Do credit shocks matter for aggregate consumption?

Tomi Kortela*

Abstract

Consumption and unsecured credit are correlated in the data. This fact has created a hypothesis which argues that the time-varying liquidity constraints – or credit shocks – matter for aggregate consumption. I conclude in a general equilibrium framework that credit shocks are not quantitatively important for aggregate economy. Hence, fluctuations in credit do not matter for the dynamics of aggregate consumption, but the existence of fixed liquidity constraint, combined with other shocks, dominate the dynamics of aggregate consumption. This result also implies that the monetary transmission mechanism does not seem to operate by affecting the availability of the credit of households.

JEL Codes: E21, E32 ,E51

Keywords: Incomplete markets, heterogeneous agents, credit shocks, liquidity constraints, monetary policy, business cycles

*Tomi Kortela, Department of Economics, FI-20014 University of Turku, Finland (e-mail: tomi.kortela@utu.fi). The programs that generate the results in this paper are available at the author's homepage: `http://taloustiede.utu.fi/laitos/henkilokunta/kortela/index.html`. I would like to thank Juha Tervala, Matti Viren and Oskari Vähämaa for their helpful comments. The author is responsible for all errors and false conclusions.

1 Introduction

The fluctuations of aggregate consumption and hence, the behavior of households, plays a central role in the dynamics of business cycles. Therefore, the determination of dynamics of aggregate consumption, which results from households responses to prevailing and expected circumstances, has been an issue of importance to policy makers and academic economists as well. The seminal work of Hall (1978) shows that one implication of the permanent income hypothesis is that predictable changes in consumption should be unrelated to information available in earlier periods. However, there are significant and well known reflections from the permanent income hypothesis as the excess sensitivity and the excess smoothness of consumption.

One hypothesis in this vein is that the availability of credit, or equally the time-varying liquidity constraint, matters for the dynamics of aggregate consumption, and hence the business cycle dynamics (Bacchetta and Gerlach, 1997; Ludvigson, 1998, 1999; Gross and Souless, 2002). This evidence is based on an analysis where the identification of shocks and issues with aggregation are not studied in detail, but they matter for the result significantly, as I will demonstrate in this paper. However, these studies conclude that the availability of credit matters for the determination of consumption. By simulating a general equilibrium model, the structure shocks can be controlled and a realistic aggregation can be given within a model. Hence, the potential flaws of previous studies can be fixed.

To study the effects of credit shocks on the aggregate consumption I use the model by Krusell and Smith (1998) and extend it by time-varying liquidity constraints. The responses of aggregate consumption on credit shocks depend on the distribution of wealth, since the marginal propensities to consume depend on the level of wealth of each individual. Thus, the type of model where the wealth distribution is endogenously determined is a natural choice to study a credit-related questions. Moreover, to compare the quantitative significance of credit shocks, productivity and employment shocks are needed to capture fluctuations in households' income. Then, one can add the credit shocks and see what their contribution for the dynamics of aggregate consumption is.

The availability of credit matters for the dynamics of aggregate consumption, if a significant part of households are liquidity constrained or the presence of liquidity constraint affects their behavior powerfully, since it might bind in the future. When credit conditions vary jointly with current aggregate circumstance, will the constrained households', i.e. households that like to consume more – but cannot – since the liquidity constraint is binding (or will bind), change their level of consumption according to the availability of credit. Hence, procyclically varying liquidity constraint, i.e. credit shocks, potentially amplify other shocks by affecting aggregate consumption, which in turn cause fluctuations in other real variables. This type of "financial accelerator " for consumption sector is analogous to that documented for investment sector (Bernanke and Gertler (1989) and Kiyotaki and Moore (1997)). Moreover, if credit shocks are a significant factor for determining the dynamics of aggregate consumption, then the permanent income hypothesis does not give a valid description for the dynamics of aggregate consumption, but households who have a strong precautionary saving motive may affect the dynamics of aggregate consumption significantly. [1]

Credit conditions are also interesting when monetary policy is examined. The monetary policy may matter via a mechanism, which is known as the credit channel of monetary transmission (see, Bernanke and Getler (1995)). This mechanism is often thought affecting firms, but it may matter for households as well. The effect may work through the balance sheet effect: a better financial position gives credit with lower costs, or by bank lending channel: bank-dependent borrowers may not get credit if the supply of credit is disrupted somehow. In this paper I focus on the latter channel, i.e. how the supply of credit matters for the dynamics of aggregate consumption. From the view point of policy makers this matter is interesting, since central bank can affect banks' lending abilities. If credit shocks matter for aggregate consumption, then the central bank could reduce the fluctuations of economy, by affecting banks' lending.

The simulations of the model imply that the time-varying credit constraint – or the credit shocks – do not matter for the determination of aggregate consumption even if the size of the shocks is set larger than the data support. The time varying credit constraint matters only for very few people, when the effects of other shocks, combined with fixed liquidity constraint, determinate

[1] Generally, the quantitative importance of precautionary saving motives for the determination of aggregate consumption is not settled (see surveys by Carroll and Kimball (2007) and Browning and Lusardi (1996)).

the dynamics of consumption. I confirm that the time-varying liquidity constraint matters for poor people's consumption decisions, but their effect on the dynamics of aggregate consumption is insignificant. Hence, it seems that the correlation between aggregate consumption and unsecured credit is caused mainly by a causality, which runs from the demand of credit to the supply of credit. That is, the supply of credit will adjust to changes in the demand of credit which in turn is moved by fluctuations in the aggregate consumption.

The paper is organized as follows: In section 2 stylized facts and literature related to credit and consumption are discussed. Section 3 shows the model and discusses the effects of time-varying liquidity constraint on agents' behavior. Section 4 delivers the results of simulations, and finally, Section 5 concludes the paper.

2 Aggregate consumption and the availability of credit

2.1 Stylized facts from the data

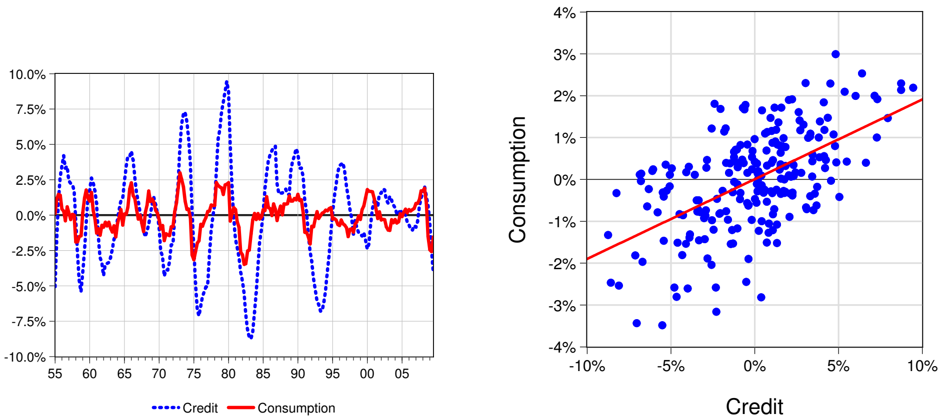
A fraction of credit relative to GDP has doubled during the 20th century in the U.S.. At the end of the 20th century, the value of outstanding unsecured credit is about 18% of GDP. Given this magnitude – at least potentially – changes in the aggregate volume of unsecured credit may matter for the performance of the whole economy. Especially, a well-known fact is that the aggregate measure of unsecured credit and the aggregate consumption are correlated as shown by Ludvigson (1999) with data from the U.S., and Bacchetta and Gerlach (1997) provides international evidence.[2]

Issues concerning credit are especially relevant due to current financial crises, since the level of credit and consumption has been sharply decreased. This fact could be interpreted so that the availability of credit has at least partly caused the drop of consumption. Hence, monetary policy could affect also the time path of aggregate consumption, if it could affect banks' lending or the supply of credit, and at the same time monetary policy can influence the course of economy.

[2]A more comprehensive analysis about credit and economic fluctuations can be found from Schularick and Taylor (2009).

Moreover, the decreased level of credit has been one motivation to stimulate aggregate demand via fiscal policy, as Mankiw (2010) puts it: " [The Obama Administration] thought that, because of the credit crisis, people were not able to obtain loans; and, because people were not able to obtain loans, there was insufficient aggregate demand." Thus, there seem to be a strong believe that the availability of credit matter for aggregate consumption.

Figure 1 shows the deviations of aggregate private consumption expenditure and the outstanding consumer credit from their trend levels, where the trends and cycle series are generated by using the Hodrick-Prescott filter. Credit covers most short- and intermediate-term credit extended to individuals which are not covered with real estate. Correlation between these two series is almost 0.6, but the main question is: which way the causality is running?[3]



(a) The deviations from the trend.

(b) Scatter between the cycle series and a regression line.

Figure 1: The deviations of consumption and credit from they trend levels in the U.S from 1955 to 2009 quarter 3.

Figure 1 shows that there is a dependency between consumption and credit and the hypothesis says that the variations in the supply of credit affects the aggregate consumption. However, it may be that the supply of credit only adjusts the changes in the demand of credit, which in turn results from the changes in the aggregate consumption. This type of causality questions are hard to solve when aggregate data is used (as in Ludvigson (1999) and Bacchetta and Gerlach (1997)),

[3] Appendix A describes the data in more detail and presents more figures.

since it is hard to find a good instrument. Estimations from micro data, where causality issues are more easy to deal with a good instrument, leaves the relevance of the results at the aggregate level open (as in Gross and Souless (2002)), since a proper way to aggregate is missing. These types of problems can be avoided by using a calibrated general equilibrium model. Within this approach, I can control the causality issues, since in the model setup I can control the shocks. Moreover, I can also discuss the relevance of the time-varying liquidity constraint at the aggregate level, since the wealth distribution is endogenously determined and it roughly equals to the wealth distribution observed in the data. This solves the issues in the aggregation.

2.2 Related literature

There are two different strands of literature which are associated with this paper. Firstly, this paper is associated with literature which tries to explain the dynamics of aggregate consumption. The correlation between consumption growth and lagged income growth has been found to be one of the most robust features of aggregate data, and this fact is contradictory with the implications of the permanent income hypothesis, as mentioned in Section 1.[4] Moreover, in the standard real business cycle model, consumption and income are correlated with each other due to productivity shocks, but consumption is less volatile than the data suggests (see, for example, King and Rebelo (1999)). Thus, the dynamics of aggregate consumption are not fully explained by current models, and fluctuations in credit could increase correlation between consumption and income, or they could increase the volatility of consumption. Generally, in this paper I ask: What is the role of credit supply for the dynamics of aggregate consumption?

