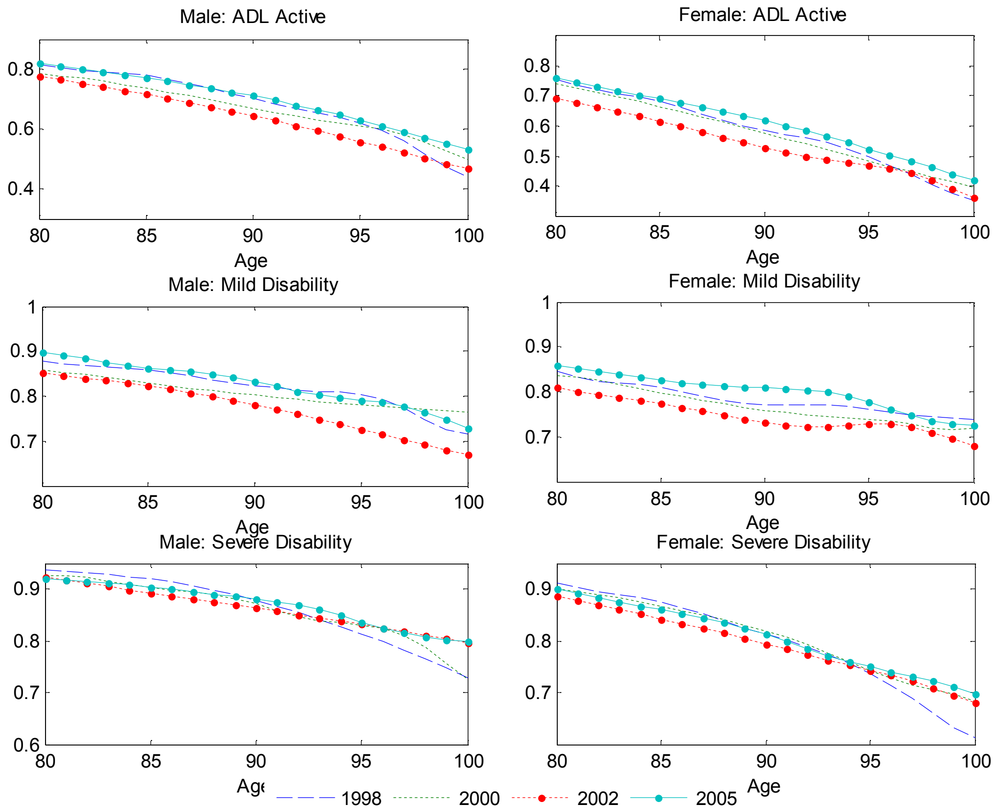
(1998-2005)



This figure plots the ratio of healthy life expectancy (HLE) to life expectancy across age and sex groups for the year 1998, 2000, 2002, and 2005. The healthy life expectancy is calculated through Sullivan's method combining the cohort life table with the period prevalence of morbidity. The life expectancy is calculated with the cohort life table. In the upper panel, bad health consists of the self-reported ratings "so-so", "bad', and "very bad". In the lower panel, bad health consists of the self-reported ratings "bad" and "very bad". These ratios are smoothed using cubic p-splines.

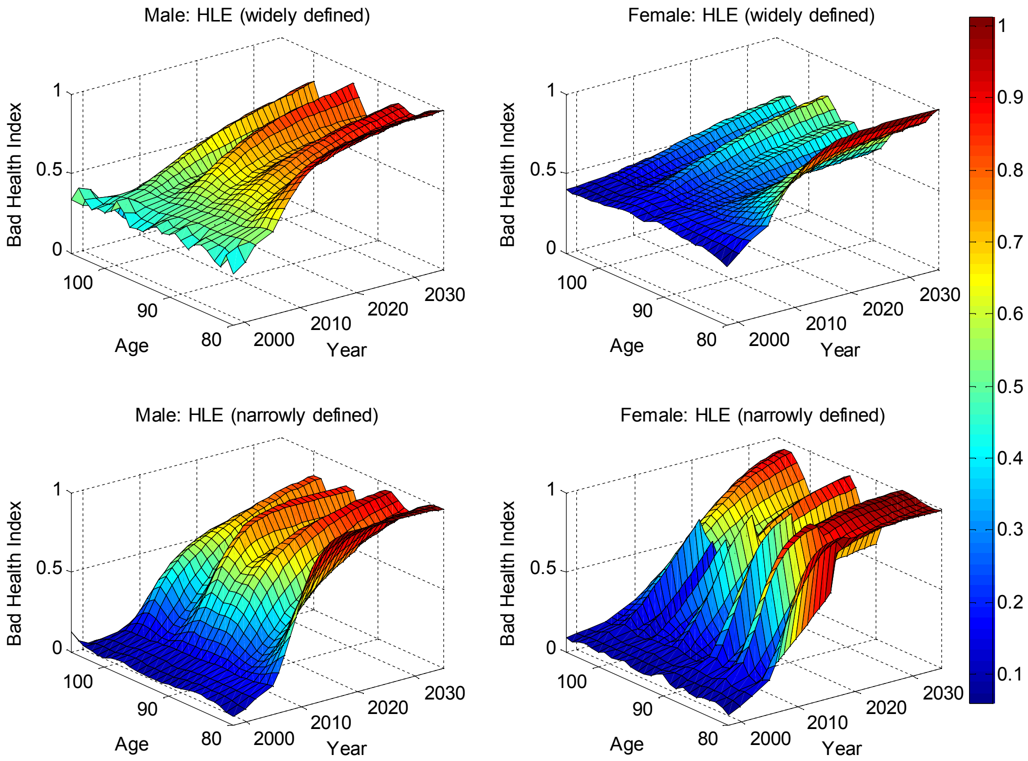
Figure 3.3: The Ratio of Disability Free Life Expectancy to Life Expectancy

(1998-2005)



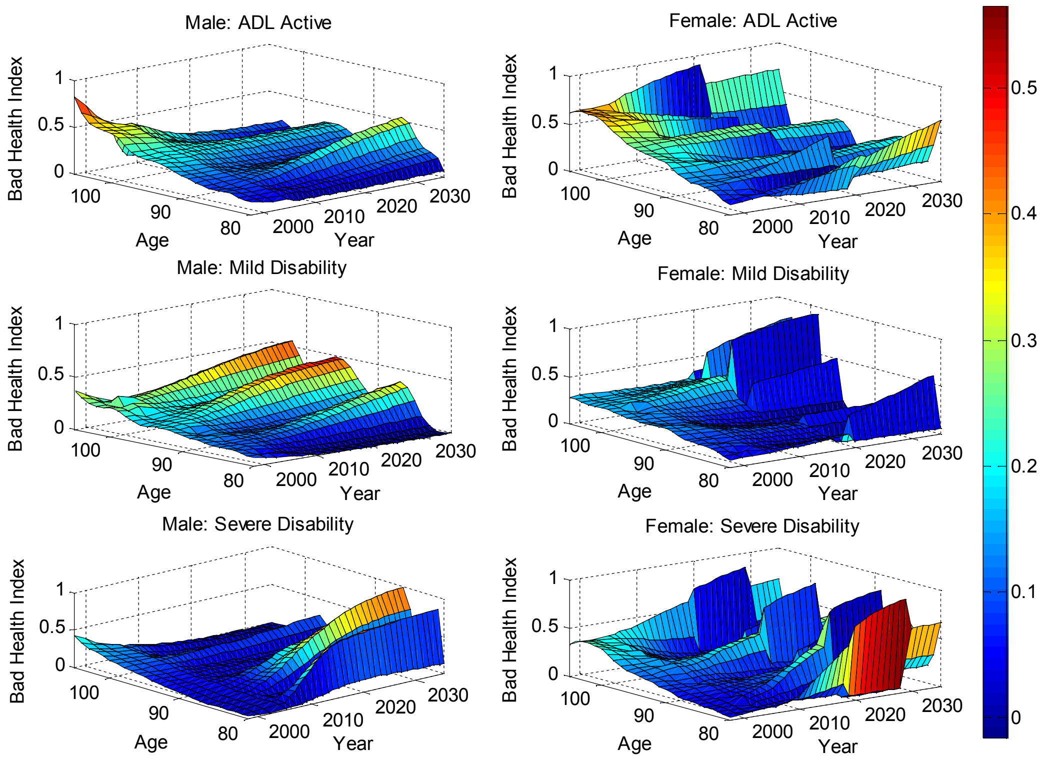
This figure plots the ratio of disability free life expectancy (DFLE) to life expectancy across age and sex groups for the year 1998, 2000, 2002, and 2005. The disability free life expectancy is calculated through Sullivan's method combining the cohort life table with the period prevalence of morbidity. The life expectancy is calculated with the cohort life table. In the upper panel, ADL active is defined as having no ADL limitations; in the middle panel, mild disability is defined as having one or two ADL limitations; in the lower panel, severe disability is defined as having three or more ADL limitations. These ratios are smoothed using cubic p-splines.

Figure 3.4: Prediction of Bad Health Index (Health Life Expectancy)



This figure plots the prediction of bad health index across age and sex groups. In the upper panel, bad health consists of the self-reported ratings “so-so”, “bad’, and “very bad”. In the lower panel, bad health consists of the self-reported ratings “bad” and “very bad”. These bad health indexes are smoothed using cubic p-splines.

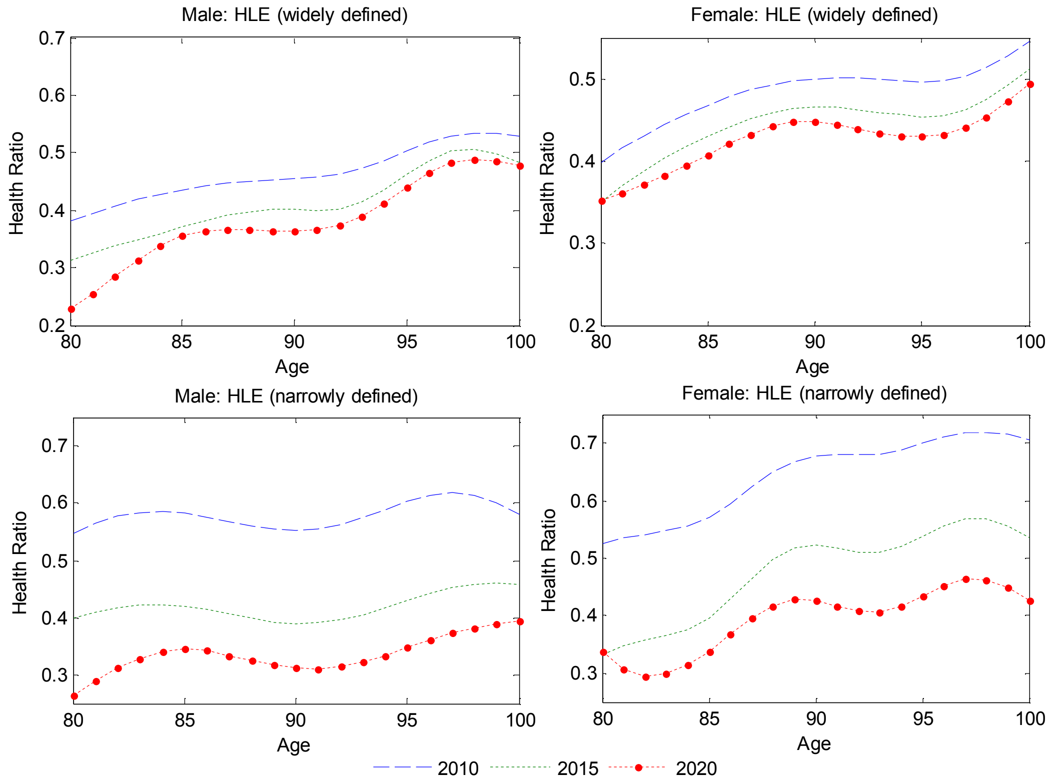
Figure 3.5: Prediction of Bad Health Index (Disability-Free Life Expectancy)



This figure plots the prediction of bad health index across age and sex groups. In the upper panel, ADL active is defined as having no ADL limitations; in the middle panel, mild disability is defined as having one or two ADL limitations; in the lower panel, severe disability is defined as having three or more ADL limitations.

Figure 3.6: The Projected Ratio of Healthy Life Expectancy to Life Expectancy

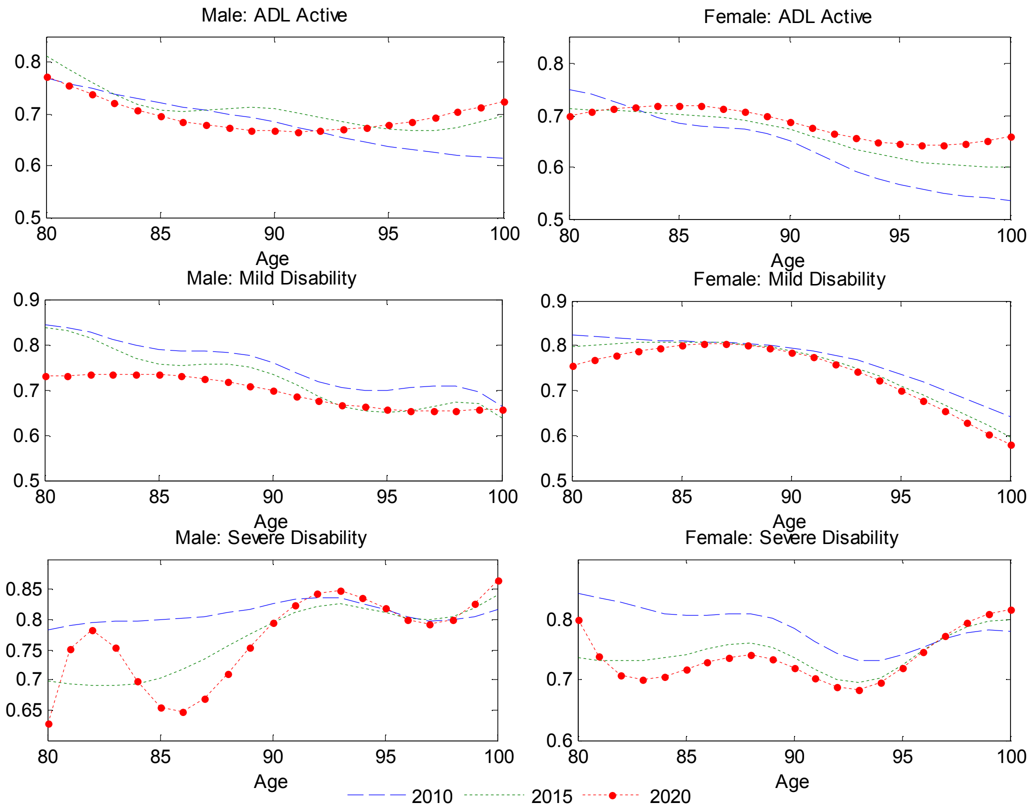
(Period Health Index)



This figure plots the projected ratio of healthy life expectancy (HLE) to life expectancy across age and sex groups for the year 2010, 2015, and 2020. The healthy life expectancy is calculated through Sullivan's method combining the cohort life table with the period prevalence of morbidity. The life expectancy is calculated with the cohort life table. In the upper panel, bad health consists of the self-reported ratings "so-so", "bad', and "very bad". In the lower panel, bad health consists of the self-reported ratings "bad" and "very bad". These ratios are smoothed using cubic p-splines.

Figure 3.7: The Projected Ratio of Disability-Free Life Expectancy to Life Expectancy

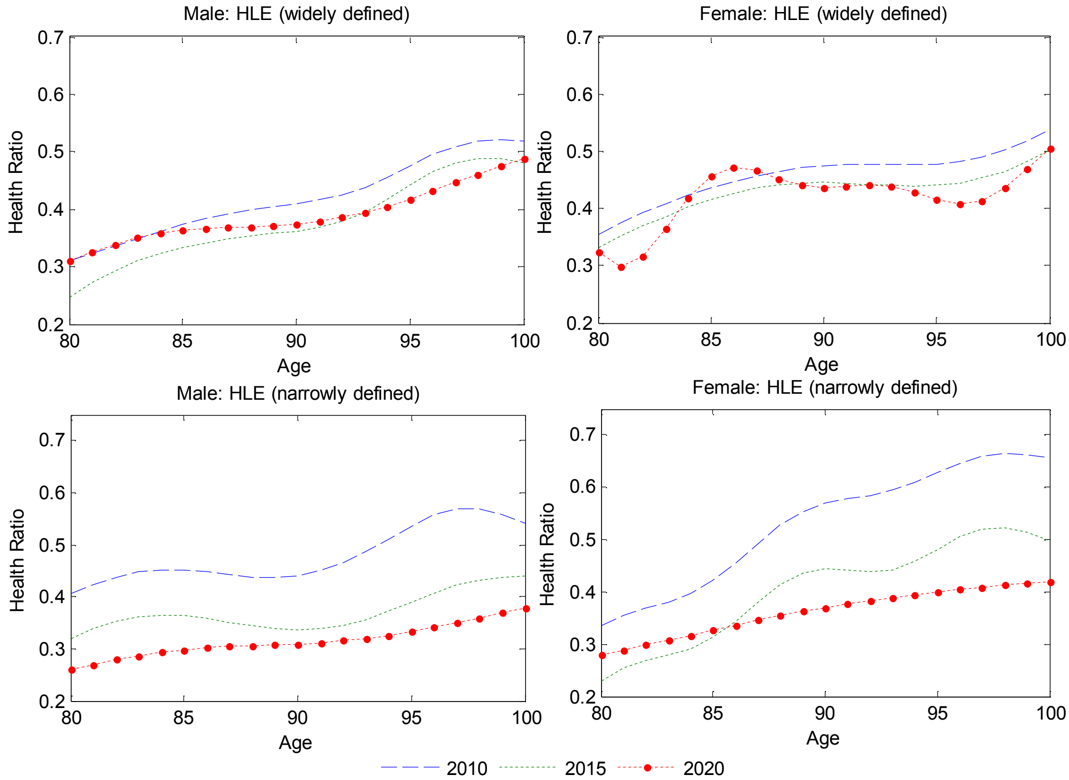
(Period Health Index)



This figure plots the projected ratio of disability free life expectancy (DFLE) to life expectancy across age and sex groups for the year 2010, 2015, and 2020. The disability free life expectancy is calculated through Sullivan's method combining the cohort life table with the period prevalence of morbidity. The life expectancy is calculated with the cohort life table. In the upper panel, ADL active is defined as having no ADL limitations; in the middle panel, mild disability is defined as having one or two ADL limitations; in the lower panel, severe disability is defined as having three or more ADL limitations. These ratios are smoothed using cubic p-splines.

