Essays on the Economics of Heterogeneity

A thesis submitted in partial fulfillment of the requirements

of the degree of Doctor of Philosophy (Ph.D.) in Economics

Nils-Holger Gudat

School of Economics and Finance

Queen Mary, University of London

October 2015

To Nadien, who had to lift my spirits more than once over the last four years;
my mother, as I couldn't have made it here without her love and support;
and Emil, whose laugh carried me through the final stages of this project.

Declaration

I wish to declare

I, Nils-Holger Gudat, confirm that the research included within this thesis is my own work or that where it has been carried out in collaboration with, or supported by others, that this is duly acknowledged below and my contribution indicated. Previously published material is also acknowledged below.

I attest that I have exercised reasonable care to ensure that the work is original, and does not to the best of my knowledge break any UK law, infringe any third party's copyright or other Intellectual Property Right, or contain any confidential material.

I accept that the College has the right to use plagiarism detection software to check the electronic version of the thesis.

I confirm that this thesis has not been previously submitted for the award of a degree by this or any other university.

Details of collaboration and publications:
Parts of Chapter 5 were undertaken as joint work with Ryan Weldzius (University of California, Los Angeles).

Signature: Nils-Holger Gudat
Date: September 30, 2015

Acknowledgements

I would like to thank my supervisors, Xavier Mateos-Planas and Winfried Koenieger, for their guidance, patience and support throughout my Ph.D. studies.

I further acknowledge the School of Economics and Finance at Queen Mary, University of London, for generous funding.

Abstract

The analysis of the effects of heterogeneity on aggregate economic outcomes has seen a resurgence in the recent macroeconomic literature. The exponential increase in computer power over the last decades has allowed researchers to solve ever more complex theoretical models with meaningful heterogeneity along various dimensions, while at the same time bringing ever more granular micro-level data to the table when testing the model predictions.

This thesis explores two varieties of this recent vintage of models of heterogeneity. The first part of the thesis explores the implications of learning about idiosyncratic income risk on the wealth distribution and compares the model results to observed data, with a focus on the effects of changes in cross-sectional income inequality. To this end, income processes with profile heterogeneity are estimated from survey data and then used as inputs for a structural model of household saving, in which households are imperfectly informed about the stochastic process governing the evolution of their lifetime income, but can learn about the underlying parameters. Model results for a standard model are compared to those of a model with consumption habits, while a structural break in the cross-sectional variance of idiosyncratic income growth rates is employed in an attempt to capture the secular rise

in income inequality observed since the late 1970s and explore its implications for the predicted wealth distribution. The second part of the thesis looks at heterogeneity on the production side of the economy and its implications for international trade. Following an existing approach in the literature, we develop testable implications of the Melitz and Ottaviano (2008) model of trade, in which firms differ in their productivity and have to make production and exporting decisions in the face of costs to trade. Our approach allows us to test the effects of NAFTA on productivity in nine manufacturing sectors in North America and thereby complement and extend the existing literature on the effects of trade liberalisations.

Contents

List of Tables

List of Figures

Chapter 1

Introduction

1.1 Motivation

Distributional questions are increasingly making a comeback in economics. In spite of the famous – or infamous – warning of **?** that the focus on questions of distribution is one of the most ”seductive (...) and poisoning” tendencies in economics[1], many fields of economics that have long relied on simplistic models of representative households and firms have increasingly taken the issue of modelling heterogeneity across economic agents seriously. At the very least since the Great Recession triggered by the financial crisis of 2007–2008, issues of distribution have also taken centre stage in the public economic discourse. Work on the increase in income inequality, especially at the top end of the income distribution, and the rising inequality in wealth holdings in advanced economies has played

[1]In fairness it has to be said that Lucas' quote is often taken out of context, as he was not actually advising against studying distributional issues entirely, but merely pointing out that economic growth has played a much more important role in raising people out of poverty than re- distribution of current resources at any point in time could have achieved.

a prominent role in the public debate in recent years, the most prominent recent example being Piketty (2014), a rare instance of a book largely based on economic scholarship being widely discussed and sold (if maybe not read) by a mainstream audience. However, while the public has only recently started to take an interest in issues of inequality and distribution, the economic literature has been developing quantitative models of heterogeneity for almost three decades. Seminal papers such as Imrohoruglu (1989), Huggett (1993), and Aiyagari (1994) have laid the groundwork for a vast literature explicitly modelling the choices of heterogeneous agents based on microeconomic evidence. A major factor in the move towards models of explicit heterogeneity have been the huge advancements in computer power in recent decades. With Moore's law still holding to this day, the transistor count of the fastest microprocessor today is about two-thousand times as high as that of the fastest microprocessor twenty-five years ago, when **?** published one of the first works that numerically solved a household savings problem under uncertainty numerically. Besides enabling researchers to numerically solve ever more complex optimisation problems with state spaces of ever more dimensions, the advancements in computer power have also vastly improved data processing capabilities, a development that in turn has led to surge in empirical work exploiting large microeconomic data sets, the results of which can then be used to validate models of household and firm behaviour.

The present work explores heterogeneity in two different classes of economic models, using both approaches outlined above. While the first part will build up towards a quantitative theoretical model of the wealth distribution, the merits of which will be evaluated against micro survey data. The second part will take the predictions of a micro-founded model of international trade and test them on data of firm behaviour disaggregated at the industry-level.

1.2 Outline

This thesis is structured as follows. Chapter 2 gives an overview of the research on theoretical models of the household wealth distribution in the last two decades. It will highlight the key empirical challenges by presenting stylized facts on the cross sectional wealth distribution in a number of countries and their evolution over time. Then, an overview of existing modelling approaches is presented,

Chapter 3 builds on the discussion in Chapter 2 by constructing a model of learning about idiosyncratic income processes and using it to simulate wealth distributions. As a first step, income processes with profile heterogeneity are estimated for different sub-periods of PSID data from 1968 to 2013 and from BHPS data in order to assess the stability of the cross-sectional variance of income growth rates across time and labour markets. The estimates are then used as inputs in a structural model of household saving first employed by Guvenen (2007), with the addition of both structural breaks in the cross-sectional variance of growth rates and habits in consumption. The models predictions for the evolution of the US consumer wealth distribution are then benchmarked against data from the Survey of Consumer Finances.

Chapter 4 gives a brief introduction into trade models based on firm-level heterogeneity, before developing an estimable model in the spirit of Chen et al. (2009). The model is then tested on a data set of prices, productivity, and markups for nine manufacturing industries in the Canada, Mexico and the United States over the period of 1988 to 2010. In an extension of the approach of Chen et al.

(2009), we also conduct a sub-sample analysis in which we split the same into fixed and free entry industries, based on a measure of firm turnover developed on the basis of prior research.

Chapter 5 concludes the thesis and discusses potential avenues for future research.

Chapter 2

Quantitative Models of the Wealth Distribution

2.1 Introduction

The distribution of wealth and income has recently made a comeback to the centre of economic discourse in advanced economies. The ongoing rise of income inequality, observed since the early 1980s especially in Anglo-Saxon countries, has received renewed attention in the public sphere since the financial started taking its toll on living standards across the world. At the same time, the best-selling book by Piketty (2014) led to a surge in interest in the role of capital in the economy, and, by extension, the distribution of wealth, both in the academic literature and the popular press.

While the broader public has only recently picked up on the issues arising around income and wealth distributions, they have sat squarely in the centre of many sub-fields of economics for a long time. The income distribution has long been of interest to labour economists trying to understand the forces shaping the evolution of earnings in the labour market, while at least the accumulation of aggregate wealth plays a central role in macroeconomic models of economic growth. This chapter, as well as chapter three, focuses on the intermediate step that takes us from an income to a wealth distribution - economic models of household saving. When attempting to build a model of the wealth distribution, the first step of course is to get an understanding of the object we want to model. To this end, this chapter starts by presenting stylised facts of the wealth distributions in advanced countries and discusses some of the limitations of the data available. It then builds a simple life-cycle model of consumption and savings to guide the following discussion and fix notation. Using this basic model, different savings motives and their importance in the context of aggregate wealth accumulation are discussed. Following this, the role of income uncertainty and market structure is examined in more detail.

2.2 Stylised facts

The most notable and consistent fact that emerges when looking at wealth distributions across all countries and different time periods is that wealth is highly unevenly distributed, much more so than income. Vermeulen (2014) argues that wealth holdings are so concentrated, that even surveys employing designs that feature oversampling of richer households (such as the US Survey of Consumer Finances (SCF), or the British Wealth and Asset Survey (WAS)) underestimate the percentage share of wealth held by the highest percentile of the wealth distribution by anywhere from one to five percentage points, while surveys that don't oversample underestimate the share by up to ten percentage points. Keeping this in mind, the een when comparing Gini indices and top shares of income and wealth, as in Table 2.1 or looking at histograms and cdfs of wealth and income distributions as in Figure 2.1. It is important to note that in producing these aggregate numbers and figures, one necessarily has to make decisions on how exactly to construct measures of income and wealth, which will have to be kept in mind when comparing model predictions with empirical numbers. When constructing an income measure, the obvious starting point are labour earnings, and for many economic applications simply observing an individual's wages will be enough. When thinking about questions of consumption smoothing though, we are ultimately interested in accounting for all claims on consumption goods available to an individual or household in a given period, and while for most people the largest part of these claims stem from labour earnings, we will also want to account for the effect of government programs (by constructing a post-tax, post-transfer income measure), income from accumulated assets, and potentially even informal insurance arrangements such as inter-vivos transfers between family and friends. In constructing wealth measures, we again have to think closely about the question we are trying to answer when constructing them. If the goal is to account for all productive capital in the economy that can be used in production, a measure of total net wealth aggregating all forms of asset and debt classes, and including some durable consumption goods such as cars. When thinking about the role of wealth in helping the household to smooth out income fluctuations, it might be more appropriate to exclude very illiquid assets such as housing, and look more closely at the role of debt for households which might be at their borrowing constraint and are thus vulnerable to reductions in their borrowing

Table 2.1: Measures of wealth concentration in different data sets.

Figure 2.1: Histograms and cdfs of household net wealth in different data sets.

limit, even though their net wealth (including illiquid assets) is positive. Finally, important questions are raised by the existence of various government and private pension schemes, which have to be factored in when constructing measures of a household's lifetime resources, but whose exact value might be uncertain (for the case of defined contribution plans) and not well understood by households themselves.

2.3 A workhorse model

The basic model underlying the discussion of savings behaviour and wealth accumulation in this chapter is the life-cycle model of household behaviour dating back to Modigliano and Brumberg (1954) [2]. The model can be written as a single household solving the problem

$$\max_{\{c_{t+j}\}_{j=0}^{T-t}} \sum_{j=0}^{\infty} \delta^{t+j} \mathbb{E}_t \big[u(c_{t+j}, z_{t+j}) \big] \tag{2.1}$$

subject to

$$a_{t+1} = (1+r)(a_t + y_t - c_t) \tag{2.2}$$

where T is the last period of the planning horizon, δ is the subjective discount factor, $u()$ is the instantaneous felicity function – usually assumed to be of the CRRA form, $\frac{c^{1-\sigma}}{1-\sigma}$, where σ is the coefficient of relative risk aversion –, c is consumption, a are financial assets, which allow the household to transfer resources across time, r is a one-period interest rate, and y is income. z is used as a stand-in variable denoting the fact that households might, in general, care about other things that are not captured by the concept of current consumption; examples would be habits or durable consumption (which break the time-separability of the utility function), leisure time, particular classes of assets (such as housing) or bequests left to future generations. While in general, $T \to \infty$ is a

[2] A more detailed treatment of the general class of models can be found both in Browning and Crossley (2001) and in Attanasio and Weber (2010), although both papers have their focus on household consumption behaviour rather than wealth accumulation.

possibility, and infinite horizon versions – first advocated by Friedman (1957) – of the life-cycle model are widely used in macroeconomic applications, the finite horizon model will be more useful for the following discussion and forms the centrepiece of this thesis for a number of reasons which will become clear as we progress.

2.4 Saving motives

When trying to understand wealth distributions through the lens of the model outlined above, the key question is: why do households save? The basic model, in which consumers only care about the time path of instantaneous utility derived from consumption, suggests that households will save if and only if it leads to preferential allocation of consumption over time – they engage in consumption smoothing. As Browning and Crossley (2001) point out, consumption smoothing can happen at different frequencies, depending on the exact set-up of the model. In Modigliano and Brumberg (1954) the main reason saving was the existence of a retirement period, which necessitates consumption smoothing over the life cycle – wealth accumulation during working life to pay for consumption in retirement. The implication of this simple model is that wealth accumulation on the household level solely depends on the length of the retirement period, while in aggregate wealth accumulation crucially hinges on the growth rate of the economy. The crucial assumption that allows Modigliani and Brumberg to focus on consumption smoothing over the life cycle was that of constant income, an assumption that is obviously incorrect and easily rejected by the data.

2.5 Income uncertainty and market structure

With the assumption of a non-constant income stream, it becomes important to think about the opportunities households have to insure themselves against these fluctuations, or, in other words, which market structure they are facing. To make income fluctuations relevant for the economic agent, the world of complete markets, in which a full set of Arrow securities covering each possible state of the world can be bought and sold, has to be abandoned in favour of market *incompleteness*. The most convenient, and at the same time most extreme, departure from the complete markets assumption is to assume away any sort of insurance markets except for very simple self-insurance through risk- free one-period bonds. This market structure is implicit in the formulation of the consumer problem in equation 2.2 – there is just one asset for the household to sell or buy, and this asset has a certain payoff in the following period, which is not contingent on the state of the world. The big advantage of this setup is tractability: simple models of this kind can often be solved analytically, and in recursive formulations of more complex problems, the simple market structure only adds one state variable to the problem. The drawback, obviously, is that this market structure is at odds with the economic reality, where households are able to buy a hoist of different assets that vary widely in liquidity as well as in the degree to which payoff are state-contingent. We defer the consideration of the role of liquidity to section 2.6, which deals with the largest asset in most households' portfolio, housing, and examine the role of insurance first. The basic idea when investigating the extent to which households have access to insurance mechanisms is to analyse the joint dynamics of income and consumption data, and compare them with the implications derived from models with different insurance mechanisms. In a complete market setup, where households can fully insure income risk, idiosyncratic changes in income should not translate into changes in consumption, implying a flat profile of cross-sectional consumption inequality over the life- cycle, irrespective of the underlying stochastic process governing income. This is not the case in the absence of insurance opportunities, with the opposite end of the model spectrum being inhabited by the Aiyagari-Bewley-Hugget-Imrohoroglu class of models (Aiyagari (1994), Bewley (1977), Huggett (1993), Imrohoruglu (1989)). These model don't feature any insurance possibilities apart from non-contingent one-period bonds and also deliver specific predictions on the relationship between income, consumption and savings[3]. The precise predictions of the model for how households will consume and save depend crucially on the specification of the stochastic process governing income uncertainty – essentially the object over which $\mathbb{E}$ in equation 4.1 is defined. When applying an income process consisting of permanent and transitory shocks to this model, the well-known[4] results that consumption should react to permanent changes in income, while transitory changes in income should be buffered by saving and dissaving in the noncontingent bond. This prediction of the model is exploited by some authors to elicit information on the decomposition of income changes into permanent and transitory shocks using consumption data: assuming that the model is correct, increases in income inequality in the data that are accompanied by contemporary increases in consumption inequality must be induced by permanent shocks to

[3]More precisely, the opposite end of the insurance spectrum would be a world that does not even offer noncontingent bonds, although this market structure is obviously not suited to examine any interesting economic question.

[4]For a rigorous derivation refer to your favourite Macroeconomics textbook, e.g. **?**, chapter 17.

income, while changes in the income distribution that do not lead to changes in the consumption distribution can be seen to be the consequence of transitory shocks. Blundell and Preston (1998) is an example of a paper employing exactly this strategy to examine data on consumption and income from the British Family Expenditure Survey to examine the properties of changes in the income distribution in Britain between 1968 and 1992. One problem of these studies however is a large literature documenting ”excess smoothness” of consumption in the data, that is showing that consumption does *not* change one-for-one even with changes in income that are known to be permanent (are very detailed account on the early research on this can be found in Deaton 1992), implying that there are at least some insurance opportunities available to households in the real world. Based on the rejection of both full and no insurance in the data, an active literature has developed trying to quantify the amount of insurance households have access to. **? ?** Heathcote et al. (2007) Blundell et al. (2008) develop a novel imputation procedure designed to alleviate measurement problems in PSID consumption data to test Kaplan and Violante (2010) examine how to what extent the empirical estimates of consumption insurance that Blundell et al. (2008) obtain can be replicated in a standard incomplete market model with capital as the only savings vehicle.

2.6 The role of housing

While much effort has been devoted to examining the implications of income risk and market structure for wealth accumulation through precautionary savings, it is undeniable that a large part of household saving happens in the form of an asset which cannot perform the role of buffering against income shocks: housing. As figure 2.1 demonstrates using data from the US SCF and the British Wealth and Asset Survey, by far the largest share of household portfolios is invested in housing wealth, with the notable exception of the very richest households. The illiquidity of housing, the high transaction costs and the consumption element of housing purchases make this asset fundamentally different from the one-period riskless bond considered in our workhorse model. A number of authors have considered the effects of allowing households to save in housing assets in addition to financial assets: Campbell and Hercowitz (2009) and Campbell and Hercowitz (2005), Yang (2009), Iacoviello (2008)

2.7 Closed and open economies

One key decision when building a model of wealth accumulation is the question of how the interest rate on savings is determined. Traditionally, the macroeconomic literature has viewed the interest rate as an endogenous parameter, pinned down by the marginal product of capital from the economies production function and the quantity of capital available, which in turn is governed by household's savings decisions. In fact, the main contribution of the seminal work by Aiyagari (1994) was to highlight the effect of idiosyncratic income risk and borrowing constraints, two key features of the heterogeneous agent models most frequently used to examine questions related to the wealth distribution, on the steady state interest rate. Aiyagari shows that compared to a standard growth model, the steady state stock of capital in a closed incomplete markets economy is higher, and, correspondingly, the steady state interest rate is lower because of precautionary savings induced by income uncertainty. Another problem introduced by endogenous interest rates is a computational one, the determination of the interest rate requires asset market clearing, which implies that household savings choices have to be consistent with each other in each period. For these reasons, many researchers have opted for treating the interest rate as an exogenous parameter, set anywhere between three (Cagetti, 2003) and 5.2 (Gourinchas and Parker, 2002) percent. Whether this is justified will depend on two things: theoretically, one has to ask whether general equilibrium effects are likely to alter the answer to the question at hand, while empirically the question of the elasticity of the interest rate to changes in aggregate wealth. In general equilibrium models in the tradition of Aiyagari (1994), this elasticity is given by the sensitivity of the marginal product of capital to the quantity of aggregate capital, which can be determined from the production function. While the Cobb-Douglas function is the function of choice in the literature (see e.g. Castaneda et al. 2003), recent work by Piketty (2014) casts doubt on the appropriateness of this assumption and argues for a functional form implying a lower elasticity of the interest rate to increases in the capital stock. Irrespective of the choice of the production function though, one has to ask who valid the assumption of a closed economy, in which household savings have direct impacts on the quantity of productive capital in the economy, is. Given the deep international integration of modern financial markets, it appears that the open economy assumption often used in international economics to describe economies that can not set interest rates might be useful when thinking about the dynamics of interest rates in response to changes in saving behaviour in the local economy

2.8 Wealth Distribution Papers

In the last years, many authors have used the increasing possibilities offered by the increase in computing power to derive an additional implication from the broad class of incomplete market models outlined above: a simulated wealth distribution. While there are many practical difficulties in creating model outputs that can reasonably compared to the data collected in surveys (some of which have been alluded to in the above discussion on the definition of wealth), in principle the simulated wealth distribution derived from life-cycle models can be used to calibrate deep parameters of the model, provide an additional test for how well the model is able to capture household savings behaviour, and shed light on which mechanisms are crucial in driving the evolution of aggregate savings at different parts of the distribution.

An early attempt to use the wealth distribution to estimate the parameters of a life-cycle model of household savings can be found in Cagetti (2003), who uses a simple model similar to the one outlined in equations 2.1 and 2.2. Important additions in his version of the model are a bequest motive – which, ceteris paribus, will increase the wealth holdings of elderly households – and a simplified pension system, which guarantees each household a pension depending on their education level, and thereby lowers wealth accumulation during working life. The idea behind the estimation strategy is simple: given a stochastic process for household income, the parameters β, σ and α pin down a solution to the household's savings problem which allows one to simulate a theoretical wealth distribution from optimal household behaviour. Therefore, it is possible to use the simulated method of moments to construct an estimator that chooses the triplet (δ, σ, α) which minimises the distance between empirical moments of the wealth distribution and its simulated counterparts. Given the high skewness of wealth data, Cagetti opts for median wealth by 5-year age group as the moment to match. As has become clear in the previous discussion, a crucial element driving household choices in the model is the income risk they face, making the choice for the stochastic process representing this risk and its calibration a crucial step in modelling wealth distributions. Cagetti opts for a process consisting of a trend growth component common to all households, an age-education component estimated for CEX data, and an MA(1) process representing the stochastic nature of income. With his calibration, Cagetti finds low degrees of persistence, with pronounced heterogeneity across education groups, and high degrees of risk aversion, implying a significant contribution of precautionary savings to aggregate wealth.

A very similar exercise is performed by Hintermaier and Koeniger (2011), who construct a minimum distance estimator based on the shape of the cross-sectional distribution of wealth at different stages of the life cycle. That is, rather than simply targeting the 50th percentile of wealth holdings as Cagetti (2003), here all percentiles of the wealth distribution from 10 to 90 are considered. Increasing the number of moments to match leads to estimates of the discount factor which are an order of magnitude more precise than in Cagetti (2003). The estimate for the discount factor, at $\hat{\delta} = 0.985$, is at the upper bound of the estimates in Cagetti (2003), while the estimated risk aversion parameter $\hat{\sigma} = 1.08$ is only a third to one sixth as large as Cagetti's estimate, depending on the subgroup under consideration.

Exercises like the ones by Cagetti (2003) and Hintermaier and Koeniger (2011) repeatedly come to one conclusion: while a simple life-cycle incomplete markets model with idiosyncratic income shocks calibrated from income data can match parts of the wealth distribution well, and generate the correct ordering of inequality in wealth, income, and consumption – wealth being more unequally distributed than income, which in turn is more unequally distributed than consumption – it fails to capture the extremely high dispersion in wealth, especially at the top of the distribution[5].

A straightforward way of improving the fit of the more standard model is employing an income process that features large persistent shocks with low probability, as first popularised by Castaneda et al. (2003). Their specification of the income process is a four-state Markov chain, the highest state of which is only reached with very low probability, has a persistence of about five years, and implies an income 1000 times higher than median income. In this setup, it is evident that simple consumption smoothing considerations lead to very high savings rates for rich households, which in turn lead to a large wealth concentration at the top end of the distribution. It is however questionable to what extent models relying on this type of income process, which cannot be reconciled with the evidence from micro-level surveys on household incomes, can be used to inform policy analysis; a recent example of this problem can be found in the work of Kindermann and Krueger (2024), who investigate optimal labour income taxation in an Aiyagari-Bewley-Huggett style model featuring a similar income process and validating their model by fitting the top tail of the empirical wealth distribution.

[5]Indeed, this is the reason cited in Hintermaier and Koeniger (2011) for excluding the top decile of the wealth distribution from the targeted moments: the model has no chance of capturing the extremely high net worth of the richest households, which exceeds 150 times average yearly income in the 2007 SCF.

Unsurprisingly, they find very high optimal tax rates of around 90 percent on top earners, however this result is entirely driven by the income process used and subsequent work by Badel and Huggett (2014) demonstrates that optimal tax rates are significantly lower if one includes an earnings process based on human capital formation, which is parametrised to mirror the empirical evolution of earnings dispersion. This shows that a model that fits the wealth distribution is not necessarily suited for policy evaluation, especially if the good fit is the artefact of model assumptions that have little empirical support and gives reason to include more realistic features of the economic environment into the model which might help to explain observed patterns in the data. A number of researchers have extended the baseline model in various dimensions, some of which we will discuss here[6].

A more realistic version on the role of the household income process in shaping the wealth distribution is the inclusion of entrepreneurial activity as an alternative to labour income. Quadrini (2000) is an early attempt to include business income in the model. His economy features infinitely lived households, that have the opportunity to undertake entrepreneurial activity, but need to save up capital in order to start a business first. After having started the business, these agents face substantially higher risk than working households, a fact that combined with high borrowing costs and infinite lives leads to wealth accumulation at the top of the distribution as large as in the data. Cagetti and Nardi (2006) improve on this model by allowing for an endogenous choice in the amount of capital invested in the business, and in their model the potentially high rates of return on business activity are the main factor affecting the right tail of the wealth distribution. This

[6]The discussion here draws on the work by Nardi (2015).

aspect makes their model a close cousins to models that feature different rates of returns for different asset classes, which we turn to later. Cagetti and Nardi (2006) also provide an empirical rationale for the modelling of entrepreneurial activity, using SCF data to show that amongst the wealthiest 1% of households, 81% are business owners or self employed, although this group of households only accounts for 17% of all households. They also show that amongst business owners, mean and median wealth are higher for those not actively engaged in managing the business, providing support for models that feature an intergenerational transfer of assets, which we turn to next.

A successful line of research extends the model by moving from a simple life- cycle perspective to an overlapping generations (OLG) model, in which inequalities can be transmitted across generations and hence accumulate over time. This transmission mechanism can work through either assets directly, by adding a bequest motive to the agents utility function which prevents them from drawing down assets in old age, or through heritability of human capital in the form of skills or learning ability. The role of inheritance rose to prominence in the empirical literature with a dispute between Kotlikoff and Summers (1981), who estimate that around 80% of total wealth is inherited, while just 20% is the result of life-cycle saving, and Modigliani (1986), who argues that the role of the sources of wealth accumulations is exactly reversed. Recently, Thomas Piketty and a number of co-authors (Piketty 2011, Piketty et al. 2014, Piketty and Zucman 2015) revive this debate using long-run time series from France and drawing on other work from the UK and Germany, finding large variations in the annual flow of inheritance as a share of total wealth, but concluding that the overall importance of inheritance in shaping the wealth distribution is closer to Kotlikoff and Summer's estimates than to Modigliani's. The correct estimation of the role of inherited wealth is further complicated by the possibility of inter vivos transfers, which are not captured by inheritance tax data. This point is made forcefully by Gale and Scholz (1994), who use data on transfers from the SCF to estimate that 20 percent of aggregate wealth is passed on across generations via inter vivos transfers (compared to 31 percent as inheritances by their accounting). While the empirical estimation of intergenerational transfers of financial assets is not entirely straightforward, the question of the intergenerational transfer of ability is even more complicated. Researchers have adopted a wide range of specifications for modelling this transfer, based on models of parental investments in their childrens' education, or taken the short cut of directly assuming that children receive draws from productivity distributions, the mean and/or variance of which are directly linked to the parental realisation of productivity. Nardi (2004) examines both bequests and intergenerational transmission of ability in tandem, and shows that while the model fit is vastly improved by this mechanism, it still misses the very high concentration of wealth in the top percentile of the wealth distribution.