Secondly, there are several papers focusing on defaults in credit markets, for example, see Athreya (2002); Chatterjee, Corbae, Nakajima, and Ríos-Rull (2007) and Atherya, Tam, and Young (2009), to name but a few. In these studies, there are endogenously determined default behavior which

[4]There are several well-known explanations for this relationship. Campbell and Mankiw (1989) add consumers into an economy who follow the "rule of thumb" of consuming their current income. Hence, myopia could explain this empirical fact. More recently, the buffer-stock behavior or precautionary saving motive is used to explain this relationship (Deaton, 1991; Carroll, 1997). However, there are not many papers which actually focus on the implications of precautionary saving for the dynamics of aggregate consumption, an exception being Ludvigson and Michaelides (2001). More detailed discussion can be found in Deaton (1992) and Browning and Lusardi (1996).

is combined with the standard incomplete markets model of Huggett (1993) or Aiyagari (1994). These types of studies are associated with this paper since they focus on the dynamics of unsecured credit markets, and the model framework is close to the one used here. A crucial exception is that I have aggregate shocks in the model (since the model is based on Krusell and Smith (1998)), but studies cited above only uses idiosyncratic shocks. Hence, those studies focus on steady state situation of the economy, but the focus in this paper is on business cycle dynamics. I do not allow defaults, since a model with defaults and aggregate uncertainty could be very hard to solve.[5] I assume that defaults are not allowed, which allows to focus on the business cycle dynamics when I can include aggregate shocks. Obviously, aggregate uncertainty is an important aspect of the model since I am concentrating on the business cycle dynamics.

So, in this paper I discuss the dynamics between consumption and unsecured credit. The paper contributes to the both strands of literature since this type of analysis has not been presented in the literature which focuses on the dynamics of aggregate consumption or in the literature which focuses on credit markets imperfections. However, the question is an important one, as discussed in Sections 1 and 2.1, since it may matter for the dynamics of aggregate consumption and it could give an important channel for monetary policy to restrain the volatility of business cycles.

[5]Solving only the steady state in the model where defaults are possible, is very time consuming. I do not know any paper where a general equilibrium model is combined with incomplete markets, options to default and aggregate uncertainty. However, allowing defaults would be an important extension to the model. But, it also should noted that many countries' legislation do not allow default.

3 The general equilibrium model with time-varying liquidity constraints

3.1 Environment

3.1.1 Production

At period t the aggregate output Y_t is produced according to Cobb-Douglas production function of capital input K_t, which depreciates at the rate $\delta \in [0,1]$, and labor input L_t:

$$Y_t = z_t K_t^{\alpha} L_t^{1-\alpha}, \tag{1}$$

with $\alpha \in [0,1]$ and $z_t \in Z = \{z_b, z_g\}$ which is (the aggregate) productivity shock which follows a first-order Markov structure. There are two aggregate states: either the state is good, $z_t = z_g$, when the economy is in a boom, or it is bad, $z_t = z_b$, when the economy is in a recession.

Factor and production markets are competitive which implies the factor prices:

$$w_t = z_t(1-\alpha)K_t^{\alpha}L_t^{-\alpha} \tag{2}$$

$$r_t = z_t \alpha K_t^{\alpha-1} L_t^{1-\alpha} - \delta. \tag{3}$$

3.1.2 Stochasticity

Assume that there is a continuum of infinitely-lived agents of measure one. Each agent in this economy faces productivity shocks $\epsilon_t \in \Upsilon = \{0,1\}$ for their labor. When $\epsilon_t = 1$ the agent is employed, and in the case of $\epsilon_t = 0$ the agent is unemployed. ϵ is statistically independent across agents and follows a first-order Markov structure, but it is correlated with the aggregate state. Hence, the joint evolution of the exogenous states follows a Markov process with transition matrix Π, with $\Pi_{zz'\epsilon\epsilon'}$ stating

$$\Pi\left(z', \epsilon' \,|z, \epsilon\right) = Pr\left(z_{t+1} = z', \epsilon_{t+1} = \epsilon' \mid z_t = z, \epsilon_t = \epsilon\right). \tag{4}$$

The transition probabilities for ϵ_{t+1} depend on z_t, i.e. agents have a higher job finding probability in good times than in bad times, but controlling for Z, individual shocks are independently distributed.

3.1.3 The problem of agents

Agents' maximization problem is following:

$$\max_{\{c_t\}_{t=0}^{\infty}} E_t U(c_t) = E_t \sum_{t=0}^{\infty} \beta^t \frac{c_t^{1-\sigma}}{1-\sigma} \quad (5)$$

$$\text{s.t.} \quad a_{t+1} + c_t = (1+r_t) a_t + \epsilon_t w_t \bar{l} + (1-\epsilon_t)\phi_0, \quad (6)$$

$$a_{t+1} \geq D_t, \quad (7)$$

$$c_t \geq 0 \quad \forall t. \quad (8)$$

Hence, agents maximize their expected discounted utility conditional today's information by choosing the level of consumption c_t. Moreover, $\beta \in (0,1)$ is the discount factor and $1/\sigma$ gives the intertemporal elasticity of substitution. Agents receive income from working, $\epsilon_t w_t \bar{l}_t$, if they are employed, or they receive $(1-\epsilon_t)\phi_0$ when they are unemployed, which is the value of their nonmarket activity – or home-produced output.[6] I will calibrate the Markov processes, which transition probabilities are given by (4), in a way that the number of agents who are unemployed is u_b in a recession and u_g in a boom ($u_g < u_b$) and the labor supply is fixed for the agents at the level $\bar{l}$. These assumptions imply that the aggregate labor supply, L_t, is known for every period.

Agents collect income from services of their capital holdings a_t, which is the only asset in the economy. Assets can be held as a store of value or agents may hold assets for a means of self-insurance against income shocks. The asset markets are incomplete in two different ways, when compared with the Arrow-Debrau economy: Firstly, there is no state contingent claims, and secondly, there are liquidity constraints. In order to rule out Ponzi schemes and to guarantee that

[6] I do not want to add government in this model, so the value of home-produced output can be thought as an unemployment benefit or it could be some type partial insurance against idiosyncratic risk. More detailed discussion about household production can be found for example at Greenwood, Rogerson, and Wright (1995). Adding a government, which transfers income from the employed to the unemployed and runs a balanced budged, is straightforward, but it does not add any substance to the model.

loans are paid back, I restrict capital holdings to satisfy $a \in A \equiv [\,\underline{a}_g, \infty\,)$, where $\underline{a}_g$ is the lowest possible level of liquidity constraint in the economy.

3.1.4 The time varying liquidity constraint

In this model, the liquidity constraint varies stochastically over time depending on aggregate state. Liquidity constraint, D_t, get value $\underline{a}_g$, when $z_t = z_g$, and when $z_t = z_b$ the value of D_t is $\underline{a}_b$. Thus, $D_t \in A = \{\underline{a}_g, \underline{a}_b\}$. I do not want to add the number of states, so I assume that liquidity constraint follows the same first-order Markov than did the productivity shocks.[7] Thus, credit shocks and productivity shocks are perfectly correlated. It is assumed that $\underline{a}_g \leq \underline{a}_b \leq 0$, which implies that, in a boom, agents may carry a larger amount of debt than in a recession. Moreover, I define *credit* as follows: an agent demands credit when her capital holdings – or net worth – is negative. Moreover, I call the changes in the liquidity constraint as *credit shocks*.

One way to interpret these credit shocks is to assume that there is a bank that decides what is the maximum level of debt that can be held in an economy. When times are good, the bank allows its customers to hold more debt than in bad times. For instance, assume that bank's loanable funds increase in a boom and decrease in a recession, which makes bank's supply of credit vary with the aggregate state. Hence, the time-varying liquidity constraint can be seen as changes in the supply of credit of banks. Moreover, Lown and Morgan (2006) provides evidence that standards in loan supply vary strongly with GDP and they conclude that some sort of friction in lending markets leads lenders to ration loans via changes in standards rather than through changes in rates. Thus, this type of modeling seems to be appropriate. [8]

These shocks (the time variation in the liquidity constraint) create a so-called procyclical "financial accelerator" in the consumption sector. That is, when an economy is moving from boom to recession, agent whose assets are $\underline{a}_g \leq a < \underline{a}_b$ must decrease their level of debt, i.e. save, so that their next period level of assets are at least at the level $\underline{a}_b$. If credit shocks matter for the dynamics of aggregate consumption, and hence business cycle dynamics, central bank may eliminate or

[7] However, nothing prevents to specify a new Markov structure for liquidity shocks.

[8] Furthermore, there is a strong positive correlation between the aggregate measure of unsecured credit and GDP. This fact supports the modeling of credit shocks in a way described above.

restrain business cycles by affecting banks' lending, i.e. by keeping liquidity constraint – or the supply of credit – fixed: $\underline{a}_g = \underline{a}_b$. That is, central bank could increase welfare by restraining fluctuations in aggregate consumption.

Defaults are not allowed, which implies that agents must always be able to to reach the higher liquidity constraint $\underline{a}_b$. Hence, given $\underline{a}_b$ the budged constraint implies, when $\{c_t\}_{t=0}^{\infty} \simeq 0$, that the lowest possible value for $\underline{a}_g$ is given by

$$\underline{a}_g = \frac{\underline{a}_b - \phi_0}{1 + r^{max}}, \tag{9}$$

where r^{max} is the highest possible interest rate in the economy. If $\underline{a}_g = \underline{a}_b$, then the liquidity constraint equals to natural borrowing limit ála Aiyagari (1994): $-\phi_0/r^{max}$. If we assume that $\underline{a}_g = \underline{a}_b = 0$ (and $\phi_0 = 0$), the model is the same as Krusell and Smith (1998).

Finally, it is good to notice that the credit defined here and the empirical measure in Section 2 are not equivalent. Here, I assume that credit is only demanded when agents' net worth is negative, but a significant part of outstanding credit is hold by households that have a positive net worth (as documented by Gross and Souless (2002)). Those households have debt (or credit) and assets such that the value of assets is greater than the value of debt, so the net worth is positive. However, Ludvigson (1999) also followed the same type of modeling as here: she used data from only such households that have a low level of assets to estimate the effects of credit shocks to aggregate consumption since it is not credible to assume that liquidity constraint would matter for households who have a great deal of assets.

3.2 Computation and endogenous labor supply

I use the same method as Krusell and Smith (1998) to solve the model, but I solve the agents' problem by using the endogenous gridpoint method (see, Carroll (2006)), where the time varying liquidity constraint is easy to accommodate.[9] The definition of recursive competitive equilibrium

[9] There are different ways to compute this type of models, see den Haan, Judd, and Juillard (2010), and other papers in that issue, and Ríos-Rull (1999). Moreover, a detailed description of this type of models without credit shocks is given, for example, by Krusell and Smith (2006).

and more detailed discussion about computation of this model is given in Appendix B. Appendix C extends the model showed here by endogenisizing the labor supply decision of agents.