Figure 3.8: The Projected Ratio of Healthy Life Expectancy to Life Expectancy

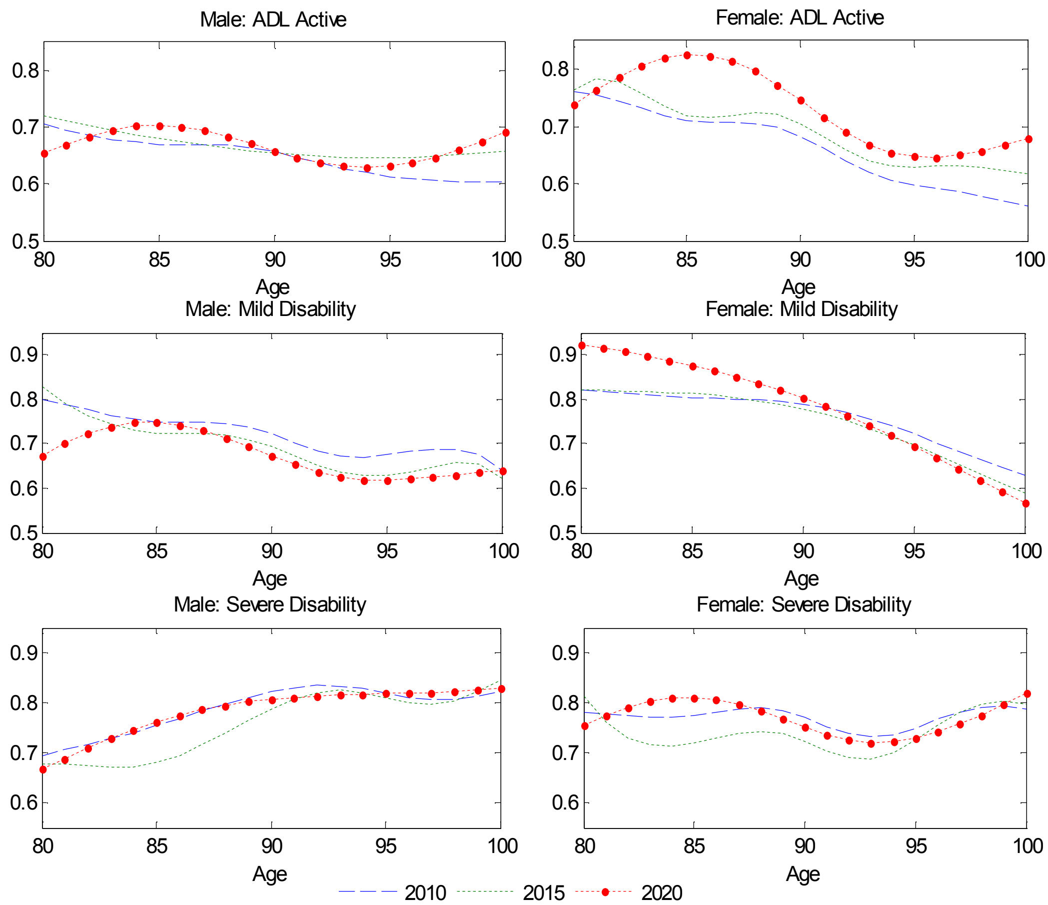
(Cohort Health Index)



This figure plots the projected ratio of healthy life expectancy (HLE) to life expectancy across age and sex groups for the year 2010, 2015, and 2020. The healthy life expectancy is calculated through Sullivan's method combining the cohort life table with the cohort prevalence of morbidity. The life expectancy is calculated with the cohort life table. In the upper panel, bad health consists of the self-reported ratings "so-so", "bad', and "very bad". In the lower panel, bad health consists of the self-reported ratings "bad" and "very bad". These ratios are smoothed using cubic p-splines.

Figure 3.9: The Projected Ratio of Disability-Free Life Expectancy to Life Expectancy

(Cohort Health Index)



This figure plots the projected ratio of disability free life expectancy (DFLE) to life expectancy across age and sex groups for the year 2010, 2015, and 2020. The disability free life expectancy is calculated through Sullivan's method combining the cohort life table with the cohort prevalence of morbidity. The life expectancy is calculated with the cohort life table. In the upper panel, ADL active is defined as having no ADL limitations; in the middle panel, mild disability is defined as having one or two ADL limitations; in the lower panel, severe disability is defined as having three or more ADL limitations. These ratios are smoothed using cubic p-splines.

Table 3.1: Sample Distribution by Sex and Age, 1998-2005

Panel A: Males

	Number of Observations				Percentage of Observations			
Age	1998	2000	2002	2005	1998	2000	2002	2005
60-64	0	0	19	9	0.00%	0.00%	0.28%	0.13%
65-69	0	0	817	841	0.00%	0.00%	11.94%	12.57%
70-74	0	0	841	838	0.00%	0.00%	12.29%	12.53%
75-79	72	21	780	828	1.98%	0.45%	11.40%	12.38%
80-84	992	1391	1098	674	27.26%	29.91%	16.04%	10.08%
85-89	795	1076	1030	1258	21.85%	23.13%	15.05%	18.81%
90-94	759	1126	1040	1098	20.86%	24.21%	15.19%	16.42%
95-99	540	519	544	561	14.84%	11.16%	7.95%	8.39%
100-104	443	463	609	513	12.17%	9.95%	8.90%	7.67%
105-109	34	49	61	68	0.93%	1.05%	0.89%	1.02%
110-114	3	5	5	0	0.08%	0.11%	0.07%	0.00%
115+	1	1	1	0	0.03%	0.02%	0.01%	0.00%
Total	3639	4651	6845	6688	100.00%	100.00%	100.00%	100.00%

Panel B: Females

	Number of Observations				Percentage of Observations			
Age	1998	2000	2002	2005	1998	2000	2002	2005
60-64	0	0	25	16	0.00%	0.00%	0.27%	0.18%
65-69	0	0	791	831	0.00%	0.00%	8.58%	9.28%
70-74	0	0	830	804	0.00%	0.00%	9.00%	8.98%
75-79	62	17	786	813	1.14%	0.26%	8.53%	9.08%
80-84	947	1274	1013	672	17.36%	19.46%	10.99%	7.51%
85-89	794	1177	1098	1305	14.56%	17.97%	11.91%	14.58%
90-94	868	1293	1286	1351	15.91%	19.75%	13.95%	15.09%
95-99	846	874	877	942	15.51%	13.35%	9.51%	10.53%
100-104	1749	1671	2215	1849	32.07%	25.52%	24.03%	20.66%
105-109	171	210	257	334	3.14%	3.21%	2.79%	3.73%
110-114	16	29	37	29	0.29%	0.44%	0.40%	0.32%
115+	1	3	4	4	0.02%	0.05%	0.04%	0.04%
Total	5454	6548	9219	8950	100.00%	100.00%	100.00%	100.00%

This table provides the sample distribution of the CLHLS by sex and age group in the years 1998, 2000, 2002, and 2005, respectively.

Table 3.2: Prevalence Rates of Self-rated Bad Health by Sex

Panel A: Wide Definition

	Males				Females			
Age	1998	2000	2002	2005	1998	2000	2002	2005
60-64	--	--	52.63%	77.78%	--	--	48.00%	43.75%
65-69	--	--	45.41%	42.09%	--	--	51.33%	46.93%
70-74	--	--	46.37%	45.58%	--	--	53.61%	50.75%
75-79	37.50%	38.10%	50.13%	50.24%	37.10%	58.82%	52.67%	52.77%
80-84	37.10%	39.83%	48.54%	51.19%	40.65%	44.27%	53.60%	52.98%
85-89	39.50%	38.48%	49.51%	47.62%	42.82%	44.60%	53.19%	47.82%
90-94	37.81%	39.52%	43.27%	44.17%	42.63%	41.61%	50.54%	45.74%
95-99	37.22%	35.84%	45.40%	42.07%	43.62%	40.27%	45.27%	45.75%
100+	34.93%	37.45%	38.46%	37.87%	40.11%	37.85%	43.22%	41.70%
Total:	37.51%	38.72%	46.19%	45.51%	41.51%	41.43%	49.21%	46.78%

Panel B: Narrow Definition

	Males				Females			
Age	1998	2000	2002	2005	1998	2000	2002	2005
60-64	--	--	10.53%	44.44%	--	--	20.00%	18.75%
65-69	--	--	11.51%	11.65%	--	--	15.30%	14.68%
70-74	--	--	11.77%	13.72%	--	--	14.82%	18.03%
75-79	8.33%	9.52%	15.77%	15.22%	8.06%	29.41%	18.07%	19.43%
80-84	7.16%	11.29%	17.30%	16.47%	8.76%	13.81%	19.45%	20.54%
85-89	8.55%	11.15%	15.53%	14.31%	8.69%	12.40%	19.95%	19.31%
90-94	6.06%	9.24%	12.40%	13.57%	10.02%	10.60%	19.28%	13.99%
95-99	7.04%	9.25%	14.34%	13.19%	10.05%	9.95%	14.14%	13.91%
100+	6.03%	9.85%	11.69%	10.84%	9.12%	10.40%	14.09%	13.90%
Total	7.09%	10.36%	13.94%	13.76%	9.26%	11.45%	16.63%	16.16%

This table presents the prevalence rates of self-rated bad health by sex for the years 1998, 2000, 2002, and 2005. In panel A, bad health consists of the self-reported ratings “so-so”, “bad’, and “very bad”. In panel B, bad health consists of the self-reported ratings “bad” and “very bad”.

Table 3.3: Prevalence Rates of ADL Limitations by Sex

Panel A: ADL Active

	Males				Females			
Age	1998	2000	2002	2005	1998	2000	2002	2005
60-64	--	--	94.74%	72.73%	--	--	100.00%	87.50%
65-69	--	--	96.08%	96.91%	--	--	96.08%	97.59%
70-74	--	--	95.12%	94.99%	--	--	92.41%	95.52%
75-79	84.72%	80.95%	89.23%	92.27%	74.19%	70.59%	89.06%	91.88%
80-84	84.48%	84.04%	82.42%	87.83%	83.00%	82.10%	78.28%	84.67%
85-89	82.26%	76.58%	76.12%	80.76%	75.19%	72.64%	67.40%	74.79%
90-94	71.54%	67.94%	66.83%	74.77%	60.71%	60.56%	54.98%	66.47%
95-99	60.74%	62.81%	57.54%	64.17%	48.58%	48.74%	48.23%	52.97%
100+	44.79%	47.53%	44.44%	50.33%	36.03%	40.14%	36.05%	42.28%
Total	72.39%	71.89%	77.38%	81.53%	56.22%	59.44%	63.16%	69.59%

Panel B: Mild Disability

	Males				Females			
Age	1998	2000	2002	2005	1998	2000	2002	2005
60-64	--	--	5.26%	0.00%	--	--	0.00%	12.50%
65-69	--	--	2.69%	2.38%	--	--	3.16%	1.81%
70-74	--	--	3.57%	2.74%	--	--	6.14%	3.48%
75-79	11.11%	19.05%	8.33%	3.99%	22.58%	11.76%	8.65%	5.54%
80-84	10.58%	11.72%	12.02%	6.38%	12.46%	11.93%	15.10%	10.12%
85-89	12.70%	15.33%	15.44%	11.53%	16.37%	17.59%	20.13%	15.48%
90-94	17.26%	20.16%	20.67%	14.66%	23.04%	24.44%	26.44%	17.47%
95-99	20.37%	20.42%	26.29%	20.32%	23.88%	26.32%	27.25%	22.82%
100+	27.08%	23.57%	32.59%	24.92%	25.97%	26.35%	30.90%	26.34%
Total	16.04%	16.92%	14.42%	10.29%	21.39%	21.54%	20.31%	15.54%

Panel C: Severe Disability

	Males				Females			
Age	1998	2000	2002	2005	1998	2000	2002	2005
60-64	--	--	0.00%	9.09%	--	--	0.00%	0.00%
65-69	--	--	1.22%	0.71%	--	--	0.76%	0.60%
70-74	--	--	1.31%	2.27%	--	--	1.45%	1.00%
75-79	4.17%	0.00%	2.44%	3.74%	3.23%	17.65%	2.29%	2.58%
80-84	4.94%	4.24%	5.56%	5.79%	4.54%	5.97%	6.61%	5.21%
85-89	5.03%	8.09%	8.45%	7.71%	8.44%	9.77%	12.48%	9.73%
90-94	11.20%	11.90%	12.50%	10.56%	16.24%	15.00%	18.58%	16.06%
95-99	18.89%	16.76%	16.18%	15.51%	27.54%	24.94%	24.52%	24.20%
100+	28.13%	27.19%	22.96%	19.38%	38.00%	33.51%	33.05%	31.38%
Total	11.35%	10.94%	8.20%	7.66%	22.38%	19.02%	16.52%	14.87%

This table presents the prevalence rates of ADLs limitations by sex for the years 1998, 2000, 2002, and 2005. In panel A, ADLs active is defined as having no ADL limitations; In panel B, mild disability defined as having one or two ADL limitations; In panel C, severe disability is defined as having three or more ADL limitations.

Table 3.4a: Trends in Healthy Life Expectancy based on Sullivan's Method, 1998-2005

Panel A: Male

	1998			2000			2002			2005		
Age	LE	HLE1	HLE2	LE	HLE1	HLE2	LE	HLE1	HLE2	LE	HLE1	HLE2
80	6.89	4.30	6.39	7.28	4.44	6.50	7.70	4.00	6.50	8.48	4.38	7.19
	(6.63-7.05)	(4.13-4.40)	(6.16-6.54)	(6.83-7.56)	(4.19-4.62)	(6.09-6.77)	(7.01-8.15)	(3.62-4.24)	(5.95-6.89)	(7.38-9.29)	(3.76-4.84)	(6.22-7.89)
85	4.82	2.94	4.44	5.14	3.17	4.60	5.45	2.89	4.67	6.13	3.32	5.27
	(4.75-4.88)	(2.90-2.98)	(4.37-4.48)	(4.97-5.25)	(3.06-3.24)	(4.44-4.70)	(5.12-5.68)	(2.71-3.02)	(4.37-4.86)	(5.42-6.61)	(2.91-3.61)	(4.65-5.70)
90	3.34	2.07	3.13	3.64	2.25	3.31	3.77	2.15	3.30	4.33	2.46	3.75
	(3.33-3.35)	(2.06-2.08)	(3.11-3.14)	(3.59-3.67)	(2.21-2.27)	(3.27-3.35)	(3.63-3.85)	(2.07-2.20)	(3.19-3.37)	(3.91-4.62)	(2.21-2.63)	(3.38-4.00)
95	2.31	1.48	2.15	2.58	1.65	2.35	2.55	1.43	2.19	3.18	1.86	2.77
	(2.31-2.31)	(1.48-1.48)	(2.15-2.15)	(2.57-2.59)	(1.65-1.65)	(2.34-2.35)	(2.51-2.57)	(1.41-1.44)	(2.16-2.21)	(2.95-3.33)	(1.71-1.96)	(2.57-2.89)

Panel B: Female

	1998			2000			2002			2005		
Age	LE	HLE1	HLE2	LE	HLE1	HLE2	LE	HLE1	HLE2	LE	HLE1	HLE2
80	8.46	4.93	7.70	8.74	4.94	7.64	8.94	4.26	7.24	9.66	4.88	7.90
	(8.12-8.73)	(4.75-5.09)	(7.39-7.94)	(8.21-9.17)	(4.65-5.19)	(7.16-8.02)	(8.21-9.54)	(3.89-4.58)	(6.66-7.74)	(8.56-10.58)	(4.28-5.45)	(6.97-8.69)
85	6.04	3.44	5.48	6.23	3.54	5.51	6.56	3.20	5.31	6.99	3.73	5.84
	(5.90-6.14)	(3.36-3.50)	(5.38-5.57)	(5.98-6.41)	(3.40-3.66)	(5.29-5.68)	(6.18-6.89)	(2.97-3.39)	(4.98-5.59)	(6.17-7.64)	(3.30-4.08)	(5.18-6.36)
90	4.26	2.39	3.82	4.40	2.61	3.95	4.54	2.32	3.73	4.94	2.69	4.26
	(4.22-4.28)	(2.37-2.41)	(3.79-3.84)	(4.31-4.47)	(2.56-2.65)	(3.87-4.00)	(4.37-4.69)	(2.23-2.41)	(3.58-3.85)	(4.50-5.32)	(2.44-2.90)	(3.86-4.61)
95	2.96	1.63	2.67	3.04	1.85	2.75	3.13	1.71	2.67	3.60	1.98	3.10
	(2.95-2.96)	(1.62-1.63)	(2.67-2.68)	(3.02-3.06)	(1.84-1.87)	(2.73-2.76)	(3.08-3.18)	(1.68-1.73)	(2.63-2.71)	(3.35-3.80)	(1.83-2.09)	(2.89-3.28)

Note: LE-life expectancy; HLE1- widely defined healthy life expectancy; HLE2-narrowly defined healthy life expectancy; 95% confidence intervals are reported in the parentheses.

This table presents the life expectancy and healthy life expectancy (HLE) for selected ages by sex groups during the sample period of 1998-2005. The life expectancy is calculated with the cohort life table, whereas the healthy life expectancy through Sullivan's method combining the cohort life table with the period prevalence of morbidity. In the widely defined healthy life expectancy (HLE1), bad health consists of the self-reported ratings "so-so", "bad', and "very bad". In the narrowly defined healthy life expectancy (HLE2), bad health consists of the self-reported ratings "bad" and "very bad".