Another line of work considers the role of preferences in driving inequality in wealth accumulation. The obvious way to affect the distribution of wealth through preferences is by letting the discount factor vary across agents, an idea that finds empirical support in work by Lawrance (1991), who finds significant heterogeneity in time preferences rates between poor and rich households using an Euler equation based regression approach on PSID income and consumption data. The first work to leverage differential discount factors to increase wealth dispersion in the Aiyagari-Bewley-Hugget framework is the seminal paper by Krusell et al. (1998), who experiment with three groups of agents exhibiting discount factors between 0.9858 and 0.993. Even with this seemingly small dispersion in preferences, the inequality in wealth holdings in the model rises dramatically, with the share of wealth held by the richest 1% of households increasing from three to 24 percent, and the Gini coefficient increasing from 0.25 to 0.82. This finding is corroborated in recent work by Carroll et al. (2014), who show that a model with a slightly higher dispersion in δ than in Krusell et al. (1998) can match both the Lorenz curve of net wealth and financial wealth almost exactly. Cozzi (2014) considers the implications of varying the other deep parameter in the preference structure, risk aversion. He solves a model in which the population of agents has a mean risk aversion of 1.07, with a variance of 0.76, and shows that including this dimension of heterogeneity helps the model fit the data almost as well as the stochastic-delta model of Krusell and Smith, although it misses the concentration in the top percentile. Importantly, this model implies a significantly lower discount factor between 0.87 and 0.89 depending on the calibration. Interestingly, Cozzi combines his analysis with the estimation of income processes similar to the restricted income processes we will estimate in chapter 3 for subsamples of the PSID grouped by risk aversion, and finds significant heterogeneity in the persistence of the permanent shock to income, estimated at 0.947 for the less risk averse subgroup and 0.935 for the group with high risk aversion. Going one step further than simply adjusting the parameters of the standard CRRA utility function, Diaz et al. (2003) depart from this utility function altogether and investigate the role of habits in the utility function, first introduced into the macroeconomic literature by Fuhrer (2000) in the context of a DSGE model of monetary policy. They show that while habits induce a significant increase in precautionary savings in the economy, they do not help to bring the model closer to the empirical dispersion of wealth holdings, and on the contrary lower the Gini coefficient compared to a model without habit formation.

As alluded to in the discussion of models with entrepreneurial activity, there is also a literature that increases wealth inequality predicted by Bewley style models by allowing for differential rates of return, a feature that finds support in a vast macro-finance literature on the equity premium puzzle (for a survey see Siegel and Thaler (1997)), as well as the literature on households' portfolio choices (, while Guiso et al. (2003) review the European evidence) Benhabib et al. (2011) devise a peculiar model of differing rates of return, where the difference don't arise across asset classes, but across generations, with each generation of a household drawing an idiosyncratic interest rate for its portfolio, which prevails for the entire span of its life[7]. Combined with altruism for future generations, this setup generates a consumption smoothing motive across generations, with generations of a household that draw a high rate of return accumulating assets to increase consumption of its descendants. Benhabib et al. also offer some empirical support for the relevance of heterogeneity in rates of return, citing a standard deviation of rates of return for housing equity of 14%, and an even higher standard deviation in the rates of return for business equity, to asset classes which account for 28.2 and 27 percent of total US household wealth, respectively.

Lastly, there might be institutional factors that exert differential influences on the savings behaviour of different agents. A prominent example of this can be found in the work of Hubbard et al. (1995), who show that in a model which includes a social security system based on asset-based means testing, something

[7]Highlighting the similarities between models of entrepreneurial activity and those featuring different rates of return, Benhabib et al. motivate the inclusion of stochastic rates of return as an attempt to capture entrepreneurial risk.

that can be found in virtually all advanced economies, there is a strong incentive for poor households not to accumulate any wealth, which increases wealth dispersion by lowering the wealth holdings at the bottom of the distribution. Other government programs such as Medicaid in the US might play a role in shaping the dissaving behaviour of elderly households, which the standard model also has problems in replicating (see Nardi et al. (2009) and 2010, Nardi et al. (2015)).

2.9 Conclusion

This chapter provides an overview of stylised facts about the wealth distributions in a number of advanced economies and presents various approaches to build economic models which can account for these stylised facts. It became clear that while saving for retirement is the main driver of wealth accumulation for large parts of the population, other factors need to be taken into consideration to explain the tails of the distribution and the behaviour of young households. Crucial aspects of an economic model of the wealth distribution are the risks households are facing – both on the income and the expenditure side – and the financial markets available to them to insure themselves against those risks and earn returns on their savings. Finally, the far right tail of the wealth distribution seems to be driven by factors beyond this, with modelling attempts featuring a vast array of different ingredients succeeding in matching the distribution of wealth even for the richest house- holds. Given that vastly different approaches manage to fit the distribution, it is fair to say that so far there is no consensus on which mechanism is the most important one to include, and that all attempts to match the observed dispersion of wealth based on one of those mechanisms likely overstate the contribution of that particular mechanism, as so far no attempts at building an overlapping generations stochastic-beta model featuring differential rates of return, a realistic tax and benefit system, entrepreneurial activity, intergenerational transmission of financial wealth and ability, and human capital formation has been made. Some progress is being made in this direction, e.g. in De Nardi and Yang (2015), who combine intergenerational transfers of wealth and ability with an income process exhibiting higher income risk for rich households. Furthermore, virtually all of the papers discussed in this chapter rely on a variation of a simple AR(1) income process, ignoring recent evidence on income processes from large administrative data sets, to be discussed in chapter 3. This means that the implications of heterogeneous income processes for the wealth distribution are not well understood, a gap in the literature that 4 will attempt to address.

Chapter 3

The Effects of Profile Heterogeneity on Estimates of Income Risk

3.1 Introduction

As has become clear from the discussion in the preceding chapter, a crucial ingredient to any model of household savings is an estimate of the risk that households are facing in the form of their income process. Traditionally, researchers have relied on a parsimonious AR(1) specification with a transitory and a persistent shock component, which can be represented as a Markov chain and thus helps to ease the computational burden. Recent research has cast doubt on the ability of this specification to accurately capture the risk faced by households in the labour market though, and advances in computational capabilities have allowed to solve models with larger state spaces, so that there is a renewed interest in estimating richer statistical processes for household income.

The labour economics literature of income processes has long attempted to model household earnings dynamics using a variety of rich time series models with different AR and MA specifications. Early attempts to exploit longitudinal data on household's income include the seminal work of MaCurdy (1982), who fits ARMA processes to the income levels of a sample of prime age males from the first ten waves of the PSID and concludes that the data is best described by either an ARMA(1,2) or an ARMA(2,1) process; Abowd and Card (1987), who analyse data from the PSID, the NLS and SIME/DIME and settle for an MA(2) description of the data as most appropriate. Both MaCurdy (1982) and Abowd and Card (1987) conclude that the autoregressive component of the stochastic process describing income residuals has to have a unit root, a conclusion that is called into question by Baker (1997), who develops econometric tests that reject a specification with $\rho = 1$, and favour a specification with what he calls heterogeneous profiles, that is, an individual specific slope component in the income process. This approach had been previously applied in longitudinal data on American scientists[8] by Weiss and Lillard (1978) and in data on 279 Swedish scientists by Hause (1980). While these papers rely on a deterministic structure for individual wage growth over the life-cycle, Guvenen (2009) offers a model that fuses these approaches, including both deterministic components for the level and slope of income, as well as a stochastic AR(1) component delivering persistent shocks. As we will base our analysis on this model, we defer the detailed model description to the next section.

While most of the work discussed so far has relied on the use of survey data of income, which is plagued by measurement error and hence cannot correctly

[8]The National Science Foundation's Register of Technical and Scientific Personell, a dataset comprised of bi-yearly income observations on Ph.D. holders in the STEM fields.

identify the variance of transitory income shocks, in recent years researchers have been able to make use of the huge data base of the US Social Security administration, which offers exact data on incomes of millions of American workers over long periods of time. The first papers to make use of this data were Kopczuk et al. (2010), who focus on the evolution of cross-sectional income inequality over time and the distinction between permanent and transitory shocks to income, and DeBacker et al. (2013), who use a similar data set of tax returns to answer a very similar question – we will return to the implications of their findings for macroeconomic models in chapter 3. More interesting in the present context is a recent paper by Guvenen et al. (2015), who use the Master Earnings File of the Social Security administration for the years 1978 to 2010 to construct an extremely large panel of income observations for a sample of 10% of all US workers that were issued a Social Security number. From this data set, the authors conclude that the distribution of income shocks is not normal, with a kurtosis ten- to fifteen times that of a Normal distribution. Fitting processes similar to that in Guvenen (2009) to the data, they conclude that the data is best described by a model including heterogeneity in individual specific growth rates and a mixture of (at least) two independent AR(1) processes with different innovation variance. Some more recent papers take the opposite stance though and argue that profile heterogeneity is in fact not present in the variance-covariance structure of income data. Hoffmann (2013) uses administrative records from the German Institut für Arbeitsmarkt- und Berufsforschung (IAB), which allows to construct individual-specific earnings histories for up to 120 quarters and is fairly large, representing a 2% sample of all German salaried employees. Given the structure of the data, it is possible to control for age and cohort effects better than in the

PSID, were small sample sizes force aggregation of age groups. Hoffman finds intercept heterogeneity (σ_α^2) to be an important feature when trying to fit the data irrespective across all specification of income processes under consideration, but argues that heterogeneity in income growth rates becomes insignificant once the variance of the initial value of the persistent component is adequately controlled for. Along similar lines, Hryshko (2012) conducts Monte Carlo simulations to show that if a misspecified HIP model is estimated on a synthetic dataset generated from an underlying process with $\sigma_\beta^2 = 0$, an econometrician will generally find statistically significant levels of profile heterogeneity. Finally, some authors have attempted to extend the basic ARMA model in other directions, adding e.g. ARCH effects to capture stochastic volatility in income innovations (Meghir and Pistaferri 2004), allowing for individual-specific income *processes*, rather than simply different means and variances for the same process (Browning et al. 2010) It is thus fair to say that the literature has not yet reached a firm conclusion on the correct specification of the income process households are facing. This chapter will undertake a modest attempt at adding to the evidence by estimating RIP and HIP processes on different samples of income data. To our knowledge, this is the first study to use all available waves for the PSID, ranging from 1968 to 2013, and the first study to estimate HIP processes from data coming from the British Household Panel Study (BHPS).

3.2 The statistical model

To inform the simulations in the following chapter, this thesis will rely on an estimated heterogeneous income profiles (HIP) income process in the spirit of

Guvenen (2009). The process to be estimated is of the form

$$y^i_{h,t} = g(\theta_t, \boldsymbol{X}^i_{h,t}) + \alpha^i + \beta^i h + z^i_{h,t} + \phi\varepsilon^i_{h,t} \tag{3.1}$$

$$z_{h,t} = \rho z_{h-1,t-1} + \pi_t \eta^i_{h,t} \tag{3.2}$$

where $y^i_{h,t}$ are the log earnings of individual i, who has h years of labour market experience in period t. The function $g()$ is assumed to be a cubic polynomial in experience, while the individual specific parameters α^i and β^i – modelled as random variables with mean zero and variance σ^2_α and σ^2_β, respectively – capture the cross-sectional profile heterogeneity. $z^i_{h,t}$ is an AR(1) process with persistence ρ and innovation variance $\eta^i_{h,t}$, which captures persistent shocks to income, while $\varepsilon^i_{h,t}$ is a purely transitory shock. Both η^i and ε^i are mean-zero i.i.d random variables with variances σ^2_η and σ^2_ε, respectively. As discussed above, the variances of both permanent and transitory shocks have seen large swings over the past decades, to capture this we are allowing for time-variation in the innovation variance (denoted π_t for the innovation to the persistent shock component and φ_t for the transitory counterpart).

To estimate the parameters of the model, an equally weighted minimum distance estimator is used to minimise the distance between the empirically observed variance-covariance structure of residual earnings (defined as $\tilde{y} \equiv y^i_{h,t} - g(\theta_t, \boldsymbol{X}^i_{h,t})$ and the variance-covariance structure implied by the model. In the present context, this strategy has first been employed by Baker (1997), who estimates a very similar model to the one described above, although the approach has been used before for estimating other models in labour economics, e.g. Abowd and

Table 3.1: Previous estimates of profile heterogeneity in different data sets

	ρ	σ^2_η	σ^2_ε	σ^2_α	σ^2_β	$cov(\alpha,\beta)$
Guvenen (2009)	0.821	0.029	0.047	0.022	0.00038	-0.23
Baker (1997)	0.423	0.089	–	0.355	0.00081	-0.014
Haider (2001)	0.639	0.057–0.166	–	0.295	0.00041	-0.0083

Card (1987). Table 3.1 summarizes findings of earlier papers. Our model implies theoretical variances and covariances given by:

$$\text{Var}(\tilde{y}^i_{h,t}) = \underbrace{\sigma^2_\alpha + 2\sigma_{\alpha\beta}h + \sigma^2_\beta}_{\text{contribution of profile heterogeneity}} + \text{Var}(z^i_{h,t}) + \phi^2_t\sigma^2_\varepsilon \tag{3.3}$$

$$\text{Cov}(\tilde{y}^i_{h,t}, \tilde{y}^i_{h+n,t+n}) = \underbrace{\sigma^2_\alpha + 2\sigma_{\alpha\beta}(h+n) + \sigma^2_\beta}_{} + \text{Var}(z^i_{h,t}) + \phi^2_t\sigma^2_\varepsilon \tag{3.4}$$

The empirical variance-covariance matrix underlying the estimation will be obtained by first calculating the covariance of residuals for each age-group in a given year, and then averaging over all age groups present in a given year. The theoretical counterpart is obtained by simply calculating the corresponding variances and covariances from the formulas above, and forming weighted averages over h with weights corresponding to the relative frequency of age-groups in the empirical data.

3.3 Prior evidence

3.4 Data

As we are interested in the variability of our estimates, we are estimating the process described both on PSID and BHPS data. PSID data has the advantage of providing a very long horizon (37 waves of data covering a total of 45 years), which allows for the analysis of subperiods to examine changes over time. The BHPS, while more limited in time (18 waves of data covering 18 years) serves as a useful comparison, while also providing excellent measures of different measures of household incomes pre- and post taxes and transfers, which we will describe in more detail below. The data is taken from all available waves of the PSID, that is years 1968 to 2013 inclusive[9]. For our baseline estimation, to ease comparisons, we stick to the sample selection criteria used in Guvenen (2009), namely:

- Household heads between the ages of 20 and 64 inclusive
- Hourly labour earnings between \$2 and \$400 in 1993 prices
- Hours worked between 520 and 5110

For inclusion in our sample, an individual has to fulfil all of the above conditions for at least 20, not necessarily consecutive, years. These sample selection criteria leave us with 1685 individuals in our final sample [10]. The main variable of interest in the analysis is labour income, for which we use the series of variables starting with `V74` in 1968[11]. Hourly earnings are taken from the variable starting with `V337` in 1968, while hours worked are taken from the variable starting with `V47`. To extract the deterministic life-cycle component of the is modelled as a cubic polynomial in experience, $g(\theta_t, \boldsymbol{X}^i_{h,t}) = \gamma_0 + \gamma_1 h + \gamma_2 h^2 + \gamma_3 h^3$. Labour market experience itself is constructed as potential experience from information on years

[9]Note that the PSID income variable refers to income in the previous year, so when we talk about data from, e.g., year 1968, it is implied that we are referring to income in 1967.

[10]To create the longitudinal data set from the PSID cross-sections, we use the excellent *PSIDtools* package (Kohler, 2015)

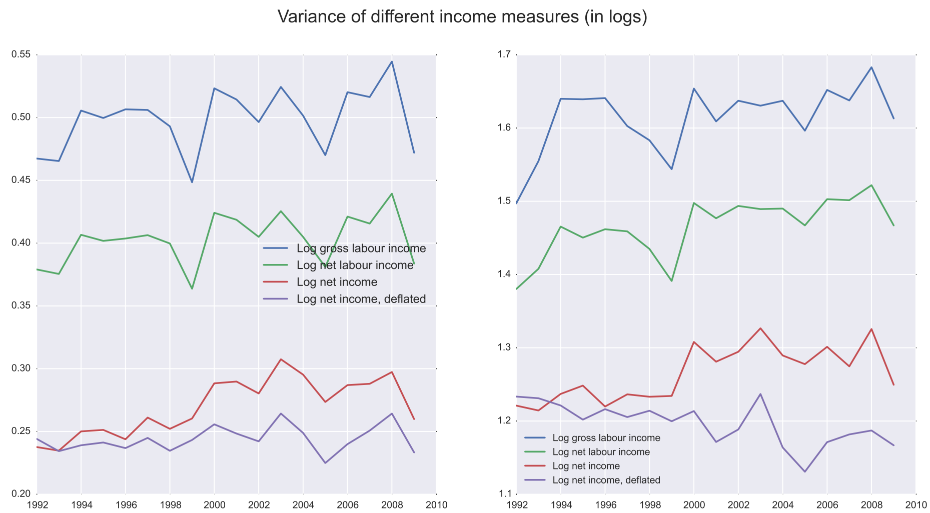
[11]A complete list of all variables used is available on my GitHub page.

of schooling.

The BHPS data we're using comes from all available waves, covering the time period from 1992 to 2008[12]. The raw data is then extended by the derived current annual and net household variable data set provided by **?**. This data set includes information on household income that takes into account various government taxes and transfers, both at the individual and the household level. For our purposes, we will use gross labour income of the household, which is available in the original BHPS data set; net household labour income, which considers taxes and tax credits, national insurance contributions, and occupational pension contributions; and net household income, which adds investment income, pension income, and transfer income to net labour income. These three variables can be seen to represent different levels of insurance available to the household: as taxes and (up to a points) National Insurance contributions in Britain are progressive, they reduce the variability of the labour income process facing the household, while the benefits system, which includes housing benefit, job seekers benefits, disability insurance and various other payments, partially insures household income against unemployment and other catastrophic shocks. It is therefore expected that these measures of income imply less risk for the household than gross labour income, an effect that we will try to quantify below. As the time dimension is notably shorter than in the PSID, we only require households to be in the sample for five years, and consider up to ten lags for the covariances of residuals. While previous authors have highlighted the importance of higher order covariances for identification of HIP processes, our sample sizes unfortunately are so small that for some cohorts there are less than 10 observations at lags larger

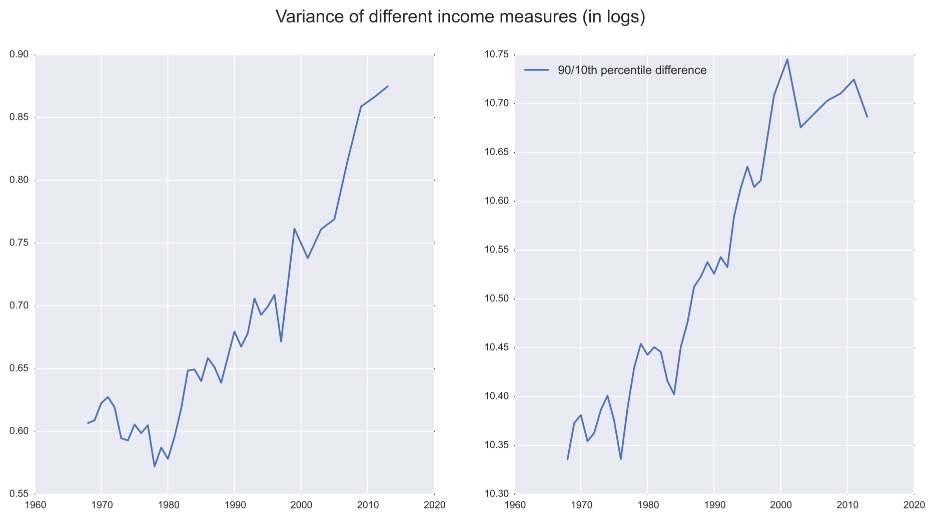
[12]To merge the BHPS data across waves, we use code provided by **?**.

Figure 3.1: Variance of log income and 90/10 percentile width for our sample of BHPS households



than five, so that considering more lags is impossible. As for the PSID, we obtain income residuals by regressing each measure of income on a cubic polynomial in experience, which is constructed from the school leaving age (or further education leaving age, where applicable). Figure 3.1 and 3.2 show trends in the variance and the inter-decile range, two widely used measures of income dispersion, for our selected sample of households. Both datasets exhibit considerable variation in the dispersion of income over the period under consideration, which motivates us to include time-varying variances for transitory and permanent shocks in the estimation.

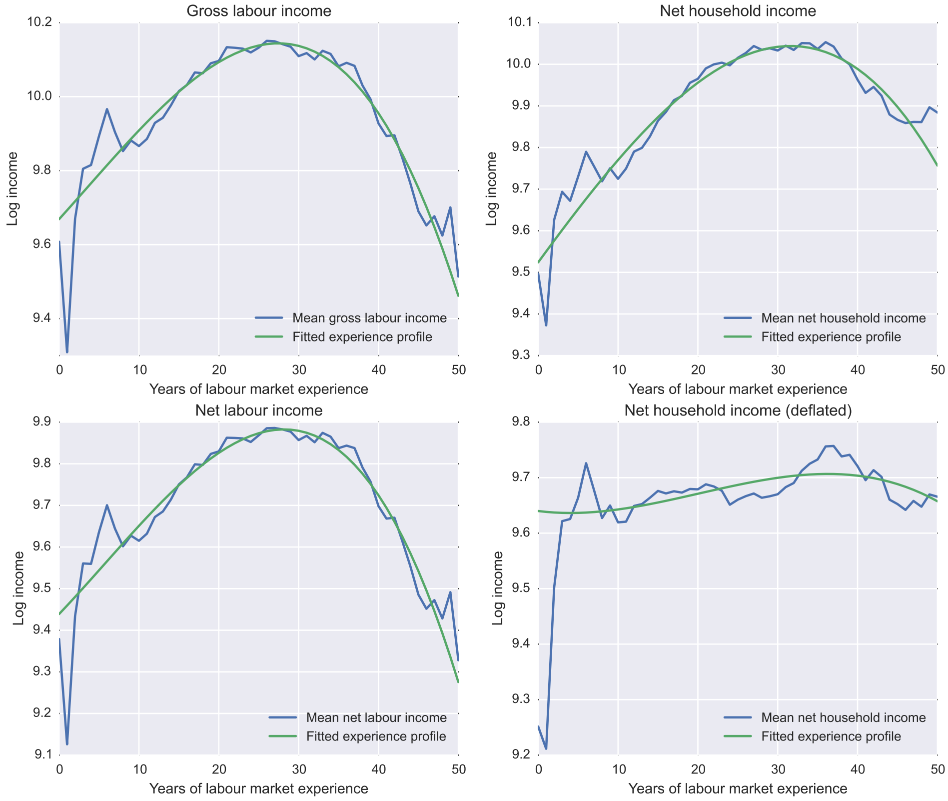
Figure 3.2: Variance of log income and 90/10 percentile width for our sample of BHPS households



3.5 Results

Table **??** displays the results for the PSID sample of households. While the results can be considered to be qualitatively similar to those found in Guvenen (2009), interestingly the estimated dispersion of individual- specific growth rates declines from 0.00031 to 0.00025, a result that confirms the same finding in Hryshko (2012). Table 3.2 shows the results of estimating both RIP and HIP processes on our sample of households from the BHPS, using the four different income measures described previously. The results are largely unsurprising qualitatively, with the variance of persistent shocks declining from 0.1 for the most volatile process (gross labour earnings) to 0.07 for net labour earnings, to 0.027 for net household income. A similar pattern can be observed for the transitory shock, declining from 0.08 to 0.07 and 0.056, respectively. The estimates for the main parameter of interest, the cross-sectional dispersion in individual specific

Figure 3.3: Log mean income and fitted experience profiles for the BHPS 1992 – 2009



growth rates β^i behaves accordingly, dropping from 0.00032 (consistent with the findings for the main PSID sample in Guvenen (2009)), to 0.00019 and 0.00011. Interestingly, some of the decrease in the parameters that increase cross-sectional dispersion over the life-cycle of a cohort is offset by a rise in the cross-sectional inequality in intercepts, Var_α rises from 0.036 in the gross labour income sample to 0.052 in the net household income sample. The persistence of

3.6 Discussion

Our estimates point to substantial uncertainty over the correct HIP process, adding to a literature that has found vastly different estimates for all of the main parameters. Further, we have documented that even applying the same estimation procedure to different subsamples of the same survey can deliver results that differ markedly. Lastly, our estimates based on different income measures from the BHPS underscore the importance of partial insurance when trying to estimate household income risk from the data. In the next chapter, we will explore the quantitative implications of these differences for wealth accumulation in life-cycle models with incomplete markets.

Table 3.2: Results for the PSID sample 1968-1996; Guvenen (2009) refers to published results, Guvenen Matlab to results obtained by running the code available on the journal website, short sample to my own estimation with the 1968-1996 data, full sample to the 1968-2013 data.

	ρ	σ^2_η	σ^2_ε	σ^2_α	σ^2_β	$\sigma_{\alpha\beta}$
Restricted income process: $\sigma^2_\beta \overset{!}{=} 0$						
Gross labour income	0.925	0.045	0.135	0.0	–	–
Net labour income	0.867	0.065	0.077	0.017	–	–
Net household income	0.921	0.026	0.046	0.012	–	–
Net household income (deflated)	0.817	0.038	0.038	0.084	–	–
Heterogeneous income process; σ^2_β unrestricted						
Gross labour income	0.719	0.106	0.080	0.036	0.00032	-0.51
Net labour income	0.808	0.073	0.070	0.032	0.00019	-0.59
Net household income	0.857	0.027	0.056	0.052	0.00011	-0.42
Net household income (deflated)	0.812	0.039	0.042	0.100	0.0	-1.0

Table 3.3: Results for the BHPS sample 1992-2009, different income measures.