3.3 The time varying liquidity constraint and decision rules

3.3.1 Parameter selection

To illustrate the effects of time varying liquidity constraint, I set most of parameters as in Krusell and Smith (1998), which are standard in the literature. However, these choices do not generate realistic wealth distribution, but here I demonstrate the effects of time-varying liquidity constraint for agents' decision rules. In Section 4 I change the model such that it generates a realistic wealth distribution and I focus on the aggregation, but here I set $\beta = 0.9894$, $\alpha = 0.36$, $\delta = 0.025$, $\sigma = 1$, $\bar{l} = 0.333$. Furthermore, I set $\underline{a}_b$ to -2.2, hence, the agent's borrowing limit in a recession is about half of their annual income. The final parameter is ϕ_0 and I set it to $\phi_0 = 0.35$. This value is higher than the data supports (the proper value is $\phi_0 = 0.1$, see Section 4), but the higher value is set here to illustrate the effects of time-varying liquidity constraint. This choice also sets $\underline{a}_g$, when $\underline{a}_b$ is fixed, as indicated by equation (9).

The Π is calibrated to roughly mimic fluctuations in the macroeconomic aggregates in observed postwar U.S. time series. The unemployment rate in a recession, u_b, is 10% when the average duration of the unemployment is 2.5 quarters, when in a boom the unemployment rate, u_g, is 4% and the average unemployment spell is 1.5 quarters. Moreover, the average duration of boom and recession is eight quarters, with parameter values $z_g = 1.01$ and $z_b = 0.99$.[10]

3.3.2 The effects of time varying credit constraint

It is well known that the lack of insurance against idiosyncratic shocks, combined with a liquidity constraint or prudence, cause a precautionary saving motive for agents (see, Deaton (1991) and Carroll (1997)). This, in turn, implies a concave consumption function, as shown in Figure 2.

[10] However, to pin down all probabilities in Π matrix we need a following restriction: $\pi_{00z_gz_b} = 1.25\pi_{00z_bz_b}$ and $\pi_{00z_bz_g} = 0.75\pi_{00z_gz_g}$ for transition probabilities $\pi_{\epsilon_t\epsilon_{t+1}z_tz_{t+1}}$ in Π. Calibration of Π follows Krusell and Smith (1998).

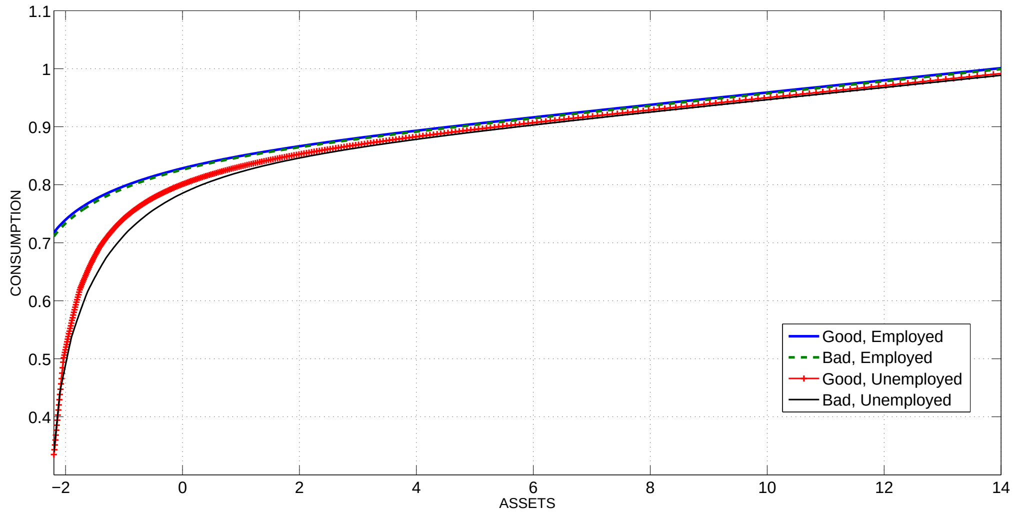


Figure 2: A sample of consumption function.

The consumption function has more curvature at the low level of assets – or it may be said that the high marginal propensity to consume (MPC) applies only for poor people – and when agent gets richer, the consumption function is almost linear. So, at the high levels of wealth the MPC approaches to the MPC implied by the representative agent model. Hence, consumption function can be approximated in linear fashion at the high levels of wealth.[11] However, at the low levels of wealth the consumption function is concave, and when a significant number of consumers hold practically no wealth, this fact questions the validity of linear consumption function as an approximation of the aggregate consumption function. Below, I focus only on the low levels of wealth, since at the high levels of wealth the marginal propensities are the same for employed and unemployed agents, as it is shown by Huggett (1993); Aiyagari (1994); Krusell and Smith (1998) and Figure 2.

The time-varying liquidity constraints matter for agents' decisions to save and consume at the low levels of wealth through two different sources. Firstly, the liquidity constraint directly matters availability of current resources which households can consume. When the aggregate state is good,

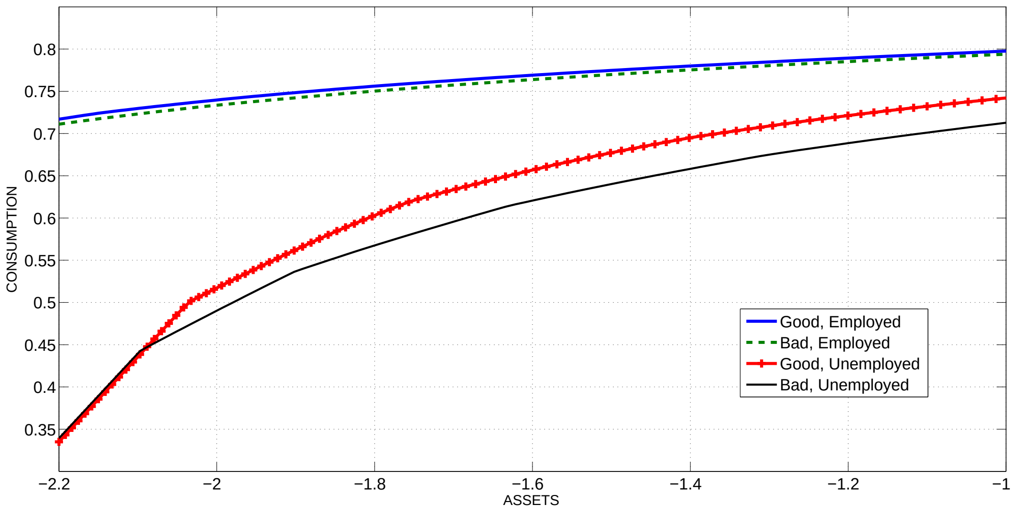
[11]The steady state level of the aggregate capital stock is 11.49 in the representative agent model. Hence, the linear approximation around the steady state value gives a good approximation for the consumption function around that point.

there are more resources – which is a consequence of the availability of extra credit – and that can be consumed. Secondly, expectations about variations in the level of the liquidity constraint matters also for the households' consumption.

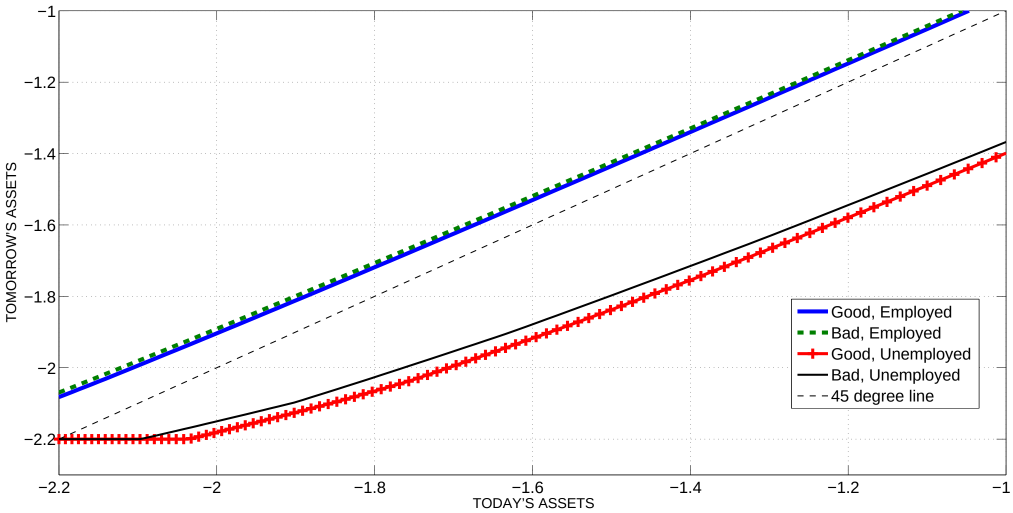
In Figures 3 and 4 there are samples of consumption functions and the decision rules. In Figure 3, the liquidity constraint is constant and, in Figure 4, there is the time-varying liquidity constraint. Decision rules tell the amount of capital which is carried into the next period, a_{t+1}, as a function of today's capital stock , a_t, and (z_t, ϵ_t). If a decision rule is above the 45 degree line, the agent is saving, and a decision rule below that line implies that the agent is consuming more than her current income is. Thus, decision rules tells the evolution of assets. Consumption functions in turn tell the amount of consumption as a function of assets and (z_t, ϵ_t). There the differences in MPCs between the two cases can be observed. Both models imply practically the same aggregate capital stock and wealth distribution, when the differences in the decision rules are not generated by differences in aggregate circumstances.

In Figure 3, the flat part of decision rules implies that the liquidity constraint restrains consumption. This happens only for unemployed agents and then the MPC is 1, but the employed agents' MPCs are much lower. Further, poor agents change their consumption significantly when their employment status changes, but when agents have more assets, i.e. agents have an insurance against income shocks, the changes in employment status generate a smaller change in consumption. Generally, the effects of liquidity constraint for consumption disappears relatively fast when agent accumulates more assets, which can be confirmed from Figure 2.