Table 3.4b: Trends in Disability-Free Life Expectancy based on Sullivan's Method, 1998-2005

Panel A: Male

	1998			2000			2002			2005		
Age	DFLE1	DFLE2	DFLE3	DFLE1	DFLE2	DFLE3	DFLE1	DFLE2	DFLE3	DFLE1	DFLE2	DFLE3
80	5.61	6.05	6.45	5.72	6.24	6.77	5.95	6.56	7.10	6.95	7.61	7.83
	(5.46-5.70)	(5.86-6.18)	(6.28-6.57)	(5.43-5.88)	(5.90-6.47)	(6.41-7.01)	(5.57-6.21)	(6.05-6.91)	(6.54-7.51)	(6.05-7.52)	(6.64-8.28)	(6.89-8.51)
85	3.79	4.15	4.47	3.77	4.28	4.64	3.92	4.47	4.89	4.71	5.29	5.54
	(3.75-3.82)	(4.10-4.19)	(4.41-4.51)	(3.68-3.83)	(4.15-4.36)	(4.51-4.72)	(3.75-4.04)	(4.24-4.63)	(4.59-5.09)	(4.20-5.03)	(4.62-5.71)	(4.82-5.94)
90	2.34	2.77	2.92	2.45	2.91	3.18	2.44	2.94	3.26	3.10	3.63	3.81
	(2.34-2.35)	(2.76-2.77)	(2.91-2.93)	(2.42-2.46)	(2.87-2.93)	(3.14-3.20)	(2.38-2.48)	(2.84-3.01)	(3.14-3.33)	(2.82-3.27)	(3.30-3.85)	(3.43-4.02)
95	1.44	1.89	1.87	1.61	2.06	2.13	1.44	1.87	2.12	2.00	2.50	2.67
	(1.44-1.45)	(1.88-1.89)	(1.87-1.87)	(1.61-1.62)	(2.05-2.06)	(2.13-2.14)	(1.43-1.45)	(1.84-1.89)	(2.09-2.14)	(1.88-2.07)	(2.34-2.61)	(2.50-2.78)

Panel B: Female

	1998			2000			2002			2005		
Age	DFLE1	DFLE2	DFLE3	DFLE1	DFLE2	DFLE3	DFLE1	DFLE2	DFLE3	DFLE1	DFLE2	DFLE3
80	6.38	7.14	7.71	6.43	7.30	7.88	6.20	7.24	7.93	7.35	8.31	8.70
	(6.22-6.51)	(6.87-7.35)	(7.47-7.90)	(6.16-6.64)	(6.92-7.62)	(7.47-8.18)	(5.83-6.51)	(6.70-7.66)	(7.43-8.38)	(6.67-7.92)	(7.32-9.07)	(7.79-9.43)
85	4.14	4.90	5.28	4.14	4.96	5.41	4.03	5.06	5.53	4.84	5.81	6.05
	(4.09-4.18)	(4.80-4.98)	(5.20-5.34)	(4.03-4.22)	(4.79-5.10)	(5.24-5.55)	(3.83-4.18)	(4.76-5.29)	(5.23-5.77)	(4.37-5.19)	(5.23-6.32)	(5.50-6.52)
90	2.46	3.26	3.45	2.54	3.32	3.61	2.43	3.34	3.63	3.08	4.00	4.03
	(2.45-2.47)	(3.24-3.28)	(3.43-3.47)	(2.50-2.56)	(3.26-3.38)	(3.56-3.66)	(2.36-2.48)	(3.21-3.45)	(3.52-3.72)	(2.85-3.27)	(3.66-4.29)	(3.71-4.30)
95	1.48	2.26	2.17	1.50	2.28	2.26	1.45	2.25	2.33	1.87	2.78	2.69
	(1.47-1.48)	(2.26-2.27)	(2.17-2.17)	(1.49-1.50)	(2.27-2.29)	(2.25-2.27)	(1.43-1.47)	(2.21-2.29)	(2.29-2.36)	(1.76-1.94)	(2.60-2.93)	(2.54-2.84)

Note: DFLE1-life expectancy with no ADL limitations; DFLE2-life expectancy with mild disability; DFLE3-life expectancy with severe disability. 95% confidence intervals are reported in the parentheses.

This table presents the disability-free life expectancy (DFLE) for selected ages by sex groups during the sample period of 1998-2005. The disability free life expectancy is calculated through Sullivan's method combining the cohort life table with the period prevalence of morbidity. The prevalence of disability is calculated based on the activities of daily living (ADL) limitations. ADL active is defined as having no ADL limitations, mild disability as having one or two ADL limitations, and severe disability as having three or more ADL limitations.

Table 3.5a: Projected Healthy Life Expectancy based on Sullivan's Method (Period Bad Health Index), 2010-2020

Panel A: Male

	2010			2015			2020		
	LE	HLE1	HLE2	LE	HLE1	HLE2	LE	HLE1	HLE2
80	9.12	3.48	4.96	10.07	3.13	3.86	12.05	3.34	3.43
	(6.75-10.87)	(2.18-4.75)	(3.18-6.53)	(6.52-12.72)	(1.34-5.39)	(1.90-6.08)	(5.53-21.07)	(0.83-7.44)	(1.12-6.13)
85	6.66	2.92	3.97	7.36	2.78	3.23	8.18	2.91	2.92
	(4.80-7.81)	(2.01-3.98)	(2.62-5.25)	(4.78-9.51)	(1.34-4.00)	(1.72-4.77)	(4.12-11.41)	(0.90-6.06)	(1.06-5.16)
90	4.80	2.27	2.68	5.30	2.24	2.12	5.85	2.29	1.82
	(3.39-5.77)	(1.47-3.02)	(1.54-3.72)	(3.10-6.80)	(0.99-3.39)	(0.88-3.44)	(2.49-8.10)	(0.64-3.85)	(0.55-3.25)
95	3.40	1.66	2.04	3.77	1.69	1.61	4.21	1.79	1.45
	(2.12-4.17)	(0.91-2.40)	(1.10-2.90)	(1.94-4.98)	(0.64-2.67)	(0.64-2.65)	(1.61-5.84)	(0.40-3.18)	(0.28-2.82)

Panel B: Female

	2010			2015			2020		
	LE	HLE1	HLE2	LE	HLE1	HLE2	LE	HLE1	HLE2
80	10.23	4.06	5.33	10.97	3.75	3.78	13.46	4.86	5.19
	(8.24-11.80)	(2.95-5.35)	(3.93-6.81)	(7.97-14.06)	(2.13-5.66)	(2.01-6.18)	(7.06-29.40)	(1.54-11.78)	(1.20-14.94)
85	7.43	3.47	4.30	7.87	3.32	3.16	8.58	3.37	2.80
	(5.88-8.88)	(2.49-4.50)	(3.10-5.52)	(5.56-9.96)	(2.09-4.57)	(1.73-4.64)	(5.07-12.59)	(1.72-5.17)	(1.18-4.74)
90	5.22	2.65	3.75	5.56	2.67	3.25	5.95	2.68	2.88
	(3.89-6.32)	(1.85-3.51)	(2.76-4.68)	(3.58-7.11)	(1.57-3.77)	(1.94-4.55)	(3.34-8.11)	(1.33-4.00)	(1.43-4.32)
95	3.62	1.92	2.56	3.91	1.96	2.17	4.20	2.04	1.87
	(2.57-4.51)	(1.24-2.53)	(1.66-3.35)	(2.24-5.16)	(1.07-2.88)	(1.09-3.30)	(1.99-5.91)	(0.96-3.16)	(0.62-3.10)

Note: LE-life expectancy; HLE1- widely defined healthy life expectancy; HLE2-narrowly defined healthy life expectancy; 95% confidence intervals are reported in the parentheses.

This table presents the projected life expectancy and healthy life expectancy (HLE) for selected ages by sex groups. The life expectancy is calculated with the cohort life table, whereas the healthy life expectancy through Sullivan's method combining the cohort life table with the period prevalence of morbidity. In the widely defined healthy life expectancy (HLE1), bad health consists of the self-reported ratings "so-so", "bad', and "very bad". In the narrowly defined healthy life expectancy (HLE2), bad health consists of the self-reported ratings "bad" and "very bad".

Table 3.5b: Projected Disability Free Life Expectancy based on Sullivan's Method (Period Bad Health Index), 2010-2020

Panel A: Male

	2010			2015			2020		
	DFLE1	DFLE2	DFLE3	DFLE1	DFLE2	DFLE3	DFLE1	DFLE2	DFLE3
80	7.09	7.74	7.25	7.66	8.35	7.23	8.84	10.27	7.93
	(5.12-8.49)	(5.95-9.23)	(4.98-8.76)	(4.64-10.60)	(5.32-10.89)	(4.12-9.61)	(4.20-16.46)	(4.67-18.70)	(2.93-16.48)
85	4.72	5.31	5.30	5.00	5.59	4.99	5.39	6.36	5.81
	(3.31-5.90)	(3.83-6.50)	(3.59-6.60)	(2.88-6.57)	(3.44-7.29)	(2.71-7.07)	(2.23-8.15)	(2.80-8.94)	(1.96-8.90)
90	3.33	3.67	4.01	3.87	3.92	4.36	4.09	4.28	4.83
	(2.02-4.17)	(2.27-4.54)	(2.64-5.05)	(2.32-5.20)	(2.37-5.30)	(2.26-5.86)	(1.90-6.04)	(1.93-5.91)	(2.03-6.81)
95	2.13	2.27	2.81	2.45	2.33	3.15	2.73	2.50	3.52
	(1.35-2.81)	(1.32-3.06)	(1.68-3.64)	(1.10-3.50)	(0.98-3.55)	(1.55-4.37)	(0.62-4.31)	(0.72-3.93)	(1.59-5.12)

Panel B: Female

	2010			2015			2020		
	DFLE1	DFLE2	DFLE3	DFLE1	DFLE2	DFLE3	DFLE1	DFLE2	DFLE3
80	7.65	8.48	8.61	8.30	9.12	8.41	9.11	10.11	11.26
	(6.26-8.87)	(6.64-9.95)	(6.91-9.98)	(5.96-10.75)	(6.33-12.13)	(5.93-11.07)	(5.00-17.35)	(5.74-13.73)	(4.77-23.98)
85	5.11	5.97	6.07	5.45	6.30	5.90	5.99	6.87	6.30
	(3.93-6.13)	(4.52-7.20)	(4.69-7.25)	(3.80-7.04)	(4.29-7.89)	(4.08-7.68)	(3.26-9.22)	(4.09-10.36)	(3.20-10.00)
90	3.49	4.25	4.17	4.00	4.56	4.27	4.35	4.75	4.44
	(2.62-4.25)	(3.10-5.18)	(3.12-5.13)	(2.63-5.11)	(2.94-5.86)	(2.77-5.68)	(2.41-5.83)	(2.66-6.52)	(2.40-6.22)
95	2.01	2.64	2.70	2.33	2.77	2.87	2.56	2.90	3.08
	(1.32-2.65)	(1.81-3.37)	(1.84-3.46)	(1.32-3.23)	(1.59-3.84)	(1.45-4.03)	(1.18-3.88)	(1.29-4.25)	(1.31-4.65)

Note: DFLE1-life expectancy with no ADL limitations; DFLE2-life expectancy with mild disability; DFLE3-life expectancy with severe disability. 95% confidence intervals are reported in the parentheses.

This table presents the projected disability-free life expectancy (DFLE) for selected ages by sex groups. The disability free life expectancy is calculated through Sullivan's method combining the cohort life table with the period prevalence of morbidity. The prevalence of disability is calculated based on the activities of daily living (ADL) limitations. ADL active is defined as having no ADL limitations, mild disability as having one or two ADL limitations, and severe disability as having three or more ADL limitations.

Table 3.6a: Projected Healthy Life Expectancy based on Sullivan's Method (Cohort Bad Health Index), 2010-2020

Panel A: Male

	2010			2015			2020		
	LE	HLE1	HLE2	LE	HLE1	HLE2	LE	HLE1	HLE2
80	9.12	2.88	3.70	10.07	2.40	3.11	12.05	2.59	2.79
	(6.75-10.87)	(1.61-4.42)	(2.22-5.40)	(6.52-12.72)	(1.10-3.97)	(1.28-5.83)	(5.53-21.07)	(0.71-6.32)	(0.64-8.04)
85	6.66	2.51	3.08	7.36	2.45	2.92	8.18	2.43	2.64
	(4.80-7.81)	(1.58-3.53)	(1.88-4.27)	(4.78-9.51)	(1.14-3.99)	(1.35-4.65)	(4.12-11.41)	(0.83-4.24)	(0.91-5.05)
90	4.80	2.05	2.15	5.30	2.06	1.84	5.85	2.35	2.22
	(3.39-5.77)	(1.22-2.83)	(1.16-3.20)	(3.10-6.80)	(0.90-3.20)	(0.70-3.11)	(2.49-8.10)	(0.52-4.33)	(0.47-3.80)
95	3.40	1.58	1.82	3.77	1.62	1.46	4.21	1.73	1.36
	(2.12-4.17)	(0.89-2.32)	(0.98-2.69)	(1.94-4.98)	(0.62-2.63)	(0.51-2.50)	(1.61-5.84)	(0.32-3.14)	(0.26-2.68)

Panel B: Female

	2010			2015			2020		
	LE	HLE1	HLE2	LE	HLE1	HLE2	LE	HLE1	HLE2
80	10.23	3.59	3.37	10.97	3.88	2.54	13.46	7.79	2.92
	(8.24-11.80)	(2.43-5.11)	(2.18-4.79)	(7.97-14.06)	(1.84-7.22)	(1.17-4.68)	(7.06-29.40)	(1.75-32.54)	(0.59-9.34)
85	7.43	3.23	3.19	7.87	3.48	2.44	8.58	4.16	2.27
	(5.88-8.88)	(2.22-4.35)	(2.13-4.34)	(5.56-9.96)	(1.92-4.72)	(1.20-3.90)	(5.07-12.59)	(1.56-9.37)	(0.83-4.39)
90	5.22	2.51	3.17	5.56	2.54	2.79	5.95	2.74	2.58
	(3.94-6.32)	(1.68-3.39)	(2.26-4.04)	(3.58-7.11)	(1.47-3.67)	(1.65-4.08)	(3.34-8.11)	(1.27-4.34)	(1.17-4.08)
95	3.62	1.84	2.31	3.91	1.90	1.95	4.20	1.98	1.69
	(2.57-4.51)	(1.17-2.50)	(1.47-3.08)	(2.24-5.16)	(1.02-2.82)	(0.98-3.03)	(1.99-5.91)	(0.93-3.14)	(0.53-2.89)

Note: LE-life expectancy; HLE1- widely defined healthy life expectancy; HLE2-narrowly defined healthy life expectancy; 95% confidence intervals are reported in the parentheses.

This table presents the projected life expectancy and healthy life expectancy (HLE) for selected ages by sex groups. The life expectancy is calculated with the cohort life table, whereas the healthy life expectancy through Sullivan's method combining the cohort life table with the cohort prevalence of morbidity. In the widely defined healthy life expectancy (HLE1), bad health consists of the self-reported ratings "so-so", "bad', and "very bad". In the narrowly defined healthy life expectancy (HLE2), bad health consists of the self-reported ratings "bad" and "very bad".

Table 3.6b: Projected Disability Free Life Expectancy based on Sullivan's Method (Cohort Bad Health Index), 2010-2020

Panel A: Male

	2010			2015			2020		
	DFLE1	DFLE2	DFLE3	DFLE1	DFLE2	DFLE3	DFLE1	DFLE2	DFLE3
80	6.54	7.37	6.48	7.28	8.43	6.92	8.39	8.34	9.36
	(4.61-8.34)	(5.33-8.98)	(4.31-8.17)	(4.16-11.41)	(5.21-11.26)	(3.60-10.56)	(3.55-16.75)	(4.34-14.26)	(2.78-27.00)
85	4.42	5.03	4.99	4.96	5.40	4.83	6.06	5.93	7.30
	(2.80-5.76)	(3.54-6.28)	(3.22-6.29)	(2.63-7.15)	(3.27-7.22)	(2.56-7.09)	(2.17-10.67)	(2.68-10.47)	(1.76-10.70)
90	3.20	3.49	4.00	3.61	3.74	4.33	4.06	4.30	4.77
	(1.87-4.21)	(2.15-4.44)	(2.61-5.03)	(1.91-5.00)	(2.16-5.18)	(2.22-5.86)	(1.73-6.61)	(1.77-6.31)	(2.01-7.53)
95	2.05	2.19	2.81	2.35	2.25	3.14	2.59	2.39	3.51
	(1.14-2.83)	(1.20-3.04)	(1.68-3.65)	(0.95-3.51)	(0.96-3.45)	(1.54-4.36)	(0.89-4.16)	(0.70-3.85)	(1.58-5.09)

Panel B: Female

	2010			2015			2020		
	DFLE1	DFLE2	DFLE3	DFLE1	DFLE2	DFLE3	DFLE1	DFLE2	DFLE3
80	7.77	8.45	7.94	8.67	9.53	9.41	10.21	12.73	8.60
	(6.24-9.27)	(6.55-10.12)	(6.27-9.46)	(5.94-13.17)	(6.21-14.99)	(5.38-14.55)	(5.03-23.19)	(5.84-35.19)	(4.51-19.99)
85	5.31	5.93	5.85	5.57	6.35	5.68	7.10	7.15	7.05
	(4.01-6.53)	(4.47-7.26)	(4.50-7.11)	(3.84-7.28)	(4.26-8.11)	(3.82-7.60)	(3.44-13.85)	(3.98-13.89)	(3.14-13.84)
90	3.65	4.21	4.10	4.11	4.51	4.19	4.42	4.87	4.41
	(2.69-4.54)	(3.05-5.16)	(3.04-5.12)	(2.67-5.32)	(2.88-5.82)	(2.70-5.65)	(2.42-6.08)	(2.60-6.91)	(2.30-6.24)
95	2.13	2.59	2.74	2.42	2.72	2.88	2.62	2.85	3.08
	(1.36-2.84)	(1.74-3.34)	(1.84-3.53)	(1.34-3.39)	(1.53-3.79)	(1.44-4.09)	(1.19-4.00)	(1.27-4.20)	(1.31-4.68)

Note: DFLE1-life expectancy with no ADL limitations; DFLE2-life expectancy with mild disability; DFLE3-life expectancy with severe disability. 95% confidence intervals are reported in the parentheses.

This table presents the projected disability-free life expectancy (DFLE) for selected ages by sex groups. The disability free life expectancy is calculated through Sullivan's method combining the cohort life table with the cohort prevalence of morbidity. The prevalence of disability is calculated based on the activities of daily living (ADL) limitations. ADL active is defined as having no ADL limitations, mild disability as having one or two ADL limitations, and severe disability as having three or more ADL limitations.

Appendix 1a: Trends in Healthy Life Expectancy based on Sullivan's Method, 1998-2005

Panel A: Male

	1998			2000			2002			2005		
Age	LE	HLE1	HLE2	LE	HLE1	HLE2	LE	HLE1	HLE2	LE	HLE1	HLE2
80	5.86	3.66	5.43	6.88	4.19	6.13	6.56	3.38	5.52	7.09	3.61	6.00
85	4.19	2.55	3.85	5.19	3.20	4.65	4.82	2.54	4.13	5.25	2.82	4.51
90	2.96	1.83	2.76	3.87	2.39	3.52	3.48	1.99	3.05	3.89	2.20	3.36
95	2.08	1.34	1.93	2.87	1.83	2.61	2.50	1.39	2.15	2.85	1.66	2.48

Panel B: Female

	1998			2000			2002			2005		
Age	LE	HLE1	HLE2	LE	HLE1	HLE2	LE	HLE1	HLE2	LE	HLE1	HLE2
80	8.03	4.69	7.31	7.68	4.31	6.69	7.74	3.65	6.24	8.44	4.21	6.86
85	5.92	3.37	5.38	5.63	3.19	4.97	5.62	2.71	4.53	6.25	3.31	5.18
90	4.28	2.40	3.84	4.04	2.40	3.63	3.98	2.02	3.25	4.51	2.45	3.88
95	3.05	1.68	2.75	2.87	1.75	2.59	2.79	1.52	2.37	3.43	1.88	2.94

Note: LE-life expectancy; HLE1- widely defined healthy expectancy; HLE2-narrowly defined healthy life expectancy;

This table presents the life expectancy and healthy life expectancy (HLE) for selected ages by sex groups during the sample period of 1998-2005. The life expectancy is calculated with the period life table, whereas the healthy life expectancy through Sullivan's method combining the period life table with the period prevalence of morbidity. In the widely defined healthy life expectancy (HLE1), bad health consists of the self-reported ratings "so-so", "bad', and "very bad". In the narrowly defined healthy life expectancy (HLE2), bad health consists of the self-reported ratings "bad" and "very bad".