	ρ	σ^2_η	σ^2_ε	σ^2_α	σ^2_β	$\sigma_{\alpha\beta}$
Restricted income process: $\sigma^2_\beta \overset{!}{=} 0$						
1968-1996 sample	0.932	0.010	0.036	0.084	–	–
1968-2013 sample	0.920	0.014	0.067	–	–	–
1968-1986 sample	0.960	0.015	0.061	0.058	–	–
1987-2013 sample	0.939	0.017	0.095	0.110	–	–
Heterogeneous income process: σ^2_β unrestricted						
1968-1996 sample	0.853	0.013	0.030	0.030	0.00031	–0.30
1968-2013 sample	0.839	0.017	0.064	0.047	0.00026	–0.32
1968-1986 sample	0.885	0.013	0.043	0.110	0.00001	-0.42
1987-2013 sample	0.854	0.032	0.085	0.097	0.00025	-0.31

Chapter 4

Wealth Distributions in Heterogeneous Income Process Models with Learning

4.1 Introduction

What factors can explain the substantial and persistent increase in US household indebtedness over the last three decades? This question has inspired a large literature that has put forward several explanations. On the side of credit supply, the institutional framework plays a central role; Campbell and Hercowitz (2005) emphasize the effects of the liberalization of the US home mortgage market in the early 1980s while Narajabad (2012) points towards improvements in banks' risk assessment capabilities to explain an increase in credit lines available to households. On the demand side, the most influential view is arguably given by Krueger and Perri (2006) who interpret the expansion of US credit markets as the rational response of consumers borrowing in order to smooth out income shocks, the variance of which has risen over time. However, this view rests on the observed increase in cross-sectional income variation being largely due to a rise in the variance of transitory idiosyncratic shocks, an interpretation that has been called into question by several authors. As an example, Kopczuk et al. (2010) find that the rise in income inequality was almost entirely driven by increases in permanent earnings inequality, with no mitigating effect of mobility across income groups that decreased at the same time as earnings inequality increased. In the same vein, DeBacker et al. (2013) use a confidential panel of tax returns from the IRS to show that all of the rise in the variance of male labour earnings between 1987 and 2009 can be attributed to a rise in the variance of the persistent part of income. In light of these difficulties, the present work aims to examine an additional mechanism that could drive household credit demand – consumption habits. In this regard, this work bears some resemblance to the prominent Rajan (2011) hypothesis that the foundations for the financial crisis of 2007/08 were laid by a credit expansion that mostly benefited low-income households. This also relates to more heterodox, post-Keynesian and Marxist explanations of rising household indebtedness that emphasize the role of debt as a substitute for stagnating or declining real wages in the middle and lower percentiles of the income distribution (see, for example, Barba and Pivetti, 2009), a mechanism of course that would require households to be – at least for some time – oblivious towards the realities of the path of their income stream. Often, behavioural explanations such as conspicuous consumption or household optimization based on a relative income hypothesis are invoked, examples include Bertrand and Morse (2013), who find empirical support for the hypothesis that consumption of lower income households is influenced by consumption of high income households, and van Treeck (2012), who presents some calculations based on Duesenberry's (1940) relative income hypothesis. Here, we try to frame this argument in terms of an arguably more standard economic model: a life-cycle model with fully optimizing rational households that derive utility from current and past consumption, while facing an uncertain income stream that they learn about over the course of their working life. The basis for the present analysis is a model introduced by Guvenen (2007), in which the income process consists of a permanent stochastic AR(1)-component, as is standard in most of the literature, and an additional deterministic term, that is different across workers and that they have to learn about in order to make precise forecasts of their lifetime income. This uncertainty, coupled with the time-inseparability of consumption introduced by habit formation, can under certain circumstances lead to an increase in the indebtedness even of households with permanently low incomes.

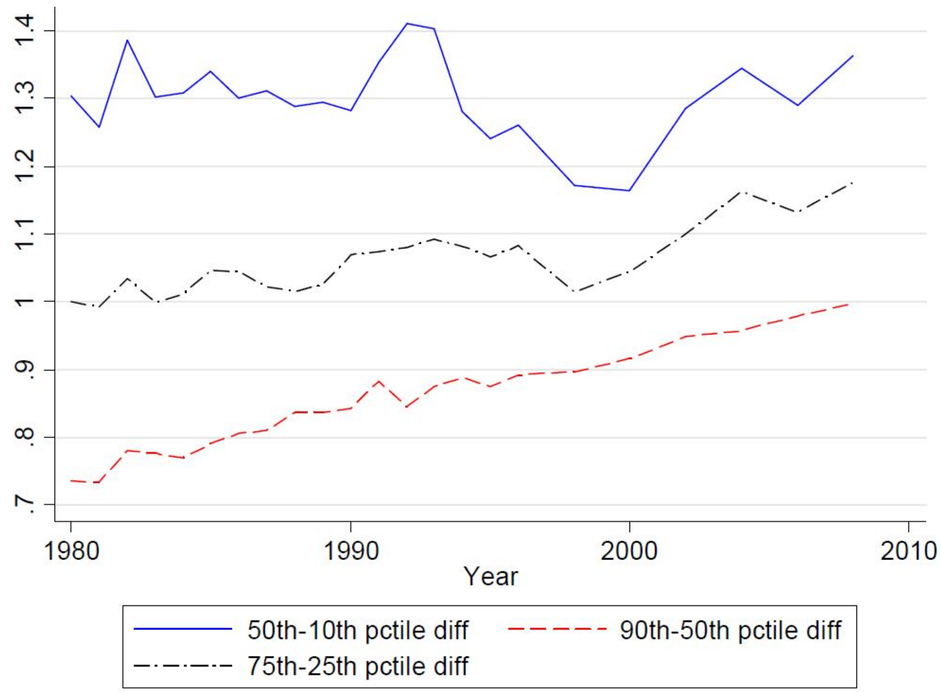
The remainder of this paper is structured as follows: Section (4.2) presents some stylized facts on the developments of the US income and wealth distribution that motivate this work. Section (4.3) briefly lays out the model, and gives analytical results for a stripped down version of the model that shed light on the mechanisms through which habit formation can generate higher indebtedness. Section (4.4) presents the results of a quantitative evaluation of the model using the income process parameters estimated in chapter 3, while section (4.5) employs a minimum distance estimator to fit the model to the empirical distribution of household wealth. Section (4.6) performs comparative statics on the parameters of the model to shed light on the mechanisms driving the models success in replicating the data. Section (4.7) discusses the results of the chapter.

4.2 Stylized Facts

The widening inequality in the U.S. income distribution is a well documented feature of the data during at least the last three decades. Numerous studies have examined the secular rise in top incomes (Piketty and Saez, 2003) and the flattening path of middle and lower incomes (Autor et al., 2005) and put forward explanations such as changes in relative demand and supply for different skill levels, the decline of union power, increases in international trade and competition (Ma, 2013) and the fall in the real value of the federal minimum wage[13]. While the exact timing and magnitude of the rise in inequality may differ slightly from one data source to the other and depending on the exact definition of income employed, its existence can be regarded as a consensus in the literature. Figure (4.1) is taken from Attanasio, Hurst and Pistaferri (2012) and shows the evolution of income inequality at different points of the income distribution from 1980 to 2010 based on PSID data. The rise in overall inequality is apparent and can be seen to be mostly driven by a surge in top incomes (even though, as the authors note, PSID data undersamples very rich households and thus most likely understates the rise in top incomes). There exists less consensus about the evolution of consumption inequality over the same period. While early prominent studies such as Krueger and Perri (2006) used CEX data to argue that there has been virtually no increase in consumption inequality and built theoretical models that could account for this puzzle, more recently other authors have found a larger increase in consumption inequality using different data sources that arguably suffer from less measurement error than the aggregate CEX data. Heathcote et al. (2010) use

[13] Some doubts on the magnitude and timing of the rising inequality are raised by Gordon (2009).

Figure 4.1: Income inequality for three income differentials, 1980-2010, PSID data

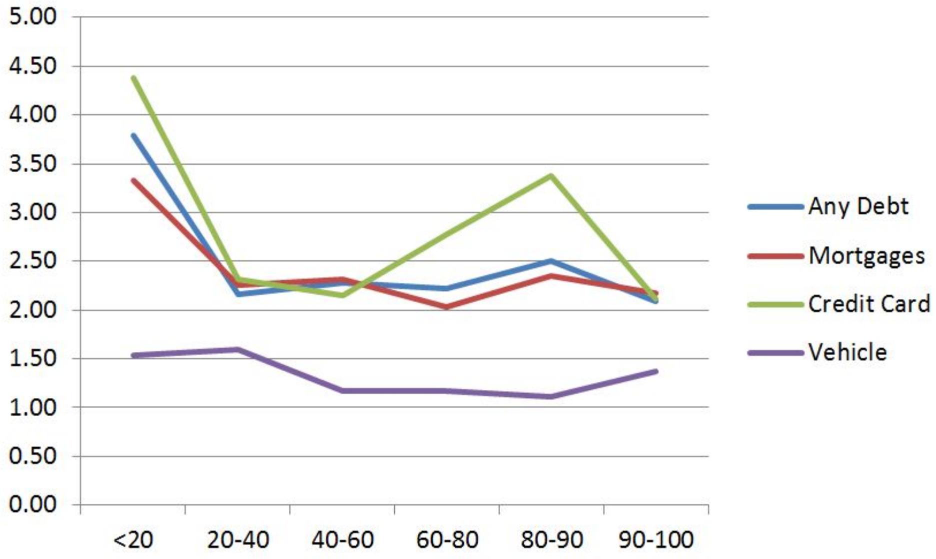


CEX spending data to document a very modest increase in consumption inequality, while Aguiar and Bils (2015) use the difference between income and spending in CEX data to document a rise in consumption inequality that is almost as large as the rise in income inequality and Attanasio et al. (2013) argue that, looking at some of the more precisely measured items in the CEX, one finds that consumption inequality has indeed tracked income inequality. For the purpose of this paper, we will use aggregate spending data from the CEX and thus assume that consumption inequality has not risen to the same extent as income inequality while keeping in mind that this is not a foregone conclusion. We will return to this point in the last chapter.

Another well documented feature of the data is the rise in debt holdings of the private sector. As with the rise in income inequality, this development has been widely noted and discussed with numerous explanations put forward, including changes in the regulatory framework and banking technology that widened credit supply. Most relevant to this work is the demand side argument of Krueger and Perri (2006), who explain the rise in indebtedness with a limited commitment model in which the variance of the transitory component rises and hence more insurance is required, and, indeed, optimal from a welfare perspective. However, as Cordoba (2008) points out, their model produces two empirically unappealing results: for one, wealth holdings are not concentrated at the top of the distribution, and second, the model predicts a large fraction of agents in the economy with negative wealth holdings, when their number really is close to zero in the data. Furthermore, their argument is weakened by a number of studies that find changes in the variance of the permanent component of income shocks to be the driving force behind the rise in income inequality. This is hard to reconcile with the fact that individuals at the lower end of the income distribution are those that increased their debt holdings the most. Figure (4.2) shows the changes in debt holdings for various debt categories calculated from SCF data for 1989 to 2007.

While the large rise in indebtedness for the lowest income group is an artefact of business owners with failed businesses in the data, it is interesting to note that the rise in overall debt has been at least as large for the 20th to 60th percentile as for the highest income percentile. This comes as a surprise if one takes into account the higher income growth rates for individuals in higher income quintile since the early 1980s. Assuming that the dispersion in incomes is mostly driven by an increase in dispersion in the permanent component of income (as suggested by, among others, Kopczuk et al., 2010), a standard life-cycle model would suggest

Figure 4.2: Changes in debt holding by income percentile, 1989-2007, Source: SCF



that while high income households should borrow against their higher future income, low income households wouldn't have an incentive to borrow when wages are stagnant. Furthermore, note that the data is not scaled by income, so that debt holdings relative to income have increased a lot more for lower income households, given that their income growth rates over the same period have been lower than those of higher income households. Indeed, Barba and Pivetti (2009) find that instalment loans and credit card debt amount to 59% of disposable income for households in the lowest income quintile of the 2004 SCF, while they amount to only 11% for the highest quintile.

One adjustment margin for households that could explain a decoupling of income and consumption inequality at least over short to medium frequencies is obviously saving. Saez and Zucman (2014) find that the share of wealth holdings of the bottom 90% of the wealth distribution has fallen from 35% in the mid 1980s to

23% in 2012, citing low growth of middle-class income, financial deregulation leading to predatory lending and behavioural biases in savings decisions as possible explanation. This paper can be seen as an attempt to investigate to what extent imperfect information of agents can account for the observed change in the wealth distribution.

- Increase in the dispersion of wealth holdings that tracked or exceeded the rise in income inequality
- Decreasing aggregate savings rate
- Prevailing misperceptions about future economic situation (Moore 2003)

4.3 The Model

The model employed is a standard incomplete markets life-cycle model of household consumption and savings as described in chapter 2, with the addition of a learning mechanism for household income, as first used by Guvenen (2007). While this model has recently been used to study household's portfolio choices (Chang et al. 2013) and the joint evolution of income and consumption inequality in a rich dynamic model featuring informal insurance mechanisms (Guvenen and Smith 2014), the implications of heterogeneous income processes and learning for the aggregate wealth distribution have so far not been examined to the best of our knowledge. Consumers maximize

$$E_0\left[\sum_{t=0}^{T}\beta^t\frac{c_t^{1-\sigma}}{1-\sigma}\right] \tag{4.1}$$

s.t.

$$a_{t+1} = (1+r)a_t + y_t - c_t \tag{4.2}$$

$$y_t^i = g(\theta^0, X_t^i) + f(\theta^i, X_t^i) + z_t^i + \epsilon_t^i \tag{4.3}$$

$$a_{t+1} \geq \underline{a} \tag{4.4}$$

where c_t is consumption in period t, a_t are asset holdings subject to a borrowing constraint $\underline{a}$, and y_t^i is individual income, which follows the heterogeneous income specification in logs discussed in chapter 3:

$$y_t^i = g(\theta^0, X_t^i) + f(\theta^i, X_t^i) + z_t^i + \epsilon_t^i$$

Here, $g(\theta^0, X_t^i)$ captures age effects and individual specific characteristics such as education, z_t^i is an autoregressive process of order one, and $f(\cdot)$ is an individual specific function that plays the decisive role in introducing heterogeneity and learning in the model.

$$f(\theta^i, X_t^i) = \alpha^i + \beta^i t$$
$$z_t^i = \rho z_{t-1}^i + \eta_t^i$$
$$\theta^i \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_\alpha^2 & \sigma_{\alpha\beta} \\ \sigma_{\alpha\beta} & \sigma_\beta^2 \end{pmatrix}\right]$$

The parameters α and β are randomly distributed over the population and govern the evolution of lifetime income over time. Furthermore, they are unknown to individuals upon entering the labour market, meaning that in order to calculate an expected lifetime income to base consumption choices on, consumers in the model have to form beliefs over the values of their individual parameters. Here again we follow Guvenen in assuming that these beliefs are formed optimally in a Bayesian fashion, which means solving a Kalman filtering problem. Denoting by S_{t+1}^i the vector of parameters α^i, β^i and z_{t+1}^i and by F the coefficient vector in the state space representation, the evolution is governed by the law of motion:

$$\hat{S}_{t|t}^i = \hat{S}_{t|t-1}^i + P_{t|t-1} H_t [H_t' P_{t|t-1} H_t + R]^{-1} (y_t^i - H_t' \hat{S}_{t|t-1}^i) \tag{4.5}$$
$$\hat{S}_{t+1|t}^i = F \hat{S}_{t|t}^i \tag{4.6}$$

where we denote by $\hat{S}_{t|t}^i$ the optimal belief about the individual specific parameters of the income process in period t after having observed the realisation of y_t^i, and by $\hat{S}^i_{t+1|t}$ the optimal forecast based on those beliefs, assuming that the transition matrix F is known to the household. $P_{t|t}$ is the variance-covariance matrix of $\hat{S}^i_{t|t}$ and R is the variance of the transitory shock. A similar expression can be derived for the evolution of $P_{t+1|t}$:

$$P_{t|t} = P_{t|t-1} - P_{t|t-1}H_t[H_t'P_{t|t-1}H_t + R]^{-1}H_t'P_{t|t-1} \tag{4.7}$$

$$P_{t+1|t} = FP_{t|t}F' + Q \tag{4.8}$$

With Q denoting the covariance matrix of the innovation in the state space representation of $\hat{S}^i_{t+1|t}$ (which is basically the innovation in the AR(1) component of earnings). Given this formulation for the evolution of beliefs, we can write the recursive version of our maximization problem as:

$$V_t(x_t, \hat{S}^i_{t|t}) = \max_{\{c^i_t, a^i_{t+1}\}} \left\{ u(c_t) + \mathbb{E}_t \left[V_{t+1}(x_{t+1}, \hat{S}^i_{t+1|t+1} | \hat{S}^i_{t|t}) \right] \right\} \tag{4.9}$$

which again has to be solved subject to the constraints, 4.2, 4.4 and 4.5-4.8. Note that given this formulation of the problem, all state variables appearing in the continuation value function on the right- hand side of the Bellman equation are functions of the realisation of income next period, so that the expectation in 4.9 has to be taken only with respect to $\hat{y}^i_{t+1}$. The distribution of next period's expectation of income is known exactly, conditional on current beliefs:

$$\hat{y}^i_{t+1} \sim \mathcal{N}(\hat{\alpha}_{t|t} + (t+1)\hat{\beta}^i_{t|t} + \rho\hat{z}_{t|t}, \sigma^2_\alpha + t^2\sigma^2_\beta + 2t\sigma_{\alpha\beta} + \sigma^2_\eta + \sigma^2_\varepsilon$$

An important issue when trying to match empirical wealth distributions is the specification of the pension system. The household problem during retirement is straightforward to solve in the absence of uncertainty; it is given by

$$V_t^R(a_t, \bar{y}) = \max_{c_t, a_{t+1}} u(c_t) + \delta V_{t+1}^R(a_{t+1}, y^R) \tag{4.10}$$

s.t.

$$a_{t+1} = (1+r)a_t + \bar{y} - c_t \tag{4.11}$$

$$y^R = M(\bar{y}, \bar{Y}) \tag{4.12}$$

$$a_{t+1} \geq \underline{a} \tag{4.13}$$

where M is a benefit function that emulates the US Social Security system and is specified following much of the literature on life-cycle models (cp. Storesletten et al. (2004), Hintermaier and Koeniger (2011), Guvenen and Smith (2014), amongst others) as a function depending on average lifetime income of an individual, $\bar{y}$, relative to the economy-wide average income $\bar{Y}$:

$$y^P = \begin{cases} 0.9\bar{y} & \text{if} \bar{y} < 0.3\bar{Y} \\ 0.27 + 0.32(\bar{y} - 0.3) & \text{if} \bar{y} \leq 2.0\bar{Y} \\ 0.814 + 0.15(\bar{y} - 2.0) & \text{if} \bar{y} \leq 4.1\bar{Y} \\ 1.129\bar{Y} & \text{if} \bar{y} > 4.1\bar{Y} \end{cases}$$

Note that this system attenuates the inequality in lifetime income created by the stochastic process for income by providing higher replacement rates for poor households than for rich households. To avoid adding another state variable to the model, we replace the true value of $\bar{y}$ by an estimate derived from running the cross-sectional regression

4.3.1 Computational Algorithm

To solve the model, we adopt a strategy similar to that in Guvenen and Smith (2014). After drawing an income distribution and simulating agent's learning given a set of initial beliefs, we construct a three-point grid for $\hat{\alpha}$, a fifteen-point grid for $\hat{\beta}$ and a seven-point grid for $\hat{z}$, all linearly spaced ranging from the lowest to the highest belief coming out of the simulation of agent's learning process. For wealth, we choose 40 grid points, exponentially spaced with a higher concentration of points at low levels of wealth. The household's pension problem can be solved analytically, while the household's working life problem is solved recursively on all grid points in the four- dimensional state space. To evaluate the continuation value function on the right- hand side of the Bellman equation, we employ quadrilinear interpolation combined with Gauss-Hermite quadrature on ten nodes for the numerical integration [14]. In the simulation step, we initialise household wealth holdings by drawing from the empirical wealth distribution for 23 to 25 year old households from the Survey of Consumer Finances, data that is available in Hintermaier and Koeniger (2011), and check the sensitivity of model results to this choice by comparing them to the alternative of zero wealth holdings at age 20 for all households.

[14] In particular, the linear interpolation was performed using the `ApproXD.jl` package (Oswald, 2014), while the Gauss-Hermite nodes were derived using the `FastGaussQuadrature.jl` package (Townsend, 2015).

4.4 Quantitative Results

Given the slow learning induced by the nature of the income process, the initial beliefs of consumers are of crucial importance for consumption decisions in the first periods of live. These in turn determine a habit stock that might (depending on the parameter choice for λ) have a long lasting effect on the marginal utility of consumption in the following periods. Hence, it is important to explore the sensitivity of results to different initial belief vectors and think about reasonable parametrizations. In a more fully specified model, one could further introduce a trade-off for agents between "comforting" expectations about their own future and the cost attached to acting on overly optimistic preferences, as for example argued by Glaeser (2004), but such a specification would require the introduction of a further unknown parameter in the utility function determining the utility of optimistic expectations and is therefore outside the scope of this work. Instead, we will focus on two baseline cases and explore the sensitivity of results to deviations from this baseline.

The first case assumes that agents entering the labour market in the model at age 25 have formed expectations based on previous observations of wage growth for workers in similar occupations to the one they are entering. Hence, we will assume that someone entering the labour market at, say, the 20th quintile of the wage distribution, will have expectations that were formed on the wage growth of workers in the 20th quintile 10 years prior to the worker entering the labour market. Note that this will have opposite effects on workers entering the labour market in the late 1970s, just before cross-sectional wage dispersion started to increase: while workers in low-skill occupations at the bottom of the wage distribution will face lower income growth rates than their predecessors, and thus growth rates below their expectations, workers at the high end of the wage distribution will see their incomes grow above expectations for the same reason. Thus, with this parametrization, poorer households will build up habit stocks that are too high relative to lifetime income early in life, with the reverse being true for high income households.

The second baseline case is inspired by the aforementioned research on people's inclination to hold optimistic beliefs as well as survey evidence on the overconfidence of economic actors. One such example would be a Gallup poll (Moore, 2003) in which 31% of respondents declared to expect to be rich at some point in their life, a number that jumps to 51% for the group of 18 to 29 year olds, where *rich* is defined as having an annual income of more than $120,000 or assets in excess of $1,000,000. DiPrete (2007) surveys a number of similar polls, compares their results with PSID data and concludes that even accounting for subjective differences in the definition of "being rich", Americans significantly overestimate the opportunity for upward income mobility over their lifetime [15]. A host of similar studies can be found and while one can certainly question whether such obviously unreasonable expectations form the basis for everyday economic decisions, they do point towards a significant amount of unwarranted optimism about the own economic future for a large part of the population. With this in mind, in the second scenario the belief vectors are parametrized to values that exceed the realized growth rates for all income brackets over the entire sample period. While comparing these two cases already gives us a good deal

[15] Interestingly, this overconfidence seems to have been dampened by the financial crisis, if more recent studies are an indication. Compare, e.g. http://www.cnbc.com/id/44559645

Table 4.1: Calibrating the model for different income risk profiles

Income Process	δ	σ
PSID 1968-1996 (no lifecycle)	0.962	1.41
PSID 1968-1996 (with lifecycle)	0.984	3.55
	(0.036)	(0.003)
BHPS gross labour income	0.958	2.24
BHPS net labour income	0.962	1.45
BHPS net household income	0.977	1.5

of information about the sensitivity of results to the belief vector, in section (4.7) we will also discuss the results using Guvenen's (2007) parametrization to make the model results directly comparable and of experimenting with more extreme values of beliefs.

4.5 Calibrating the model

Similar to Hintermaier and Koeniger (2011), we calibrate the model using a minimum distance estimator that minimizes the difference between wealth holdings at percentiles 10 to 90 of the net wealth distribution for different ages. The values for the SCF can be readily obtained from the code of Hintermaier and Koeniger (2011), while we use the UK Wealth and Asset survey to derive similar statistics for the UK for fitting the model when the income process is derived from BHPS data. The results can be seen in table 4.1.

Table 4.2: Parameters for comparative statics

	δ	σ	ρ	σ^2_η	σ^2_ε	σ^2_α	σ^2_β	$cov(\alpha, \beta)$
Lowest realization	0.94	1.05	0.72	0.01	0.02	0.01	0.00068	-1.
Baseline	0.96	2.0	0.85	0.03	0.05	0.05	0.00038	-0.3
Highest realizatoin	0.98	3.0	0.92	0.05	0.13	0.10	0.00001	0.

4.6 Comparative Statics

Given the largely disappointing results of the calibration and simulation exercises, we now turn to some comparative statics exercises to elicit what features of the model are crucial to get closer to the shape of the observed wealth distribution. To do so, we pick a reasonable baseline calibration from the set of available parameters estimated for different income processes in chapter 3, and then vary each of the 8 parameters governing the model solution by solving the model in turn for its highest and lowest realization. The parameter values used are summarized in table 4.2.