In Figure 4, it can be seen that the variation of liquidity constraint only matters for the poorest agents in the economy. Then, it determines almost completely the consumption of unemployed agents whose assets are below the level $\underline{a}_b = -2.2$. Thus, changes in the aggregate state – and in the liquidity constraint – also changes the consumption of unemployed agent. Thus, the MPC out of credit is high as document by Gross and Souless (2002). Moreover, the liquidity constraint also restrains consumption of the employed agent in a bad state. For instance, assume that economy is in a good state and an employed agent's assets are at a level -2.4, and then a recession comes, and her credit is cut off, when she has to drop her consumption (see Figure 4). The same applies

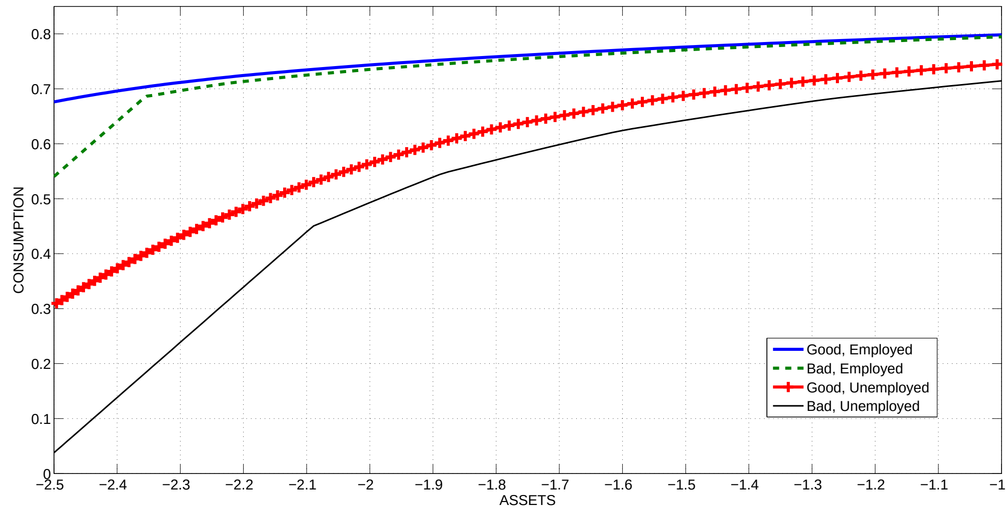


(a) Consumption functions

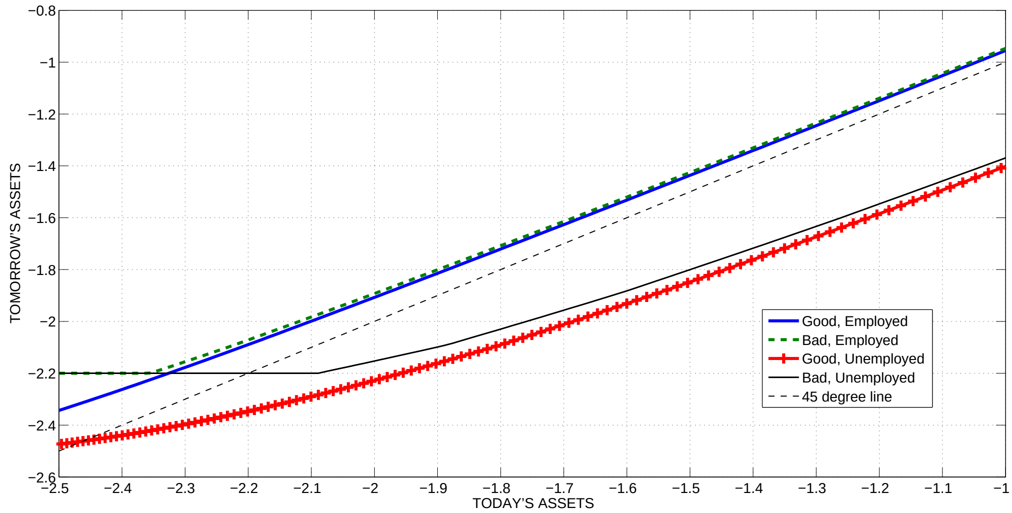


(b) Decision rules

Figure 3: A sample of consumption functions and decision rules in the case of constant liquidity constraint. Picture is the same as in Figure 2, but it only focuses on the low level of assets.



(a) Consumption functions



(b) Decision rules

Figure 4: A sample of consumption functions and decision rules with time-varying liquidity constraint

also to unemployed agent. Hence, the availability of current resources – or credit – matter for the consumption of agents, but in a very limited way, since it only matters for the poorest ones.

If the two cases are compared, several differences can be found. Firstly, there is a higher MPC at the low levels of assets when liquidity constraint is time-varying. The higher liquidity constraint "forces" agents to keep extra balances in the bad aggregate state compared to the good state. Since agents have these extra balances, they can consume more from their increased income, which implies the higher MPC. Thus, these extra balances boost the growth of consumption when agents' income increases. However, when the assets reach the level 1.2 the difference in marginal propensities between the two cases is practically zero.

Secondly, the most important difference is that when the liquidity constraint is constant only the individual state defines agents' consumption (and the evolution of assets). As in Figure 3, where the level of consumption mainly depends on the individual state, i.e. the agents' employment status. But, when the liquidity constraint is time-varying, the aggregate state matters for the level of consumption, since the liquidity constraint varies with the aggregate state. This obviously only holds for agents' who are influenced by the change of the liquidity constraint. However, the supply of credit is correlated perfectly with the movements of aggregate state when the effects of the changes in the aggregate state are amplified by the changes in the supply of credit. So, there are larger "jumps" in consumption function between different aggregate states when the liquidity constraint is time-varying (see, Figures 3 (a) and 4 (a)). Basically, this is the mechanism that makes the aggregate consumption to fluctuate more tightly with the GDP, i.e. this mechanism is "the financial accelerator" for the household sector.

Potentially, credit shock may matter, but it must be noticed that I used here a way too large value of ϕ_0 only to illustrate the effects of liquidity constraint. With smaller values ϕ_0 – which are supported by the data – the effects of the time-varying liquidity constraint gets smaller since the difference between $\underline{a}_g$ and $\underline{a}_b$ is smaller, as implied by equation (9). Decision rules with a more realistic value of ϕ_0 and with endogenously determined labor supply are discussed in Appendix D. However, conclusions are the same as here.

Just by studying consumption functions and decision rules I cannot conclude anything about the quantitative importance of credit shocks for the dynamics of aggregate consumption. There could be a large number of agents with a low level of assets when they matter for the determination of aggregate consumption, or most people could be in the linear part of the consumption function, where the effects of credit shocks do not matter. In any case, it is evident that we need a model with a realistic wealth distribution or we may as well say that aggregation matters in these types of questions.

4 Simulations

4.1 Matching the wealth distribution

Here, I generate a realistic wealth distribution into the model, but it requires some changes. Now I set ϕ_0 at a reasonable level, i.e. $\phi_0 = 0.1$. Thus, the income of unemployed agent is about 13% of employed agent labor income. This parameter is important since it defines the magnitude of credit shock, or the gap between $\underline{a}_g$ and $\underline{a}_b$, as indicated by equation (9). Now the time-variation in the liquidity constraint is about 10% of agents' labor income. This choice is in line with the estimates of time-varying liquidity constraint given by Ludvigson (1999). She estimates that the upper limit for the variation in the amount of credit for "poor" agents is 12.5% and the lower limit is 6.7% of their labor income. I also consider larger variation in the liquidity constraint by setting $\phi_0 = 0.35$. Other parameters are as given in Section 3.3.

For the calibration of the wealth distribution I use the facts provided by Budria, Diaz-Gimménez, Quadrini, and Ríos-Rull (2002).[12] Generating the large group of poor agent is quite straightforward, just increase the magnitude of income of unemployed agent, ϕ_0, which then generates more poor people. Thus, this "social security" removes the agent's need for saving as suggested by Hubbard, Skinner, and Zeldes (1995). However, the generation of realistic right tale of the wealth distribution is problematic and I use the stochastic-β model (see, Krusell and Smith (1998) and Krusell, Mukoyama, Sahin, and Smith (2009)), where the discount factor is stochastic which

[12] They define wealth as the net worth of households where the definition includes the value of financial and real assets of all kinds net of various kinds of debts.

enables the thick right tale for the wealth distribution.[13]

So, I add another aspect of heterogeneity into the model: agents' discount factors are ex ante identical, but they follow a Markov process. One interpretation could be that the discount factor may vary between the generations of the dynasty. More precisely, I assume that β can get three different values and I keep the average value of β at the same level as previously, i.e. 0.9894. The distribution is symmetric around its mean, when the high and low values of β are ± 0.0036 from the average. The transition probabilities are set as follows: 1) in the invariant distribution 80% of the agents has the average value of β and 10% are at the other values of β, 2) there are no transition between the extreme values of β, 3) the average duration of the highest and lowest β's is 50 years, which is roughly the lenght of one generation in the dynasty.

The first set of models considers versions of the model, which was introduced in Section 3. I consider five different versions of it:

- *Complete Markets.* This is a RBC-model where the supply of labor of agents is fixed, but the aggregate labor varies, as described in Section 3. However, there is a perfect insurance against idiosyncratic shocks.
- *Incomplete Markets.* This is the model of Krusell and Smith (1998) where $\phi_0 = 0.1$ and the liquidity constraint is fixed.
- *Credit Shocks.* This is the model introduced in Section 3 with $\phi_0 = 0.1$. Note that the time-varying liquidity constraint – or credit shocks – are now added to *Incomplete Markets* model.
- *Incomplete Markets II.* This is the same model as the *Incomplete Markets* model, but now $\phi_0 = 0.35$.
- *Credit Shocks II.* This is the same model as *Incomplete Markets II*, but now I have added the credit shocks. Note that the larger value of ϕ_0 implies larger credit shocks. Hence, credit

[13] There are also other ways to generate a realistic wealth distribution. Huggett (1996) shows that a life-cycle model generates a quite realistic wealth distribution. Further, one might let the rate of returns differ between agents as shown by Quadrini (2000) and Cagetti and De Nardi (2006) or there could be a drastic dispersion in wages, see Castañeda, Díaz-Giménez, and Ríos-Rull (2003).

shocks in the *Credit Shocks II* -model are larger than in the *Credit Shocks* model.

The second set of models are versions of the stochastic-β -model. I consider the last four cases from the first set of models. Table 1 summaries the aspects on the wealth distribution of models where the simulations were 5000 periods long.

Table 1: The distribution aspects of wealth

Model	Mean K_t	Std. K_t	% of wealth hold by top 1%	20%	60%	Fraction with wealth ≤ 0	Gini coefficient
Benchmark:							
Complete Markets	11.49	0.29					
Incomplete Markets	11.57	0.26	13%	58%	87%	1%	0.53
Credit Shocks	11.57	0.26	13%	58%	87%	1%	0.53
Incomplete Markets II	11.56	0.20	13%	85%	97%	8%	0.80
Credit Shocks II	11.56	0.20	13%	85%	97%	8%	0.80
Stochastic-β:							
Incomplete Markets	12.02	0.26	35%	89%	98%	11%	0.84
Credit Shocks	12.02	0.25	35%	89%	98%	11%	0.84
Incomplete Markets II	12.00	0.22	48%	102%	103%	55%	0.98
Credit Shocks II	12.00	0.22	48%	102%	104%	55%	0.98
Data			35%	82%	99%	10%	0.80

Table 1 shows that wealth is very unequally distributed in the U.S.: the richest percentage hold 35% of all the wealth when the poorest 40% only hold 1% of the wealth, which implies a high Gini-coefficient.[14]

All the benchmark models generate wealth distributions in which the wealth is too equally distributed. As we noted above, it is difficult to generate an adequate number of rich households.

[14]The gini-coeffecient is calculated from the simulated data by using the following formula:

$$\text{Gini-coeffiecient} = \frac{1}{N}\left[N+1-2\left(\frac{\sum_{i=1}^{N} N+1-a_i}{\sum_{i}^{N} a_i}\right)\right],$$

where a_i is in ascending order and N is number of observations.