Appendix 1b: Trends in Disability-Free Life Expectancy based on Sullivan's Method, 1998-2005

Panel A: Male

	1998			2000			2002			2005		
Age	DFLE1	DFLE2	DFLE3	DFLE1	DFLE2	DFLE3	DFLE1	DFLE2	DFLE3	DFLE1	DFLE2	DFLE3
80	4.88	5.20	5.55	5.47	5.93	6.43	5.20	5.65	6.11	5.93	6.44	6.58
85	3.37	3.64	3.93	3.83	4.33	4.69	3.54	3.99	4.36	4.10	4.57	4.77
90	2.11	2.46	2.60	2.60	3.09	3.37	2.29	2.75	3.03	2.82	3.27	3.43
95	1.32	1.71	1.69	1.78	2.28	2.36	1.43	1.84	2.09	1.80	2.25	2.40

Panel A: Male

	1998			2000			2002			2005		
Age	DFLE1	DFLE2	DFLE3	DFLE1	DFLE2	DFLE3	DFLE1	DFLE2	DFLE3	DFLE1	DFLE2	DFLE3
80	6.16	6.81	7.38	5.80	6.48	7.00	5.54	6.32	6.95	6.56	7.31	7.69
85	4.10	4.82	5.21	3.82	4.51	4.95	3.56	4.38	4.80	4.40	5.21	5.45
90	2.49	3.28	3.48	2.37	3.06	3.35	2.17	2.94	3.21	2.84	3.65	3.70
95	1.52	2.33	2.24	1.42	2.15	2.14	1.32	2.01	2.09	1.78	2.64	2.57

Note: LE-life expectancy; DFLE1-life expectancy with no ADL limitations; DFLE2-life expectancy with mild disability; DFLE3-life expectancy with severe disability.

This table presents the life expectancy and disability-free life expectancy (DFLE) for selected ages by sex groups during the sample period of 1998-2005. The life expectancy is calculated with the period life table, whereas the disability free life expectancy through Sullivan's method combining the period life table with the period prevalence of morbidity. The prevalence of disability is calculated based on the activities of daily living (ADL) limitations. ADL active is defined as having no ADL limitations, mild disability as having one or two ADL limitations, and severe disability as having three or more ADL limitations.

Chapter 4: Export Credit Insurance and Trade Promotion*

4.1 Introduction

Since there is a host of studies indicating the causality from export growth to economic growth (Mah, 2006),[1] the great collapse of international trade during the recent financial crisis[2] has focused governments and businesses attention on methods of promoting exports. As 80 to 90 percent of international trade relies on some form of export credit, credit insurance, or guarantee (Auboin, 2007),[3] the declining availability of trade finance and its increasing costs are considered as the most important factors after demand causing the export collapse (Mora and Powers, 2009). In response, well-developed export credit insurance or guarantee programs are drawing more attention across industrialized countries as well as emerging economies. For example, the European Commission temporarily authorized governments of EU member countries to provide short-term export credit insurance, which is by EU laws prohibited, to limit the adverse impact of crisis on exporting firms.[4] Officially supported Export Credit Agencies (ECAs) expanded their new commitments between 30 and 50 percent up to mid-2009 (OECD, 2009).

While official ECAs have been the single largest class of public financial institution and insure roughly 10 percent of global trade (Berne Union, 2007),[5] it is not until the recent economic and financial crisis that export credit insurance comes to the attention of academic researchers. By far there is a lack of theoretical foundation for understanding the nature of export credit insurance. In particular, there are no theoretical models deriving how export credit insurance allows exporters to offer

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* I am grateful to the participants of Euler Hermes Guest Lecture in Paris for very helpful comments.

[1] For a recent survey on the empirical and theoretical relevance of trade for economic growth, see Levine (2005).

[2] For example, while world GDP in this period contracted by about 5%, international trade fell much more sharply, by about 30% (Baldwin, 2009)

[3] The terms *insurance* and *guarantees* are often used interchangeably in literature, referring to the coverage against losses extended by a specialized institution to an exporter or financial institution.

[4] For state aid decisions regarding public provision of short-term export credit insurance, see the State Aid Register on the Directorate General of Competition (http://ec.europa.eu/competition/state_aid/register/).

[5] Since export credit insurance is not necessary for the trade within multinational firms, the actual figure for non-multinational trade insured is almost twice as high.

competitive payment terms and to promote exports levels. On the other hand, the limited empirical evidence exclusively covers developed countries, even though developing countries are increasingly becoming important players in this field. This paper presents such a theoretical model and empirical evidence to fill in these gaps.

The paper is related to two strands of theoretical literature. First, it builds on a small but growing literature on payment terms in international trade. Focusing on the case of homogeneous exporters, Schmidt-Eisenlohr (2009) is the first to formally model the choice of payment terms by exporters and shows that the optimal terms should be determined by cross-country differences in contractual enforcement and financing costs. More specifically, exporters located in countries with lower financing cost or weaker contract enforcement should export with Open Account terms, for example, offering trade credit, to their counterparts in countries with higher financing costs or stronger contract enforcement. Antràs and Foley (2011) develop their theoretical model directly built on Schmidt-Eisenlohr (2009) and predict the pattern of optimal payment terms based on an imperfect contract approach. With unique transactions data from a large US food exporter, they test these predictions and some extensions. Other papers focus on bank-intermediated terms. Olsen (2011) argues that enforcement between banks might be easier than between trading partners. As the outcome of reputation-building mechanisms, bank-intermediated terms thus could mitigate the imperfect contractual enforcement in international trade. Ahn (2011) studies why international trade might be riskier and derives the macroeconomic implications from trade credit constraints in a financial crisis. He addresses that differing precision levels of banks' screening tests imply that banks know better local firms than foreign firms. Glady and Potin (2011) focus on the role of letters of credit in eliminating commercial default risks for exporters and importers. The second strand of theoretical literature explores the influence of export credit insurance on exports. Though several studies (Rienstra-Munnicha and Turvey, 2002; Dewit, 2001; Fort et al., 1996; Funatsu, 1986) show that export credit insurance has a strong positive effect on promoting exports, Fitzgerald and Monson (1988) argue that these promotion effects might be conditional on, for example, products characteristics. Moreover, given public resources needed for establishing these insurance programs, whether the exporting countries can gain from export credit insurance is questioned (Abraham and Dewit, 2000). Basically, this strand of literature implicitly assumes *OA* as the only payment choice faced by exporters, without considering the impact of alternative payment terms on export levels.

In this paper, we focus on both *Open Account* terms (OA) and *Cash in Advance* terms (CIA), as they account for the bulk of international trade. While existing theoretical literature often assumes the “take-it-or-leave-it” strategy offered by exporters, the focus of this paper is instead on importers making decisions on payment terms, due to the change from a seller’s to a buyer’s market in international trade (Guadagnoli, 1968; Gunasekaran et al., 2006).[1] In addition, our model allows for the scenario of risk-averse agents. On the one hand, prior studies, especially the payment terms literature, only take into account the case of risk-neutrality; on the other hand, our theoretical framework finds different results between risk neutral and risk averse agents.

The empirical literature providing evidence on the relationship between export credit insurance and trade promotion is relatively small, partly because of unavailable data. By far these empirical works have not been able to provide conclusive results. For example, while some studies (Egger and Url, 2006; Baltensperger and Herger, 2009; Moser et al., 2008; van der Veer, 2010; Felbermayr and Yalcin, 2011; Badinger and Url, 2012) find a positive impact of export credit insurance on exports, others (Huszagn and Greene, 1982; Mah, 2006) uncover no supportive evidence. The mixed conclusions might result from cross-country differences in business cultures, proxies as variables of interest, and different empirical methodologies. With an unbalanced panel data covering China’s 181 trading partners over the period 2001 and 2006, we conduct a test for the relationship between public provision of export credit insurance and exports promotion. The empirical part of our paper differs from the existing

[1] For example, it is reported that even European Aerospace Defence & Space Co., the parent company of Airbus, is considering to create its in-house bank as offering financial services becomes an important part of its sales effort. Many multinational companies including Siemens and Daimler have established banks to underpin their businesses by offering loans and guarantees to customers (the Wall Street Journal, *“EADS Mulls Creation of Own Bank”*, June 1-3, 2012).

literature in three ways. First, the prior empirical research focuses exclusively on OECD member countries.[1] To the best of our knowledge, this is the first study to focus on a developing country.[2] As exporters in developing countries usually trade in low-margin products in long supply chains and rely more on trade finance to support their exports, our empirical results is relevant to the current debate whether developing countries should establish their own export credit agencies. Second, the case of China is interesting. On the one hand China is now the world's largest exporter with increasing exports of capital goods in international trade.[3] On the other hand, the China Export Credit Insurance Corporation (SINOSURE), the officially-supported Export Credit Agency (ECA) in China, is the single largest official export credit insurance provider worldwide. It is reported that China's cheap export credit insurance has cut its competitors out of business opportunities worldwide. This makes Chinese export credit insurance programs a new concern for developed countries, such as the U.S., Japan, and the EU. Therefore, understanding the nature of this relationship is central to academic economists, business representatives, and policy makers. Third, the export credit insurance market in China provides an interesting setting. Since the 1990s, the export credit insurance programs in industrialized countries have been liberalized, with official ECAs mainly concentrating on the medium- and long-term businesses[4] and the private sector having dominated the short-term field. For example, while the official ECAs account for around 60 percent of premiums and 80 percent of claims in medium- and long-term businesses (Baltensperger and Herger, 2009), 95 percent of short-term businesses are underwritten by the private sector in the EU (Wang et al., 2005). However, existing empirical literature only covers either *official* ECAs or the *private* sector. Given that the impact of private export credit insurance on trade promotion can be expected to differ

[1] For example, Germany (Moser, Nestmann and Wedow, 2008), OECD member countries (Baltensperger and Herger, 2009), Canada (Kotowski, 2007), Austria (Egger and Url, 2006), Japan (Mah, 2006), and the Netherlands (van der Veer, 2010).
[2] Based on the World Bank country classification, China was a lower-middle income country during our sample period of 2001-2006.
[3] China's export of capital goods has grown by almost three-fold from USD 82.6 billion in 2000 to USD 268.3 billion in 2004 (EXIM, 2006).
[4] The medium and long-term businesses refer to the credit extended between one and five year and over fiver years, respectively.

from that of its public counterparts (van der Veer, 2010), conclusions resulting from incomplete data might be biased. On the contrary, SINOSURE is the only export credit insurer in China, offering both short-term and long-term businesses. This unique market structure makes our data more complete.

Our paper presents the following main theoretical findings. First, offering *OA* terms in international trade, actively or passively, can expand exports levels. As a result, *OA* terms can be used as a competitive marketing strategy in securing international contracts and in boosting exports sales. Second, taking into account international regulations and business practice, export credit insurance programs cannot be effective policy tools in expanding exports under the risk neutral assumption. Nevertheless, once changing this assumption to risk-aversion, we theoretically approve their effectiveness without breaking the legal and/or financial obligations. Finally, regardless of risk neutrality or risk aversion, our theoretical results find that it is the insurance premium that matters for the effectiveness of these programs.

The empirical findings from both static and dynamic models are in line with our theoretical conclusions. For example, the elasticity estimate in the static model shows that exports would, *ceteris paribus*, increase by 0.088 percent if SINOSURE expands its insurance programs by 1 percent. Given that 7 percent of Chinese ordinary exports were insured in 2006, this corresponds to a 1.26 multiplier, i.e., 1 unit of insurance leads to 1.26 units of exports.[1] Moreover, the empirical results shed some light on the role of export credit insurance in diversifying export destinations, especially to relatively poor (and usually highly risky) countries. Finally, the sensitivity analysis confirms the robustness of our empirical results.

The remainder of this paper is organized as follow. In section 2, we provide a brief introduction to international payment terms and why export credit insurance might matter. Section 3 presents our theoretical framework. Section 4 describes data, econometric specifications, and estimation results. We provide the concluding

[1] The calculation follows Felbermayr and Yalcin (2011), With exports being 100 and insurance level 7, a 1 percent increase in insurance (level change 0.07) leads to a 0.088 percent increase in exports (level change of 0.088). The insurance multiplier is 0.088/0.07=1.26.

remarks in section 5.

4.2 Why Might Export Credit Insurance Matter?

Many factors, including quality, price, and delivery date, affect the success of exporting transactions (Marx, 1963). Nevertheless, international payment terms and availability of trade finance have been becoming important determinants in promoting exports. Broadly speaking, these payment terms in international trade can be classified into three types: i) O*pen Account* terms (OA), where payment is due after the arrival of the goods; ii) *Cash in Advance* terms (CIA), where payment is due before shipment is made; and iii) *Bank-Intermediated* terms, where banks provide letters of credit (LCs) guaranteeing payment on behalf of importers upon presentation by importers' banks of shipping documents or other documentary collection services (e.g. *Document against Payment* and *Document against Acceptance*). For a detailed description of these payment terms, see US Department of Commerce (2008).

Bank-Intermediated terms, especially *LCs*, has been the dominant form of payment in international trade for centuries, but its popularity is significantly fading due to the expensive fees charged by banks, restrictive and inconvenient terms as well as recent innovations of financial products and information technology (Park, 2011). In 2008-2009, for example, the aggregate value of *LCs* represented only about 10 percent of the value of world merchandise trade (SWIFT, 2009). Exporters might reasonably prefer *CIA*, as it is clearly risk-free except for consequences arising from the potential non-delivery of goods by themselves. In practice, however, the increasing sales of capital goods in international markets, the change from sellers' to buyers' markets, and the increasing industrialization in developing countries since the 1950s have made *OA* the most common method of payment in international trade (Guadagnoli, 1968). For example, Asmundson et al. (2011) and IMF (2009) respectively report that 38-45 and 42-48 percent of global merchandise trade is done through OA, whereas Mann (2000) suggests this number as high as 72 percent. In the 2009 International Credit & Collection Survey conducted by FCIB, more than 50 percent of respondents report OA as the top payment method (Schmidt-Eisenlohr, 2009).

Nevertheless, *OA*, as the most risky payment method for exporters, also results in more inconveniences for exporters, though it does enhances exporters' competitiveness in international markets and induce export opportunities. On the one hand exporters usually face more non-payment risks[1] that are different from those faced by firms who do not engage in international trade. Because of cross-country differences in legal systems, languages, and willingness of governments to enforce international contracts, it is more difficult for exporters to enforce contracts across borders. On the other hand, exports take significantly more time in physical transportation, especially by sea, than domestic sales. Amiti and Weinstein (2009) estimate that the median amount of time in transit is approximately two months. In other words, exporters usually will not receive payment for 2-6 months after shipping the goods under OA terms. Furthermore, few financial institutions accept uninsured foreign account receivable as collateral to provide financing, which implies more working capital required by exports under OA than by exports under other payment terms or domestic sales.

[***Insert Figure 4.1***]

Export credit insurance could be a useful financing and sales tool for exporters. First, export credit insurance allows exporter to offer competitive OA terms to foreign buyers, while protects exporters against the risk of non-payment by foreign buyers. With reduced risk, exporters could compete more vigorously in the global market, increase export sales, and establish market share in emerging and developing countries. Kim and Rhe (2009) argue that export credit insurance, coupled with other supporting measures by the Korean government, rapidly transforms South Korean firms such as LG and Samsung from domestic players to full-fledged multinational firms. Second, financial institutions are more willing to increase exporters' borrowing capacity and to offer attractive financing terms, once foreign account receivables are

[1] Posner (1997) classifies these risks into three types, i.e. commercial, political and economic risks. Commercial risks arise from non-payment of an obligation because of business events such as bankruptcy, insolvency, and protracted default; political risks include restrictions of foreign exchange conversion, of transfer payment, cancellation of import or export permit imposed by the government of the importing country; economic risks arise from the weakness of a country's economic conditions.

insured by ECAs. For example, as the risk weight of export credit insurance financing is set to zero in China, Chinese lenders are more likely to offer financing to exporters. In 2010 about 20 percent of the US$ 196 billion insured exports received export credit insurance financing (SINOSURE, 2010). Third, by adjusting premium and coverage policy, export credit insurance could also be a policy instrument for political and/or diplomatic goals. Figure 4.1 presents the diagram of an export credit insurance transaction.

Moreover, export credit insurance programs contribute to improving trade balances, increasing exchange reserves, and reducing domestic unemployment (Mutharika, 1976). UNCTAD (1976) claims that the involved countries providing these programs benefit directly in three ways, i.e., in reducing the costs of information collection on importers, in providing collaterals for exporters in acquiring finance, and in creating export promotion value by protecting exporters from non-payment losses. For a detailed historical evolution of export credit insurance and product description, see Gianturco (2001).

4.3 Theoretical Framework

Following prior studies on payment terms (Schmidt-Eisenlohr, 2009) and insurance (Funatsu, 1986), we now model the impact of payment terms on an importer's decision and the role by export credit insurance programs in mitigating risk as well as promoting exports. Unlike Schmidt-Eisenlohr (2009), in our two-country-two-date model, it is the importer instead of the exporter that exercises more bargaining power on the choice of payment terms, as the international trade has changed from a seller's to a buyer's market. Moreover, our two-country-two-date model only allows for *OA* terms and *CIA* terms, since *Bank-Intermediated* terms account for a rather small share of international trade. For simplicity, we assume that at $t=0$ the goods are produced in the exporting country i and delivered, and at $t=1$ the goods arrive in the importing country j and are sold by the importer. If the importer pays the exporter at $t=1$, this export transaction is conducted on *OA* terms; otherwise, when the importer pays the exporter at $t=0$ it is on *CIA* terms.