Changing the variance of the cross-sectional distribution of intercepts does not influence the results in any meaningful ways, as could have been anticipated from the fact that α in effect parallel shifts the entire life-cycle profile of households up or down, which, given that almost all households are far enough away from the borrowing constraint at all times, and in the absence of any different savings behaviour of rich households in the model (as e.g. found in the data by Dynan et al. 2004), means that savings behaviour is not affected by this change. Similarly, changing the variance of the transitory shock does not alter the results significantly, save for an overall increase in wealth holdings for the highest value of σ^2_ε. [NOTE: IF TIME PERSISTS, THINK ABOUT HOW THIS COMPARES TO KRUEGER/PERRIS RESULTS AND WHAT IT MEANS FOR THE CROSS SECTIONAL

VARIANCE OF WEALTH HOLDINGS!][16]. The two parameters that have a markedly larger influence on the *shape* of the predicted percentile distribution, and hence help the model get closer to the data moments, are the persistence of the AR(1) component and the variance of its innovations. Figures 4.3 and 4.4 show the effects of varying the persistence of the AR(1) component of the income process for prime age households and households by age group, respectively. When increasing ρ to 0.92, the predicted wealth distribution becomes notably more curved, while the effect of lowering ρ from 0.85 to 0.72 is significantly smaller. This is not very surprising, as the implications of lowering ρ for the half-life of a persistent shock become less severe the lower the starting value of ρ – as figure 4.15 demonstrates, the half life of a persistent shock under the baseline $\rho = 0.85$ is about four years, while for $\rho = 0.72$ it is two years and for $\rho = 0.92$ it is eight years. Figures 4.5 and 4.6 display the results for changes in the variance of persistence shocks. Just as in the case of an increase in persistence ρ, increasing the variance of the persistent shocks helps to increase the curvature of the predicted wealth distribution, by lowering savings at the lower and and increasing wealth holdings at the upper end at the same time. Indeed, both changes in ρ and in σ_η^2 bring the model parametrisation closer in line with that of Hintermaier and Koeniger (2011), who are using $\rho = 0.95$ and $\sigma_\eta^2 = 0.47$ in their baseline calibration. Importantly, ρ and σ_η^2 have similar effects on the income distribution that differ from the effects of increases in σ_α^2 and σ_ε^2, as evidenced in table 4.3. It appears that a crucial ingredient if the model if it is to match the empirical wealth distribution is the inequality in lifetime income, and, importantly, the source of this inequality. As can be seen in figures 4.7 and 4.8, changing the dispersion of individual- specific

[16]Graphical results can be found in the Appendix

growth rates of income does not have the same effects on the aggregate wealth distribution as changes in ρ or σ_η^2. The reason for this is that rich households in a world in which lifetime income inequality is high mostly because of the size and persistence of permanent shocks need to save in periods of high income, as the effect of the good shock will wear off and might be overlaid by the effects of a large negative shock in the future, while households that are rich in a world where income inequality is high because of inequality in deterministic growth rates will have high income growth across their life-cycle for certain, and hence don't need to save less to achieve consumption smoothing[17]. We then have to conclude that the very essence of the difference between HIP and RIP models of the income process – a lower persistence and variance of the AR(1) component of income, offset by variation in individual-specific, deterministic income growth rates – is what keeps it from matching the empirical profile of wealth holdings. Indeed, our model nests the model in Hintermaier and Koeniger (2011) as a special case with σ_α^2 and σ_β^2 equal to zero, and as figures 4.13 and 4.14 in the appendix show, the model fits the data well with this version of the RIP process.

The finding that it is mainly the variability of lifetime income that drives wealth accumulation in the model echoes the work of Floden (2008), who shows that the Aiyagari (1994) result of an increase in aggregate wealth holdings in incomplete markets economies with idiosyncratic income variations obtains even when all uncertainty about future income is removed, so that saving is purely driven by the consumption smoothing motive.

An important part of the mechanism explored quantitatively above was the

[17] In fact, to the extent that households know about their high income growth rate early in life, they will save *less* than poor households, who are potentially facing negative income growth rates.

Table 4.3: Standard deviation of lifetime income (multiples of baseline)

	ρ	σ_η^2	σ_ε^2	σ_α^2	σ_β^2	$cov(\alpha, \beta)$
Lowest realisation	-0.09	-0.06	-0.04	0.02	-0.29	-0.22
Highest realisation	0.31	0.35	0.09	0.11	0.41	0.05

Figure 4.3: Comparative statics for variance of individual-specific intercepts, prime age

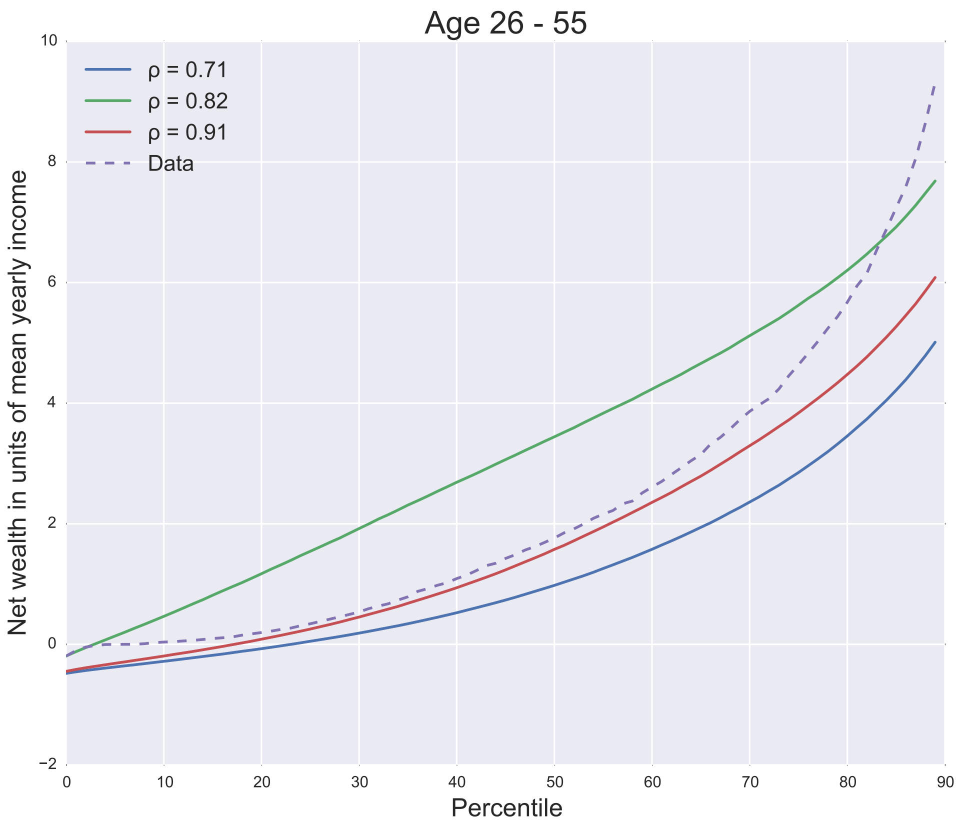


Figure 4.4: Comparative statics for variance of individual-specific intercepts, by age groups

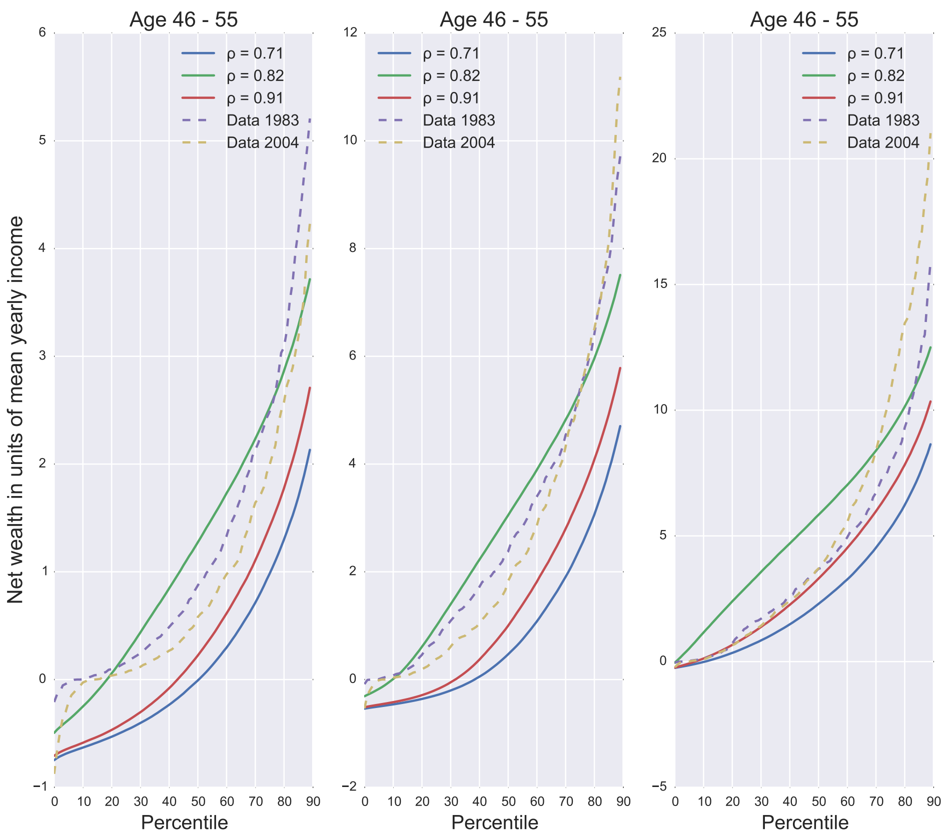


Figure 4.5: Comparative statics for variance of individual-specific intercepts, prime age

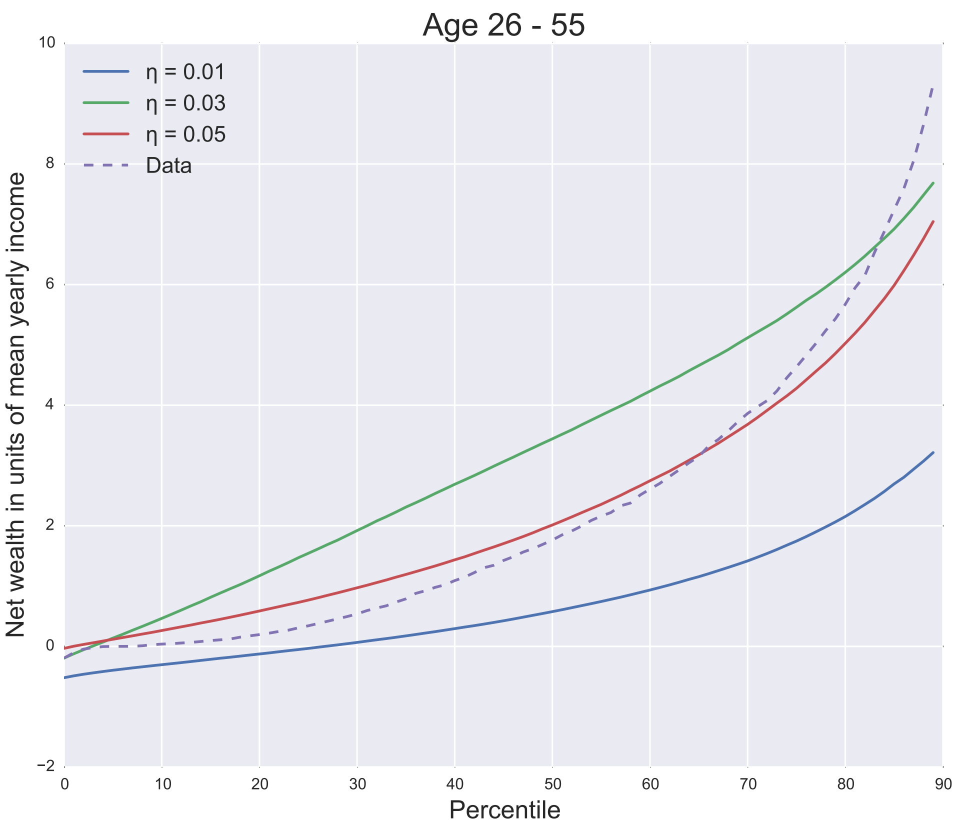


Figure 4.6: Comparative statics for variance of individual-specific intercepts, by age groups

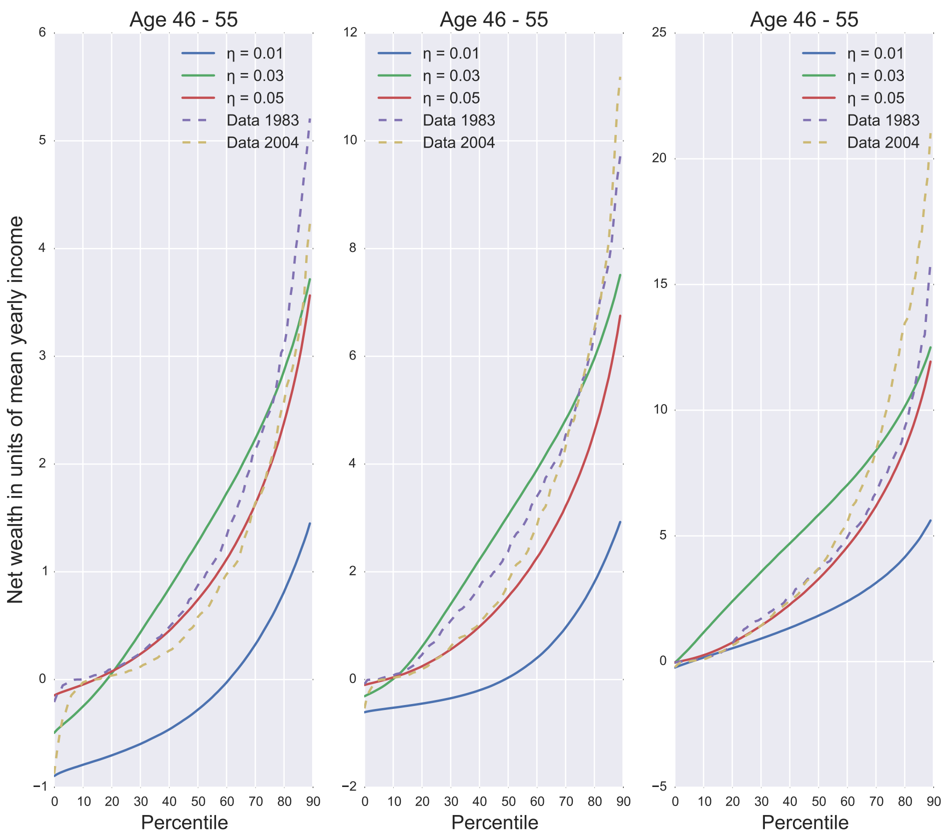


Figure 4.7: Comparative statics for variance of individual-specific growth rates, prime age

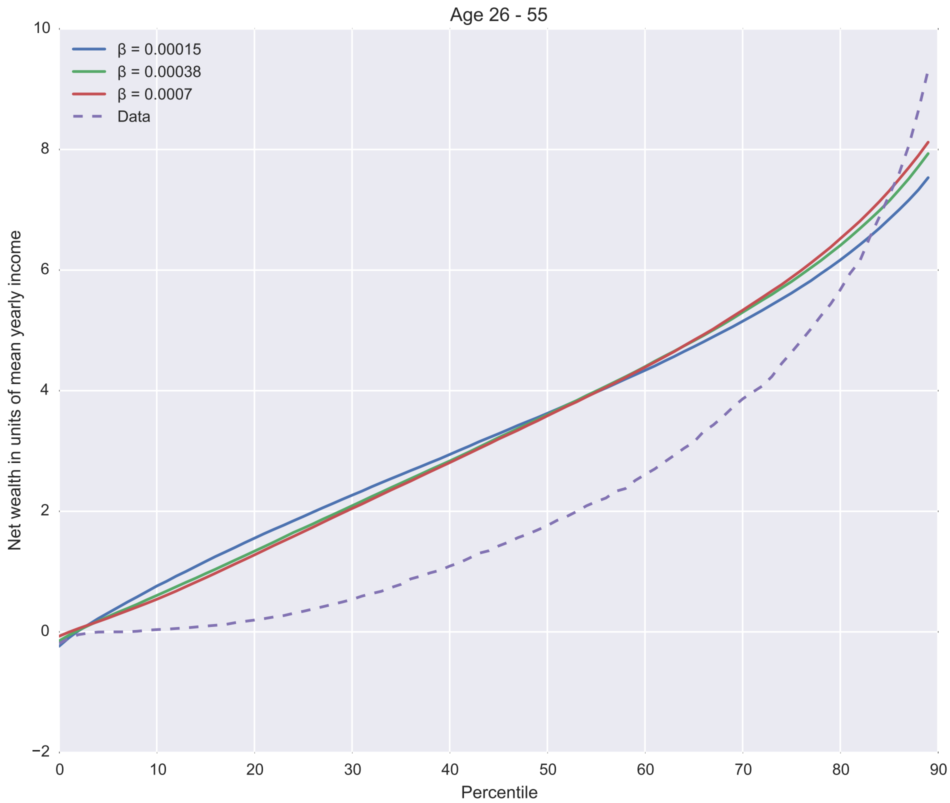
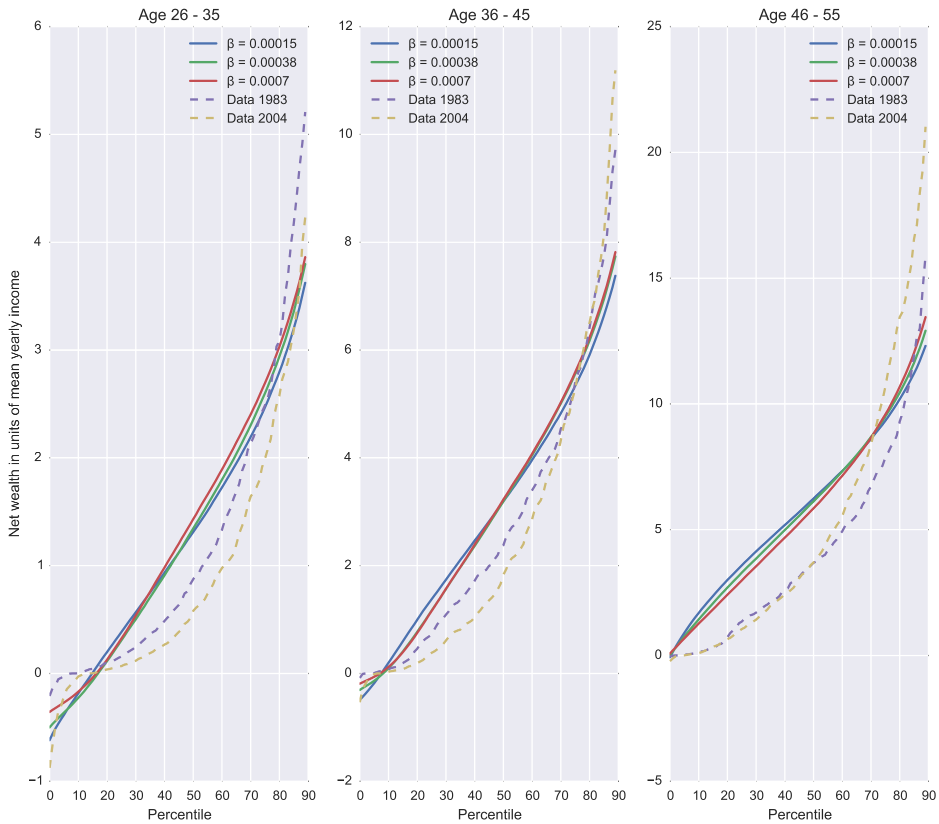


Figure 4.8: Comparative statics for variance of individual-specific growth rates, by age groups

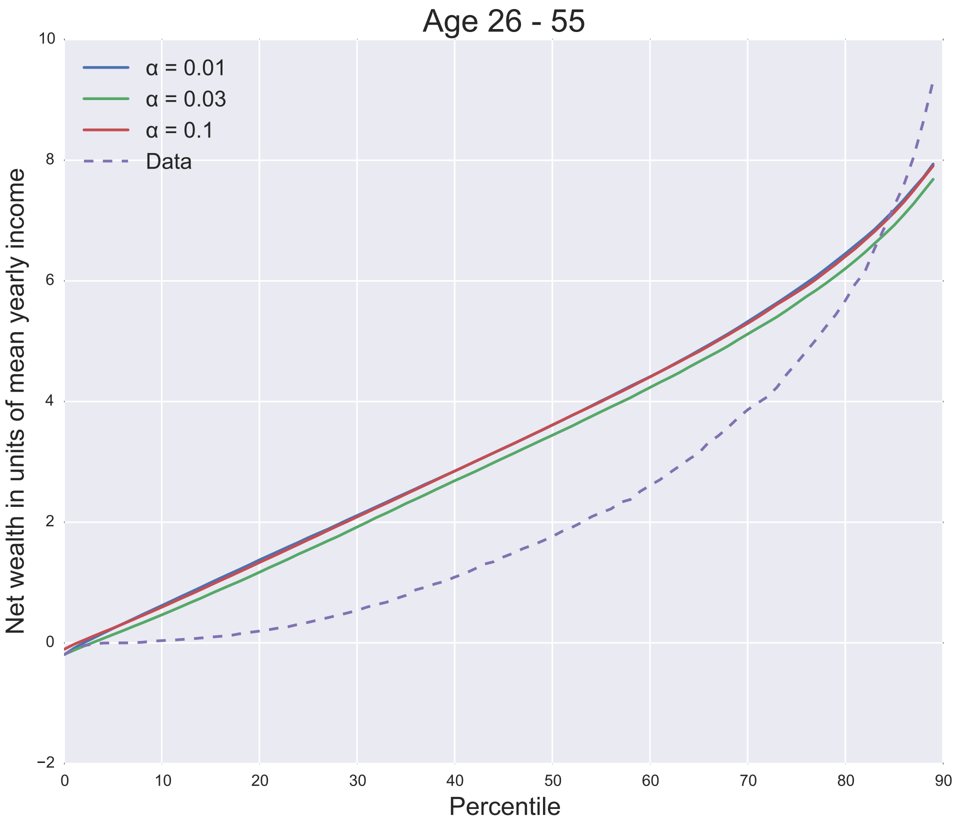


interaction between profile heterogeneity, initial beliefs and learning, the speed of which in turn depended on the nature of the income process underlying the simulations. Obviously, estimating the model using a more standard income process without profile heterogeneity, as is done in most of the life-cycle literature, would eliminate this mechanism completely, as there would be no meaningful learning about the income process. However, recent work by Hoffmann (2013) shows that specification error in the income process can severely bias econometric results towards either over- or underestimating the importance of profile heterogeneity. Hoffmann proposes a more general and flexible specification, which is still tractable enough to be used in a dynamic programming problem.

4.7 Discussion

As this chapter has shown, the learning model of heterogeneous income processes fails in capturing the dynamics of the wealth distribution under all calibrations derived from empirical data on income processes. Comparing the model output of different counterfactual parametrisations, it became clear that the main reason behind this is not the learning mechanism itself, but the different income distribution and risk implied by the heterogeneous income process. To salvage the model, ad-hoc changes to the belief structure of agents can be made, although at this point it becomes a bit of a free-for-all and the model can be made to predict any pattern in the data with a suitable choice of initial beliefs. Building on the work in this chapter, future research should consider the implications of other more realistic income processes on the wealth distribution, to the extent that they can be formulated parsimoniously enough not to increase the computational burden beyond reason. An example would be the work by Meghir and Pistaferri (2004), who model the conditional variance of income shocks using an ARCH model and show analytically that the addition of individual- specific heterogeneity in the innovation variance leads to both a larger dispersion of savings rates and higher aggregate saving. A further case of interest would be the specification derived by Guvenen et al. (2015), which adapts the income process used in this chapter by adding two more AR(1) components with different innovation variances, so that households are subject to potential shocks of different magnitude. As the evidence points to this process being the best description of the income risk households are facing in reality, the implications of this process for the wealth distribution should be investigated further.

Figure 4.9: Comparative statics for variance of individual-specific intercepts, prime age



4.8 Appendix A: Comparative statics results

Figure 4.10: Comparative statics for variance of individual-specific intercepts, by age group