Increasing the value of income in the unemployed state (see, *Credit Shocks II* and *Incomplete Markets II*) increases the number of poor people as expected. The stochastic-β model (with $\phi_0 = 0.1$) generates a quite realistic wealth distribution, in which we have more rich people, which results from the fact that they have a lower discount factor than the poor people. This is the first choice to study the dynamics of consumption since it generates a realistic wealth distribution, which is essential. The agents' consumption decisions depend crucially on the level of wealth, which makes the aggregation – or the shape of wealth – an important part of the model.[15]

Based on the conclusions made from the shape of decision rules, it is expected that the credit shocks do not have any effect on the distribution of wealth. Credit shocks only matter for poor people, who do not have assets by their definition of being poor. Hence, the wealth distribution is the same with and without the credit shocks. However, credit shocks may matter for the dynamics of aggregate consumption since significant number of households hold practically no wealth, but they are responsible for a large part of aggregate consumption.

4.2 The time series properties of aggregate consumption with and without credit shocks

One way to find out the effects of credit shocks for business cycle dynamics is to contrast a set of aggregate statistics generated by a model where credit shocks do not exist, then add credit shocks to the same model, and generate the same set of aggregate statistics. If credit shocks do matter for business cycle dynamics, should consumption's relative standard deviation to the standard deviation of GDP be higher than in the case without the credit shocks. Moreover, the cross-correlation between consumption and GDP should increase. These both effects comes from the fact that poor households do not matter for capital accumulation or the formation of GDP, but they are responsible for a significant amount of consumption. Hence, consumption should be more volatile when credit shocks do exist. Further, when credit shocks and productivity

[15] In the extreme case (stochastic-β with $\phi_0 = 0.35$), the high income in the unemployed state combined with variation in the discount factor generates a wealth distribution where the wealth is too unequally distributed when compared against the values provided by the data. Half of people have a negative net worth which implies that rich people capital holdings are greater than the productive capital stock K_t. This explains why the richest 60% hold more than 100% of wealth.

shocks are perfectly correlated should cross-correlation between consumption and GDP increase if credit shocks matter for aggregate consumption. Furthermore, I have reported the autocorrelation function of consumption (3 lags) to see does credit shocks matter for it. Table 2 considers the time series properties of consumption and GDP of the same simulated data as used in Table 1. I have used the same shocks in all simulations when the results of models can be compared to each other.

Table 2: Time series properties of aggregate consumption

Model	The relative std. of C_t to the std. of Y_t	Autocorrelation of C_t with			Cross-correlation of C_t with		
		C_{t-1}	C_{t-2}	C_{t-3}	Y_t	Y_{t-1}	Y_{t-2}
Benchmark:							
Complete Markets	37%	0.99	0.97	0.95	0.68	0.69	0.70
Incomplete Markets	38%	0.93	0.90	0.87	0.78	0.72	0.70
Credit Shocks	40%	0.93	0.90	0.87	0.78	0.72	0.70
Incomplete Markets II	47%	0.83	0.75	0.69	0.93	0.75	0.67
Credit Shocks II	47%	0.83	0.75	0.68	0.93	0.75	0.67
Stochastic-β:							
Incomplete Markets	42%	0.89	0.85	0.80	0.84	0.75	0.70
Credit Shocks	42%	0.89	0.85	0.80	0.84	0.74	0.70
Incomplete Markets II	51%	0.80	0.71	0.63	0.94	0.75	0.65
Credit Shocks II	51%	0.80	0.70	0.62	0.95	0.75	0.65

The result in Table 2 is quite unambiguous: credit shocks do not matter for aggregate consumption. The relative standard deviation between consumption and GDP is the same and regardless of the existence of credit shocks. Only expectation is the case between *Incomplete Markets* and *Credit Shocks* models, but even then the difference is small. Moreover, stochastic-β model with $\phi_0 = 0.10$, which generates a realistic wealth distribution, shows that credit shocks does not matter for aggregate consumption. Finally, it should be noticed that even if I let the credit shocks be larger than data implies the previous conclusion holds.

The robustness of the simulations is discussed in Appendix E. I consider two extensions: Firstly, I set $\sigma = 5$ and, secondly, I consider a model where the leisure is valued. The conclusions made in this Section also applies in these extensions. Thus, these results apply even if I allow lower intertemporal elasticity of substitution and if I let the supply of labor be endogenously determined.

Furthermore, Appendix F reports the values of simulations where these models are compared against the data. It can be said that the representative agent model generates a way too low correlation between consumption and GDP. This can be fixed by introducing the incomplete markets, idiosyncratic shocks and $\phi_0 = 0.10$, when the correlation between consumption and GDP is 0.80. Moreover, if the stochastic-β model is used with the same parametrization the correlation is 0.86. In the data the correlation is 0.9. Adding the credit shocks into the models in these simulations does not generate any larger correlation between consumption and GDP. Furthermore, it should be noticed, that if a lot of poor households are generated (stochastic-β models with $\phi_0 = 0.35$), the correlation between consumption and GDP is almost one, but the wealth distribution is unrealistic. However, even then the addition of the credit shocks do not matter for the dynamics of aggregate consumption.

So, the simulations imply that the changes in the supply of credit do not matter for aggregate consumption. Thus, the correlation between credit and consumption in the data derives from the causality, which is running from demand of credit to the supply of credit. In other words, we may say that the shocks in the supply of credit do not matter for aggregate consumption. The effects of time-varying liquidity constraint disappear fast when agents accumulate assets. Hence, the dynamics of aggregate consumption is dominated by the agents who have assets such that the variations of liquidity constraint do not matter for them. However, the presence of liquidity constraint matters for them, but the changes in the liquidity constraint are not significant. That is, there are very few people who are so poor that the liquidity constraint is actually binding for them, and hence, its variations are not significant for the dynamics of the aggregate consumption. Rather, the fluctuations in consumption are generated by fluctuations in employment and by the fluctuations in the risk of being unemployed. That is, the circumstances in the labor market matter more than circumstances in the credit market.

This implies that monetary policy cannot restrain the fluctuations of consumption by affecting the credit supply of banks. So, the financial acceleration mechanism is not important enough in order to matter for the dynamics of aggregate consumption. However, the financial acceleration mechanism may matter for firms, which in turn affects employment, and hence, the supply of credit for firms may matter also for consumption.[16] Further, it must noted that even if credit shocks do not matter for aggregate consumption they could have a significant welfare effects. If consumption of the poorest households in the economy depend on credit – and if their utility function is concave – then the changes in the supply of credit may matter when one discusses in the terms of utility: small changes in consumption creates large changes in terms of utility due to concavity of utility function. Thus, affecting the amount of credit, when it is allocated on households that need it the most, may be welfare increasing monetary policy, even if its aggregate effects are not significant.

The results in this paper do not support the conclusion made in Bacchetta and Gerlach (1997), Ludvigson (1999) and Gross and Souless (2002), since these paper conclude that variations in the credit matter for the dynamics of aggregate consumption. The difference in results could be caused by improper aggregation methods and by problems in causality question in papers sited above (see Section 2 for discussion). However, the result of this paper supports the conclusion made by Ludvigson (1998) where she concludes that variation in the supply of credit may be quantitatively quite small for aggregate economy. Here I showed that fluctuations in credit do not matter at all for the dynamics of consumption.

Finally, Tables 1 and 2 (and Appendix F) clearly show the importance of wealth distribution when the dynamics of aggregate consumption is modeled.[17] Depending on the shape of simulated wealth distribution the correlation between aggregate consumption and GDP varies from 0.6 to almost 1.[18] So, the aggregation do matter. Generally, when the behavior of aggregate consumption is modeled the main question is: How do different types of shocks affect aggregate consumption? Here I have shown that credit shocks matter only for poor people whose contribution for the

[16]Generally, the effects of credit shocks of this type are studied recently by Nolan and Thoenissen (2009) and Jermann and Quadrini (2009) in a general equilibrium framework.

[17]See Carroll (2000) who discusses also the importance of aggregation when the aggregate consumption is modeled.

[18]Note that all these models are based on optimization behavior. Hence, I do not need "ad hoc assumptions" about hand-to-mouth (or non-ricardian) consumers to create a high correlation between GDP and consumption, which are some times used to deliver that correlation.

dynamics of aggregate consumption is insignificant. Hence, one of the main lessons given by this paper is that to model and to understand the dynamics of aggregate consumption we need a model in which the wealth distribution is endogenously determined. This is basically shown in Figure 2.

5 Conclusion

The well known positive correlation between credit and consumption has created a hypothesis according to which the supply of credit matters for the dynamics of consumption. That is, the time variation in the liquidity constraint, which can be seen as fluctuations in the supply of credit, generates a financial accelerator for the households sector which matter for the dynamics of aggregate consumption and amplifies the effects of credit shocks wider into the economy. However, I argued that the literature which has found evidence that supports the hypothesis has ignored two important questions. Firstly, the key question being which way the causality is running in the credit market: Does the supply of credit merely adjust to the changes in demand of credit or vice versa? Secondly, the results which are delivered by a partial equilibrium analysis or are done by using micro data can not directly discuss the relevance of the hypothesis in the determination of aggregate consumption since a proper aggregation is missing. This type of problems can be resolved by a general equilibrium model which was used in this paper.

The decision rules showed that the time-varying liquidity constraints matter for the consumption decision of households. Thus, the empirical and theoretical findings, that the time-varying liquidity constraint matters, are basically correct. However, they do not matter for the dynamics of *aggregate* consumption since the time-variation in the liquidity constraint has effects only for the poorest household in the economy and contribution of these poor households is insignificant for the aggregate economy. Moreover, the time-varying liquidity constraints do not matter for determination of aggregate consumption even if I let shocks be larger than the data implies. These facts imply a conclusion that the causality between credit and consumption, which is detected from the aggregate data, is mainly running from the demand of credit to the supply of credit. Thus, the supply of credit adjusts changes in demand. It seems that the variations on productivity and labor market conditions combined with a fixed liquidity constraint generate most of fluctuations in aggregate consumption. Thus, the existence of liquidity constraint matters, but its possible variations in time do not generate additional variations on the aggregate consumption.

This result also implies that monetary policy cannot directly matter for the dynamics of aggregate consumption by affecting the supply of credit of banks. Hence, it seems unlikely that the monetary transmission mechanism could work by changing the availability of credit for households, which in turn could matter for aggregate consumption. However, it is possible that the credit channel of monetary transmission works through firms, which affects the labor market conditions, and hence, the availability of credit matters for aggregate consumption.

The simulations clearly showed that the key for understanding the dynamics of aggregate consumption is to focus on the economics of wealth distribution. The different wealth distributions – or equally different aggregations – significantly contributes to the time series properties and correlations of consumption and GDP. When marginal propensities to consume depend on the wealth, the realistic wealth distribution is the key to reliable evaluation of how different types of shocks or policies influence on the aggregate consumption.

Finally, it would be interesting to expand the model in a way that households can default their debt as it is done by Chatterjee, Corbae, Nakajima, and Ríos-Rull (2007). Secondly, we should include a portfolio choice into the model, especially from the data we know that some households hold assets and credit at the same time. Understanding this type of behavior could be essential for understanding the effects of credit to aggregate consumption. Thirdly, in this paper I have discussed only the role of unsecured debt, but this type of analysis should also extend for collateralized debt as well.