Given a buyer's market situation in international trade, we assume that the exporter is a price-taking competitive firm, i.e., exporting at p^{CIA} under *CIA* and p^{OA} under *OA*, respectively. However, the revenue of the importer, $R(x)$, is strictly increasing and concave in terms of quantity sold, i.e., $R^{'}(x) > 0$ and $R^{''}(x) < 0$. The objective of both trading partners is to maximize the expected utility of profits, where the utility function satisfies $u^{'}(\cdot) > 0$ and $u^{''}(\cdot) \le 0$. Both the importer and exporter face uncertainties, represented by λ_i for the exporting country i and λ_j for the importing country j that might make them unable to fully honor contractual obligations or to receive the full payment. These uncertainties can be classified into three types, i.e., commercial, political, and economic (Posner, 1997). Commercial uncertainties arise from non-payment of an obligation because of business events such as bankruptcy, insolvency, and protracted default; political uncertainties include restrictions of foreign exchange conversion, of transfer payment, cancellation of import, or export permit imposed by the government of the importing country; economic ones arise from the weakness of a country's economic conditions. λ_i and λ_j are independent random variables, distributed between 0 and 1, with $E(\lambda_i) = \overline{\lambda_i}$ and $E(\lambda_j) = \overline{\lambda_j}$. For example, under *OA* terms, the unanticipated restriction of transfer payment in the importing country j implies that the importer can only pay λ_j of the agreed payment, $p^{OA}x$. On the other hand, under *CIA* terms, the unanticipated political instability in the exporting country i means that the exporter can only produce and deliver λ_i of the contract quantity, x. Moreover, both exporters and importers under different payment terms are perfectly and costlessly arbitraged. As a result, under the assumption of zero risk premiums, p^{CIA} and p^{OA} should follow lemma 1.

Lemma1. *In the exporting country:* $p^{CIA} = \dfrac{p^{OA}\overline{\lambda_j}}{1+r_i}$; *in the importing country:*

$p^{CIA} = \frac{p^{OA}\overline{\lambda_i}}{1+r_j}$, where r_i and r_j are the costs in country i and j, respectively.

Proof: See the Appendix C.

4.3.1 Importers

As an exporter rarely has a unique product or service that it can exercise market power in offering payment terms in its favor, we first determine the importing behavior under different payment terms. A representative exporter is considered in the analysis.

Under *CIA* terms, the importer's decision problem at $t=1$ is described as follows:

$$Max_x E\left[u\left(\pi_j^{CIA}\right)\right] = Max_x E\left[u\left(\lambda_i R(x) - (1+r_j)p^{CIA}x\right)\right] \tag{4.1}$$

Similarly, under *OA* terms the importer optimizes its following objective function at $t=1$:

$$Max_x E\left[u\left(\pi_j^{OA}\right)\right] = Max_x E\left[u\left(R(x) - \lambda_j p^{OA}x\right)\right] \tag{4.2}$$

Lemma2. *When the importer is risk averse, he always imports more under the OA terms than under the CIA terms regardless of the risk level of his country; when the importer is risk neutral, he imports more under the OA terms than under the CIA terms only if his country isn't risk free.*

Type of Importer	Risky Importing Countries ($0<\overline{\lambda_j}<1$)	Risk-Free Importing Countries ($\overline{\lambda_j}=1$)
Risk neutral	$x^{OA} > x^{CIA}$	$x^{OA} = x^{CIA}$
Risk averse	$x^{OA} > x^{CIA}$	$x^{OA} > x^{CIA}$

Proof: See the Appendix C.

Lemma 2 above shows the export-promoting characteristic of *OA* terms in international trade. As totally risk-free countries are rare in the real business world, offering *OA* terms can be an effective marketing strategy in securing business opportunities overseas and in expanding exports sales, regardless of the risk attitude of the importer.

4.3.2 Exporters and Export Credit Insurance

When exporters offer *OA* terms for their international sales, no matter whether passively or actively, they have to face increasing risks associate with non-payment possibilities. In this part, we compare export levels with- and without insurance programs. Without buying the insurance, the exporter at $t=0$ maximizes the following objective function:

$$\underset{x}{Max}\ E\left[u\left(\pi_i^{OA,N}\right)\right] = Max_x E\left[u\left(\frac{\lambda_j p^{OA} x}{1+r_i} - f(x)\right)\right] \tag{4.3}$$

where $f(x)$ is the exporter's cost function satisfying $f^{'}(x) > 0$ and $f^{''}(x) > 0$.

If the exporter buys insurance, he pays the premium, w, for his $p^{OA}x$ export value at $t=0$; at $t=1$ if the risk occurs, the exporter will be compensated by his loss. The exporter makes decisions on export volume at $t=0$, maximizing the following objective function:

$$\underset{x}{Max}\ E\left[u\left(\pi_i^{OA,I}\right)\right] = Max_x E\left[u\left(\frac{p^{OA} x}{1+r_i} - f(x) - wp^{OA}x\right)\right] \tag{4.4}$$

The premium is predetermined by the insurance contract. It is argued that government-supported ECAs can achieve their export promoting goals by adjusting insurance premium. Therefore, there are three insurance contracts available based on the following pricing options:

Very fairly priced: $w < \dfrac{(1-\overline{\lambda_j})}{1+r_i}$; Fairly priced: $w = \dfrac{(1-\overline{\lambda_j})}{1+r_i}$; or Over priced:

$$w > \frac{(1-\overline{\lambda_j})}{1+r_i} \tag{4.5}$$

We now compare the optimal exports levels with and without insurance, taking into account risk neutrality and risk aversion.

Lemma 3. *When the exporter is risk neutral, export credit insurance programs can boost more exports only if the insurance is very fairly priced; when the exporter is risk averse, both very fairly priced and fairly priced insurance programs can always boost* *more exports. The export-promoting effectiveness of over priced insurance programs for depends on risk-aversion levels.*

Insurance premium	Risk Neutral	Risk Averse
Very fairly priced	$x^I > x^N$	$x^I > x^N$
Fairly priced	$x^I = x^n$	$x^I > x^N$
Over priced	$x^I < x^N$	Depending on risk-aversion levels

Proof: See the Appendix C.

[**Insert Figure 4.2 Here**]

In practice, export subsidies are prohibited by international regulations, and official ECAs are required to reach a break-even position in the long run. As a result, offering very fairly priced insurance programs is legally and financially impossible. Moreover, as non-for-profit public entities, ECAs seldom charge over-priced premiums given their export promotion mandate. Our theoretical results show that, when exporters are risk neutral, fairly priced export credit insurance cannot be an effective policy instrument of export promotion. Nevertheless, the risk-neutral assumption might be admittedly restrictive. When exporters are risk averse, the insurance programs, even fairly priced, do effectively promote more exports without breaking their legal and/or financial obligations. Even when over priced, export credit insurance programs may still promote more exports, depending on the exporters' risk aversion attitudes. Figure 4.2 simulates the relationship between risk aversion levels and the export-enhancing effect of export credit insurance programs. These results under the risk-averse assumption are relevant to the current debate whether governments should get directly involved in providing export credit insurance.

4.4 International Trade and Export Credit Insurance in China

Given the unique characteristics of Chinese exports and its export credit insurance market, we briefly provide some background information before our empirical work. More importantly, we explain why we use ordinary exports instead of total exports as the dependent variable in our empirical work.

China's increasing integration into the world economy over the past three decades, especially after its entry to the World Trade Organization (WTO), has resulted in an astounding growth in exports. During the period of 1981 and 2010, China's exports expanded from only USD 22 billion to USD 1,577 billion, with its share of the world merchandise exports increasing from 1.1 percent to over 10 percent during the same period. One startling feature of China's exports is its processing exports, which have accounted for more than half of the total exports since 1995. As a popular export pattern in many developing countries, processing exports are characterized by importing raw materials or other intermediate inputs and, after assembling or processing domestically, then re-exporting the final products to the world market. Jointly with foreign-invested enterprises (FIEs), processing export regime has been the driving force of China's rapidly growing exports and contributed to China's export sophistication (Yu, 2010). Unlike processing exports, ordinary exports are usually carried out by domestic firms, referring to the business activities of purchasing raw materials as well as producing domestically and exporting final products. In this paper we only use ordinary exports as a dependent variable. On the one hand, most of the processing exports occur as intra-firm transactions without the need of export credit insurance; on the other hand, the empirical evidence suggests that neither processing exports nor FIEs contribute to China's real economic growth, though they are main contributors to the global upgrading of China's exports; instead, the growth gains are only limited to the ordinary exports undertaken by domestic firms (Jarreau and Poncet, 2011).

[**Insert Figure 4.3 Here**]

In order to promote its exports, the Chinese government tentatively began its export credit insurance program through the People's Insurance Company of China (PICC) in 1985, via its branch companies in Shanghai and Tianjin, respectively. In 1988, the State Council officially authorized the PICC to provide this program nationwide on behalf of the Chinese government and, at the same time, set up the export credit insurance fund. Initially, PICC only focused its support to promote the export of Chinese mechanical and electronic products on short-term credit terms while medium-and long term insurance schemes were not provided until 1992.[1] In 1994 the Export-Import Bank of China (China Eximbank), the official export credit financing agency wholly owned by the Chinese government, was established and also provided export credit insurance in addition to its direct export credit business. Due to the discretionary functions assigned to each agency, there was an obviously significant overlap among them, causing low efficiency. By October 2001, only USD 18 billion exports had been accumulatively insured.

[***Insert Table 4.1 Here***]

In 2001, China became a member of the World Trade Organization (WTO). Partly due to its "going out" initiative and the shortcomings of this dual-oligopoly regime, the State Council created the China Export Credit Insurance Corporation (Sinosure) in 2001 as a wholly state-owned company with the register capital of RMB 4 billion,[2] combining the export credit insurance business from both China Eximbank and PICC. Nowadays, Sinosure is the only insurer specializing in export credit insurance in China. According to the figures reported by SINOURE, the volume of export credit insurance expanded more than 20 times between 2001 and 2007, from about US$ 1.45 billion to US$ 39.7 billion, which coincides by and large with the growth rate in ordinary exports, from US$ 111.88 billion to US$ 538.46, during the same period.

4.5 Empirical Effect of Export Credit Insurance on Exports

4.5.1 Model Specification and Data

In this section, we develop an empirical model to test our theoretical results. More precisely, we use the gravity model that incorporates insurance variables as our variables of interest and also controls for other factors of bilateral trade. Not only has the gravity model become the main framework for conducting empirical analysis of international trade, it also has been extensively used in the empirical literature of export credit insurance (see, Egger and Url, 2006; Moser et al., 2008; Baltenspergen

[1] Usually there are two types of medium-and long term export credit insurance, i.e., buyer's credit insurance and supplier's credit insurance. PICC issued its first supplier's credit insurance policy in 1993 for the export of agricultural machinery to Cuba and buyer's credit insurance policy in 1994 for the power station project in Indonesia, respectively.
[2] 1 USD=6.49 RMB, http://www.oanda.com, 19th May 2011.

and Herger, 2009; van der Veer, 2010; Janda et al., 2010 Felbermayr and Yalcin, 2011). We estimate the following specification of the gravity model:

$$\ln EXP_{i,t} = \alpha_0 + \alpha_1 Insurance_{i,t} + \alpha_2 \ln PCGDP_{i,t} + \alpha_3 \ln EXC_{i,t} + \alpha_4 \ln MI_{i,t} + \alpha_5 \ln GFCF_{i,t}$$

$$+ \alpha_6 RISK_{i,t} + \alpha_7 \ln DIST_i + \alpha_8 BORD_i + \alpha_9 LANG_i + \mu_i + \varepsilon_{i,t} \qquad (4.5.1)$$

where $\ln(.)$ donates the logarithmic operator, i index for trade partner, and t index for years between 2001 and 2006, μ_i is the unobservable trading partner effect, and $\varepsilon_{i,t}$ is the stochastic error term assumed to have a constant variance as well as a zero mean, respectively.

$EXP_{i,t}$ is the dependent variable, denoting Chinese ordinary exports to trade partner i in year t. $Insurance_{i,t}$ is the variable of interest in our model specification. As in Felbermayr and Yalcin (2011), $Insurance_{i,t}$ is either the logarithm of real insured exports to trade partner i in year t ($\ln ECI_{i,t}$), or a dummy variable equal to 1 if exports to trade partner i in year t are insured ($DECI_{i,t}$). While the coefficient of $\ln ECI_{i,t}$ measures the elasticity of exports with respect to the insurance quantity, the estimate on $DECI_{i,t}$ measures to what extent the availability of export credit insurance affects exports value. The estimated coefficient α_1 is expected to be positive, as export credit insurance programs are supposed to promote exports that might not be realized otherwise. $PCGDP_{i,t}$ is the GDP per capital of trade partner i in year t and used as a proxy for import demand. All these variables are converted into real US dollars with 2000 as the base year.

$EXC_{i,t}$ represents the exchange rate between trade partner i and China in year t; $MI_{i,t}$ is the share of manufacturing imports in total merchandise imports for trade partner i in year t, serving a proxy of its relative factor endowment; $GFCF_{i,t}$ is the gross fixed capital formation to GDP ratio, measuring the investment rate of trade partner i in year t; $RISK_{i,t}$ measures the risk level for trade partner i in year t with 0 for the safest countries and 7 for the riskiest ones; $DIST_i$ is the weighted distance between China and trade partner i; $BORD_i$ is a binary variable with 1 if trade partner i share a border with China; $LANG_i$ is a binary variable with 1 if trade partner i share a common language with China. Table 4.2 summarizes the definitions, sources and measurement unit of the variables.

[***Insert Table 4.2 Here***]

Let us now turn to the presentation of the data set. Our ordinary exports as well as insurance data cover 201 trading partners and are obtained from DRCNET Statistical database System and SINOSURE, respectively. With the data over the period between 2001 and 2006, this would first give us a total of 1206 observations. As our model specification includes a number of control variables, we match the exports and insurance data with other variables in equation (5.1) from various sources. After eliminating missing values, this leaves us an unbalanced panel data of 181 trading partners and 1030 observations between 2001 and 2006 (see appendix A for the list of countries and territories included in the data set). We do not require a balanced panel and use all available observations. Nevertheless, we must take into account a relatively short time series with respect to a relatively large number of trading partners. In our model specifications, we use the logarithmic transformation to mitigate against heteroscedasticity and also to convert estimated coefficients into elasticity for direct comparison. However, since 231 observations with zero value for the insurance variable, taking logarithmic transformation of insured ordinary exports ($ECI_{i,t}$) would reduce our data set to 799 observations. This not only substantially reduces the number of retained observation but also might arises a loss of information. As the common practice is to add a small constant to the data before logarithmic transformation, we add 1 to $ECI_{i,t}$ for its logarithmic transformation. Admittedly, this practice is arbitrary and different constants might result in inconsistent results. Nevertheless, the sensitivity analysis that chooses different constants (0.5 and 0.1) or deletes zero-value observations confirms the robustness of our results. For the sensitivity analysis result, see appendix B. Moreover, we also categorize these trading partners into four income groups according to the World Bank country classification criteria[1] and test the impact of export credit insurance across income groups. Table 4.3 reports the summary statistics and correlation matrix. Although our dataset is unbalanced, the average length of period for each trading partner in the dataset is 5.7 years, with 95% trading partners having observations at least 3 years. Consistent with previous studies, both insurance variables tend to correlate positively with export levels. Nevertheless, at this level of analysis, one should be cautious about drawing strong causal inferences from the estimates, as there might be a two-way causation between insurance variables and export levels.

[***Insert Table 4.3 Here***]

4.5.2 Estimation and Results

We estimate equation (5.1) using fixed effects (FE) estimation. First, the observations in our panel data cover most of China's trading partners worldwide and cannot be described as being random from a given population. Second, the Hausman test rejects random effects (RE) specifications no matter which insurance variable is used.

Before examining the FE estimation results, we would like to highlight the potential endogeneity issues of insurance variables. First, there might be a two-way causation between insurance variables and export levels. Since uninsured account receivables from foreign countries are usually not accepted as collaterals by financial institutions, the possibility that increasing exports result in purchasing more export credit insurance to get access to export financing is equally possible; second, unobserved common factors could determine both exports and insurance variables simultaneously, which can cause spurious correlation between the two variables of interest. Third, the insurance data can also suffer from measurement errors. The unique characteristic of export credit insurance is that exporters, after each export

[1] The four groups include low-income countries, low-middle income countries, upper-middle income countries, and high-income countries. The historical classifications during the sample period could be obtained at: http://data.worldbank.org/about/country-classifications/a-short-history

delivery, should declare their transactions to insurers for coverage. Given different reporting frequencies, measurement errors might arise. To address these potential heterogeneity issues that could cause estimation bias, we instrument insurance variables with their lagged values in our fixed effects estimation. Panel C of Table 4.3 shows the positive correlation between insurance variables and their lagged values, as well as between lagged values and exports levels.

We use the Hansen's *J* statistic and Cragg-Donald *F* statistic or Kleibergen-Paap rk *F* statistic to choose valid instrument sets. To a large extent, the consistency of the coefficient estimates by the IV estimators depends on the validity of instrument sets used in our estimation. We use the Hansen's *J* statistic to carry out the test of over-identification when the model is over identified, namely the number of included endogenous variables is less than the number of instruments excluded from equation (5.1). The *J* statistic follows a chi-squared distribution under the null hypothesis that our instruments are valid. Even when the parameters can be identified, estimates from IV regressions might still be biased because of a weak identification problem, i.e. exogenous variables are only weakly correlated with the instruments. The test of weak identification can be carried out by Cragg-Donald *F* statistic (not robust to non-i.i.d error) or Kleibergen-Paap rk *F* statistic. Based on these criteria, two, three, and four lags of variables of interest are used as instrumental variables.

[***Insert Table 4.4 Here***]

The FE estimation results of equation (5.1) with (column (5) and (6)) and without (column (1) and (3)) instruments are shown in Table 4.4. For comparison, we also report the results from RE estimation in column (2) and (4). First, as the *p*-value of *J*-statistic reported in table 4.4 is 0.212, we cannot reject the null hypothesis of the validity of instruments.[1] As a result, the instrument sets used in our FE IV estimations are valid. Second, The statistic values for the weak identification test are 13.208 and 49.578, respectively, both of which exceed the Stock-Yogo critical value for maximum size at 10%. Thus, we cannot reject the null hypothesis that IV estimators do not suffer from weak identification, supporting our results reported in (5) and (6). Finally,

[1] In (6) only one lag is used as an instrument; thus, no over-identification test is carried out.

we use the chi-squared Hausman test for the endogeneity of insurance variables. As the *p*-values for each model specification are 0.106 and 0.162, respectively, the null that both FE and FE IV estimators are consistent cannot be rejected. This implies that estimation results in (1) and (3) do not seem to suffer from endogeneity of insurance variables. Therefore, we now focus on FE estimates in columns (1) and (3).