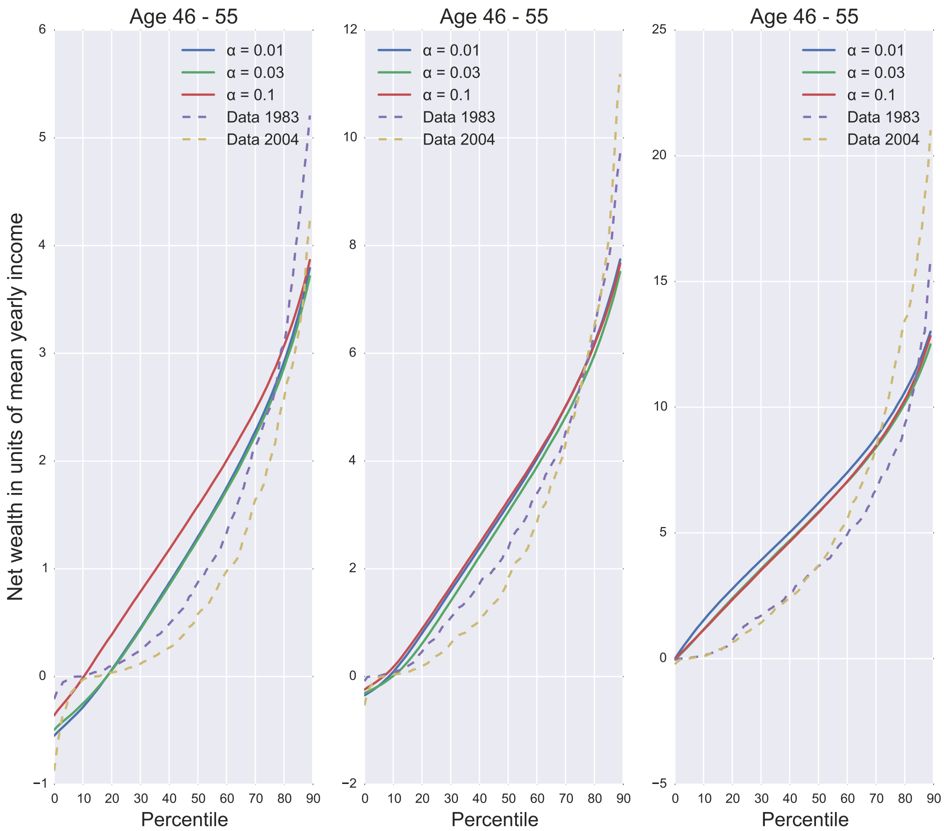


Figure 4.11: Comparative statics for variance of transitory shocks, prime age

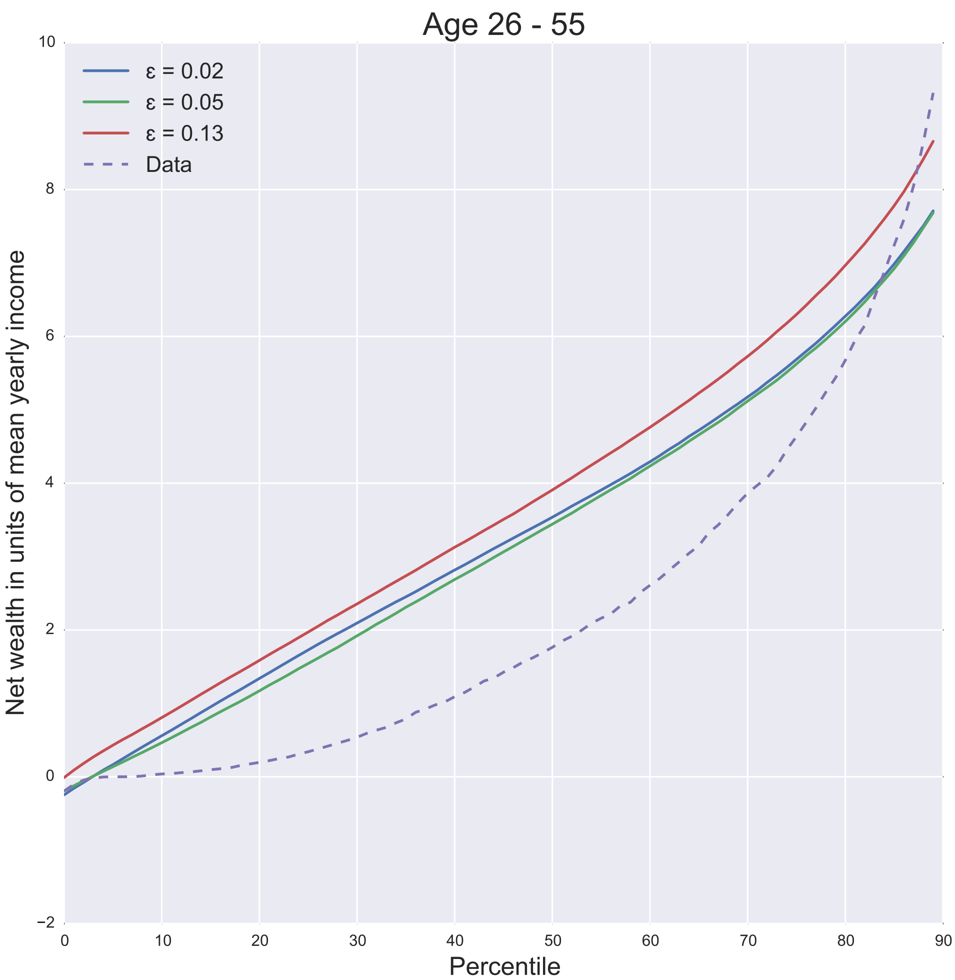


Figure 4.12: Comparative statics for variance of transitory shocks, by age group

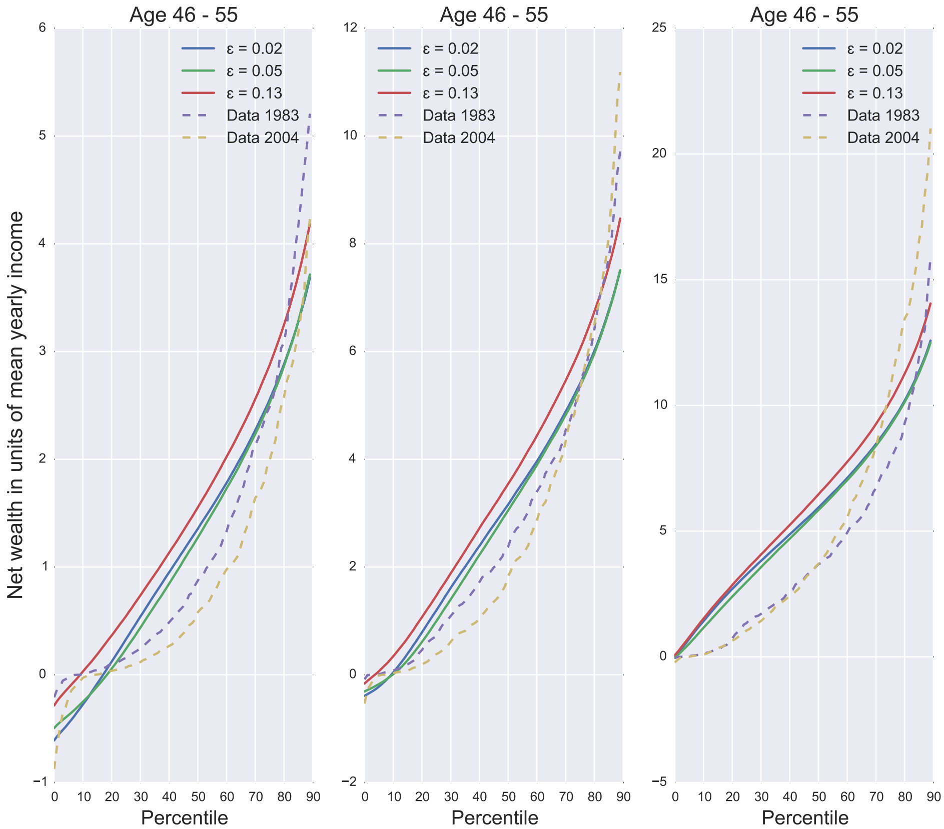


Figure 4.13: Model fit when income is an RIP process with $\rho = 0.95$ and $\sigma_\eta^2 = 0.5$

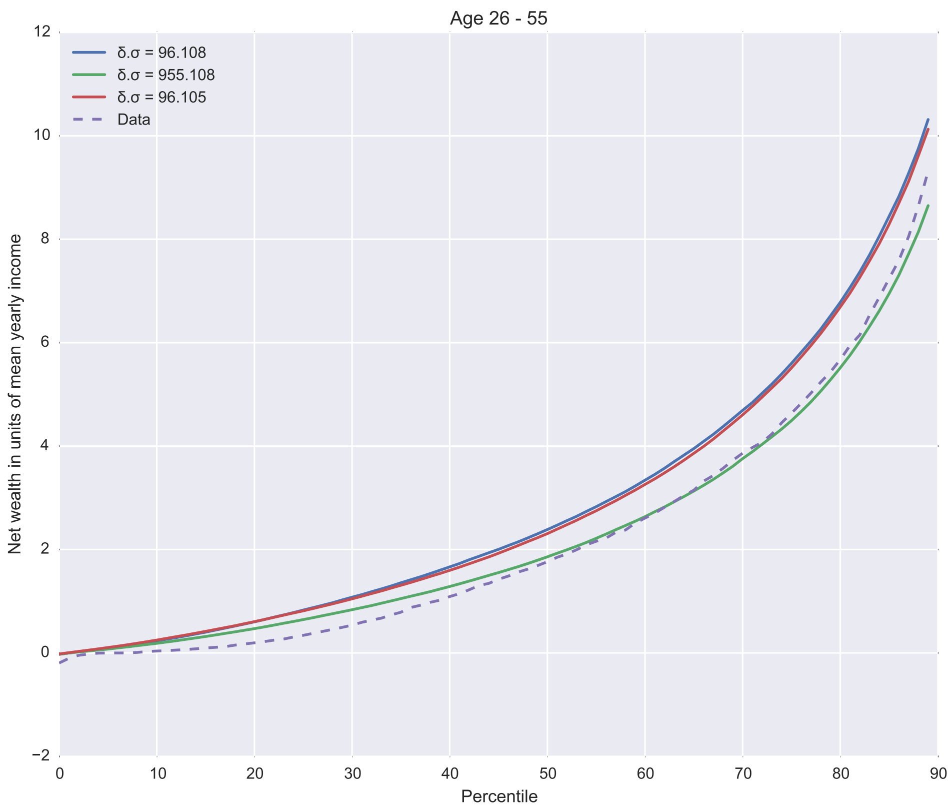


Figure 4.14: Model fit when income is an RIP process with $\rho = 0.95$ and $\sigma_\eta^2 = 0.5$, by age groups

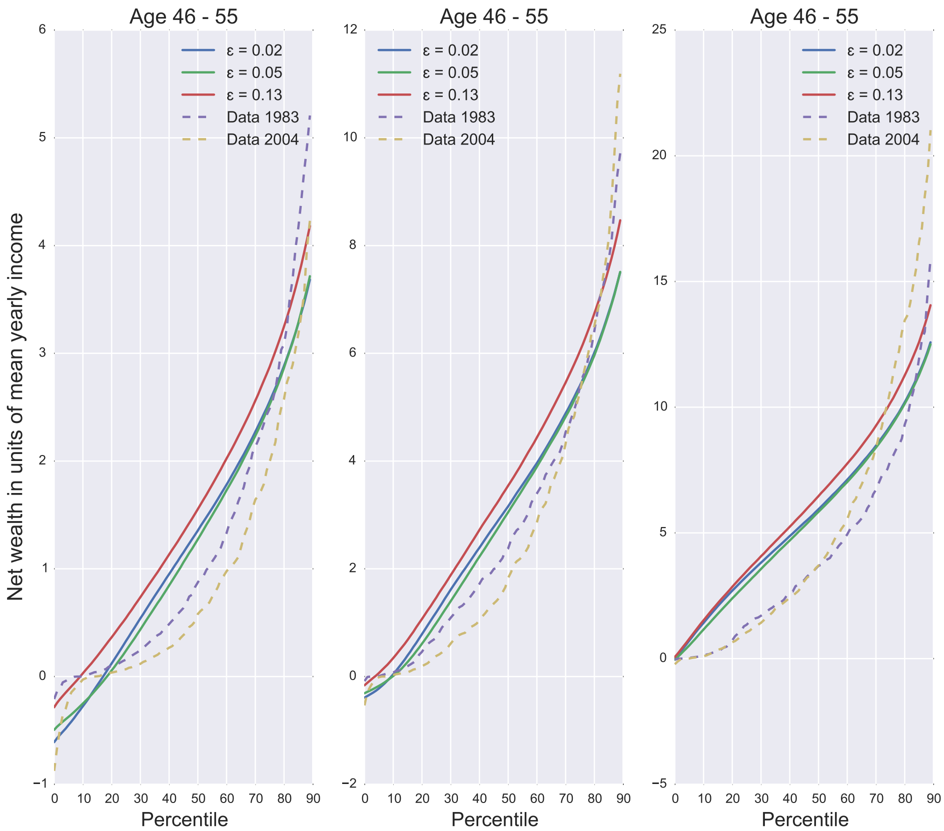
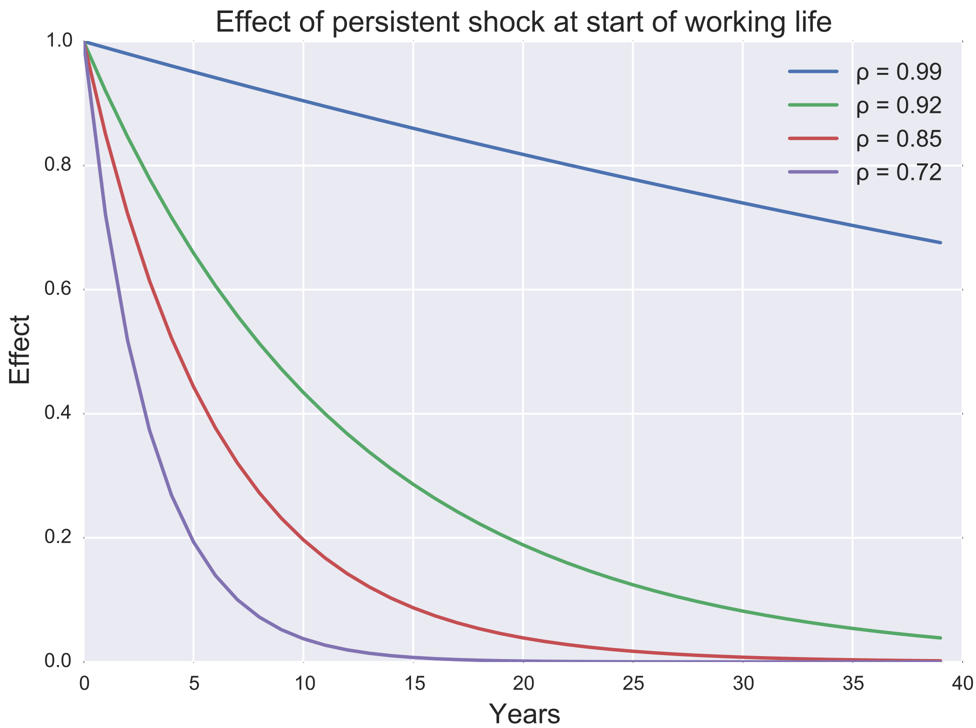


Figure 4.15: Effects of lowering ρ on half life of persistent shocks



Chapter 5

The Competitive Effects of Trade Liberalisation in North America: An Empirical Application of the Melitz and Ottaviano Model

5.1 Introduction

The economic benefits of free trade are arguably one of the most uncontroversial results of economic research, both theoretically and empirically. However, to this date, free trade is by no means uncontroversial in the public sphere, as is evidenced by the fierce opposition that the proposed transatlantic free trade agreement between the US and Europe is facing. Hence, international trade has remained an active field in economic research, a field which has seen major advancements in the past two decades in incorporating firm-level heterogeneity coupled with consumer love of variety into trade models that can account for the firm-level responses to increasing trade openness and the large share of intra-industry trade in the international flow of goods and services [18]. This new vintage of trade models predicts additional welfare gains from trade stemming from reallocations of production to more productive firms (as in Melitz, 2003) or increases in firms' efforts to innovate (as in Grossman and Helpman, 1990). To some extent, these new models of trade also help reconcile the unambiguously positive stance of economic researchers on trade liberalization with the public opposition to it – models taking into account explicitly the heterogeneity across agents of firms within a country show that while on aggregate there are significant efficiency gains from free trade, there are also firms and workers who will lose out individually, and can only benefit from a trade liberalization if either the aggregate gains are redistributed in some way to ensure a Pareto improving allocation, or if they can benefit from the reallocation of production to more productive firms by switching to those firms. DixCarneiro (2014) builds a structural model of the Brazilian labor market to estimate the labor market effects of trade liberalization and finds that, depending on the assumptions about capital mobility, the reallocation of workers across sectors can take up to 30 years.

While these new models of international trade are well grounded in empirical evidence coming from micro data, there are surprisingly few tests of the model predictions for aggregate variables which are decisive for the predicted welfare gains from trade. Recently, Arkolakis et al. (2012a,b) call into question the importance of firm-level heterogeneity by showing that in a lass class of trade

[18]A comprehensive survey of trade models with love of variety preferences and firm-level heterogeneity can be found in Melitz and Trefler (2012).

models, the additional welfare gains are fairly small and actually even smaller if consumers don't have CES utility. The response of Melitz and Redding (2013) shows that there is still considerable disagreement over how to theoretically evaluate the additional welfare gains from firm selection, and Costinot and Rodriguez-Clare (2014) review the effects of trade liberalizations in a wider class of new trade models to highlight the importance of the market structure under consideration – depending on whether a one- or multi-sector model is used and the degree of competition assumed, gains from trade are estimated to range from 4% to 40% of non-free-trade welfare. These facts m motivate us to test the Melitz-Ottaviano model directly in aggregate data on prices, markups and productivity. To do so, we estimate the effects of trade liberalization on the competitive environment in manufacturing markets of the member countries of the North American Free Trade Agreement (NAFTA). We employ an estimation procedure based on the Melitz and Ottaviano (2008) model introduced by Chen et al. (2009), which to our knowledge is the only empirical application of a model with firm-level heterogeneity on aggregate data. Chen et al. (2009) derive estimable regression equations from the model's equilibrium conditions that allow us to test the effects of trade openness on relative price levels, markups and labor productivities of two trading partners. It is further possible to differentiate between the effects of trade in the short run, which, in the model, refers to an economy without relocation decisions for firms, and in the long run, when firms are free to choose their home market for production. However, as the underlying model is static, no direct results on the time path of the impact of trade liberalization can be obtained. We try to address this issue by dividing our sample in ways that make it more amenable to a model-based estimation. Contrary to Chen et al. (2009), we directly observe tariff rates between the three countries in our sample and hence use those as a direct measure of trade openness. Additionally, we test for the effects of third-country trade openness on the relative performance of two countries that are linked through trade, predictions for which can be derived from the multi-country version of the Melitz and Ottaviano model. Our dataset comprises of nine manufacturing sectors in Canada, Mexico and the US, covering the time period from the introduction of NAFTA in 1994 up to 2006, which gives us reason to believe that we are able to capture the long run effects of policy changes even in industries with low firm churning rates.

Our findings support the main model predictions, with tariff barriers stifling domestic competition, leading to higher producer prices and markups as well as lower productivity. In the immediate years after the free-trade agreement when tariff barriers are reduced, relative prices and markups decrease as relative productivity increases, thus giving rise to competitive effects. The results in the long-run, however, are not as clear cut, with some effects reversing as predicted by the model while some effects persist. This is also confirmed by directly looking at the reaction of industries with different entry barriers to changes in trade openness.

The paper is organized as follows: Section 5.2 gives a survey of the previous literature assessing the effects of trade liberalizations in general and of NAFTA specifically. Section 5.3 briefly summarizes the Melitz and Ottaviano (2008) model, derives the most important equilibrium conditions and explains the estimation strategy used in Chen et al. (2009). Section 5.4 then presents our application of the model by giving an overview of the data used and our estimation procedure. The results of our regressions and possible shortcomings as well as extensions of our approach are discussed in Section 5.5; Section 5.6 concludes.

5.2 Related Literature

As free trade has been an active topic in economic research since the times of Ricardo, the literature on the welfare gains from trade is immense. Of particular interest to us of course are papers that investigate the economic effects of NAFTA directly, as well as papers that form the theoretical foundation for our estimation strategy.

The effects of free trade in North America have been scrutinized in a large number of papers over the past two decades, starting with work on the predecessor to NAFTA, the 1987 Canada and US free trade agreement (CUSFTA). Head and Ries (1999) document rationalization effects in Canadian plants as a reaction to decreases in Canadian import duties. Trefler (2004), focusing on the CUSFTA, uses a reduced form econometric approach to find large improvements in labour productivity and decreases in employment after the implementation of CUSFTA, coupled with slightly lower import prices and larger volumes of trade. Fukao, Okubo and Stern (2003) derive regression equations from a partial equilibrium model with imperfect competition to estimate the extent to which NAFTA was trade diverting rather than creating and find responses that vary by industry. Romalis (2007) examines both CUSFTA and NAFTA with a strategy based on estimating demand and supply elasticities and finds a large effect of NAFTA on trade volumes, with only minor price changes and, subsequently, only small changes in welfare. Calderon-Madrid and Voicu (2007) use plant-level panel data from Mexico to show that while productivity increases followed the tariff reductions, the responses of plant-level productivity are very unevenly distributed, with larger plants benefiting disproportionately from productivity increases. The

Melitz (2003) model that is at the heart of our analysis is also put to a test with US manufacturing data by Bernard, Jensen and Schott (2006a), who use plant-level data to estimate the effects of changes in the costs of trade, as measured by tariff rates and transportation cost, on productivity growth and firm entry and exit. Their findings confirm the micro-level implications derived from the assumptions on the productivity distribution in Melitz (2003), which we will highlight in the following section. Other papers have used the structure provided by the Melitz and Ottaviano (2008) model to assess the effects of trade liberalization in other parts of the world: Bellone et al. (2008) use price-cost margins of French manufacturing firms to test the models predictions on the effects of market size, import penetration and exporting status on markups and productivity and confirm that all predictions hold. Corcos et al. (2011) estimate structural parameters in order to simulate counterfactual scenarios by changing the costs of trade between countries. Their exercise shows that the firm selection mechanism is crucial for the magnitude of the welfare gains from trade and the potential gains for a country depend on country size as well as remoteness. The paper that is closest to our own work is Chen et al. (2009), who use the equilibrium expressions for prices, markups and productivity from the Melitz-Ottaviano model to estimate the effects of trade liberalization using a dataset that includes data on 10 manufacturing sectors in seven European countries for the period 1989-1999 with country-pair regressions. There results suggest that trade openness leads to an increase in competitiveness in the short-run with diminishing and at times reversed effects in the long-run, as predicted by the model.

5.3 Model and Estimation Equations

The Melitz and Ottaviano (2008) model is a synthesis of the contributions of Melitz (2003), who introduces firm heterogeneity through random draws of a cost parameter for firms entering the market, and Ottaviano et al. (2002), who develop a model with endogenous markups arising from a linear consumer demand system with horizontal product differentiation. The model yields equilibrium conditions that determine a cost cut-off level, i.e. a level of productivity below which firms are not able to compete in the marketplace. This cut-off level uniquely determines all relevant aggregate variables in the model, namely the distribution of prices, markups and productivity. Importantly, the equilibrium conditions of the model economy are different depending on whether firm entry is allowed or not. Without firm entry, the model captures a short-run equilibrium, with the cost cutoffs in two markets given by:

$$N = \bar{N}\left(\frac{c_D}{c_M}\right)^k + \bar{N}^* \frac{1}{\tau^k}\left(\frac{c_D}{c_M^*}\right)^k \tag{5.1}$$

$$N^* = \bar{N}^*\left(\frac{c_D^*}{c_M^*}\right)^k + \bar{N}\frac{1}{(\tau^*)^k}\left(\frac{c_D^*}{c_M}\right)^k \tag{5.2}$$

Here, a star denotes the foreign market, $\bar{N}$ is the fixed number of incumbents in a market and N is the number of firms that are producing. c_M is the upper bound of the distribution of cost draws, c_D is the cut-off level, i.e. the highest cost draw that allows a firm to earn non-negative profits. $\tau > 1$ is the iceberg cost of trade faced by foreign companies exporting to the domestic market and can be interpreted as a measure of trade costs, tariffs and other impediments to trade.

The long-run equilibrium of the economy allows for firm entry into a market, so that the number of firms in a market is now endogenously determined by a zero profit condition for entrants that balances a fixed cost of entry with the expected profits when drawing a cost level from the (known) cost distribution of a country. The equilibrium conditions pinning down the cost cut-off are

$$c_D = \left[\frac{\phi c_M^k}{L}\frac{1-(\tau^*)^{-k}}{1-(\tau\tau^*)^{-k}}\right]^{\frac{1}{k+2}} \tag{5.3}$$

$$c_D^* = \left[\frac{\phi c_M^k}{L^*}\frac{1-\tau^{-k}}{1-(\tau\tau^*)^{-k}}\right]^{\frac{1}{k+2}}, \tag{5.4}$$

where L is the size of the domestic market. Since all aggregate variables in the Melitz and Ottaviano model are linear functions of the cost cut-off, equations describing the relative price, markup and productivity levels in two countries connected by trade can easily be found by simply dividing the expressions for c_D by those for c_D^*. This gives, for the price level in the short run:

$$\left(\frac{\bar{p}}{\bar{p}^*}\right)^k = \left(\frac{c_D}{c_D^*}\right)^k = \left(\frac{c_M}{c_M^*}\right)^k \frac{\bar{N}^*}{\bar{N}}\frac{N}{N^*}\frac{1+\frac{\bar{N}}{\bar{N}^*}\frac{1}{(\tau^*)^k}\left(\frac{c_M^*}{c_M}\right)^k}{1+\frac{\bar{N}^*}{\bar{N}}\frac{1}{\tau^k}\left(\frac{c_M}{c_M^*}\right)^k} \tag{5.5}$$

and in the long run:

$$\left(\frac{\bar{p}}{\bar{p}^*}\right)^{(k+2)} = \left(\frac{c_D}{c_D^*}\right)^{(k+2)} = \left(\frac{c_M}{c_M^*}\right)^k \frac{L^*}{L}\frac{1-\frac{1}{\tau^k}}{1-\frac{1}{(\tau^*)^k}} \tag{5.6}$$

These two equations capture one of the central predictions of the Melitz and Ottaviano model: asymmetrical trade liberalizations will have opposing effects on competitiveness in the short and the long run. By equation (5.5), lowering trade barriers induces a fall in the cost cutoff, and hence decreases in prices and markups and increases in productivity. In the long run, however, the effects are reversed, as an increase in trade costs induces firms to choose the relatively more protected market for production, thereby increasing competition in markets that are shielded from foreign firms.

Chen et al. (2009) show that it is possible to substitute out the trade cost term with an openness term that is derived from a measure of foreign firms market share in the domestic market. However, since we are interested in the effect of tariff rates on competitiveness, we use tariff data directly as a proxy for τ. This strategy should pick up the effects of tariff rates in our estimation if other determinants of trade openness (e.g. oil prices (Kilian et al., 2009), credit conditions (Chor and Manova, 2012), shared culture and language between countries) do not vary systematically across industries. However, as a first step, we will replicate their analysis exactly in our data set (albeit with different instruments for openness), which requires us to make the same substitution, which is:

$$\frac{1}{\tau^k}\left(\frac{c_M}{c_M^*}\right)^k = \frac{\theta}{1-\theta} \tag{5.7}$$

Similarly, an expression for the average markup can be derived. The determination of the average markup is equivalent to the one for average prices so expressions for the short– and long–run impacts of openness on markups can readily be derived. Somewhat more problematic is the index for productivity, as the model requires knowledge of a firm's unit costs c, which are not observable. Chen et al. work around this issue by assuming away differences in capital costs, so that average industry productivity can be approximated by the ratio of nominal wages to labour productivity: $\bar{c} = \frac{w}{z}$. If it is additionally assumed that unit labour costs only depend on nominal wages, the ratio of domestic to foreign labour productivity can be written as:

$$\frac{z}{z^*} = \frac{w}{w^*}\frac{\overline{c}^*}{\overline{c}} \tag{5.8}$$

If the least competitive firm in an industry with a productivity draw at the upper bound of the distribution c_M has labour productivity z_M and labour is perfectly mobile between firms, equation (5.8) implies $\frac{z}{z^*} = \frac{w}{w^*}\frac{c_M^*}{c_M}$. This relationship can then be used in an analogous fashion as before to construct an expression relating openness to productivity. In the short run, equation (5.8) can be amended to yield:

$$\left(\frac{z}{z^*}\right)^k = \left(\frac{z_M}{z_M^*}\right)^k \frac{(\bar{N}/N)}{(\bar{N}^*/N^*)} \frac{1+\frac{\bar{N}*}{\bar{N}}\frac{\theta}{1-\theta}}{1+\frac{\bar{N}}{\bar{N}^*}\frac{\theta^*}{1-\theta^*}} \tag{5.9}$$

Higher values of θ thus lead to higher productivity (conditional on $\bar{N}/N$), as they force lower productivity firms to shut down production. For the long run, equation (5.5) combined with the expression for labour productivity gives:

$$\left(\frac{z}{z*}\right)^{k+2} = \left(\frac{w}{w^*}\right)^2 \frac{L}{L^*}\left(\frac{z_M}{z_M^*}\right)^k \frac{1-\frac{\theta}{1-\theta}}{1-\frac{\theta^*}{1-\theta^*}} \tag{5.10}$$

Larger markets exhibit higher labour productivity, while the effects of θ and θ^* are the opposite of those in the short–run.