Appendices

A The data of credit and consumption

A.1 Data description

Data sources: the time-series of consumption and GDP are from SourceOECD National Accounts Statistics: Quarterly National Accounts Vol 2009 release 11 and the time series of credit is from Federal Reserve Board's G19 statistical release. The consumption is measured from the national accounts as private consumption expenditure and the credit is the outstanding consumer credit which covers most short- and intermediate-term credit extended to individuals, excluding loans secured by real estate. When data is deflated, the GDP deflator is used. Data is quarterly data which is seasonally adjusted and the range is from 1955 to 2009q3.

A.2 Additional Figures for Section 2

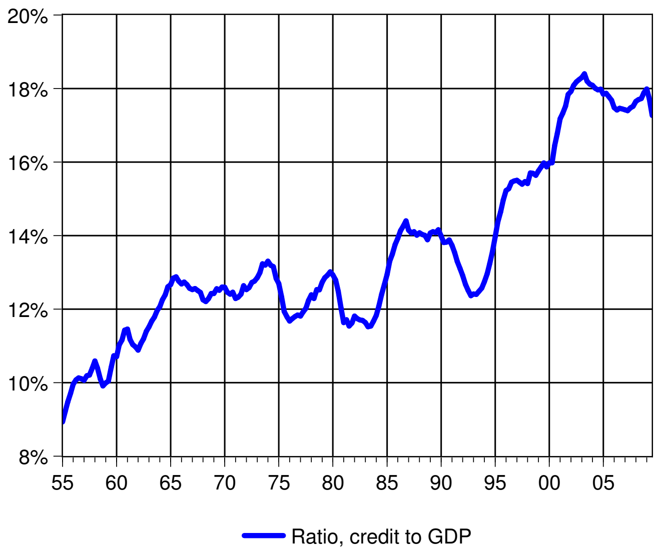
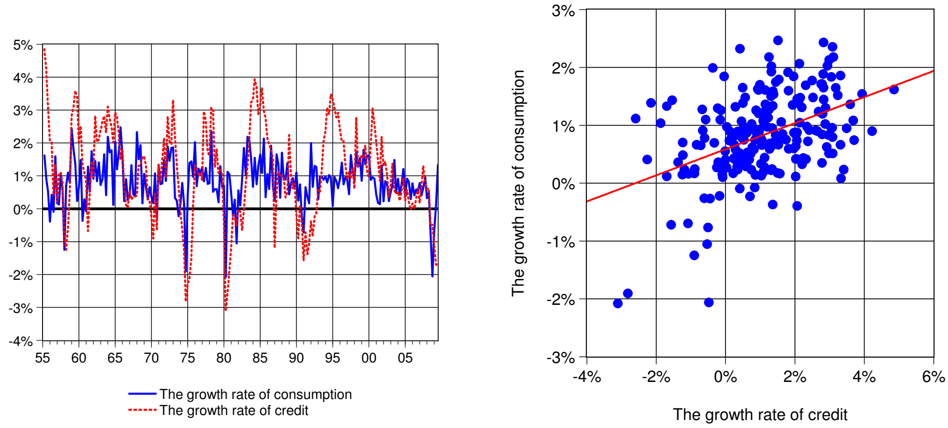


Figure A1: The ratio, credit to GDP.

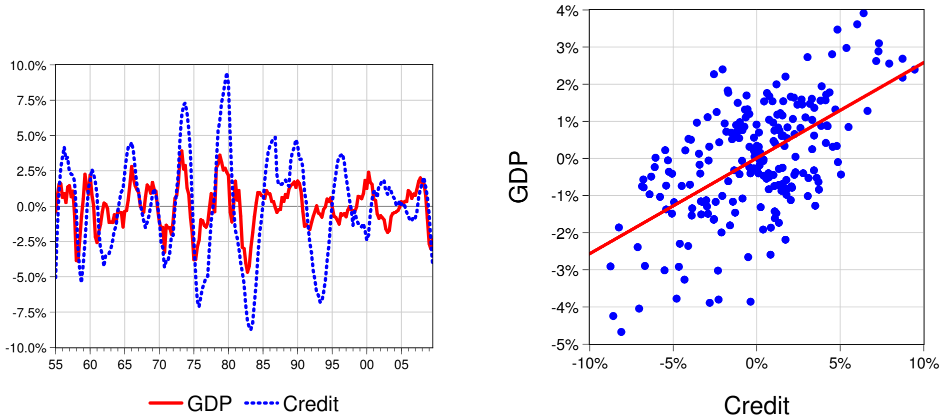


(a) Growth rates

(b) Scatter between growth rates and a regression line.

Figure A2: The growth rate of consumption and credit in the U.S from 1955 to 2009 quarter 3.

Figure A3: The volume of consumption and credit during the current financial crises.



(a) The deviations from the trend.

(b) Scatter between the cycle series and a regression line.

Figure A4: The deviations of GDP and credit from they trend levels in the U.S from 1955 to 2009 quarter 3.

B The details of the solution method

B.1 A recursive competitive equilibrium

To solve the model, it must firstly define in a recursive form. An agent's position at a point of time is described by individual state vector $s_t \in S$, where $s_t = (a_t, \epsilon_t, z_t)$ and $S = A \times \Upsilon$. Further, let $\mathcal{B}$ be the Borel σ-algebra in S and a probability measure μ over $\mathcal{B}$ describe how many types of agents there are in the economy at time t for any interval $B \in \mathcal{B}$, hence $\mu_t(s_t, B)$.

Different agents have different amount of wealth when they have different propensities to save. However, agents must be able to predict tomorrow's factor prices. That is, they must predict K_{t+1} in order to know the relevant prices (factor prices) for decision making. Hence, these prices depend on μ_t and z_t, and therefore, the relevant aggregate state is (μ_t, z_t). Moreover, K_{t+1} depend on stochastic evolution of μ_t. To formulate the problem recursively we need transition function Γ for μ which makes possible to predict K_{t+1}. That is,

$$\mu_{t+1} = \Gamma(\mu_t, z_t, z_{t+1}) \tag{A1}$$

where Γ also depend on z_{t+1} since the fraction of agents which are employed or unemployed tomorrow depend on z_{t+1}.

Now agents' problem given by equations (5)-(8) can be rewritten in a recursive form

$$
\begin{aligned}
V(a,\epsilon,\mu,z) &= \max_{c\in\mathbb{R}^+, a'\in A} \left\{ U(c) + \beta \sum_{\epsilon'\in\Upsilon, z'\in Z} \Pi_{zz'\epsilon\epsilon'} V\left(a',\epsilon',\mu',z'\right) \right\} && \text{(A2)}\\
\text{s.t.} \quad a' + c &= \left[1 + r(K,L,z)\right] a + w(K,L,z)\bar{l}\epsilon + (1-\epsilon)\phi_0 && \text{(A3)}\\
a' &\geq D(z) && \text{(A4)}\\
\mu' &= \Gamma(\mu, z, z') && \text{(A5)}
\end{aligned}
$$

where pricing functions $w(K,L,z)$ and $r(K,L,z)$ are given by equations (2) and (3). Problems of this type have a solution that I denote by the set of decision rules: $c = g^c(a,\epsilon,\mu,z)$ and $a' = g^{a'}(a,\epsilon,\mu,z)$ and the recursive competitive equilibrium can be defined.

Definition A1. ***Recursive competitive equilibrium*** *consist of value function* $V(a,\epsilon,\mu,z)$*, optimal decision rules* $c = g^c(a,\epsilon,\mu,z)$ *and* $a' = g^{a'}(a,\epsilon,\mu,z)$*, pricing functions* $w(K,L,z)$*,* $r(K,L,z)$ *and the law of motion for* μ*:* Γ*, such that following conditions holds:*

1. ***Agents optimize****: given* $w(K,L,z)$ *and* $r(K,L,z)$ *value function* $V(a,\epsilon,\mu,z)$ *solves the problem given by equations (A2)-(A5) and* $c = g^c(a,\epsilon,\mu,z)$ *and* $a' = g^{a'}(a,\epsilon,\mu,z)$ *are the associated decision rules for all* (a,ϵ,μ,z)*.*

2. ***The firm optimizes****: given prices* w *and* r *the representative firm chooses* K *and* L *optimally, as given by equations (2) and (3), for all* (z,μ)*.*

3. ***Consistency condition between aggregate and individual behavior****:*

    - *The law of motion for* μ*,* Γ*, is generated by exogenous probabilities* Π *from the Markov* *chain and policy function* $g^{a'}(a, \epsilon, \mu, z)$ *as follows:*

$$\begin{aligned} \mu'(s', B) &= \Gamma_B(\mu, z, z') = \int_S Q(s, B)\mu(ds, B), \quad \text{where} \\ Q(s, B) &= \sum_{\epsilon' \in B_\epsilon} \Pi_{zz'\epsilon\epsilon'} \mathbf{I}_{g^{a'}(a,\epsilon,\mu,z) \in B_a} \end{aligned}$$

for all $B \in \mathcal{B}$ *and* (μ, z, z'), *with* $\mathbf{I}$ *being an indicator function that takes the value of one if the statement is true and otherwise zero.*

- *The aggregate asset holdings are given by* $A = \int_S a\mu(ds, B)$ *and* $A' = \int_S g^{a'}(a, \epsilon, \mu, z)\mu(ds, B)$,
- *aggregate consumption is given by* $C = \int_S g^c(a, \epsilon, \mu, z) d\mu(ds, B)$, *for all* (z, μ).

4. ***Markets clear***:
   - *the asset market clears:* $K = A$,
   - *the goods market clears:* $C + K' = zF(K, L) + (1 - \delta)K$, *where* $zF(K, L)$ *is given by equation (1) and*
   - *the labor market clears:* $L = \int_S \epsilon \bar{l} d\mu(ds, B)$

for all (z, μ).