All model specifications fit the data well, with results meeting theoretical expectations. Consistent with prior empirical studies, the estimates of the insurance variable, either the log one or the binary one, suggest a significantly positive effect on exports across all specifications. In column (1) the point estimate of log insured exports is 0.088, suggesting that exports would expand, *ceteris paribus*, by 0.088 percent given a one percent increase in insured exports. As 7 percent Chinese ordinary exports were insured in 2006, the insurance multiplier based on back-on-envelope calculations is 1.26.[1] Additionally, the point estimate of 0.434 in column (3) suggests that once the insurance programs were used for a trading partner, exports to this export destination could be, *ceteris paribus*, 43.4 percent larger than otherwise these programs were not available. More interestingly, our elasticity estimate seems bigger than those of prior studies on developed countries using similar empirical estimation strategies.[2] As exporters in developing countries usually trade in low-margin products in long supply chains, they usually face more risk exposures in foreign markets and more reply on trade finance to support their exports. Thus, our empirical results could be relevant to the current debate whether developing countries should establish their own export credit agencies. Nevertheless, our elasticity point estimate also indicates diminishing returns to scales, suggesting that large expansions of export credit insurance programs might not be desirable.

Regarding the other explanatory variables, the estimate of GDP per capita, risk levels of trading partners, and exchange rates meet our expectations, namely, China

[1] The calculation follows (Felbermayr and Yalcin, 2011). With exports being 100 and insurance level 7, a 1 percent increase in insurance (level change of 0.07) leads to a 0.088 percent increase in exports (level change of 0.088). The insurance multiplier is 0.088./0.07=1.26.

[2] For example, 0.014 for Germany with static fixed effect estimation (Felbermayr and Yalcin, 2011), 0.005 for Czech Republic with static fixed effects estimation (Janda et al., 2010), and 0.023 for Germany with static random effects estimations (Moser et al., 2008). However, one should be cautious with direct comparison due to different sample period, variables of interests, etc.

exports, *ceteris paribus*, more to trading partners with high import demand, measured by GDP per capita, and whose currency appreciates against Chinese yuan; but less to those with higher risk levels. However, the estimates of the ratio of manufacturing imports to total merchandise imports as well as the share of gross fixed capital formation to GDP are statistically insignificant, which is inconsistent with findings of prior studies. Since the bulk of Chinese ordinary exports went to developed countries in our sample period,[1] this noticeable result implies dissimilar factor endowment between China and its main trading partners during the sample period.

4.5.3 Dynamic Export Credit Insurance Effect

Given the potentially dynamic nature of the data-generating process, static estimation results can be biased (Egger and Pfaffermayr, 2004; Moser et al., 2008). Moreover, export credit insurance, coupled with repeated transactions, can reduce asymmetric information. Once trading partners establish their reputation, exports volume could expand even without costly insurance. Therefore, we incorporate the dynamic process in the following model specification to take into account the dynamic effect of export credit insurance.

$$\ln EXP_{i,t} = \beta_0 + \beta_1 \ln EXP_{i,t-1} + \beta_2 Insurance_{i,t} + \beta_3 \ln PCGDP_{i,t} + \beta_4 \ln EXC_{i,t} + \beta_5 \ln MI_{i,t} + \beta_6 \ln GFCF_{i,t} + \beta_7 RISK_{i,t} + \beta_8 \ln DIST_i + \beta_9 BORD_i + \beta_{10} LANG_i + \mu_i + \varepsilon_{i,t} \tag{4.5.2}$$

With the lagged dependent variable included in explanatory variable set, the fixed effects estimation might yield biased results (Anderson and Hsiao, 1981). Instead, we use the system GMM estimator (Blundell and Bond, 1998) to estimate exports-insurance relation while including both fixed effects and past exports to control for unobservable heterogeneity and state dependence, respectively.

[***Insert Table 4.5 Here***]

The system GMM estimation results of equation (5.2) are shown by column (2)

[1] For example, the U.S. and EU accounted for 17% and 21%, respectively, Chinese ordinary exports in 2006.

and (4) in table 4.5. For comparison, we also report the results from the pooled OLS estimation in column (1) and (2). Again, before explaining the estimates, we empirically test our key exogeneity assumption in (5.2) that historical exports as well as trading partners' characteristics are exogenous to current shocks or innovations in exports. All system GMM estimations pass the Hansen test of over-identification. With *p*-values of 0.826 and 1.000 respectively, this indicates the validity of the entire set of over-identification conditions and suggests no endogeneity issues present in our models. Table 4.5 also reports *AR* (1) and *AR* (2) tests for the null hypothesis of no first or second order correlation, respectively. Under the assumption of our model specification, if enough lags have been included to account for dynamic endogeneity, there should be a serial correlation in the residuals in first-order difference but no serial correlation in second-order difference. All models pass the *AR* tests. With *p*-values of *AR* (1) less than 1% and of *AR* (2) larger than 1% in all estimations, this suggests the existence of first-order serial correlation but absence of second-order serial correlation. Finally, the *p*-values of the difference-in-Hansen test of 0.947 and 1.000, respectively, implying that we cannot reject the null hypothesis that the additional subset of instruments in the system GMM estimation is exogenous.

The point estimates of the lagged dependent variable, 0.375 in column (2) and 0.374 in column (4) respectively, are statistically significant, which validates the dynamic data-generating process. The estimates of the insurance variables are statistically positive, implying a positive impact of export credit insurance on exports. Take the log insurance variable for example. The short-term elasticity estimate is 0.033, meaning a 0.033 percent export expansion resulting from a 1 percent increase in insurance provision. Taking into account the long-term effect, the elasticity estimate is 0.052.[1] With a 7 percent Chinese ordinary exports insured in 2006, the insurance multipliers based on back-on-envelope calculations are 0.47 for the short-term and 0.74 for the long-term, respectively.[2] Thus, these results indicate the effectiveness of

[1] 0.033/(1-0.375)=0.052

[2] These calculations again follow Felbermayr and Yalcin (2011). With exports being 100 and insurance level 7, a 1 percent increase in insurance (level change of 0.07) leads to a 0.033 percent increase in exports short-term. The short-term insurance multiplier is thus 0.033/0.07=0.47. Similarly, the long-term insurance multiplier is 0.052/0.007=0.74.

export credit insurance programs in promoting exports. As for the other explanatory variables, the estimates on GDP per capital, exchange rate, and risk are statistically significant with expected signs, in line with our static model estimations. The estimates of ratio of gross fixed capital formation to GDP and of share of manufacturing imports to total merchandise imports are again statistically insignificant, rejecting the hypothesis of similar factor endowment. Moreover, distance, border effect and language effect do not seem to play a significant role in Chinese exports promotion, at least in our sample period.

4.5.3 Insurance Effect across Income Groups

In addition to risk reduction and promoting exports, another main purpose of export credit insurance programs is to diversify export destinations and thus to decrease excessive exposures to specific destinations. During our sample period, the share of ordinary exports to low-income as well as high-income countries decreased from 8.6 percent and 75 percent in 2001 to 7.3 percent and 70 percent in 2006, respectively. The same indicator for lower-middle-income as well as upper-middle-income countries jumped from 8.3 percent and 8 percent in 2001 to 10 percent and 13 percent in 2006. Therefore, we re-estimate (5.1) using fixed effects estimation and (5.2) using system GMM estimation across income groups to test the possible roles played by export credit insurance in changes in export destinations.

[***Insert Table 4.6 Here***]

Table 4.6 reports both static and dynamic insurance effects across income groups. The estimation results show that, in the case of static model, China's export credit insurance programs positively promote exports to all income groups except for upper-middle-income countries. In terms of elasticity estimate magnitude, the insurance effect is strongest for lower-middle-income countries, with 1 percent more insurance provision leading to a 0.091 percent increase in exports. To better understand the magnitude across income groups, we again calculate insurance multipliers. In 2006 4.32 percent exports to low-income countries, 5.41 percent to lower-middle income countries, and 6.01 percent to high-income countries were insured, the corresponding multipliers for each income group are 1.37, 1.68, and 0.98, This suggests that China's export credit insurance programs boost more exports to relatively poor countries, implying its mission achievement, i.e., reducing excessive dependence on few high-income export destinations and diversifying exports markets. However, our dynamic model estimation shows that the insurance effect is statistically significant only for high-income countries.

4.6 Conclusions

It is not until the recent economic and financial crisis that export credit insurance comes to the attention of academic researchers. While more than 10 percent of global trade is covered by export credit insurance, there is a lack of theoretical foundation for understanding its nature, and no empirical work in the context of developing countries. In this paper, we present such a theoretical model and empirical evidence to fill in these gaps.

The contribution of this paper is threefold. First, we show how *OA* terms can be used as an effective marketing tool in securing international contracts and in expanding export sales. In particular, offering OA terms is more necessary for exporters located in developing countries because of their weak bargaining power and usually low-value-added products. Second, we show that export credit insurance programs, under the risk aversion assumption, boost exports without breaking their legal and financial obligations. Finally, our empirical results are in line with those of the theoretical models. For example, the elasticity estimate in static models shows that exports would, *ceteris paribus*, by 0.088 percent, which corresponds a 1.26 insurance multiplier. Moreover, the insurance effect across income groups shows that these programs diversify export destinations and reduce excessive exposures to specific country groups.

Our results also suggest a number of policy implications. First, in order to secure international contracts and to expand export levels, governments shall encourage their exporters to use competitive Open Account (OA) terms. This is more important for exporters located in developing countries, as they trade in low-margin products in long supply chains and have less bargaining powers. Second, in response to export market frictions under OA terms, national governments shall establish their own export credit agencies (ECAs) to underwrite risks and to provide trade financing, especially when financial markets are underdeveloped. Finally, the effectiveness and efficiency of these insurance programs to some extent depend on pricing and policy. It is the price rather than availability of export credit insurance that matters for export promotion.

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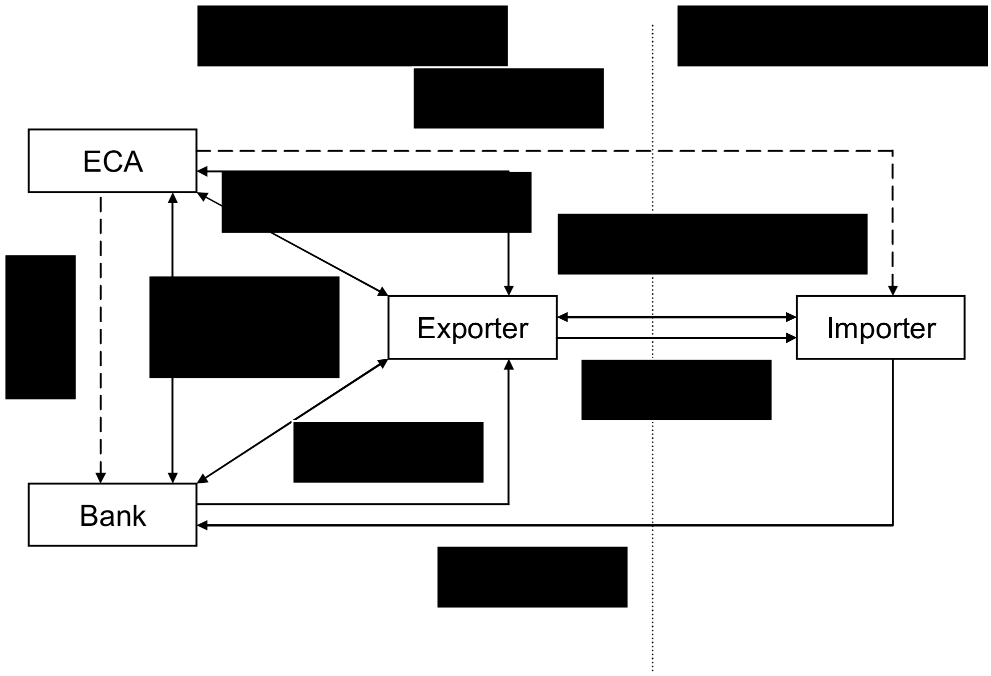
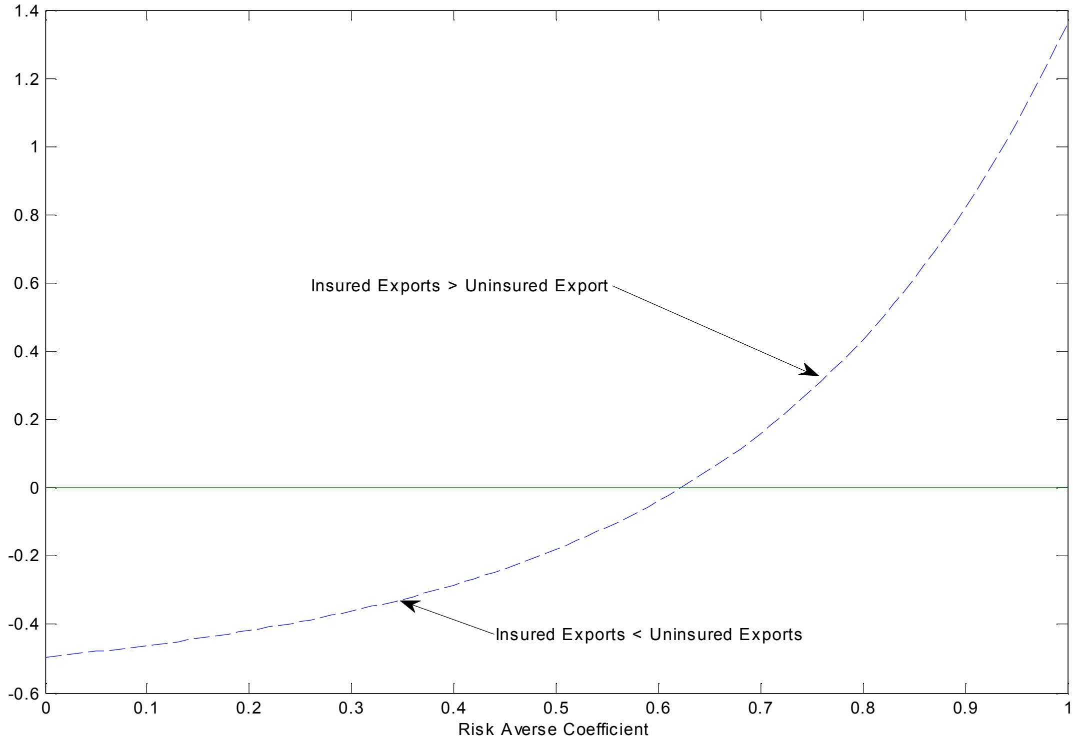
Figure 4.1: Export Credit Insurance Diagram



Explanations:

1. The exporter negotiates with the importer and Export Credit Agency for export contract and insurance contract, respectively;
2. The exporter, Export Credit Agency, and bank sign a three-party financing contact using the insured account receivable as a collateral;
3. The exporter delivers the goods;
4. The bank provides export financing immediately after the shipment;
5. The importer fulfills its contractual obligation and transfers the payment directly to the bank.
6. If the importer default its payment, the Export Credit Agency pays the claims to the bank;
7. The Export Credit Agency negotiates with the importer and collects the debt;

Figure 4.2: Risk Aversion Levels and Export Credit Insurance



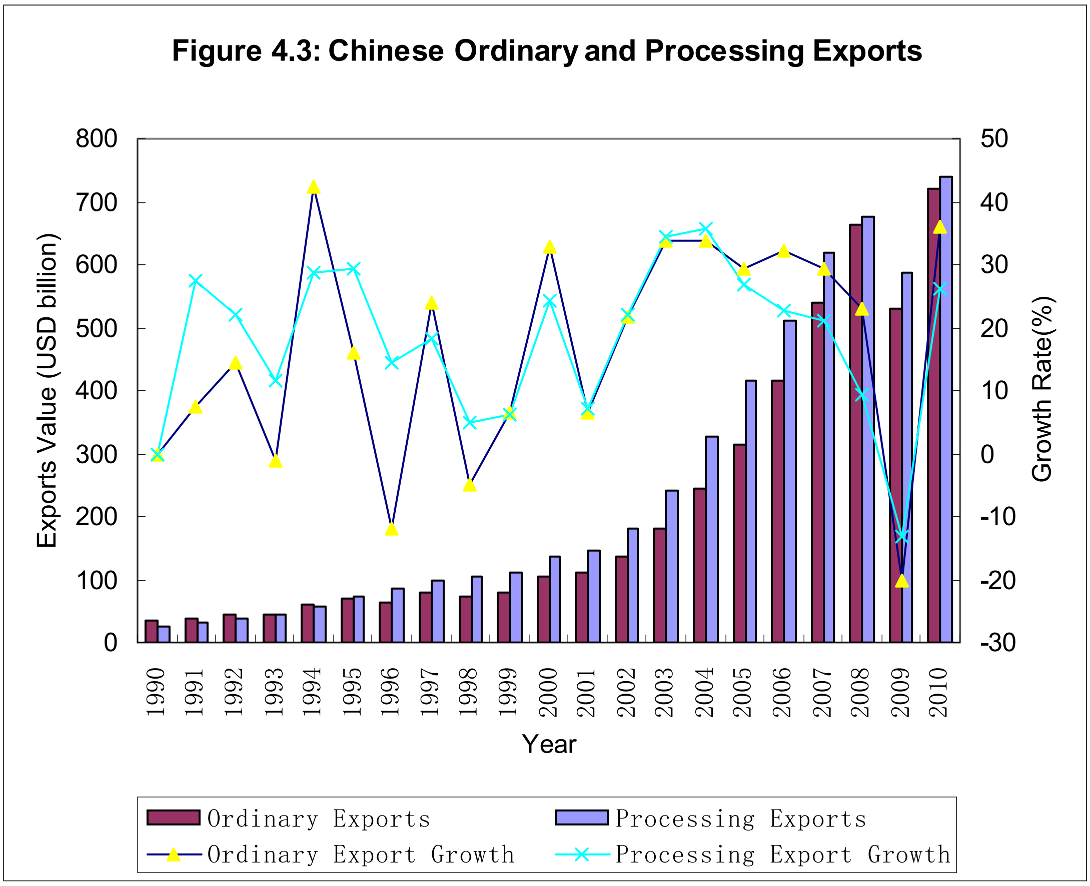
This figure plots the simulated relationship between risk aversion attitudes and the export-promoting effectiveness of export credit insurance program. We assume that a representative exporter uses the following constant relative risk aversion (CRRA) utility function:

$u(\pi) = \dfrac{\pi^{1-\gamma}}{1-\gamma}$, where γ is the risk aversion level.

Then whether insurance programs can boost more exports depends on $H(\gamma)$:

$$H(\gamma) = f'(x^I) - f'(x^N) = p^{OA}\left(\frac{1-\overline{\lambda_j}}{1+r_i} - w\right) - \frac{Cov(u'(\pi_i^{OA,N}), \lambda_j)}{E\left[u'(\pi_i^{OA,N})\right]} \cdot \frac{p^{OA}}{1+r_i}$$

$H(\gamma)$ is increasing with risk aversion levels (γ). When $H(\gamma)$ is positive (above the green line), export credit insurance programs can always be effective in promoting more exports, even when they are over priced.