5.3.1 The Role of Market Entry

Following the arguments in Trefler (2004), we want to exploit the nature of NAFTA being close to a natural experiment and hence try to identify the effect of the policy measures (i.e. the changes in tariff rates) separately from the effects of trade openness in general. There is evidence that trade openness – measured by the import penetration of a certain country or industry, as in Chen et al. (2009) – is affected by a number of external forces, including oil prices (Kilian et al., 2009), credit conditions (Chor and Manova, 2012), shared culture and language between countries and many more. Therefore, we deconstruct the iceberg costs of trade into two parts: $\tau^{lh} = \frac{Tr^{lh}}{\theta^{lh}}$, where $Tr^{lh} > 1$ is the tariff rate for trade between countries l and h and $\theta^{lh} > 1$ captures the additional costs of trade imposed by the aforementioned factors. Then, the import penetration can be viewed as a measure of θ^{lh}, as in Chen et al. (2009), while a carefully constructed tariff measure can directly account for the effect of NAFTA-mandated changes in the trade environment. Obviously, the import penetration in a sector depends on the tariff measure as well, so an instrumental variable approach has to be taken in order to identify this effect. We defer the discussion of the construction of the tariff measure and the choice of instruments to the following chapter. Prior work of Bernard et al. (2006b) suggests that tariff rates throughout the 1980s, at an average level between four and five percent, accounted for about the same fraction of trade costs as costs directly attached to shipping the good, i.e. freight and insurance, so we expect them to have a sizeable impact on trade flows between countries and hence the competitive environment.

As we have seen in the exposition of the Melitz and Ottaviano model above, there is one crucial caveat in taking the model to the data: due to the static nature of the model, the comparative static results just compare one steady state with another, while being silent about the transitional dynamics. The estimation strategy of Chen et al. (2009) tries to account for this by estimating an error correction model to identify the long-run separately from the short-run, but their results – just as ours – are mixed for the long run and it cannot be ruled out that this is due to the estimation procedure. Therefore, we try to address this issue in a more direct way: as short- and long-run in the model differ only in the possibility of firm entry, we separate industries into those with a fixed number of firms and those with low entry barriers. This distinction then gives us industries that represent the short- and long-run and we can directly investigate whether the coefficients on the relevant variables differ significantly[19]. This approach, however, leads to two issues that need to be addressed before implementation. First, it is not *a priori* obvious how to measure the entry conditions in an industry; while the theoretical model uses the number of firms, this could in practice either refer to firms or to establishments (i.e. different production sites run by the same parent company), or even to employees, as firms in the model use unit labour input. Second, there is no reason to believe that different measures of entry and exit dynamics are exogenous with respect to trade openness – indeed in the model trade openness is a key factor in the entry decision of firms, but in the real world there might be various other factors that might lead to industries being asymmetrically affected by a change in trade costs, hence biasing our results. To tackle both these issues, we aim to construct a robust measure of industry dynamics by aggregating multiple studies that examine firm and employment turnover in Canada, Mexico and the United States as well as Europe over different

[19]We were inspired to do so by Head and Ries (1999) who use the classification to test competing theories of trade that rely on different market structures.

Table 5.1: Market Structure measures used, numbers in percent

Study	Subject	Highest Turnover	Lowest Turnover
Dunne et al. (1988)	Entry Rates (4-yearly) U.S. 63-82	Instruments (60.3) Lumber (49.70) Printing (49.0)	Leather (29.4) Food Processing (23.9) Tobacco (20.5)
Samianego (2008)	Entry Rates (yearly) Europe 97-04	Paper, printing, software (15.6) Textiles (11.9) Petroleum and Coal (11.9)	Chemicals (9.5) Plastics (9.4) Food Products (9.1)
Brown (2004)	Employment renewal Canada 73-96	Plastic (79.5) Furniture (79.4) Fabricated Metals (77.2)	Primary Metals (33.6) Paper (32.4) Tobacco (4.2)
Foster et al. (2006)	Job creation (yearly) U.S. 72-98	Lumber (11.8) Apparel (11.2) Miscellaneous (11.0)	Paper (5.9) Petroleum (5.9) Tobacco (5.1)
Baldwin et al. (1994)	Job turnover (yearly) Canada 73-86	Furniture (26.5) Machinery (26.3) Lumber (25.7)	Petroleum (14.1) Primary Metals (13.5) Paper (10.7)
Baldwin et al. (1994)	Job turnover (yearly) U.S. 73-86	Lumber (27.2) Apparel (25.5) Leather (22.5)	Petroleum (14.6) Chemicals (14.0) Paper (13.3)

time periods. With this, we hope to identify those industries that are either very dynamic or very static over a broad set of different measures, regions and time periods. Table 5.1 gives an overview of the studies used and a glance at their respective results, showing considerable variation in the dynamics of entry and job creation in different manufacturing sectors.

In order to aggregate the different studies, we compute percentile-based rankings of the industries for each study (to account for the different number of industries across studies) and then average the percentiles across studies. Based on these average percentiles, we can then split the sample according to the short- and long-run distinction made in the model: those industries above the 70th percentile are taken to represent the dynamic, "free entry" sample and thus the long run, while those industries below the 40th percentile are taken to represent the short run. This procedure leads us to split the sample three-ways: Tobacco, Food Processing, Paper, Chemicals, Primary Metals and Petroleum industries fall into the long run category, while Furniture, Wood, Nonelectrical Machineries, Fabricated Metals, Printing, Apparel, and Instruments are taken to represent the short run of the model. The remaining industries are too close to the median to be classified either way and are thus dropped from the sample, which leaves us with 1863 year-industry-country pair observations for the free entry sample, and 1701 observations for the fixed entry sample[20].

A little thought experiment may clarify the role that market entry effects play in muddling the distinction between short– and long–run equilibria. The Melitz and Ottaviano (2008) model yields opposing predictions on the effects of trade liberalization on country-level economic variables such as prices, productivity and mark-ups. The reason for the differences, as we have seen, lies in the assumptions on market structure: there are two different equilibria depending on whether

[20]Due to different classification systems, the aggregation of studies was not always exact and some industry groups are quite heterogeneous when sub-industries are considered. For further details on the aggregation see Appendix B

entry into a market is allowed. We repeat them here for convenience:

$$c_D^k = c_M^k \frac{\bar{N}^*}{N^*}\left(1 + \frac{\bar{N}}{\bar{N}^*}\frac{\theta^*}{1-\theta^*}\right)$$
$$c_D^{k+2} = \frac{\phi c_M^k}{\Upsilon L}\left(1 - \frac{\theta^*}{1-\theta^*}\right)$$

In model terms, only one of these two equations holds at any given time, and it is posited that the first equation captures the short run effects of trade liberalization, while in the long run firms are allowed to enter the markets and the effects of trade barriers are determined by the second equation. No further assumptions on the nature of the firm's entry decisions or capital adjustment costs are made that could help separate short- from long run. However, in reality, it seems to be more natural to assume that there is a gradual evolution from one equilibrium to the other, and this view is borne out by data on firm entry and exits showing that in a given year, only between five and ten percent of firms in a given industry are new entrants, while over longer horizons this figure goes up to 80 percent. Hence, it seems to be reasonable to model the transition from the short- to the long run equilibrium by introducing a parameter α that governs the fraction of firms entering an industry. The effects of this parameter are most clear on the productivity side, given that firms cannot change their productivity level, the new productivity distribution will be a weighted average of new entrants' and existing firms' productivity. As the examples in Chen et al. are formulated with respect to relative prices, and we are using their notation, we will discuss the effects of limited firm entry in the price level case as well. The argument carries through if one is ready to assume a nominal rigidity that prevents incumbents from re-optimizing their prices, similar to the assumptions made in New Keynesian monetary models. Similar to the productivity level, the price level is then a weighted average of new and old prices (for simplicity, here we abstract from substitution effects induced by the new relative prices of new and old producers):

$$
\begin{aligned}
\bar{p} &= \alpha \bar{p}^{LR} + (1-\alpha)\bar{p}^{SR} \\
&= \alpha c_D^{LR} + (1-\alpha) c_D^{SR} \\
&= \alpha \left(\frac{\phi c_M^k}{\Upsilon L} \left(1 - \frac{\theta^*}{1-\theta^*} \right) \right)^{\frac{1}{k+2}} + (1-\alpha) \left(c_M^k \frac{1}{\frac{\bar{N}}{N} \left(1 + \frac{\bar{N}^*}{\bar{N}} \frac{\theta}{1-\theta} \right)} \right)^{\frac{1}{k}}
\end{aligned}
$$

where the second line drops the constant linking price level and cost cut-off for notational simplicity. It can easily be seen that the introduction of the α parameter makes the expression for the price level hugely complicated and eliminates the possibility to cancel out most constant terms by using relative prices as was done in Chen et al. (2009). Obviously, the above expression is impossible to take to the data in the hope of identifying any of the parameters.

Let's consider a simplified version of the above. Assume that relative prices levels in the short- and long run, respectively, are given by:

$$
\begin{aligned}
\frac{\bar{p}^{SR}}{\bar{p}^{*SR}} &= \left(\frac{c_M}{c_M^*} \right)^k \frac{(\bar{N}^*/N^*)}{(\bar{N}/N)} \frac{\rho^*}{\rho} \\
\frac{\bar{p}^{LR}}{\bar{p}^{*LR}} &= \left(\frac{c_M}{c_M^*} \right)^k \frac{L^*}{L} \frac{(1-\rho^*)}{(1-\rho)}
\end{aligned}
$$

This is a simplified version of the equilibrium conditions in Chen et al. using the notation of Melitz and Ottaviano in which trade freeness is measured by $\rho \in (0,1)$. It captures the main essence of the model, in the short run relative prices depend on the number of firms and negatively on trade freeness (increasing ρ will decrease

$\bar{p}$), while in the long country size matters and prices depend positively on trade freeness (increasing ρ decreases $1-\rho$ and thus increases $\bar{p}$). Now assume further, that price setting decisions and substitution behavior of consumer is such that we can aggregate *relative* price levels in the same way we aggregated individual price levels before. Then:

$$\begin{aligned}\frac{\bar{p}}{\bar{p}^*} &= \alpha\frac{\bar{p}^{LR}}{\bar{p}^{*LR}} + (1-\alpha)\frac{\bar{p}^{SR}}{\bar{p}^{*SR}} \\ &= \alpha\left(\left(\frac{c_M}{c_M^*}\right)^k \frac{L^*}{L}\frac{(1-\rho^*)}{(1-\rho)}\right) + (1-\alpha)\left(\left(\frac{c_M}{c_M^*}\right)^k \frac{(\bar{N}^*/N^*)}{(\bar{N}/N)}\frac{\rho^*}{\rho}\right)\end{aligned}$$

Here, the fundamental identification problem becomes apparent: in the first term on the right hand side of the equation, the effect of ρ on $\bar{p}$ is positive, while in the second term it is negative. However, the size and sign of the composite effect will be governed by α, which is unobservable. In order to estimate the effects of trade openness on prices, we have to control for firms entry behavior. While this might well be endogenous to changes in trade policy, it is reasonable to assume that different industries have different entry conditions due to fixed costs inherent in the business model. We can try to exploit this variation in entry conditions by sorting businesses according to the ease of entry; then, ceteris paribus, an industry with lower barriers to entry should exhibit a response to trade liberalization along the lines that the model predicts for the long run equilibrium (as the value of α increases, $\bar{p}$ approaches $\bar{p}^{LR}$), while an industry with high entry barriers subject to the same trade liberalization should see a very different reaction.

One way to alleviate this problem is by trying to use information on α in the estimation. Splitting the sample based on our aggregated turnover measures can be seen as a crude approximation to this, as can be the construction of dummy variables for high and low turnover industries. The most direct way, however, would be to use information on industry turnover rates directly. Obviously, this brings back the very same endogeneity problems we described above that were one reason to aggregate the studies in the first place, which makes it important to instrument for entry and exit rates in industries using turnover measurements for different periods than the one considered in the estimation. The variable construction will be explained in more detail in the next section.

5.4 Application

Starting from the equations for prices, productivity and markups derived within the Melitz-Ottaviano framework, we can derive estimable log-linearized equations analogous to those in Chen et al. The estimation equation for prices is given by:

$$\begin{aligned}\Delta \ln\left(\frac{\bar{p}_{it}}{\bar{p}^*_{it}}\right) =& \beta_0 + \beta_1 \Delta \ln \tau_{it} + \beta_2 \Delta \ln \tau^*_{it} + \beta_3 \Delta \ln D_{it} + \beta_4 \Delta \ln D^*_{it} \\ & + \gamma \left[\ln\left(\frac{\bar{p}_{it-1}}{\bar{p}^*_{it-1}}\right) + \delta_0 + \delta_1 \ln L_{t-1} + \delta_2 \ln L^*_{t-1} + \delta_3 \ln \tau_{i,t-1} + \delta_4 \ln \tau^*_{i,t-1}\right] + \varepsilon_{ijt}\end{aligned} \tag{5.11}$$

In the above equation, the number of firms serving the domestic market, N, has been replaced by the more readily observable number of domestic firms producing for the domestic market, D, where $D = N\left(\frac{c_D}{c_M}\right)^k$. The short–run dynamics are estimated in the first part of the equation, with regressors expressed in first differences. The long run is represented by the term in brackets. From the perspective of this model, we would expect $\beta_1 > 0$, an increase in domestic import tariffs increases relative prices in the short-run, and correspondingly $\beta_2 > 0$. The model predicts a dampening effect of the number of domestic firms on domestic prices, which should be reflected by $\beta_3 < 0$, and the opposite for foreign firms, $\beta_4 < 0$. As we expect the coefficient on the error correction term, γ, to be negative, a reversal the

As previously discussed, all aggregate variables (prices, markups, productivity) are ultimately functions of the cost-cutoff level c_D, leading to very similar estimation equations for our three dependent variables. The equation markups is:

$$\begin{aligned}\Delta \ln\left(\frac{\bar{\mu}_{it}}{\bar{\mu}^*_{it}}\right) =& \beta_0 + \beta_1 \Delta\tau_{it} + \beta_2\Delta\tau^*_{it} + \beta_3\Delta\ln\theta_{it} + \beta_4\Delta\ln\theta^*_{it} + \beta_5\Delta\ln D_{it} + \beta_6\Delta\ln D^*_{it} \\ &+ \gamma\left[\ln\left(\frac{\bar{\mu}_{it-1}}{\bar{\mu}^*_{it-1}}\right) + \delta_0 + \delta_1\ln L_{t-1} + \delta_2\ln L^*_{t-1} + \delta_3\tau_{i,t-1} + \delta_4\tau^*_{i,t-1}\right] + \varepsilon_{ijt}\end{aligned} \tag{5.12}$$

The effect of tariffs, openness, number of firms and market size on productivity is estimated by:

$$\begin{aligned}\Delta \ln\left(\frac{\bar{z}_{it}}{\bar{z}^*_{it}}\right) =& \beta_0 + \beta_1 \Delta\tau_{it} + \beta_2\Delta\tau^*_{it} + \beta_3\Delta\ln D_{it} + \beta_4\Delta\ln D^*_{it} \\ &+ \gamma\left[\ln\left(\frac{z_{it-1}}{z^*_{it-1}}\right) + \delta_0 + \delta_1\ln L_{t-1} + \delta_2\ln L^*_{t-1} + \delta_3\tau_{i,t-1} + \delta_4\tau^*_{i,t-1}\right. \\ &\left. + \delta_5\ln w_{i,t-1} + \delta_6\ln w^*_{i,t-1}\right] + \varepsilon_{ijt}\end{aligned} \tag{5.13}$$

where δ_7 and δ_8 capture the effects of changes in nominal wages in the long run. The intercepts β_0 are introduced to capture differences in country–specific technology as Chen et al. depart from the baseline Melitz-Ottaviano model by allowing for such differences. While in the baseline, these vary by country-pair, we check the robustness of the specification by allowing fixed effects at a sectoral level.

5.4.1 Preferential Trade Liberalization

The model results and estimation equations presented so far all referred to a unilateral trade liberalization in a simplified two-country setup[21]. While making the exposition clearer and helping to elicit the effects at work in the model, this setup is clearly not an accurate description of the reality of trade relationships in modern industrialized economies. Taking the United States as an example, while the two other countries in our data set, Canada and Mexico, are its largest trading partners, they only account for 16.6 and 13.5% of all US trade by value, respectively[22]. Even the largest 30 US trading partners only account for about 86% of US trade, highlighting the fragmented nature of international trade. While the Melitz-Ottaviano model can be extended to an arbitrary number of countries, it is clearly not feasible to assemble a data set on all trade partners of the NAFTA countries. We do however want to recognize the multi-country structure of NAFTA by taking into account third country effects of trade barriers. Here, NAFTA can be interpreted as a preferential liberalization of Mexico *vis-a-vis* the US and Canada, as Mexico had the highest tariff barriers to start off with. In the three country case, we expect the country with the lowest sum of bilateral trade barriers to have the lowest cost cutoff, as it becomes the best export hub. To account for this, we amend equations 5.11, 5.12 and 5.13 by including the relevant third country

[21] Note that a bilateral trade liberalization – changing τ and τ^* by the same amount – would not lead to the discussed short- and long run changes in cost cutoffs for two countries, but instead to a decline in the cost cutoffs in both countries both in the short and the long run.

[22] See Top U.S. Trade Partners, U.S. International Trade Administration

tariffs. The estimation equation for the effects of trade barriers on prices then becomes:

$$\begin{aligned}\Delta \ln \left(\frac{\bar{p}_{it}}{\bar{p}^*_{it}}\right) =& \beta_0 + \beta_1 \Delta \ln \tau_{it} + \beta_2 \Delta \ln \tau^*_{it} + \beta_3 \Delta \ln \tau^{ht}_{it} + \beta_4 \Delta \ln \tau^{th}_{it} + \beta_5 \Delta \ln \tau^{ft}_{it} + \beta_6 \Delta \ln \tau^{th}_{it} \\ &+ \beta_7 \Delta \ln D_{it} + \beta_8 \Delta \ln D^*_{it} + \beta_9 \Delta \ln D^t_{it} \\ &+ \gamma \left[\ln \left(\frac{\bar{p}_{it-1}}{\bar{p}^*_{it-1}}\right) + \delta_0 + \delta_1 \ln L_{t-1} + \delta_2 \ln L^*_{t-1} + \delta_3 \ln L^t_{t-1} + \delta_4 \ln \tau_{i,t-1} \right. \\ &\left. + \delta_5 \ln \tau^*_{i,t-1} + \delta_6 \Delta \ln \tau^{ht}_{it} + \delta_7 \Delta \ln \tau^{th}_{it} + \delta_8 \Delta \ln \tau^{ft}_{it} + \delta_9 \Delta \ln \tau^{th}_{it} \right] + \varepsilon_{ijt}\end{aligned} \tag{5.14}$$

where now h is the domestic economy, f is the foreign economy, and, with a slight abuse of notation, a t superscript denotes the third country for each country pair (e.g. when estimating the Canada-US relationship, τ^{th} are Mexican tariffs on Canadian goods, while τ^{ht} are Canadian tariffs on Mexican goods). Both the equations for markups and productivity will be amended accordingly.

5.4.2 Dataset

The database we utilize covers the period 1988-2014 for NAFTA member countries – Canada, Mexico, and the US – and nine manufacturing sectors at the ISIC two digit level, which includes 86 industries . For our factory gate price data, we use the producer price index (PPI) as reported by CANSIM, the Banco de Mexico, and the U.S. Bureau of Labor Statistics, respectively. All indices are normalized to equal 100 in 2003. While the majority of the manufacturing data collected is reported at the two-digit level according to ISIC Rev. 3, we aggregate all data according to NACIS in order to keep consistency throughout the analysis (see Table 5.4 for the manufacturing classification breakdown). While the main part of our analysis rests on data aggregated at the two-digit level, we were also able to assemble a data set at the four-digit level, which we will use to check the robustness of our results.

The value of markups is not easily observable, and thus we follow the calculation as outlined in the recent literature on industrial organization, and similarly used by Chen et al. (2009), although with a subtle modification. We compute average markups as the ratio of sectoral turnover relative to total variable costs, which are computed as the sum of intermediate inputs and labour costs as reported by the OECD STAN database.[23] Due to the unavailability of data on sectoral turnover, we use sectoral production as a proxy. While turnover may be slightly higher than production[24] in a given year if all of the produced goods are sold along with any stored goods from previous years, according to the OECD these measures will converge in the long term. Fixed costs are excluded from the calculation, as they will cause a negative bias between markups and openness. As the number of foreign firms increases due to a decrease in trade costs, the market share for domestic producers falls; because this will spread fixed costs across a smaller share of production, average total costs will increase contemporaneously (Chen et al., 2009).

Labor productivity is calculated as the ratio between real value added and total employment. Value added is reported by the OECD STAN database, while employment data is provided by LABORSTA, the statistical department of the

[23] In contrast, Chen et al. (2009) calculate average markups as the ratio of turnover relative to the sum of the costs of materials, consumables, and staff costs.

[24] Production represents the value of goods produced in a year, whether they are sold or stocked.

International Labor Organization (ILO).

The main explanatory variable in this analysis is the tariff imposed on foreign products. The simple average for tariffs disaggregated at the two-digit level (ISIC Rev. 2) imposed on the bi-lateral trading partners within NAFTA were taken from the World Integrated Trade Solution (WITS), which is a resource developed by the World Bank. The changes in import tariffs across all industries for each country-pair are illustrated in Figures 5.1 – 5.6, including the maximum and minimum tariff for each year. The tariffs imposed by the U.S. on Canadian and Mexican goods, and those imposed by Canada on Mexican and U.S. goods approached zero by 1999–2000, while the Mexican imposed tariffs fluctuated drastically throughout the time period, with some tariffs reaching 30%. The average, maximum, and minimum tariffs by country and sector are also detailed in Table 5.3, as well as the other main variables in this analysis.

To construct the openness variable, we calculate the ratio of imports relative to the sum of imports and domestic production, as in Chen et al. (2009). The bilateral trade data for each country-pair comes from the OECD STAN database and measured in current USD. Domestic production is calculated as the difference between total sectoral output and exports. The sectoral output data are also taken from the OECD STAN database (measured in current units of national currency) and converted to current USD using the OECD-reported exchange rates. In order to check the reliability of our measure of openness, we also use the UPenn openness index.

As discussed in the previous section, for all of the log-linearized equations, we replace the number of firms serving the domestic market, N, with the number of domestic firms producing for the domestic market, D. Unfortunately, this data is not available for all three countries during the specified time period, and thus we utilize the number of establishments, which will always be higher than the firm count as each firm may have multiple establishments. As long as the average number of establishments per firm remains constant, this should not present a problem, as our model is estimated in first differences. It is however not obvious that this relationship will remain constant in response to a trade liberalization. In fact, the main channel through which welfare gains arise in the model is the reallocation of production from unproductive to more productive firms, with less productive firms exiting the market and more productive firms expanding. If this displacement happens through larger firms taking over establishments of less productive ones, we would expect the number of establishments to stay constant, while the number of domestic producers falls (i.e. the number of establishments per firm increases). If on the other hand larger firms are simply able to expand production in existing establishments, this effect would be absent.

The control variables used in the regressions include nominal wages and size of the economy, both of which are provided by LABORSTA. Wages are disaggregated according to ISIC Rev. 3 and reported in national currency units per hour for all wage earners (as before, we convert all data into ISIC Rev. 2 and current USD). For the size of the economy L, we utilize the total economically active population for manufacturing. Moreover, there are missing values for the US and Mexico[25] and thus we use interpolated data for these years.

[25]We use interpolated data for the years 1999, 2001, and 2003 for the US, and 1992, 1994, 1996, 1998, 2001-2003 for Mexico.

5.4.3 Estimation

As outlined at the beginning of Section 5.4, we follow the estimation strategy of Chen et al. (2009); however, while they use changes in domestic and foreign import penetration in sector i at time t as the main explanatory variables for changes in price, markups, and labor productivity, we use this as a control variable and instead rely on the domestic tariff rate (τ) imposed on foreign goods imported from the trading partner and the foreign tariff rate (τ^*) imposed on domestic goods exported to the trading partner as the main explanatory variables. To test the competitive effects of trade liberalization, we use the difference in differences approach with fixed–effects on the country–pair, industry, and year. In the short run we use the log first-difference in the explanatory and dependent variables, whereas we use a lag operator on the explanatory variables and an error correction term to estimate the dynamics in the long run. Moreover, because our variables are stationary in a unit root sense and serially correlated, we utilize a panel-specific AR(1) autocorrelation structure and perform our regressions using a Generalized Least Squares estimation strategy.

Table 5.2 outlines the comparative statics for the theoretical model, with subscript sr denoting the ”short run” and lr denoting the ”long run”. Notice that in the long run theory suggests that the pro–competitive effects are reversed and actually take an anti–competitive nature as firms are able to relocate to new markets. Interestingly, as we will exhibit in the following section, our analysis does not provide the same long-run dynamics.

Table 5.2: Comparative Statics – Model Predictions

Regressor	Dependent Variables					
	$\bar{p}_{sr}$	$\bar{p}_{lr}$	μ_{sr}	μ_{lr}	z_{sr}	z_{lr}
τ	+	−	+	−	−	+
τ^*	−	+	−	+	+	−
D	−		−		+	
D^*	+		+		−	
L		−		−		+
L^*		+		+		−

5.5 Results & Discussion

Tables 5.5, 5.6 and 5.7 present our results on the short-run effects of trade liberalization on prices, markups and productivity, respectively. Column (1) in each table presents the results from our theoretical estimations in equations 5.11, 5.12, and 5.13, respectively. Beginning with table 5.5, we see that the signs on the tariff measures are as predicted – a decrease in the domestic tariff will decrease the relative price in the short-run – but only the foreign tariff measure is significant. The measure of openness, on the other hand, is as predicted in the model and both coefficients are significant at the 1% level. Finally, contrary to the model's predictions the number of firms serving the domestic market does not have any effect on prices. The results for this model specification on markups are similar, with the openness measure as predicted and significant and no effect from the change in domestic firms (see Table 5.6); in this case, however, the change in the domestic tariff is positive as predicted and significant at the 10% level, whereas the foreign tariff rate has the opposite effect than the model predicts, albeit insignificant. Finally, Table 5.7 shows the effects on industry productivity with different results than predicted by the model. Although the domestic tariff measure is positive and significant, we see that the openness measures have the opposite effect than the model predicts and are highly significant; an increase in domestic import penetration actually brings about a *decrease* in productivity in the short-run.

Columns (2) and (3) are modified to include the log first-difference in relative tariffs and openness, as well as the log first-difference in the lagged dependent variable.

In the short run, the signs for all short–run effects of tariff reductions are as predicted and highly significant. Table 5.5 presents the effects of tariff reductions on prices in the short run. A decrease in domestic tariffs causes a decrease in relative prices, whereas foreign tariffs actually increase prices. The openness variables that are the main explanatory variable in Chen et al. (2009) are not significant when the tariffs are included, as the tariff provides a more accurate measure of openness between the country-pair; it should be noted, however, that the signs on the openness variable follow the predicted signs from the model when tariffs are excluded from the regression analysis.