B.2 Computational strategy

The problem is that I cannot solve the agents' optimization problem since it depends on μ, which is endogenous state variable, and it is in principle infinite dimensional object. To compute the equilibrium I need some way to present the distribution of assets holdings and I use approximation given by Krusell and Smith (1998).[19]

It is assumed that agents only use partial information from μ when they predict future prices. To be exact I assume that agents just use the first moment, m_1, of μ (i.e. K) in addition to z. One way to interpret this method is to say that agents are boundedly rational since agents do not use all available information. However, it can be shown that the information, which is not

[19] For recent discussion about this approach see Maliar, Maliar, and Valli (2010).

used for forecasting prices, is simply not useful – agents are not boundedly rational at all, but unknown variables (prices) depend only on the first moment of μ.[20] Moreover, I need to specify the law of motion Γ. I assume that Γ have a simple log-linear form and I denote this functions as $K' = \Gamma_K(K, z, z')$. That is, I define $K' = \Gamma_K(K, z, z')$ as follows:

$$\log K_{t+1} = \begin{cases} \gamma_{gg0} + \gamma_{gg1} \log K_t & \text{when} \quad z_t = z_g, z_{t+1} = z_g \\ \gamma_{gb0} + \gamma_{gb1} \log K_t & \text{when} \quad z_t = z_g, z_{t+1} = z_b \\ \gamma_{bg0} + \gamma_{bg1} \log K_t & \text{when} \quad z_t = z_b, z_{t+1} = z_g \\ \gamma_{bb0} + \gamma_{bb1} \log K_t & \text{when} \quad z_t = z_b, z_{t+1} = z_b \end{cases} \tag{A6}$$

Then the agents' recursive maximization problem, i.e. equations (A2)-(A5), can be rewritten with partial information as follows:

$$V(a, \epsilon, K, z) = \max_{c \in \mathbb{R}^+, a' \in A} \left\{ U(c) + \beta \sum_{\epsilon' \in \Upsilon, z' \in Z} \Pi_{zz'\epsilon\epsilon'} V\left(a', \epsilon', K', z'\right) \right\} \tag{A7}$$

$$\text{s.t.} \quad a' + c = [1 + r(K, L, z)]\, a + w(K, L, z)\bar{l}\epsilon + (1 - \epsilon)\phi_0 \tag{A8}$$

$$a' \geq D(z) \tag{A9}$$

$$K' = \Gamma_K(K, z, z') \tag{A10}$$

I use endogenous gridpoint method by Carroll (2006) to solve the problem, where the time varying liquidity constraint is easy to accommodate (see, Section B.3). This maximization problem gives a decision rule $g^{a'}(a, \epsilon, z, K)$, which could be used in simulations. In simulations I obtain time series for K_t which in turn can be used to update the initial guess for Γ_K, and when the parameters of Γ_K are converged, the model is solved.

I used a following setup in the simulations: number of households was 5000 and the number of simulated periods was 5000. I used only observations from 1000-5000 in the OLS-estimations, since the first 1000 observations may be influenced by the initial conditions of simulation.

[20] A short discussion about different interpretations can be found from Young (2010).

B.3 The details of the endogenous gridpoint method

Note that w_t, r_t, w_{t+1} and r_{t+1} are given by K, z and Γ_K, and these values the agent knows when she solves the maximization problem. The Euler equations for agents' problem given by equations (A7)-(A10) are

$$c_t^{-\sigma} \quad \geq \quad \beta E_t \left[(1+r_{t+1})c_{t+1}^{-\sigma}\right] \quad \forall \quad t, K, z, \epsilon. \tag{A11}$$

If I now substitute the budget constraint to the Euler equations for consumption, I get

$$\begin{aligned} &[(1+r_t)a_t + w_t - a_{t+1}]^{-\sigma} \\ &\qquad \geq \beta E_t \left\{(1+r_{t+1}) \left[(1+r_{t+1})a_{t+1} + w_{t+1}\bar{l} - a_{t+2}\right]^{-\sigma}\right\} \quad \text{if} \quad \epsilon_t = 1, \\ &[(1+r_t)a_t + \phi_0 - a_{t+1}]^{\sigma} \\ &\qquad \geq \beta E_t \left\{(1+r_{t+1}) \left[(1+r_{t+1})a_{t+1} + \phi_0 - a_{t+2}\right]^{-\sigma}\right\} \qquad \text{if} \quad \epsilon_t = 0, \end{aligned} \tag{A12}$$

for all t, K, z.

Let me now fix the gridpoint for a_{t+1} and $a_{t+2} = g^{a_t+2}(a_{t+1}, \epsilon_{t+1}, z_{t+1}, K_{t+1})$ is the policy function. Now I can solve a_t as function of the fixed gridpoint and other exogenous variables from (A12). That is,

$$\begin{aligned} a_t &= \frac{\left\{\beta E_t \left\{(1+r_{t+1})\left[(1+r_{t+1})a_{t+1}+w_{t+1}\bar{l}-a_{t+2}\right]^{-\sigma}\right\}\right\}^{-\frac{1}{\sigma}} - w_t\bar{l} + a_{t+1}}{1+r_t} \quad \text{if} \quad \epsilon_t = 1 \\ a_t &= \frac{\left\{\beta E_t \left\{(1+r_{t+1})[(1+r_{t+1})a_{t+1}+\phi_0-a_{t+2}]^{-\sigma}\right\}\right\}^{-\frac{1}{\sigma}} - \phi_0 + a_{t+1}}{1+r_t} \quad \text{if} \quad \epsilon_t = 0, \end{aligned} \tag{A13}$$

for all t, K, z. With a help of Π I can evaluate the conditional expectation. Hence, I have defined the endogenous gridpoints a_t for a_{t+1}.

The last phase is updating the policy function $g^{a_{t+2}}$ by interpolation, when I can notice the effects of the liquidity constraint. Iteration may be stopped when $\max\left\{\left|g_n^{a_{t+2}} - g_{n+1}^{a_{t+2}}\right|\right\} <$ some predetermined error tolerance.

C Endogenous labor supply

The utility function of agents is following when leisure is valued

$$U(c_t, 1-l_t) = \sum_{t=0}^{\infty} \beta^t \frac{\left[c_t^{\phi}(1-l_t)^{1-\phi}\right]^{1-\sigma}}{1-\sigma}, \tag{A14}$$

where $1-\phi$ is the share parameter for leisure in the composite commodity. Each agent is endowed with one unit of time when the amount of leisure is $1-l_t$. Given that $\epsilon_t = 1$, i.e. agent has opportunity to work, they can decide their labor supply. Agents receive income from working ,$\epsilon_t w_t l_t$, if they are employed ($\epsilon_t = 1$).

When the supply of labor is endogenous variable, the aggregate labor supply, L_t, is unknown for each individual since they can only observe their own labor supply decision. Hence, I need a forecasting function Θ for L_t:

$$L_t = \Theta(\mu_t, z_t), \tag{A15}$$

which depends on the distribution of agents μ_t as well as aggregate state. I can not use μ_t when I solve the model, and hence, I use the same partial information approach as previously. Agents' only use the mean of μ to predict the current aggregate labor supply. That is,

$$\begin{aligned} L_t &= \Theta_K(K_t, z_t) \\ \log L_t &= \begin{cases} \theta_{g0} + \theta_{g1}\log K_t & \text{when} \quad z_t = z_g \\ \theta_{b0} + \theta_{b1}\log K_t & \text{when} \quad z_t = z_b. \end{cases} \end{aligned} \tag{A16}$$

With this approximation I can solve agents' problem recursively.

Note that Θ_K does not forecast L_t perfectly – for perfect aggregation I should have μ as an argument for agents problem – which implies that market clearing would never hold exactly. Market clearing would require that L_t is known perfectly. This is only a problem when leisure is valued since agent know K_t, ϵ_t and z_t at the beginning of every period, when today's prices (r_t

and w_t) are known if L_t is known. However, in this case L_t is unknown and approximated by Θ_K, which implies that markets would not clear every period.

There are two options: if deviations from market clearing are not large one could accept those, but a more attractive option is clear market for every t. Hence, I must modify the decision rules such that agents can react when they observe today's prices. With these decision rules I can confirm that markets clear at every point of time in simulations. More precisely, I let value function (or decision rules) explicitly depend on L, $V^n(a, \epsilon, z, K, L)$, but when this value function (or decision rule) is updated, I set $V^{n+1}(a, \epsilon, z, K, L) = V^n(a, \epsilon, z, K; \Gamma_K, \Theta_K)$. Hence, agents view unknown prices as given by Γ_K and Θ_K, but when they observe the unknown prices they change optimally their behavior such that markets clear every period.

I use endogenous gridpoint method by Carroll (2006) here as well to solve the problem,[21] where the time varying liquidity constraint is easy to accommodate (see, Section C.1). This maximization problem gives decision rules $g^{a'}(a, \epsilon, z, K, L)$ and $g^l(a, 1, z, K, L)$, which could be used in simulations. In simulations I obtain time series for $\{K_t\}_{t=0}^{5000}$ and $\{L_t\}_{t=0}^{5000}$ which can be used to update our initial guess for Γ_K and Θ_K. To obtain a series for L I must clear labor market at every period by iterating, i.e. we must find L which solves

$$L = \int_S g^l(a, \epsilon, z, K, L)\mu(ds, B), \tag{A17}$$

which also matters for K' through $g^{a'}(a, \epsilon, z, K, L)$.

C.1 The details of the endogenous gridpoint method for the model with valued leisure

Note that w_t, r_t, w_{t+1} and r_{t+1} are given by K, z, Γ_K and Θ_L, which are given by the agent when she solves the maximization problem. This enables a significant simplification of Euler equations.

[21]The standard RBC-model can be solved by using a generalization of this method by Barillas and Fernández-Villaverde (2007).

The Euler equations for agents' problem with endogenous labor supply are

$$\begin{aligned}
c_t^{\phi(1-\sigma)-1}(1-l_t)^{(1-\phi)(1-\sigma)} &\geq \beta E_t\left[(1+r_{t+1})c_{t+1}^{\phi(1-\sigma)-1}(1-l_{t+1})^{(1-\phi)(1-\sigma)}\right] && \text{(A18)}\\
l_t &= 1-\frac{1-\phi}{\phi}\frac{c_t}{w_t} && \text{(A19)}\\
&\quad \text{if} \quad \epsilon_t = 1, \\
c_t^{\phi(1-\sigma)-1} &\geq \beta E_t\left[(1+r_{t+1})c_{t+1}^{\phi(1-\sigma)-1}(1-l_{t+1})^{(1-\phi)(1-\sigma)}\right] && \text{(A20)}\\
&\quad \text{if} \quad \epsilon_t = 0, \\
&\quad \forall \quad t, K, z, L.
\end{aligned}$$

Moreover, I can substitute (A19) into the budged constraint, which yields

$$\begin{aligned}
c_t &= \phi\left[(1+r_t)a_t + w_t - a_{t+1}\right] \quad \text{if} \quad \epsilon_t = 1,\\
c_t &= (1+r_t)a_t + \phi_0 - a_{t+1} \qquad \text{if} \quad \epsilon_t = 0,
\end{aligned} \tag{A21}$$

for all t, K, z, L

If I now substitute (A19) and (A21) to the Euler equations for consumption, I get

$$\begin{aligned}
&\{\phi\left[(1+r_t)a_t + w_t - a_{t+1}\right]\}^{-\sigma}\left(\tfrac{1-\phi}{\phi w_t}\right)^{(1-\phi)(1-\sigma)}\\
&\qquad \geq \beta E_t\left[(1+r_{t+1})c_{t+1}^{\phi(1-\sigma)-1}(1-l_{t+1})^{(1-\phi)(1-\sigma)}\right] \quad \text{if} \quad \epsilon_t = 1,\\
&\left[(1+r_t)a_t + \phi_0 - a_{t+1}\right]^{\phi(1-\sigma)-1}\\
&\qquad \geq \beta E_t\left[(1+r_{t+1})c_{t+1}^{\phi(1-\sigma)-1}(1-l_{t+1})^{(1-\phi)(1-\sigma)}\right] \quad \text{if} \quad \epsilon_t = 0,
\end{aligned} \tag{A22}$$

for all t, K, z, L. Note that leading (A21) one period forward I can write

$$\begin{aligned}
&c_{t+1}^{\phi(1-\sigma)-1}(1-l_{t+1})^{(1-\phi)(1-\sigma)}\\
&\qquad = \{\phi\left[(1+r_{t+1})a_{t+1} + w_{t+1} - a_{t+2}\right]\}^{-\sigma}\left(\tfrac{1-\phi}{\phi w_{t+1}}\right)^{(1-\phi)(1-\sigma)} \quad \text{if} \quad \epsilon_{t+1} = 1\\
&c_{t+1}^{\phi(1-\sigma)-1}(1-l_{t+1})^{(1-\phi)(1-\sigma)}\\
&\qquad = \left[(1+r_{t+1})a_{t+1} + \phi_0 - a_{t+2}\right]^{\phi(1-\sigma)-1} \quad \text{if} \quad \epsilon_{t+1} = 0,
\end{aligned} \tag{A23}$$

for all t, K, z, L.