Source: National Bureau of Statistics, China.

Table 4.1: Operation Performance of the SINOSURE, 2001-2007

Year	Export Insured (A)	Export Value: Total (B)	Export Value: Ordinary Export (C)	% Export Insured: Total A/B	% Export Insured: Ordinary Export A/C	Premium (D)	Recoveries (E)	Claims (F)	(D+E)/F
2001	1.45	266.10	111.88	0.55	1.30	N/A	N/A	N/A	N/A
2002	2.75	325.60	136.19	0.85	2.02	55.00	30.12	70.00	121.60
2003	5.71	438.23	182.03	1.30	3.14	100.00	18.46	98.00	120.87
2004	13.30	593.32	243.61	2.24	5.46	192.00	36.67	99.00	230.98
2005	21.21	761.95	315.06	2.78	6.73	278.00	33.85	110.00	283.50
2006	29.57	968.94	416.20	3.05	7.10	360.00	66.08	169.00	252.12
2007	39.63	1217.78	538.46	3.25	7.36	444.00	86.21	282.00	188.02

Unit: USD billion for A, B and C; USD million for D, E, and F;

Source: SINOSURE annual reports and China Statistical Yearbook, author's calculation.

This table presents the SINOSURE's business activities and operation results from 2001 to 2007. Column 2 is the exports insured by SINOSURE, while column 3 and 4 are China's total exports and general exports, respectively. In China exports are officially classified as Ordinary Trade Export and Processing Trade Export. For the latter, Chinese firms firstly import materials or components, and then export the finished products to their foreign suppliers. During the production process, the imported inputs remain the property of foreign suppliers. Thus, this kind of exports does not face non-payment risk. Therefore, when calculating the proportion of exports covered, the appropriate measure should be the ratio of exports insured to the ordinary exports. Column 7 is the total income by providing insurance services to exporters. Recoveries, also known as collection, are the amounts obtained from the foreign buyer following payment of a claim to an exporter or bank under insurance policies or guarantees. Usually, recoveries are shared between the insurer and the exporter in the same proportion as the percentage of cover and exporter retention under the insurance contract. Column 9 is the amount that the exporters file for payment under insurance policy resulting from nonpayment of the foreign buyer.

Table 4.2: Variable Description

Variable	Description	Source
$EXP_{i,t}$	Real ordinary exports from China to country i in year t in USD million. For calculating real ordinary exports, the US GDP deflator (base year 2000) is used.	DRCNET Statistical database System; Word Bank Development Indicators 2012
$ECI_{i,t}$	Real insured exports from China to country i in year t in USD million. For calculating real insured exports, the US GDP deflator (base year 2000) is used.	SINOSURE; World Bank Development Indicators 2012
$DECI_{i,t}$	Binary variable with value one if exports to country i in year t are insured	SINOSURE
$PCGDP_{i,t}$	Real GDP per capita of county i in year t in USD. For calculating real GDP per capita, the US GDP deflators with base year 2000 are used.	Undata; World Bank Development Indicators 2012; ADB;
$EXC_{i,t}$	Exchange rate for y i in year t. Local currency unit per Chinese yuan.	Undata; World Bank Development Indicators 2012.
$GFCF_{i,t}$	The percentage of gross fixed capital formation in GDP of country i in year t.	Undata; World Bank Development Indicators 2012
$MI_{i,t}$	The percentage of manufacturing imports in total merchandise imports of country i in year t.	Undata; World Bank Development Indicators 2012
$DIST_i$	Weighted distance between country i and China in thousand kilometers	CEPII
$LANG_i$	Binary variable with value one if country i share the common language with China.	CEPII
$BORD_i$	Binary variable with value one if country i share border with China.	CEPII
$RISK_{i,t}$	Risk of country i in year t on an eight-point scale, with 0 for the safest countries and 7 for the riskiest ones.	OECD

Table 4.3: Summary Statistics and Correlation

Panel A: Statistical Summary

Variable	Obs	Mean	Std. Dev.	Min	Max
$EXP_{i,t}$	1030	1211.78	3990.31	0.00	59046.58
$ECI_{i,t}$	1030	62.31	529.70	0.00	14941.95
$DECI_{i,t}$	1030	0.78	0.42	0.00	1.00
$PCGDP_{i,t}$	1030	8612.42	11934.98	108.90	65430.60
$EXC_{i,t}$	1030	79.21	315.89	0.01	3135.41
$GFCF_{i,t}$	1030	21.70	7.78	2.00	79.43
$MI_{i,t}$	1030	65.48	13.08	13.14	91.78
$DIST_i$	1030	9.49	3.86	1.17	19.11
$BORD$	1030	0.05	0.23	0.00	1.00
$LANG$	1030	0.03	0.17	0.00	1.00
$RISK_{i,t}$	1030	4.24	2.60	0.00	7.00

Panel B: Correlation: All

	$EXP_{i,t}$	$ECI_{i,t}$	$DECI_{i,t}$	$EXC_{i,t}$	$GFCF_{i,t}$	$MI_{i,t}$	$BORD$	$LANG$	$RISK_{i,t}$	$DIST_i$	$PCGDP_{i,t}$
$EXP_{i,t}$	1.00										
$ECI_{i,t}$	0.45	1.00									
$DECI_{i,t}$	0.16	0.06	1.00								
$EXC_{i,t}$	-0.01	-0.02	0.04	1.00							
$GFCF_{i,t}$	0.00	0.03	-0.10	0.05	1.00						
$MI_{i,t}$	0.12	0.09	0.28	0.04	-0.05	1.00					
$BORD$	0.13	0.14	0.05	0.11	0.06	0.04	1.00				
$LANG$	0.21	0.21	0.09	-0.04	0.00	0.20	0.26	1.00			
$RISK_{i,t}$	-0.27	-0.10	-0.13	0.19	-0.08	-0.38	0.05	-0.19	1.00		
$DIST_i$	-0.23	-0.09	-0.16	0.03	-0.11	-0.10	-0.38	-0.31	0.19	1.00	
$PCGDP_{i,t}$	0.33	0.14	0.03	-0.15	0.00	0.30	-0.06	0.14	-0.70	-0.12	1.00

Panel C: Correlation: Insurance and Exports

	$EXP_{i,t}$	$ECI_{i,t}$		$EXP_{i,t}$	$DECI_{i,t}$
$ECI_{ii,t-1}$	0.32	0.27	$DECI_{i,t-1}$	0.14	0.89
$ECI_{i,t-2}$	0.96	0.99	$DECI_{i,t-2}$	0.14	0.89
$ECI_{i,t-3}$	0.95	0.98	$DECI_{i,t-3}$	0.19	0.62
$ECI_{i,t-4}$	0.92	0.98	$DECI_{i,t-4}$	0.22	0.52
$ECI_{i,t-5}$	0.92	0.98	$DECI_{i,t-4}$	0.22	0.56

Table 4.4: Static Effect of Export Credit Insurance on Chinese Exports, 2001-2006

Dep. Variable: $\ln EXP_{i,t}$	FE (1)	RE (2)	FE (3)	RE (4)	FE (5)	FE (6)
$\ln ECI_{i,t}$	0.088***	0.257***	--	--	0.107***	--
	(0.014)	(0.023)			(0.026)	
$DECI_{i,t}$	--	--	0.434***	0.954***	--	0.653*
			(0.098)	(0.118)		(0.339)
$\ln PCGDP_{i,t}$	4.731***	0.440***	4.925***	0.609***	3.434***	4.699***
	(0.436)	(0.139)	(0.422)	(0.149)	(0.736)	(0.492)
$\ln EXC_{i,t}$	0.249***	0.167***	0.245**	0.188***	0.142	0.235**
	(0.091)	(0.050)	(0.098)	(0.065)	(0.144)	(0.099)
$\ln MI_{i,t}$	-0.222	0.114	-0.291	-0.266	-0.055	-0.398
	(0.213)	(0.186)	(0.226)	(0.239)	(0.198)	(0.248)
$\ln GFCF_{i,t}$	0.187	0.400**	0.185	0.571***	0.058	0.227
	(0.185)	(0.180)	(0.184)	(0.173)	(0.199)	(0.155)
$RISK_{i,t}$	-0.104*	-0.140**	-0.130**	-0.199***	-0.020	-0.190***
	(0.053)	(0.064)	(0.058)	(0.069)	(0.081)	(0.058)
$\ln DIST_i$	--	-1.140***	--	-1.129***	--	--
		(0.349)		(0.377)		
$BORD_i$	--	0.203	--	0.474	--	--
		(0.891)		(0.915)		
$LANG_i$	--	0.422	--	0.386	--	--
		(0.718)		(0.808)		
No. of Observations	1024	1024	1024	1024	312	831
No. of Countries	181	181	181	181	156	173
R-squared	0.442	0.245	0.446	0.233	0.051	0.431
Chi2 Hausman: FE Vs. RE	240.59***		321.00***		--	--
Weak Identification Test	--		--		13.208	49.578
Over identification: *p*-value	--		--		0.212	--
Endogeneity Test: *p*-value	--		--		0.106	0.162

Note: The table reports regression coefficients and, in parentheses, the associated robust standard errors. * significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent. All variables are in logarithm except for *RISK, BORD* and *LANG*. Original values of *ECI* are added 1 before logarithmic transformation. Constant and country effects included but not reported. In (1)-(4) within R-squared is reported; in (5) and (6) centered R-squared is reported. Variables of interest are assumed to be exogenous in (1)-(4), while (5)-(6) use lagged variable of interest as instruments to take into account potential endogeneity of variable of interest. We use Hansen J Statistic for over-identification test, Cragg-Donald Wald F statistic or Kleibergen-Paap rk Wald F statistic for weak identification test, and Hausman Chi2 for endogeneity test. All the models are estimated with Stata SE 11.2 using XTREG and XTIVREG2 command. In (5) and (6), two, three, and four lags of variable of interest are used as instrumental variables.

Table 4.5: Dynamic Effect of Export Credit Insurance on Chinese Exports, 2001-2006

Dep. Variable: $\ln EXP_{i,t}$	Pooled OLS (1)	System GMM (2)	Pooled OLS (3)	System GMM (4)
$\ln ECI_{i,t}$	0.033***	0.033**	--	--
	(0.011)	(0.014)		
$DECI_{i,t}$	--	--	0.182**	0.198*
			(0.079)	(0.112)
$\ln EXP_{i,t-1}$	0.371***	0.375***	0.364***	0.374***
	(0.069)	(0.085)	(0.070)	(0.110)
$\ln PCGDP_{i,t}$	3.057***	2.965***	3.142***	3.079***
	(0.458)	(0.655)	(0.454)	(0.733)
$\ln EXC_{i,t}$	0.191***	0.154*	0.198***	0.184
	(0.063)	(0.091)	(0.064)	(0.114)
$\ln MI_{i,t}$	-0.231	-0.257	-0.242	-0.232
	(0.150)	(0.234)	(0.157)	(0.251)
$\ln GFCF_{i,t}$	0.153	0.019	0.173	0.124
	(0.116)	(0.167)	(0.119)	(0.193)
$RISK_{i,t}$	-0.098**	-0.161*	-0.118***	-0.145*
	(0.040)	(0.082)	(0.041)	(0.087)
$\ln DIST_i$	-2.179***	27.689	-2.246***	24.093
	(0.271)	(18.360)	(0.276)	(21.044)
$BORD_i$	2.511**	42.518	2.710***	54.352
	(0.971)	(79.935)	(0.960)	(60.541)
$LANG_i$	-3.321***	79.157	-3.560***	--
	(1.163)	(72.596)	(1.159)	
No. of Observations	834	834	834	834
No. of Countries	--	180	--	180
R-squared	0.986	--	0.986	--
AR (1) test (*p*-value)	--	0.054	--	0.063
AR (2) test (*p*-value)	--	0.347	--	0.328
Hansen test (*p*-value)	----	0.826	--	1.000
Diff-in-Hansen Test of exogeneity (*p*-value)	--	1.000	--	0.947

Note: The table reports regression coefficients and, in parentheses, the associated robust standard errors. * significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent. All variables are in logarithm except for *RISK, BORD* and *LANG*. Original values of *ECI* are added 1 before logarithmic transformation. Constant and country effects included but not reported. All the models are estimated with Stata SE 11.2, using XTABOND2 command for system GMM.

Table 4.6: Insurance Effect across Income Groups, 2001-2006

Variable of Interest	$\ln ECI_{i,t}$		$DECI_{i,t}$	
	FE	System GMM	FE	System GMM
	(1)	(2)	(3)	(4)
Low-income	0.059**	0.003	0.417***	0.040
	(0.029)	(0.026)	(0.141)	(0.275)
No. of observation	264	204	261	204
No. of Countries	54	50	54	50
Within R-squared:	0.342	--	0.363	--
AR (1) test (*p*-value)	--	0.049	--	0.043
AR (2) test (*p*-value)	--	0.927	--	0.820
Hansen test (*p*-value)	--	0.996	--	0.945
Diff-in-Hansen Test of exogeneity (*p*-value)	--	1.000	--	1.000
Lower-middle Income	0.091***	0.116	0.222*	0.227
	(0.032)	(0.096)	(0.118)	(0.713)
No. of observation	284	235	284	235
No. of Countries	58	57	58	57
R-squared:	0.666	--	0.654	--
AR (1) test (*p*-value)	--	0.099	--	0.122
AR (2) test (*p*-value)	--	0.598	--	0.613
Hansen test (*p*-value)	--	0.946	--	0.976
Diff-in-Hansen Test of exogeneity (*p*-value)	--	1.000	--	1.000
Upper-middle Income	0.038	0.040	0.252	-0.523
	(0.030)	(0.037)	(0.264)	(7.978)
No. of observation	195	160	195	160
No. of Countries	41	40	41	40
R-squared:	0.476	--	0.481	--
AR (1) test (*p*-value)	--	0.009	--	0.067
AR (2) test (*p*-value)	--	0.068	--	0.165
Hansen test (*p*-value)	--	0.998	--	--
Diff-in-Hansen Test of exogeneity (*p*-value)	--	1.000	--	--
High Income	0.059**	0.154*	1.172***	0.761**
	(0.030)	(0.086)	(0.308)	(0.308)
No. of observation	284	235	284	235
No. of Countries	53	53	53	53
R-squared:	0.407	--	0.465	--
AR (1) test (*p*-value)	--	0.051	--	0.183
AR (2) test (*p*-value)	--	0.140	--	0.452
Hansen test (*p*-value)	--	--	--	1.000
Diff-in-Hansen Test of exogeneity (*p*-value)	--	--	--	1.000

Note: The table reports regression coefficients and, in parentheses, the associated robust standard errors. * significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent. Original values of *ECI* are added 1 before logarithmic transformation. Constant, country effects and other explanatory variables included but not reported. All the models are estimated with Stata SE 11.2, using XTABOND2 command for system GMM and XTREG for Fixed Effects estimation.

Appendix A: List of Countries and Territories by Geographic Region

Region	Name
Africa	Angola, Benin, Burkina Faso, Burundi, Central Africa, Comoros, Cote d'Ivoire, Eritrea, Ethiopia, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Madagascar, Malawi, Mali, Mauritania, Mozambique, Niger, Nigeria, Rwanda, Sao Tome and Principle, Senegal, Sierra Leone, Sudan, Tanzania, Togo, Uganda, Zambia, Zimbabwe, Algeria, Cameroon, Cape Verde, Egypt, Morocco, Namibia, South Africa, Swaziland, Tunisia, Botswana, Gabon, Libya, Mauritius, Seychelles
America	Haiti, Nicaragua, Belize, Bolivia, Colombia, Cuba, Dominica Rep., Ecuador, El Salvador, Guatemala, Guyana, Honduras, Jamaica, Paraguay, Peru, Saint Vincent & Grenadines, Surinam, Argentina, Brazil, Chile, Costa Rica, Dominica, Grenada, Mexico, Panama, Saint Lucia, St. Kitts-Nevis, Trinidad and Tobago, Uruguay, Venezuela, Antigua and Barbuda, Aruba, Bahamas, Barbados, Bermuda, Cayman Islands, Netherlands Antilles, Turks and Caicos Islands
Asia	Armenia, Azerbaijan, Bangladesh, Bhutan, Cambodia, Georgia, India, Indonesia, Kyrgyzstan, Mongolia, Nepal, Pakistan, Republic of Yemen, Timor-Leste, Vietnam, Indonesia, Iran, Iraq, Jordan, Kazakhstan, Maldives, Palestine, Philippines, Sri Lanka, Syria, Thailand, Turkey, Lebanon, Malaysia, Oman, Saudi Arabia, Bahrain, Brunei, Hong Kong, Israel, Japan, Republic of Korea, Kuwait, Macao, Qatar, Singapore, Taiwan, United Arab Emirates
Pacific	Papua New Guinea, Solomon Islands, Fiji, Kiribati, Samoa, Tonga, Tuvalu, Vanuatu, Cook Islands, Australia, French Polynesia, New Caledonia, New Zealand
European Union	Bulgaria[1], Romania[1], Czech[2], Estonia[2], Hungary[2], Latvia[2], Lithuania[2], Malta[2], Poland[2], Slovakia[2], Cyprus[2], Slovenia[2], Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden, United Kingdom, Cyprus, Slovenia
Europe[3]	Moldavia, Albania, Russia, Belarus, Bosnia and Herzegovina, Macedonia, Serbian, Croatia, Andorra, Iceland, Norway, San Marino, Switzerland
North America	Canada, Greenland, United States

Note 1: These countries officially joined in the European Union on 1st January 2007.

Note 2: These countries officially jointed the European Union on 1st May 2004.

Note 3: Excluding European Union member counties.