Similar to relative prices, Table 5.6 focuses on price markups, and suggests that a decrease in domestic tariffs will likewise decrease domestic markups, with profit margins actually increasing with foreign tariffs. While the coefficients are no longer significant, the signs still match the predicted theory and hold with the different model specifications. In contrast, Table 5.7 focuses on labor productivity, and suggests that domestic tariff reductions will increase productivity, with foreign tariffs causing the opposite effect.

The main contribution of this paper comes from the long–run effects of trade liberalization as presented in Tables 5.8, 5.9, and 5.10. Table 5.8 focuses on the long–run effects of liberalization on relative prices. While the sign on the coefficient in question (i.e., lagged domestic tariffs) is positive, which is in direct contrast to the theory of Melitz and Ottaviano (2009), the results are not significant. However, the market size (L) has a positive and highly significant effect on relative prices in the long–run, thus contradicting theory that the most productive firms will relocate to a less competitive market and the short–run gains from trade will converge back to their equilibrium levels. As firms leave the market, relative prices remain low according to this analysis.

While the sign on tariffs was in contrast to the theory, the competitive effect of trade openness on relative markups (as presented in Table 5.9) does follow the theory of Melitz and Ottaviano, with decreasing tariffs causing an increase in relative markups in the long–run. Moreover, now the size of the market (L) has a negative impact on markups, which supports the anti-competitive effects in the long–run when firms have the option to relocate to a less competitive market.

Finally, Table 5.10 presents the results for the long–run effects of tariff reductions on labor productivity. Similar to the theoretical predictions, labor productivity is reversed in the long run.

While the estimation results of Chen et al. on country-pairs within the European Union followed those predicted by the model of Melitz and Ottaviano, the long–run results in this analysis were in contradiction to the theory with regards to prices; however, the models predictions do hold for relative markups and productivity. The estimation results for the short–run follow the model's predictions and are highly significant.

5.6 Conclusion

The only empirical application of the Melitz–Ottaviano (2008) model to date suggested that the long–run effects of trade liberalization are anti–competitive, that is, there will be a reversal in any competitive gains as firms are allowed to move to new markets. However, largely due to the year restrictions in their database, the results from Chen et al. (2009) are insignificant in the long run, and thus merely suggestive. While this paper replicates their analysis with only minor conceptual changes, our use of NAFTA as a defining multilateral trade agreement and the 12-years of data available after its implementation, provides new insights into the long–run dynamics of international trade agreements. While the theory suggests a reversal of competitive effects in the aggregate, this paper illustrates that the competitive effects are merely assuaged, but certainly not reversed. This adds credence to the pro-liberalization camp of policy makers who argue for the social welfare improving competitive effects of trade liberalization in the short–, medium–, and long term.

5.7 Appendix A: Figures, Summary Statistics, Results

Figure 5.1: Canadian Tariff on Mexican Goods

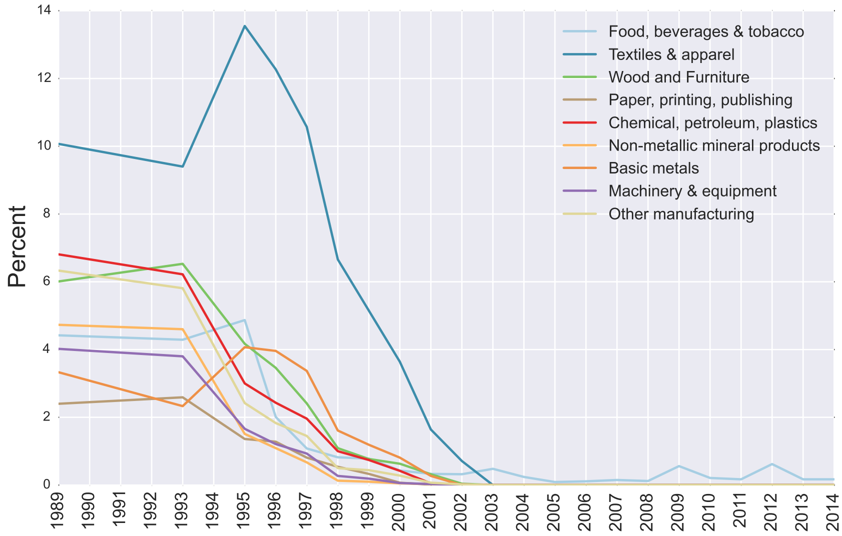
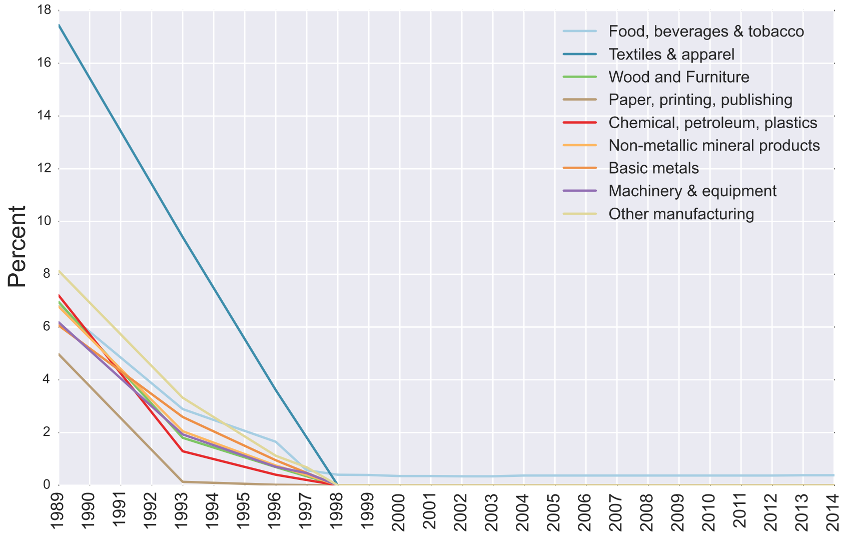


Figure 5.2: Canadian Tariff on U.S. Goods



26

[26] The majority of output tables in this paper has been produced using the stargazer package (Hlavac, 2004)

Figure 5.3: Mexican Tariff on Canadian Goods

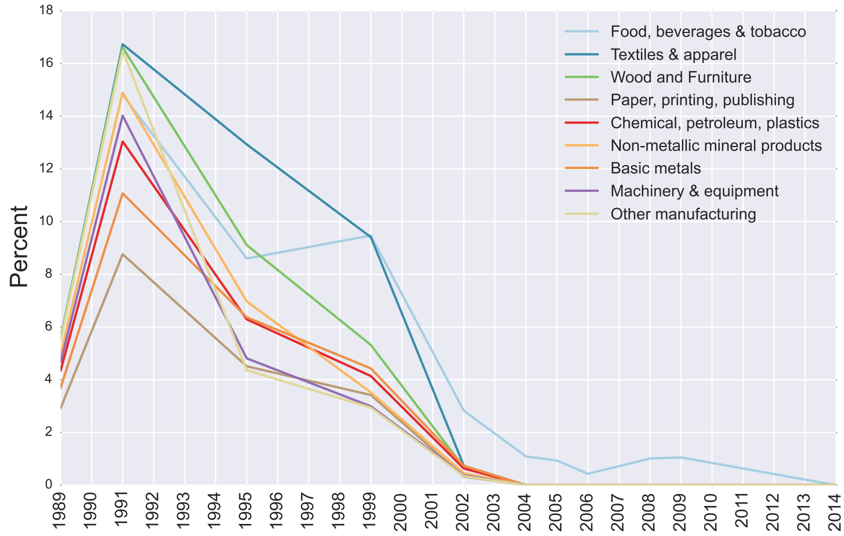


Figure 5.4: Mexican Tariff on U.S. Goods

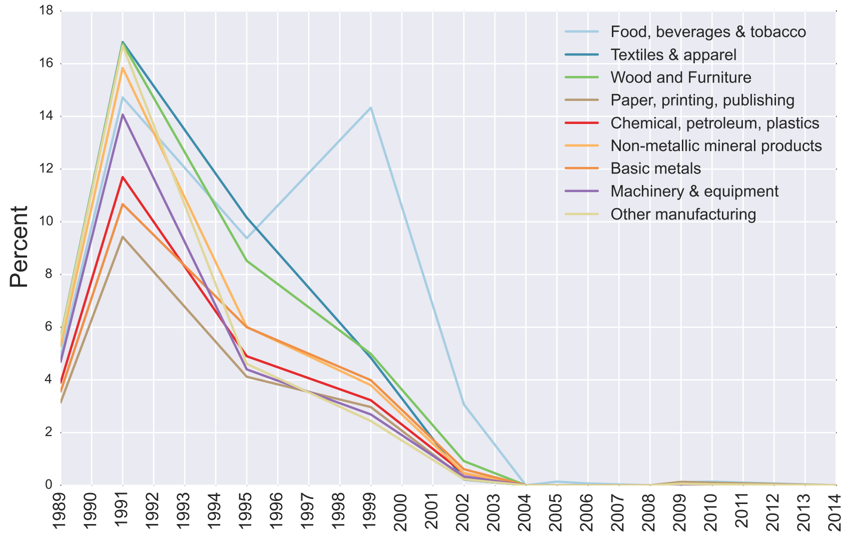


Figure 5.5: U.S. Tariff on Canadian Goods

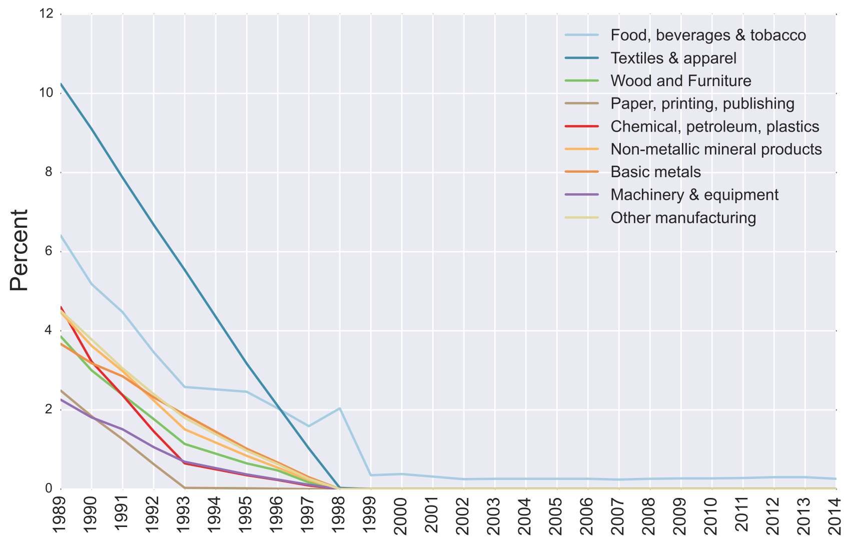


Figure 5.6: U.S. Tariff on Mexican Goods

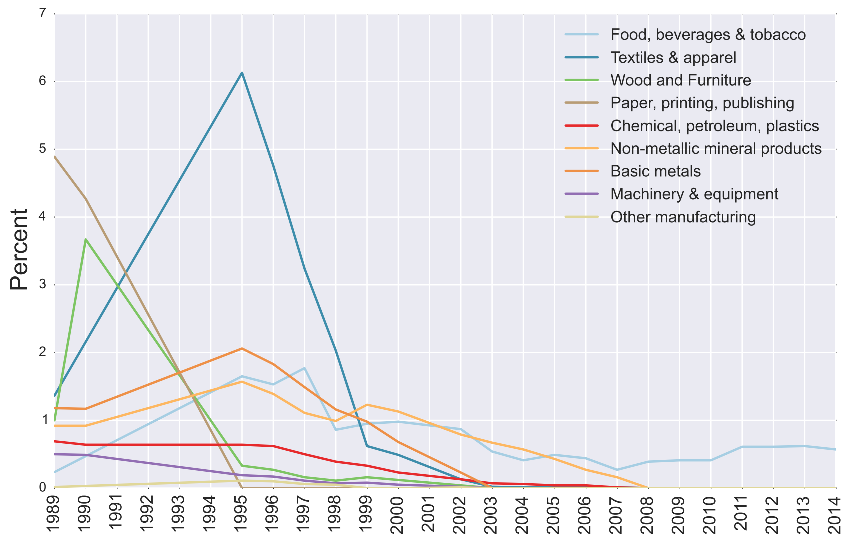


Table 5.3: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
exp_f	702	76,233,571,691.000	198,643,966,085.000	399,038,863	1,890,000,000,000
gdp_can	594	908.568	278.187	536.500	1,370.640
gdp_mex	594	1,036.795	315.456	560.660	1,566.310
gdp_usa	594	9,807.745	2,991.049	5,482.130	14,498.930
cpi_can	675	79.697	12.487	56.340	100.000
cpi_mex	675	48.219	32.559	1.560	100.000
cpi_usa	675	75.546	14.894	50.300	100.000
open_ind_can	810	59.378	12.446	37.550	75.580
open_ind_mex	810	34.822	17.307	13.210	62.320
open_ind_usa	810	22.673	3.691	17.190	30.970
ppi_mex	810	57.485	51.438	0.100	276.590
tau_s_can_mex	540	1.829	3.193	0.000	17.780
tau_s_can_usa	540	2.440	5.051	0.000	26.440
tau_s_mex_can	405	8.654	8.751	0.000	30.530
tau_s_mex_usa	405	7.611	8.552	0.000	28.800
tau_s_usa_can	621	0.994	1.780	0.000	10.600
tau_s_usa_mex	621	1.717	2.654	0.000	11.810

5.8 Appendix B: Industry list, NAICS classification

Table 5.4: Industry List, NAICS 4-digit

NAICS 4-digit Industry	
3111	Animal Food Manufacturing
3112	Grain and Oilseed Milling
3113	Sugar and Confectionery Product Manufacturing
3114	Fruit and Vegetable Preserving and Specialty Food Manufacturing
3115	Dairy Product Manufacturing
3116	Animal Slaughtering and Processing
3118	Bakeries and Tortilla Manufacturing
3119	Other Food Manufacturing
3121	Beverage Manufacturing
3132	Fabric Mills
3133	Textile and Fabric Finishing and Fabric Coating Mills
3149	Other Textile Product Mills
3152	Cut and Sew Apparel Manufacturing
3159	Apparel Accessories and Other Apparel Manufacturing
3169	Other Leather and Allied Product Manufacturing
3211	Sawmills and Wood Preservation
3212	Veneer, Plywood, and Engineered Wood Product Manufacturing
3219	Other Wood Product Manufacturing
3221	Pulp, Paper, and Paperboard Mills
3222	Converted Paper Product Manufacturing

3231	Printing and Related Support Activities
3241	Petroleum and Coal Products Manufacturing
3251	Basic Chemical Manufacturing
3254	Pharmaceutical and Medicine Manufacturing
3255	Paint, Coating, and Adhesive Manufacturing
3256	Soap, Cleaning Compound, and Toilet Preparation Manufacturing
3259	Other Chemical Product and Preparation Manufacturing
3262	Rubber Product Manufacturing
3271	Clay Product and Refractory Manufacturing
3273	Cement and Concrete Product Manufacturing
3274	Lime and Gypsum Product Manufacturing
3279	Other Nonmetallic Mineral Product Manufacturing
3312	Steel Product Manufacturing from Purchased Steel
3313	Alumina and Aluminum Production and Processing
3314	Nonferrous Metal (except Aluminum) Production and Processing
3315	Foundries
3321	Forging and Stamping
3322	Cutlery and Handtool Manufacturing
3323	Architectural and Structural Metals Manufacturing
3324	Boiler, Tank, and Shipping Container Manufacturing
3325	Hardware Manufacturing
3326	Spring and Wire Product Manufacturing
3327	Machine Shops; Turned Product; and Screw, Nut, and Bolt Manufacturing
3329	Other Fabricated Metal Product Manufacturing

3331	Agriculture, Construction, and Mining Machinery Manufacturing
3332	Industrial Machinery Manufacturing
3333	Commercial and Service Industry Machinery Manufacturing
3334	Ventilation, Heating, Air-Conditioning, & Commercial Refrig. Eq. Manuf.
3335	Metalworking Machinery Manufacturing
3336	Engine, Turbine, and Power Transmission Equipment Manufacturing
3339	Other General Purpose Machinery Manufacturing
3342	Communications Equipment Manufacturing
3344	Semiconductor and Other Electronic Component Manufacturing
3345	Navigational, Measuring, Electromedical, and Control Instrum. Manuf.
3351	Electric Lighting Equipment Manufacturing
3352	Household Appliance Manufacturing
3353	Electrical Equipment Manufacturing
3359	Other Electrical Equipment and Component Manufacturing
3362	Motor Vehicle Body and Trailer Manufacturing
3363	Motor Vehicle Parts Manufacturing
3371	Household and Institutional Furniture and Kitchen Cabinet Manufacturing
3372	Office Furniture (including Fixtures) Manufacturing
3379	Other Furniture Related Product Manufacturing
3399	Other Miscellaneous Manufacturing

5.9 Appendix C: Regression Results

Table 5.5: Prices (Short Run), all country pairs

	Dependent variable:					
	$\Delta \log \left(\frac{p}{p^*}\right)$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \log \tau_t$	0.0002	0.0003	-0.003	0.002	-0.003	0.002
	(0.001)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
$\Delta \log \tau_t^*$	-0.003^{**}	-0.004^{**}	-0.002	-0.004	-0.002	-0.004
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
$\Delta \log D_t$	0.011	0.013^{*}	0.010	0.018	0.010	0.018
	(0.007)	(0.008)	(0.009)	(0.020)	(0.009)	(0.020)
$\Delta \log D_t^*$	-0.019	-0.014	-0.017	-0.186	-0.017	-0.186
	(0.023)	(0.023)	(0.019)	(0.266)	(0.019)	(0.266)
Observations	984	984	354	318	354	318
R^2	0.011	0.009	0.033	0.010	0.033	0.010

Note: *p<0.1; **p<0.05; ***p<0.01
(1),(3): Fixed effects country-industry (2),(4): Fixed effects country pair

Table 5.6: Markups (Short Run), all country pairs

	Dependent variable:			
	$\Delta \log \left(\frac{\mu}{\mu^*}\right)$			
	(1)	(2)	(3)	(4)
$\Delta \log \tau_t$	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
$\Delta \log \tau_t^*$	0.00003	0.00003	0.0002	0.0002
	(0.001)	(0.001)	(0.001)	(0.001)
$\Delta \log \theta$			-0.024^{***}	-0.024^{***}
			(0.005)	(0.006)
$\Delta \log \theta^*$			0.028^{***}	0.028^{***}
			(0.009)	(0.009)
$\Delta \log D_t$	-0.003	-0.002	-0.005	-0.003
	(0.009)	(0.009)	(0.009)	(0.009)
$\Delta \log D_{t-1}$	0.049	0.006	0.037	-0.008
	(0.050)	(0.056)	(0.049)	(0.055)
Observations	306	306	302	302
R^2	0.009	0.006	0.109	0.107

Note: *p<0.1; **p<0.05; ***p<0.01
Fixed effects for country pair

Table 5.7: Productivity (Short Run), all country pairs

	Dependent variable:			
	$\Delta \log \left(\frac{z}{z^*}\right)$			
	(1)	(2)	(3)	(4)
$\Delta \log \tau_t$	0.007 (0.005)	0.007 (0.006)	0.009^{**} (0.004)	0.009^{**} (0.004)
$\Delta \log \tau_t^*$	−0.006 (0.005)	−0.006 (0.005)	−0.003 (0.004)	−0.003 (0.004)
$\Delta \log \theta_t$	−0.415 (0.264)	−0.389 (0.283)		
$\Delta \log \theta_t^*$	0.767^{*} (0.425)	0.681 (0.482)		
$\Delta \log D_t$			-0.329^{***} (0.035)	-0.322^{***} (0.036)
$\Delta \log D_t^*$			0.656^{***} (0.057)	0.660^{***} (0.059)
diff(log(firms_h))			−0.012 (0.061)	−0.012 (0.062)
diff(log(firms_f))			0.428 (0.333)	0.359 (0.380)
Observations	324	324	320	320
R^2	0.027	0.023	0.428	0.432
Note:			*p<0.1; **p<0.05; ***p<0.01 Fixed effects for country pair	

Table 5.8: Prices (Long Run), all country pairs

	Dependent variable: $\Delta \log \left(\frac{p_t}{p_t^*}\right)$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \log \tau_t$	-0.002	0.0001	-0.009	0.004	-0.008	0.005
	(0.002)	(0.002)	(0.011)	(0.004)	(0.006)	(0.003)
$\Delta \log \tau_t^*$	0.0004	0.0003	0.004	0.001	0.003	0.001
	(0.003)	(0.002)	(0.012)	(0.005)	(0.008)	(0.004)
$\Delta \log D_t$	0.003	0.005	0.006	0.014	0.004	0.013
	(0.007)	(0.008)	(0.009)	(0.019)	(0.010)	(0.020)
$\Delta \log D_t^*$	-0.011	-0.007	-0.014	0.241	-0.010	0.094
	(0.022)	(0.023)	(0.018)	(0.284)	(0.019)	(0.210)
$\log \left(\frac{p_{t-1}}{p_{t-1}^*}\right)$	-0.123^{***}	-0.009	-0.141^{***}	-0.216^{***}	-0.031	-0.035
	(0.024)	(0.021)	(0.041)	(0.052)	(0.031)	(0.046)
$\log \tau_{t-1}$	-0.006^{**}	-0.003^{**}	-0.014	-0.005	-0.012	-0.003
	(0.002)	(0.001)	(0.016)	(0.004)	(0.007)	(0.002)
$\log \tau_{t-1}^*$	0.001	0.0003	0.008	-0.001	0.007	-0.00001
	(0.003)	(0.001)	(0.016)	(0.005)	(0.007)	(0.001)
$\log L_{t-1}$	0.237	0.068	0.383	0.638	0.210	0.323
	(0.242)	(0.264)	(0.333)	(0.650)	(0.360)	(0.665)
$\log L_{t-1}^*$	-0.463^{*}	-0.243	-0.584^{*}	-0.941	-0.359	-0.580
	(0.253)	(0.276)	(0.350)	(0.680)	(0.377)	(0.694)
Observations	984	984	354	318	354	318
R^2	0.120	0.063	0.125	0.150	0.068	0.073

Note: *p<0.1; **p<0.05; ***p<0.01
Fixed effects for country pair

Table 5.9: Markups (Long Run), all country pairs

	Dependent variable:			
	$\Delta \log \left(\frac{\mu}{\mu^*}\right)$			
	(1)	(2)	(3)	(4)
$\Delta \log \tau$	0.001	0.0004	0.001	0.0005
	(0.001)	(0.001)	(0.001)	(0.001)
$\Delta \log \tau^*$	0.001	0.001	0.00002	0.0003
	(0.001)	(0.001)	(0.001)	(0.001)
$\Delta \log \theta$			-0.032^{***}	-0.027^{***}
			(0.006)	(0.006)
$\Delta \log \theta^*$			0.048^{***}	0.095^{***}
			(0.010)	(0.016)
$\Delta \log D_t$	-0.0004	0.012	-0.004	0.006
	(0.009)	(0.008)	(0.009)	(0.007)
$\Delta \log D_t^*$	0.027	-0.055	0.034	-0.063
	(0.053)	(0.050)	(0.051)	(0.047)
$\log \left(\frac{\mu_{t-1}}{\mu_{t-1}^*}\right)$	0.010	-0.460^{***}	0.003	-0.454^{***}
	(0.007)	(0.042)	(0.007)	(0.039)
τ_{t-1}	-0.001	-0.002^{**}	-0.001	-0.002^{**}
	(0.001)	(0.001)	(0.001)	(0.001)
τ_{t-1}^*	0.001	0.001^{*}	-0.0001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
$\log \theta_{t-1}$			-0.010^{***}	-0.010^{*}
			(0.003)	(0.005)
$\log \theta_{t-1}^*$			0.008^{**}	0.037^{***}
			(0.003)	(0.010)
L_{t-1}	-0.156^{*}	-0.128^{*}	-0.255^{***}	-0.185^{***}
	(0.080)	(0.068)	(0.080)	(0.066)
L_{t-1}^*	0.139^{*}	0.104	0.230^{***}	0.138^{**}
	(0.081)	(0.068)	(0.081)	(0.068)
Observations	306	306	302	302
R^2	0.040	0.332	0.183	0.491
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$	
			Fixed effects for country pair	

Table 5.10: Productivity (Long Run), all country pairs

	Dependent variable:			
	$\Delta \log \left(\frac{z}{z^*}\right)$			
	(1)	(2)	(3)	(4)
$\Delta \log \tau_t$	0.0002	-0.001	0.004	0.003
	(0.005)	(0.004)	(0.004)	(0.004)
$\Delta \log \tau_t^*$	0.001	0.004	-0.001	0.002
	(0.005)	(0.005)	(0.005)	(0.005)
$\Delta \log \theta$			-0.245^{***}	-0.214^{***}
			(0.040)	(0.042)
$\Delta \log \theta^*$			0.574^{***}	0.451^{***}
			(0.070)	(0.131)
$\Delta \log D_t$	-0.428^{*}	0.409^{*}	-0.179	0.262
	(0.246)	(0.221)	(0.210)	(0.208)
$\Delta \log D_t^*$	0.336	-0.427	0.167	-0.175
	(0.393)	(0.358)	(0.345)	(0.353)
$\log \left(\frac{z_{t-1}}{z_{t-1}^*}\right)$	-0.145^{***}	-0.348^{***}	-0.089^{***}	-0.308^{***}
	(0.016)	(0.022)	(0.015)	(0.033)
$\log \tau_{t-1}$	-0.008	-0.009^{*}	-0.007	-0.006
	(0.006)	(0.005)	(0.005)	(0.005)
$\log \tau_{t-1}^*$	0.006	0.013^{**}	0.0004	0.006
	(0.005)	(0.005)	(0.005)	(0.005)
$\log \theta_{t-1}$			-0.012	-0.092^{**}
			(0.021)	(0.043)
$\log \theta_{t-1}^*$			-0.010	0.119
			(0.021)	(0.078)
$\log L_{t-1}$	0.569	-1.531^{***}	-0.523	-1.625^{***}
	(0.623)	(0.559)	(0.539)	(0.538)
$\log L_{t-1}^*$	-0.777	1.740^{***}	0.198	1.416^{***}
	(0.636)	(0.568)	(0.547)	(0.543)
$\log w_{t-1}$	0.160^{**}	0.181^{**}	0.068	0.216^{**}
	(0.063)	(0.090)	(0.058)	(0.100)
$\log w_{t-1}^*$	-0.230^{***}	-0.584^{***}	-0.063	-0.129
	(0.069)	(0.117)	(0.062)	(0.142)
Observations	324	324	320	320
R^2	0.290	0.543	0.510	0.613
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$			
	Fixed effects for country pair or industry/country pair			

Chapter 6

Conclusion

Throughout this thesis, an outline of affine term structure models is provided. This particular class of term structure models has been made very popular in recent years due to its ability to capture the dynamics of yields both across their time series and cross-section and its ease in imposing the absence of arbitrage, allowing in turn the obtention of adaptable risk premia specifications. Affine term structure models have the advantage of allowing various extensions, in a wide range, to their basic primary setup, asserting their importance in the literature. However, difficulties do arise in their estimation and in the interpretation of the latent factors used. This thesis addresses both problems by utilizing a specific structure to the factor loadings, known as the Nelson-Siegel method. The estimation of this term structure model not only circumvents the global optimum issues but further provides some interpretation to the factors, given the level, slope and curvature factors of the Nelson-Siegel interpolation are not only intuitive in their nature, but also have reliable macroeconomic links.