Appendix B: Sensitivity Analysis of Insurance Effect, 2001-2006

Dep. Variable: $\ln EXP_{i,t}$	FE (1)	FE (2)	FE (3)	Sys GMM (4)	Sys GMM (5)	Sys GMM (6)
$\ln ECI_{i,t}$	0.059***	0.084***	0.077***	0.019**	0.028**	0.029**
	(0.011)	(0.013)	(0.011)	(0.008)	(0.011)	(0.013)
$\ln EXP_{i,t-1}$	--	--	--	0.617***	0.376***	0.357***
				(0.086)	(0.098)	(0.091)
$\ln PCGDP_{i,t}$	4.376***	4.682***	4.574***	1.458***	2.980***	3.139***
	(0.452)	(0.435)	(0.433)	(0.542)	(0.688)	(0.800)
$\ln EXC_{i,t}$	0.249***	0.247***	0.242***	0.106*	0.184**	0.183*
	(0.058)	(0.090)	(0.086)	(0.063)	(0.088)	(0.101)
$\ln MI_{i,t}$	-0.192	-0.216	-0.205	-0.263**	-0.228	-0.132
	(0.134)	(0.212)	(0.210)	(0.126)	(0.206)	(0.201)
$\ln GFCF_{i,t}$	-0.031	0.183	0.173	0.007	0.126	0.095
	(0.165)	(0.184)	(0.182)	(0.139)	(0.176)	(0.173)
$RISK_{i,t}$	-0.135**	-0.104*	-0.106**	-0.116*	-0.117**	-0.123*
	(0.056)	(0.053)	(0.053)	(0.064)	(0.053)	(0.070)
$\ln DIST_i$	--	--	--	13.468	--	5.348
				(20.043)		(10.164)
$BORD_i$	--	--	--	39.928	--	--
				(55.926)		
$LANG_i$	--	--	--	--	--	--
No. of Observations	799	1024	1024	669	834	831
No. of Countries	157	181	181	156	180	173
Within R-squared	0.610	0.443	0.448	--	--	0.431
Chi2 Hausman: FE Vs. RE	533.15***	255.16***	169.70***	--	--	
Endogeneity Test: *p*-value	0.000	0.000	0.000	--	--	
AR (1) test (*p*-value)	--	--	--	0.001	0.057	0.060
AR (2) test (*p*-value)	--	--	--	0.520	0.343	0.320
Hansen test (*p*-value)	--	--	--	1.000	1.000	1.000
Diff-in-Hansen Test (*p*-value)	--	--	--	0.999	1.000	1.000

Note: The table reports regression coefficients and, in parentheses, the associated robust standard errors. * significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent. All variables are in logarithm except for *RISK, BORD* and *LANG*. Constant and country effects included but not reported. All the models are estimated with Stata SE 11.2 using XTREG and XTABOND2 command. 0.5 and 0.1 are added to original values of ECI in (2) and (5), as well as (3) and (6), respectively, before logarithmic transformation.

Appendix C: Theoretical Deduction Process

Proof of Lemma 1

Given that both exporters and importers under different payment terms are perfectly and costlessly arbitraged, p^{CIA} and p^{OA} in the exporting country i, under the assumption of zero risk premium, should satisfy:

$$p^{CIA} = E\left[m \cdot \lambda_j p^{OA}\right] = E\left[m \cdot \lambda_j\right]p^{OA} = E[m]E\left[\lambda_j\right]p^{OA} = \frac{1}{1+r_i} p^{OA}\overline{\lambda_j} \qquad \text{(L1.1)}$$

where r_i is the financing cost in country i and m is the stochastic discount factor. Otherwise if $\frac{p^{OA}\overline{\lambda_j}}{1+r_i} > p^{CIA}$, the *OA* exporter can, without producing himself, buy the goods from the *CIA* exporter under *CIA* terms and then export at under *OA* terms; or, if $\frac{p^{OA}\overline{\lambda_j}}{1+r_i} < p^{CIA}$, the *CIA* exporter can, without producing himself, buy the goods from the *OA* exporter at *OA* terms and then export at *CIA* terms.

Similarly, p^{CIA} and p^{OA} in the importing country j under the no-risk-premium assumption should satisfy:

$$p^{CIA} = E\left[m \cdot \lambda_i p^{OA}\right] = E\left[m \cdot \lambda_i\right]p^{OA} = E[m]E\left[\lambda_i\right]p^{OA} = \frac{1}{1+r_j} p^{OA}\overline{\lambda_i} \qquad \text{(L1.2)}$$

where r_j is the financing cost in country j and m is the stochastic discount factor. Otherwise, if $\frac{p^{CIA}(1+r_j)}{\overline{\lambda_i}} > p^{OA}$, the *CIA* importer would buy the goods from the *OA* importer directly rather than import them from country i; or if $\frac{p^{CIA}(1+r_j)}{\overline{\lambda_i}} < p^{OA}$, the *CIA* importer could re-sell the goods to the *OA* importer.

Proof of Lemma 2

Using lemma 1, we rewrite the objective function for the *CIA* importer (1) as follows:

$$Max_x E\left[u\left(\pi_j^{CIA}\right)\right] = Max_x E\left[u\left(\lambda_i R(x) - \frac{(1+r_j)\overline{\lambda_j}}{1+r_i} p^{OA} x\right)\right] \qquad \text{(L2.1)}$$

The first order conditions of equation (L2.1) is:

$$E\left[u^{'}(\pi_j^{CIA})\left(\lambda_i R^{'}(x)-\frac{(1+r_j)\overline{\lambda_j}}{1+r_i}p^{OA}\right)\right]=0$$

$$\Rightarrow E\left[u^{'}(\pi_j^{CIA})\lambda_i\right]R^{'}(x)=E\left[u^{'}(\pi_j^{CIA})\right]\frac{1+r_j}{1+r_i}p^{OA}\overline{\lambda_j}$$

$$\Rightarrow \left\{E[u^{'}(\pi_j^{CIA})]\overline{\lambda_i}+Cov(u^{'}(\pi_j^{CIA}),\lambda_i)\right\}R^{'}(x)=E[u^{'}(\pi_j^{CIA})]\frac{1+r_j}{1+r_i}p^{OA}\overline{\lambda_j}$$

$$\Rightarrow R^{'}(x^{CIA})=\frac{E[u^{'}(\pi_j^{CIA})]}{E[u^{'}(\pi_j^{CIA})]\overline{\lambda_i}+Cov(u^{'}(\pi_j^{CIA}),\lambda_i)}\cdot\frac{1+r_j}{1+r_i}p^{OA}\overline{\lambda_j} \qquad \text{(L2.2)}$$

The first order condition of (2) is:

$$E\left[u^{'}(\pi_j^{OA})\left(R^{'}(x)-\lambda_j p^{OA}\right)\right]=0$$

$$\Rightarrow E\left[u^{'}(\pi_j^{OA})\right]R^{'}(x)=E\left[u^{'}(\pi_j^{OA})\lambda_j\right]p^{OA}$$

$$\Rightarrow E\left[u^{'}(\pi_j^{OA})\right]R^{'}(x)=\left\{E\left[u^{'}(\pi_j^{OA})\right]E\left[\lambda_j\right]+Cov(u^{'}(\pi_j^{OA}),\lambda_j)\right\}p^{OA}$$

$$\Rightarrow R^{'}(x^{OA})=\frac{E\left[u^{'}(\pi_j^{OA})\right]\overline{\lambda_j}+Cov(u^{'}(\pi_j^{OA}),\lambda_j)}{E\left[u^{'}(\pi_j^{OA})\right]}p^{OA} \qquad \text{(L2.3)}$$

The second order conditions of (L2.1) and (2) satisfy, respectively:

$$E\left[u^{''}(\pi_j^{CIA})\left(\lambda_i R^{'}(x)-\frac{(1+r_j)\overline{\lambda_j}}{1+r_i}p^{OA}\right)^2+u^{'}(\pi_j^{CIA})\lambda_i R^{''}(x)\right]<0 \qquad \text{(L2.4)}$$

$$E\left[u^{''}(\pi_j^{OA})\left(R^{'}(x)-\lambda_j p^{OA}\right)^2+u^{'}(\pi_j^{OA})R^{''}(x)\right]<0 \qquad \text{(L2.5)}$$

since $u^{'}(\cdot)>0$, $u^{''}(\cdot)\le 0$, and $R^{''}(\cdot)<0$.

If the importer is ***risk neutral,*** i.e. $u^{''}(\cdot)=0$, $u^{'}(\cdot)$ is a constant. So, the covariance terms in equation (L2.2) and (L2.3) are equal to zero. Thus, (L2.2) can be expressed by:

$$R^{'}(x^{CIA})=\frac{\overline{\lambda_j}}{\overline{\lambda_i}}\cdot\frac{1+r_j}{1+r_i}p^{OA} \qquad \text{(L2.6)}$$

Similarly, (L2.3) is rewritten as:

$$R^{'}(x^{OA})=p^{OA}\overline{\lambda_j} \qquad \text{(L2.7)}$$

Given lemma 1, from (L2.6) and (L2.7) we find:

$$\frac{R'(x^{CIA})}{R'(x^{OA})} = \frac{\overline{\lambda_j}}{\overline{\overline{\lambda_i}}} \cdot \frac{1+r_j}{1+r_i} \cdot \frac{1}{\overline{\overline{\lambda_j}}} = \frac{1}{\overline{\overline{\lambda_j}}} \geq 1$$

$$\Rightarrow R'(x^{CIA}) \geq R'(x^{OA})$$

$\Rightarrow R'(x^{CIA}) = R'(x^{OA})$ if $\overline{\lambda_j} = 1$; or, $R'(x^{CIA}) > R'(x^{OA})$ if $\overline{\lambda_j} < 1$

$\Rightarrow x^{CIA} = x^{OA}$ if $\overline{\lambda_j} = 1$; or, $x^{CIA} < x^{OA}$ if $\overline{\lambda_j} < 1$ (L2.8)

since $R''(\cdot) < 0$.

In the case of a ***risk-averse*** exporter, i.e. $u''(\cdot) < 0$, the covariance term $Cov\left[u'(\pi_j^{CIA}), \lambda_i\right]$ is negative, since $u'(\pi_j^{CIA})$ is decreasing with λ_i. Then, with lemma 1, (L2.2) can be expressed as:

$$R'(x^{CIA}) = \frac{1+r_j}{1+r_i} p^{OA} \frac{E[u'(\pi_j^{CIA})]\overline{\lambda_j}}{E[u'(\pi_j^{CIA})]\overline{\lambda_i} + Cov(u'(\pi_j^{CIA}), \lambda_i)}$$

$$\Rightarrow R'(x^{CIA}) > \frac{1+r_j}{1+r_i} p^{OA} \frac{E[u'(\pi_j^{CIA})]\overline{\lambda_j}}{E[u'(\pi_j^{CIA})]\overline{\overline{\lambda_i}}} = \frac{1+r_j}{1+r_i} p^{OA} \frac{\overline{\lambda_j}}{\overline{\overline{\lambda_i}}} = p^{OA}$$

$$\Rightarrow R'(x^{CIA}) > p^{OA} \qquad \text{(L2.9)}$$

For the *OA* importer, since $u'(\pi_j^{OA})$ is increasing with λ_j, the covariance term $Cov\left[u'(\pi_j^{OA}), \lambda_j\right]$ in (L2.3) is positive. Thus, (L2.3) is expressed as:

$$R'(x^{OA}) = p^{OA} \frac{E[u'(\pi_j^{OA})]\overline{\lambda_j} + Cov(u'(\pi_j^{OA}), \lambda_j)}{E[u'(\pi_j^{OA})]}$$

$$\Rightarrow R'(x^{OA}) < p^{OA} \frac{E[u'(\pi_j^{OA})]\overline{\lambda_j}}{E[u'(\pi_j^{OA})]} \Rightarrow R'(x^{OA}) < p^{OA}\overline{\lambda_j} \qquad \text{(L2.10)}$$

From (L2.9) and (L2.10), we find:

$$R'(x^{OA}) < R'(x^{CIA}) \Rightarrow x^{OA} > x^{CIA} \qquad \text{(L2.11)}$$

since $\overline{\lambda_j} \leq 1$ and $R''(\cdot) < 0$.

We summarize the results in the following table:

Type of Importers	Risky Importing Countries	Risk-Free Importing Countries

	$(0<\overline{\lambda_j}<1)$	$(\overline{\lambda_j}=1)$
Risk neutral	$x^{OA}>x^{CIA}$	$x^{OA}=x^{CIA}$
Risk averse	$x^{OA}>x^{CIA}$	$x^{OA}>x^{CIA}$

<u>Proof of Lemma 3</u>

The first order condition of (3) is:

$$E\left[u'\left(\pi_i^{OA,N}\right)\left(\frac{\lambda_j p^{OA}}{1+r_i}-f'(x)\right)\right]=0$$

$$\Rightarrow E\left[u'\left(\pi_i^{OA,N}\right)\lambda_j\right]\frac{p^{OA}}{1+r_i}=E\left[u'\left(\pi_i^{OA,N}\right)\right]f'(x)$$

$$\Rightarrow f'(x^N)=\frac{E\left[u'\left(\pi_i^{OA,N}\right)\lambda_j\right]}{E\left[u'\left(\pi_i^{OA,N}\right)\right]}\frac{p^{OA}}{1+r_i}$$

$$\Rightarrow f'(x^N)=\frac{E\left[u'\left(\pi_i^{OA,N}\right)\right]\overline{\lambda_j}+Cov(u'\left(\pi_i^{OA,N}\right),\lambda_j)}{E\left[u'\left(\pi_i^{OA,N}\right)\right]}\frac{p^{OA}}{1+r_i} \qquad \text{(L3.1)}$$

The first order of (4) is:

$$E\left[u'\left(\pi_i^{OA,I}\right)\left(\frac{p^{OA}}{1+r_i}-f'(x)-wp^{OA}\right)\right]=0$$

$$\Rightarrow \frac{p^{OA}}{1+r_i}-f'(x)-wp^{OA}=0$$

$$\Rightarrow f'(x^I)=\frac{p^{OA}}{1+r_i}-wp^{OA} \qquad \text{(L3.2)}$$

The second order conditions of (3) and (4) satisfy, respectively:

$$E\left[u''\left(\pi_i^{OA,N}\right)\left(\frac{\lambda_j p^{OA}}{1+r_i}-f'(x)\right)^2-u'\left(\pi_i^{OA,N}\right)f''(x)\right]<0$$

$$E\left[u''\left(\pi_i^{OA,I}\right)\left(\frac{p^{OA}}{1+r_i}-f'(x)-wp^{OA}\right)^2-u'\left(\pi_i^{OA,I}\right)f''(x)\right]<0 \qquad \text{(L3.3)}$$

since $u'(\cdot)>0$, $u''(\cdot)\le 0$, and $f''(x)>0$.

If the exporter is ***risk neutral,*** i.e. $u^{''}(\cdot)=0$, $u^{'}(\cdot)$ is a constant. So, the covariance term in equation (L3.1) is equal to zero. Thus, (L3.1) can be expressed by:

$$f^{'}(x^{N})=\frac{E\left[u^{'}\left(\pi_i^{OA,N}\right)\lambda_j\right]\overline{\lambda_j}}{E\left[u^{'}\left(\pi_i^{OA,N}\right)\right]}\frac{p^{OA}}{1+r_i}=\frac{p^{OA}}{1+r_i}\overline{\lambda_j} \quad \text{(L3.4)}$$

We now compare export levels with and without insurance. From (L3.2) and (L3.4), we obtain:

$$f^{'}(x^{I})-f^{'}(x^{N})=\frac{p^{OA}}{1+r_i}-wp^{OA}-\frac{p^{OA}}{1+r_i}\overline{\lambda_j}$$

$$\Rightarrow f^{'}(x^{I})-f^{'}(x^{N})=p^{OA}(\frac{1-\overline{\lambda_j}}{1+r_i}-w) \quad \text{(L3.5)}$$

When the insurance is ***very-fairly priced***, i.e. $w<\frac{(1-\overline{\lambda_j})}{1+r_i}$, (L3.5) can be expressed as:

$$f^{'}(x^{I})-f^{'}(x^{N})>0\Rightarrow x^{I}>x^{N} \quad \text{(L3.6)}$$

since $f^{''}(\cdot)>0$.

When the insurance is ***fairly priced***, i.e. $w=\frac{(1-\overline{\lambda_j})}{1+r_i}$, (L3.5) can be expressed as:

$$f^{'}(x^{I})-f^{'}(x^{N})=0\Rightarrow x^{I}=x^{N} \quad \text{(L3.7)}$$

Finally, we consider the case of ***over-priced*** insurance, i.e. $w>\frac{(1-\overline{\lambda_j})}{1+r_i}$. From (L3. 5), we find:

$$f^{'}(x^{I})-f^{'}(x^{N})<0\Rightarrow x^{I}<x^{N} \quad \text{(L3.8)}$$

In the case of a ***risk-averse*** exporter, i.e. $u^{''}(\cdot)<$, from (L3.1) and (L3.2) we obtain:

$$f^{'}(x^I) - f^{'}(x^N) = p^{OA}(\frac{1-\overline{\lambda_j}}{1+r_i} - w) - \frac{Cov(u^{'}(\pi_i^{OA,N}), \lambda_j)}{E\left[u^{'}(\pi_i^{OA,N})\right]} \cdot \frac{p^{OA}}{1+r_i} \quad \text{(L3.9)}$$

where the covariance term is negative since $u^{'}(\pi_i^{OA,N})$ is decreasing with λ_j,

When the insurance is ***very-fairly priced***, i.e. $w < \frac{(1-\overline{\lambda_j})}{1+r_i}$, (L3.9) can be expressed as:

$$f^{'}(x^I) - f^{'}(x^N) > 0 \Rightarrow x^I > x^N \quad \text{(L3.10)}$$

since $f^{''}(\cdot) > 0$.

When the insurance is ***fairly priced***, i.e. $w = \frac{(1-\overline{\lambda_j})}{1+r_i}$, (L3.9) can be expressed as:

$$f^{'}(x^I) - f^{'}(x^N) > 0 \Rightarrow x^I > x^N \quad \text{(L3.11)}$$

When the insurance is ***over-priced***, i.e. $w > \frac{(1-\overline{\lambda_j})}{1+r_i}$, from (L3.9) we obtain:

$$x^I > x^N \text{ if } \frac{1-\overline{\lambda_j}}{1+r_i} - w > \frac{Cov(u^{'}(\pi_i^{OA,N}), \lambda_j)}{E\left[u^{'}(\pi_i^{OA,N})\right]} \cdot \frac{1}{1+r_i}$$

$$x^I = x^N \text{ if } \frac{1-\overline{\lambda_j}}{1+r_i} - w = \frac{Cov(u^{'}(\pi_i^{OA,N}), \lambda_j)}{E\left[u^{'}(\pi_i^{OA,N})\right]} \cdot \frac{1}{1+r_i}$$

$$x^I < x^N \text{ if } \frac{1-\overline{\lambda_j}}{1+r_i} - w < \frac{Cov(u^{'}(\pi_i^{OA,N}), \lambda_j)}{E\left[u^{'}(\pi_i^{OA,N})\right]} \cdot \frac{1}{1+r_i} \quad \text{(L3.12)}$$

Taken together, we summarize the results in the following table:

Insurance premium	Risk Neutral	Risk Averse
Very fairly priced	$x^I > x^N$	$x^I > x^N$
Fairly priced	$x^I = x^n$	$x^I > x^N$
Over priced	$x^I < x^N$	Depending on risk aversion levels