The present thesis introduces and employs dynamic term structure models to macroeconomic and financial research questions. More precisely, this study initially pertains to financial markets by establishing a tie between interest rates and exchange rates. The study follows by concerning itself with macroeconomic objectives, by exploiting the relationship between yields and inflation.

In a first instance, this study exploits a theoretical relationship between interest rates and exchange rates, namely the uncovered interest rate parity, with the aim to extract currency risk premia through a bilateral affine term structure model with stochastic volatility. The method proposed consists of developing an affine Arbitrage-Free class of dynamic Nelson-Siegel term structure models (AFNS) with stochastic volatility to obtain the domestic and foreign discount rate variations, which in turn are used to derive a representation of exchange rate depreciations. The manipulation of no-arbitrage restrictions allows to endogenously capture currency risk premia. The estimation exercise comprises of a state-space analysis using the Kalman filter. The imposition of the Dynamic Nelson-Siegel (DNS) structure allows for a tractable and robust estimation, offering significant computational benefits, whilst no-arbitrage restrictions enforce the model with theoretically appealing properties. Empirical findings suggest that estimated currency risk premia are able to account for the forward premium puzzle.

In a second instance, inflation expectations and inflation risk premia are derived using a shadow rate class of term structure models. In response to the recent financial crisis, the Bank of England reduced short term interest rates to 0.5%. With such low short term rates, traditional term structure models are likely to be inappropriate for estimating inflation expectations and risk premia, because expectations based on such models might implicitly violate the zero lower bound condition. In this segment both the nominal and real UK term structure of interest rates are studied, using the dynamic term structure model introduced by, which imposes the non-negativity of nominal short maturity rates. Estimates of the term premia, inflation risk premia and market-implied inflation expectations are provided. Findings indicate that the zero lower bound specification is necessary to reflect countercyclicality in nominal term premia projections and that medium and long term inflation expectations have been contained within narrower bounds since the early 1990s, suggesting monetary policy credibility after the introduction of inflation targeting.

For my future research projects, I wish to draw from the analysis and discussion of this thesis and elaborate further on this strand of the literature, this time emphasizing on the joint effect of monetary economics and finance on asset prices, financial markets and monetary policy. Two main perspectives emerge within my research agenda. A potential project, that inclines more towards macroeconomic concepts, consists in building an extension of the two above-mentioned models by constructing a Taylor rule type of model which would further extend to include growth. Furthermore, an alternative suggests to further exploit the interaction between macroeconomic and financial data to explore a gap in the literature. Specifically, the study includes providing an economic interpretation to the latent factors, used in the state-space representation, by venturing towards macro-finance models and high frequency data. This analysis is built on the prior belief that assets are affected by macroeconomic conditions but simultaneously suffer from microstructure phenomena.

Notwithstanding the extensions listed above, it is crucial to note that the most important message to draw from this thesis is that the literature on risk premia is still at its infancy due to the striking complexity involved in estimating an unobservable variable which nonetheless contains a very rich informational content. In turn, in future research, I wish to investigate the sensitivity of the price of risk, and consequently of risk premia, to different specifications in the mean reversion matrix of the states' dynamics. The aim is to determine a preferred specification for dynamic term structure models using a Bayesian shrinkage estimation approach.

To conclude, this thesis builds a spherical account of the versatility of affine models by implementing them to distinct monetary finance applications. Several of the pending issues in the literature are addressed and the grounds for future interesting questions are paved.

Bibliography

Abowd, John M and David Card, "Intertemporal Labor Supply and Long-term Employment Contracts," *American Economic Review*, March 1987, *77* (1), 50–68. 38, 41

Aguiar, Mark and Mark Bils, "Has Consumption Inequality Mirrored Income Inequality?," *American Economic Review*, September 2015, *105* (9), 2725–56. 54

Aiyagari, S Rao, "Uninsured Idiosyncratic Risk and Aggregate Saving," *The Quarterly Journal of Economics*, August 1994, *109* (3), 659–84. 13, 23, 25, 26, 68

Arkolakis, Costas, Arnaud Costinot, and Andres Rodriguez-Clare, "New Trade Models, Same Old Gains?," *American Economic Review*, February 2012, *102* (1), 94–130. 85

_ , _ , Dave Donaldson, and Andres Rodriguez-Clare, "The Elusive Pro-Competitive Effects of Trade," 2012. Working Paper. 85

Attanasio, Orazio and Guglielmo Weber, "Consumption and Saving: Models of Intertemporal Allocation and Their Implications for Public Policy," *Journal of Economic Literature*, September 2010, *48* (3), 693–751. 20

_ , **Erik Hurst, and Luigi Pistaferri**, "The Evolution of Income, Consumption, and Leisure Inequality in the US, 1980-2010," in "Improving the Measurement of Consumer Expenditures," National Bureau of Economic Research, Inc, 2013. 54

Autor, David H., Lawrence F. Katz, and Melissa S. Kearney, "Trends in U.S. Wage Inequality: Re-Assessing the Revisionists," NBER Working Papers 11627, National Bureau of Economic Research, Inc September 2005. 53

Badel, Alejandro and Mark Huggett, "Taxing top earners: a human capital perspective," Working Papers 2014-17, Federal Reserve Bank of St. Louis July 2014. 30

Baker, Michael, "Growth-Rate Heterogeneity and the Covariance Structure of Life-Cycle Earnings," *Journal of Labor Economics*, April 1997, *15* (2), 338–75. 38, 41, 42

Baldwin, John, Timothy Dunne, and John Haltiwanger, "A Comparison of Job Creation and Job Destruction in Canada and the United States," 1994. CES Research Paper. 97

Barba, Aldo and Massimo Pivetti, "Rising household debt: Its causes and macroeconomic implications–a long-period analysis," *Cambridge Journal of Economics*, January 2009, *33* (1), 113–137. 51, 56

Bellone, Flora, Patrick Musso, Lionel Nesta, and Frederic Warzynski, "Endogenous Markups, Firm Productivity and International Trade: : Testing SomeMicro-Level Implications of theMelitz-Ottaviano Model," Working Papers 08-20, University of Aarhus, Aarhus School of Business, Department of Economics September 2008. 90

Benhabib, Jess, Alberto Bisin, and Shenghao Zhu, "The Distribution of Wealth and Fiscal Policy in Economies With Finitely Lived Agents," *Econometrica*, 01 2011, *79* (1), 123–157. 34

Bernard, Andrew B., J. Bradford Jensen, and Peter K. Schott, "Survival of the best fit: Exposure to low-wage countries and the (uneven) growth of U.S. manufacturing plants," *Journal of International Economics*, January 2006, *68* (1), 219–237. 90

_ , _ , and _ , "Trade costs, firms and productivity," *Journal of Monetary Economics*, July 2006, *53* (5), 917–937. 95

Bertrand, Marianne and Adair Morse, "Trickle-Down Consumption," Working Paper 18883, National Bureau of Economic Research March 2013. 51

Bewley, Truman, "The permanent income hypothesis: A theoretical formulation," *Journal of Economic Theory*, December 1977, *16* (2), 252–292. 23

Blundell, Richard and Ian Preston, "Consumption Inequality And Income Uncertainty," *The Quarterly Journal of Economics*, May 1998, *113* (2), 603–640. 24

_ , Luigi Pistaferri, and Ian Preston, "Consumption Inequality and Partial Insurance," *American Economic Review*, December 2008, *98* (5), 1887–1921. 24

Brown, Mark W., "Renewing Canada's Manufacturing Economy: A Regional Comparison, 1973-1996," Technical Report 11 2004. 97

Browning, Martin and Thomas F. Crossley, "The Life-Cycle Model of Consumption and Saving," *Journal of Economic Perspectives*, Summer 2001, *15* (3), 3–22. 20, 21

— , **Mette Ejrns, and Javier Alvarez**, "Modelling Income Processes with Lots of Heterogeneity," *Review of Economic Studies*, 2010, *77* (4), 1353–1381. 40

Cagetti, Marco, "Wealth Accumulation over the Life Cycle and Precautionary Savings," *Journal of Business & Economic Statistics*, July 2003, *21* (3), 339–53. 26, 27, 28

— **and Mariacristina De Nardi**, "Entrepreneurship, Frictions, and Wealth," *Journal of Political Economy*, October 2006, *114* (5), 835–870. 30, 31

Calderon-Madrid, Angel and Alexandru Voicu, "The NAFTA Tide : Lifting the Larger and Better Boats," 2007. Working Paper. 89

Campbell, Jeffrey R. and Zvi Hercowitz, "The Role of Collateralized Household Debt in Macroeconomic Stabilization," NBER Working Papers 11330, National Bureau of Economic Research, Inc May 2005. 25, 50

— **and** — , "Welfare implications of the transition to high household debt," *Journal of Monetary Economics*, January 2009, *56* (1), 1–16. 25

Carroll, Christopher D., Jiri Slacalek, and Kiichi Tokuoka, "The Distribution of Wealth and the MPC: Implications of New European Data," *American Economic Review*, May 2014, *104* (5), 107–11. 33

Castaneda, Ana, Javier Diaz-Gimenez, and Jose-Victor Rios-Rull, "Accounting for the U.S. Earnings and Wealth Inequality," *Journal of Political Economy*, August 2003, *111* (4), 818–857. 26, 29

Chang, Yongsung, Jay Hong, and Marios Karabarbounis, "Life Cycle Uncertainty and Portfolio Choice Puzzles," 2013 Meeting Papers 595, Society for Economic Dynamics 2013. 58

Chen, Natalie, Jean Imbs, and Andrew Scott, “The dynamics of trade and competition,” *Journal of International Economics*, February 2009, *77* (1), 50–62. 14, 86, 87, 90, 93, 95, 96, 100, 106, 107, 111

Chor, Davin and Kalina Manova, “Off the cliff and back? Credit conditions and international trade during the global financial crisis,” *Journal of International Economics*, 2012, *87* (1), 117–133. 93, 95

Corcos, Gregory, Massimo Del Gatto, Giordano Mion, and Gianmarco I P Ottaviano, “Productivity and Firm Selection: Quantifying the ’New’ Gains From Trade,” *Economic Journal*, 2011, *122*, 754–798. 90

Cordoba, Juan-Carlos, “U.S. inequality: Debt constraints or incomplete asset markets?,” *Journal of Monetary Economics*, March 2008, *55* (2), 350–364. 55

Costinot, Arnaud and Andres Rodriguez-Clare, “Trade Theory with Numbers: Quantifying the Consequences of Globalization,” in Gita Gopinath, Elhanan Helpman, and Ken Rogoff, eds., *Handbook of International Economics, Vol. 4*, Amsterdam: Elsevier, 2014, pp. 197–261. 86

Cozzi, Marco, “Risk Aversion Heterogeneity, Risky Jobs and Wealth Inequality,” Working Papers 1286, Queen’s University, Department of Economics December 2014. 33

Deaton, Angus, *Understanding Consumption* number 9780198288244. In ‘OUP Catalogue.’, Oxford University Press, 1992. 24

DeBacker, Jason, Bradley Heim, Vasia Panousi, Shanthi Ramnath, and Ivan Vidangos, “Rising Inequality: Transitory or Persistent? New Evidence from a Panel of U.S. Tax Returns,” *Brookings Papers on Economic Activity*, 2013, *46* (1 (Spring)), 67–142. 39, 51

Diaz, Antonia, Josep Pijoan-Mas, and Jose-Victor Rios-Rull, "Precautionary savings and wealth distribution under habit formation preferences," *Journal of Monetary Economics*, September 2003, *50* (6), 1257–1291. 33

DiPrete, Thomas A, "Is This a Great Country? Upward Mobility and the Chance for Riches in Contemporary America," *Research in Social Stratification and Mobility*, 2007, *25*, 89–95. 64

DixCarneiro, Rafael, "Trade Liberalization and Labor Market Dynamics," *Econometrica*, 2014, *82* (3), 825–885. 85

Dunne, Timothy, Mark J Roberts, and Larry Samuelson, "Patterns of firm entry and exit in U.S. manufacturing industries," *RAND Journal of Economics*, 1988, *19* (4), 495–515. 97

Dynan, Karen E., Jonathan Skinner, and Stephen P. Zeldes, "Do the Rich Save More?," *Journal of Political Economy*, April 2004, *112* (2), 397–444. 66

Floden, Martin, "Aggregate Savings When Individual Income Varies," *Review of Economic Dynamics*, January 2008, *11* (1), 70–82. 68

Foster, Lucia, John Haltiwanger, and Namsuk Kim, "Gross Job Flows for the U.S. Manufacturing Sector: Measurement from the Longitudinal Research Database," Technical Report 2006. 97

Friedman, Milton, *A Theory of the Consumption Function*, National Bureau of Economic Research, Inc, 1957. 21

Fuhrer, Jeffrey C., "Habit Formation in Consumption and Its Implications for Monetary-Policy Models," *American Economic Review*, June 2000, *90* (3), 367–390. 33

Fukao, Kyoji, Toshihiro Okubo, and Robert M. Stern, "An econometric analysis of trade diversion under NAFTA," *The North American Journal of Economics and Finance*, March 2003, *14* (1), 3–24. 89

Gale, William G. and John Karl Scholz, "Intergenerational Transfers and the Accumulation of Wealth," *Journal of Economic Perspectives*, Fall 1994, *8* (4), 145–160. 32

Glaeser, Edward L., "Psychology and the Market," *American Economic Review*, May 2004, *94* (2), 408–413. 63

Gordon, Robert J., "Misperceptions About the Magnitude and Timing of Changes in American Income Inequality," NBER Working Papers 15351, National Bureau of Economic Research, Inc September 2009. 53

Gourinchas, Pierre-Olivier and Jonathan A. Parker, "Consumption Over the Life Cycle," *Econometrica*, January 2002, *70* (1), 47–89. 26

Grossman, Gene M and Elhanan Helpman, "Trade, Innovation, and Growth," *American Economic Review*, May 1990, *80* (2), 86–91. 85

Guiso, Luigi, Michael Haliassos, and Tullio Jappelli, "Household stockholding in Europe: where do we stand and where do we go?," *Economic Policy*, 04 2003, *18* (36), 123–170. 34

Guvenen, Fatih, "Learning Your Earning: Are Labor Income Shocks Really Very Persistent?," *American Economic Review*, June 2007, *97* (3), 687–712. 14, 52, 58

_ , "An Empirical Investigation of Labor Income Processes," *Review of Economic Dynamics*, January 2009, *12* (1), 58–79. 38, 39, 41, 42, 43, 46, 48

— **and Anthony A. Smith**, "Inferring Labor Income Risk and Partial Insurance From Economic Choices," *Econometrica*, November 2014, *82*, 2085–2129. 58, 61, 62

— **, Fatih Karahan, Serdar Ozkan, and Jae Song**, "What Do Data on Millions of U.S. Workers Reveal about Life-Cycle Earnings Risk?," Working Papers 719, Federal Reserve Bank of Minneapolis January 2015. 39, 76

Haider, Steven J, "Earnings Instability and Earnings Inequality of Males in the United States: 1967-1991," *Journal of Labor Economics*, October 2001, *19* (4), 799–836. 42

Hause, John C, "The Fine Structure of Earnings and the On-the-Job Training Hypothesis," *Econometrica*, May 1980, *48* (4), 1013–29. 38

Head, Keith and John Ries, "Rationalization effects of tariff reductions," *Journal of International Economics*, April 1999, *47* (2), 295–320. 89, 96

Heathcote, Jonathan, Fabrizio Perri, and Giovanni L. Violante, "Unequal We Stand: An Empirical Analysis of Economic Inequality in the United States: 1967-2006," *Review of Economic Dynamics*, January 2010, *13* (1), 15–51. 53

— **, Kjetil Storesletten, and Giovanni L Violante**, "Consumption and Labour Supply with Partial Insurance: An Analytical Framework," CEPR Discussion Papers 6280, C.E.P.R. Discussion Papers May 2007. 24

Hintermaier, Thomas and Winfried Koeniger, "On the Evolution of the US Consumer Wealth Distribution," *Review of Economic Dynamics*, April 2011, *14* (2), 317–338. 28, 29, 61, 62, 65, 67, 68

Hlavac, Mark, "stargazer: LaTeX code and ASCII text for well-formatted regression and summary statistics tables. R package version 5.1," CRAN 2004. 115

Hoffmann, Florian, "HIP, RIP and the Robustness of Empirical Earnings Processes," 2013. Working Paper. 39, 75

Hryshko, Dmytro, "Labor income profiles are not heterogeneous: Evidence from income growth rates," *Quantitative Economics*, 07 2012, *3* (2), 177–209. 40, 46

Hubbard, R Glenn, Jonathan Skinner, and Stephen P Zeldes, "Precautionary Saving and Social Insurance," *Journal of Political Economy*, April 1995, *103* (2), 360–99. 34

Huggett, Mark, "The risk-free rate in heterogeneous-agent incomplete-insurance economies," *Journal of Economic Dynamics and Control*, 1993, *17* (5-6), 953–969. 13, 23

Iacoviello, Matteo, "Household Debt and Income Inequality, 1963-2003," *Journal of Money, Credit and Banking*, 08 2008, *40* (5), 929–965. 25

Imrohoruglu, Ayse, "Cost of Business Cycles with Indivisibilities and Liquidity Constraints," *Journal of Political Economy*, December 1989, *97* (6), 1364–83. 13, 23

Kaplan, Greg and Giovanni L. Violante, "How Much Consumption Insurance beyond Self-Insurance?," *American Economic Journal: Macroeconomics*, October 2010, *2* (4), 53–87. 24

Kilian, Lutz, Alessandro Rebucci, and Nikola Spatafora, "Oil shocks and external balances," *Journal of International Economics*, April 2009, *77* (2), 181–194. 93, 95

Kindermann, Fabian and Dirk Krueger, "High Marginal Tax Rates on the Top 1%? Lessons from a Life Cycle Model with Idiosyncratic Income Risk," PIER Working Paper Archive 14-036, Penn Institute for Economic Research, Department of Economics, University of Pennsylvania October 2024. 29

Kohler, Ulrich, "PSIDTOOLS: Stata module to facilitate access to Panel Study of Income Dynamics (PSID)," Statistical Software Components, Boston College Department of Economics January 2015. 43

Kopczuk, Wojciech, Emmanuel Saez, and Jae Song, "Earnings Inequality and Mobility in the United States: Evidence from Social Security Data since 1937," *The Quarterly Journal of Economics*, February 2010, *125* (1), 91–128. 39, 51

Kotlikoff, Laurence J and Lawrence H Summers, "The Role of Intergenerational Transfers in Aggregate Capital Accumulation," *Journal of Political Economy*, August 1981, *89* (4), 706–32. 31

Krueger, Dirk and Fabrizio Perri, "Does Income Inequality Lead to Consumption Inequality? Evidence and Theory," *Review of Economic Studies*, 2006, *73* (1), 163–193. 50, 53, 55

Krusell, Per, Anthony A. Smith, and Jr., "Income and Wealth Heterogeneity in the Macroeconomy," *Journal of Political Economy*, October 1998, *106* (5), 867–896. 32, 33

Lawrance, Emily C, "Poverty and the Rate of Time Preference: Evidence from Panel Data," *Journal of Political Economy*, February 1991, *99* (1), 54–77. 32

Lucas, Robert, "The Industrial Revolution - Past and Future," Essay, Federal Reserve Bank of Minneapolis May 2004.

Ma, Lin, "Globalization and Top Income Shares," Technical Report, University of Michigan 2013. Working Paper. 53

MaCurdy, Thomas E., "The Use of Time Series Processes to Model the Error Structure of Earnings in a Longitudinal Data Analysis," *Journal of Econometrics*, 1982, *18* (1), 83–114. 38

Meghir, Costas and Luigi Pistaferri, "Income Variance Dynamics and Heterogeneity," *Econometrica*, 01 2004, *72* (1), 1–32. 40, 76

Melitz, Marc J., "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity," *Econometrica*, November 2003, *71* (6), 1695–1725. 85, 90, 91

_ **and Daniel Trefler**, "Gains from Trade When Firms Matter," *Journal of Economic Perspectives*, Spring 2012, *26* (2), 91–118. 85

_ **and Gianmarco I. P. Ottaviano**, "Market Size, Trade, and Productivity," *Review of Economic Studies*, January 2008, *75* (1), 295–316. 86, 90, 91

_ **and Stephen J. Redding**, "New Trade Models, New Welfare Implications," NBER Working Papers 18919, National Bureau of Economic Research, Inc March 2013. 86

Modigliani, Franco, "Life Cycle, Individual Thrift, and the Wealth of Nations," *American Economic Review*, June 1986, *76* (3), 297–313. 31

Modigliano, Franco and Richard Brumberg, "Utility Analysis and the Consumption Function: An Interpretation of Cross-Section Data," in K. Kurihara, ed., *Post Keynesian Economics*, New Brunswick: Rutgers University Press, 1954. 20, 21

Moore, David W., "Half of Young People Expect to Strike It Rich," March 2003. 64

Narajabad, Borghan Nezami, "Information Technology and the Rise of Household Bankruptcy," *Review of Economic Dynamics*, October 2012, *15* (4), 526–550. 50

Nardi, Mariacristina, "Wealth Inequality and Intergenerational Links," *Review of Economic Studies*, 07 2004, *71*, 743–768. 32

Nardi, Mariacristina De, "Quantitative Models of Wealth Inequality: A Survey," NBER Working Papers 21106, National Bureau of Economic Research, Inc April 2015. 30

Nardi, Mariacristina De and Fang Yang, "Wealth Inequality, Family Background, and Estate Taxation," NBER Working Papers 21047, National Bureau of Economic Research, Inc March 2015. 36

Nardi, Mariacristina De, Eric French, and John B. Jones, "Why Do the Elderly Save? The Role of Medical Expenses," *Journal of Political Economy*, 02 2010, *118* (1), 39–75. 35

_ , _ , and John Bailey Jones, "Life Expectancy and Old Age Savings," *American Economic Review*, May 2009, *99* (2), 110–15. 35

_ , _ , _ , and Jeremy McCauley, "Medical Spending of the U.S. Elderly," NBER Working Papers 21270, National Bureau of Economic Research, Inc June 2015. 35

Oswald, Florian, "High Dimensional Function Approximation in Julia," `https://github.com/floswald/ApproXD.jl` 2014. 62

Ottaviano, Gianmarco I. P., Takatoshi Tabuchi, and Jacques-Francois Thisse, "Agglomeration and Trade Revisited," *International Economic Review*, 2002, *43* (2), 409–436. 91

Piketty, Thomas, "On the Long-Run Evolution of Inheritance: France 1820–2050," *The Quarterly Journal of Economics*, 2011, *126* (3), 1071–1131. 31

_ , *Capital in the 21st Century*, Harvard University Press, 2014. 13, 16, 26

_ **and Emmanuel Saez**, "Income Inequality In The United States, 1913-1998," *The Quarterly Journal of Economics*, February 2003, *118* (1), 1–39. 53

_ **and Gabriel Zucman**, "Wealth and inheritance in the long run," in Anthony B. Atkinson and Francois Bourguignon, eds., *Handbook of Income Distribution*, Amsterdam: North-Holland, 2015, pp. 1303–1368. 31

_ , **Gilles Postel-Vinay, and Jean-Laurent Rosenthal**, "Inherited vs self-made wealth: Theory & evidence from a rentier society (Paris 18721927)," *Explorations in Economic History*, 2014, *51* (C), 21–40. 31

Quadrini, Vincenzo, "Entrepreneurship, Saving and Social Mobility," *Review of Economic Dynamics*, January 2000, *3* (1), 1–40. 30

Rajan, Raghuram, *Fault Lines: How Hidden Fractures Still Threaten the World Economy*, Princeton University Press, 2011. 51

Romalis, John, "NAFTA's and CUSFTA's Impact on International Trade," *Review of Economics and Statistics*, 2007, *89* (3), 416–435. 89

Saez, Emmanuel and Gabriel Zucman, "Wealth Inequality in the United States since 1913: Evidence from Capitalized Income Tax Data," NBER Working Paper October 2014. 56

Siegel, Jeremy J. and Richard H. Thaler, "Anomalies: The Equity Premium Puzzle," *Journal of Economic Perspectives*, Winter 1997, *11* (1), 191–200. 34

Storesletten, Kjetil, Christopher I. Telmer, and Amir Yaron, "Consumption and risk sharing over the life cycle," *Journal of Monetary Economics*, April 2004, *51* (3), 609–633. 61

Townsend, A., "FastGaussQuadrature.jl," `https://github.com/ajt60gaibb/FastGaussQuadrature.jl` (GitHub repository) 2015. 62

Trefler, Daniel, "The Long and Short of the Canada-U.S. Free Trade Agreement," *American Economic Review*, 2004, *94* (4), 870–895. 89, 94

van Treeck, Till, "Did inequality cause the U.S. financial crisis?," IMK Working Paper 91-2012, IMK at the Hans Boeckler Foundation, Macroeconomic Policy Institute 2012. 52

Vermeulen, Philip, "How fat is the top tail of the wealth distribution?," Working Paper Series 1692, European Central Bank July 2014. 17

Weiss, Yoram and Lee A Lillard, "Experience, Vintage, and Time Effects in the Growth of Earnings: American Scientists, 1960-1970," *Journal of Political Economy*, June 1978, *86* (3), 427–47. 38

Yang, Fang, "Consumption over the Life Cycle: How Different is Housing?," *Review of Economic Dynamics*, July 2009, *12* (3), 423–443. 25

Zeldes, Stephen P, "Optimal Consumption with Stochastic Income: Deviations from Certainty Equivalence," *The Quarterly Journal of Economics*, May 1989, *104* (2), 275–98.