Fix the gridpoint for a_{t+1} and $a_{t+2} = g^{a_t+2}(a_{t+1}, \epsilon_{t+1}, z_{t+1}, K_{t+1})$, which is the policy function. When I can solve a_t as function of the fixed gridpoint and other exogenous variables from (A22). That is,

$$
\begin{aligned}
a_t &= \frac{\phi^{-1}\left\{\frac{\beta E_t\left[(1+r_{t+1})c_{t+1}^{\phi(1-\sigma)-1}(1-l_{t+1})^{(1-\phi)(1-\sigma)}\right]}{\left(\frac{1-\phi}{\phi w_t}\right)^{(1-\phi)(1-\sigma)}}\right\}^{-\frac{1}{\sigma}} - w_t + a_{t+1}}{1+r_t} \quad \text{if} \quad \epsilon_t = 1 \\
a_t &= \frac{\left\{\beta E_t\left[(1+r_{t+1})c_{t+1}^{\phi(1-\sigma)-1}(1-l_{t+1})^{(1-\phi)(1-\sigma)}\right]\right\}^{\frac{1}{\phi(1-\sigma)-1}} - \phi_0 + a_{t+1}}{1+r_t} \quad \text{if} \quad \epsilon_t = 0,
\end{aligned}
\tag{A24}
$$

for all t, K, z, L. With a help of (A23) and Π I can evaluate the conditional expectation. Hence, I have defined the endogenous gridpoints a_t for a_{t+1}. The last phase is updating the policy function by interpolation.

D Decision rules for extended models

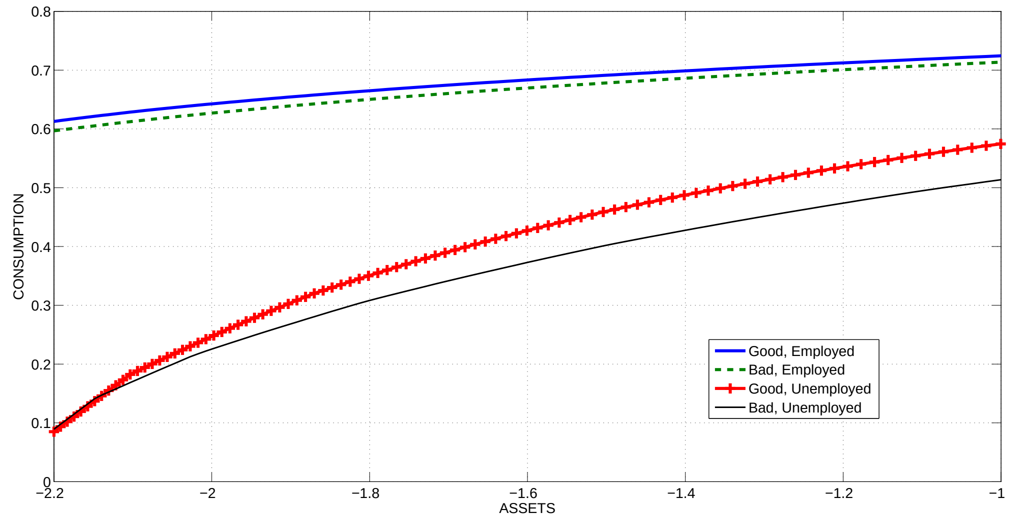
D.1 Decision rule with the smaller value of income in the unemployed state

Here I have set the value of $\phi_0 = 0.1$. Other parameters are the same as in Section 3.3. Figures A5 and A6 show the results, which are almost equivalent to the results in Section 3.3, but the effects of liquidity constraint is harder to see since the variation in the liquidity constraint is smaller.

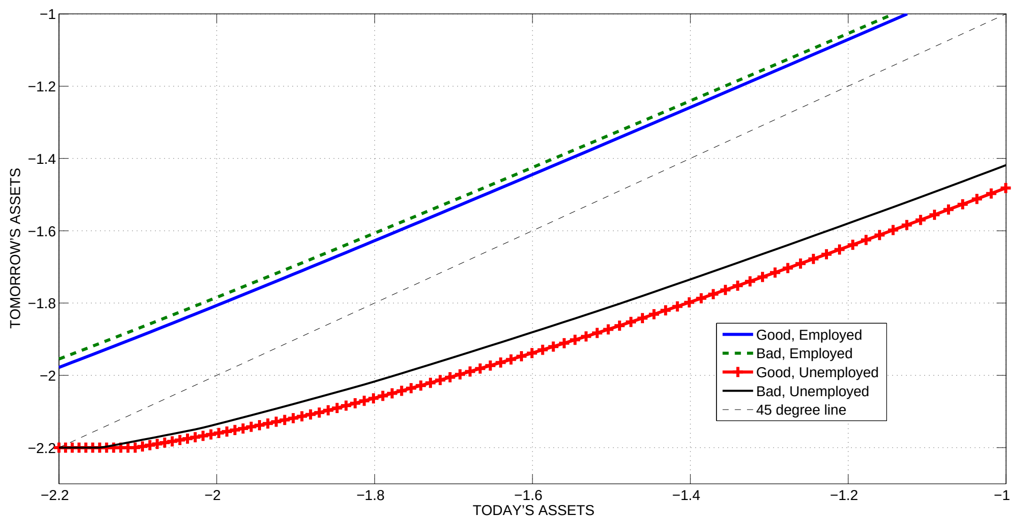
The only difference is that the liquidity constraint is not binding for employed households when the aggregate state is bad. When $\phi_0 = 0.35$ the liquidity constraint was binding (at the very low levels of assets) also for employed households in the bad aggregate state, this effect is now missing. This is caused by the smaller variations between the liquidity constraints. Expect for this departure conclusions given in Section 3.3 also applies here.

D.2 Decision rules and the endogenous labor supply

The parameters are the same as in the Section 3.3 and but $\phi_0 = 0.1$. Figure A7 provides the decision rules when the liquidity constraint is constant and Figure A8 shows the same rules when

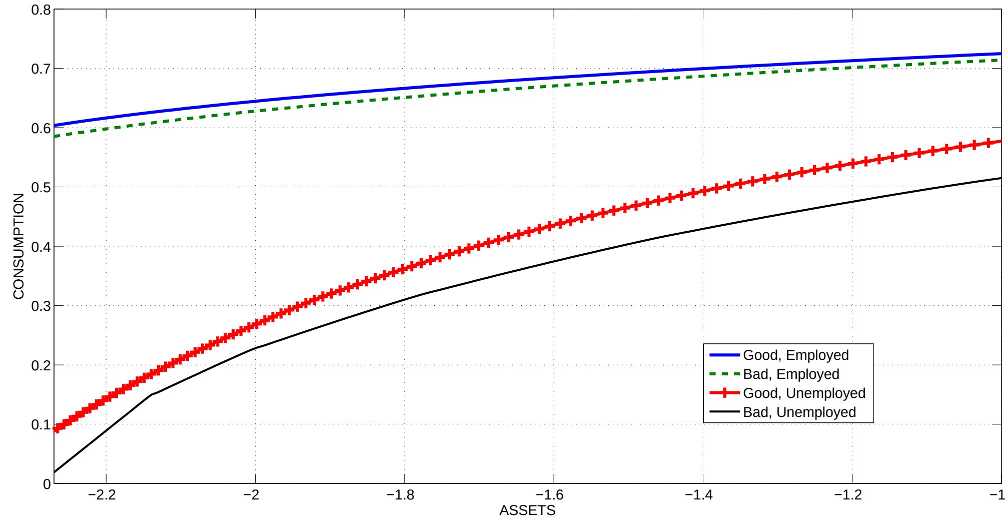


(a) Consumption functions

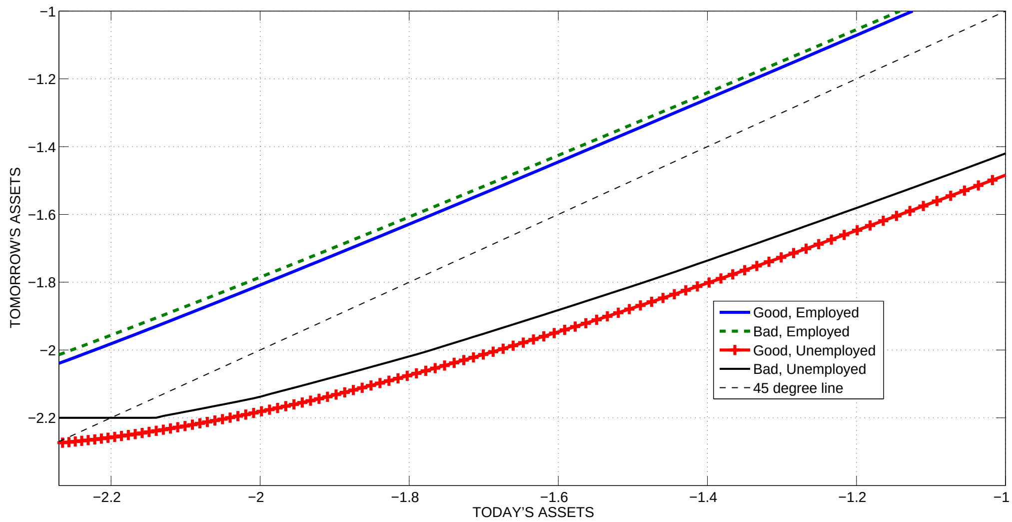


(b) Decision rules

Figure A5: A sample of consumption functions and decision rules in the case of constant liquidity constraint.



(a) Consumption functions



(b) Decision rules

Figure A6: A sample of consumption functions and decision rules with time-varying liquidity constraint there is the time-varying liquidity constraint.

The same conclusion applies here as in the baseline case.

E The robustness of the simulations

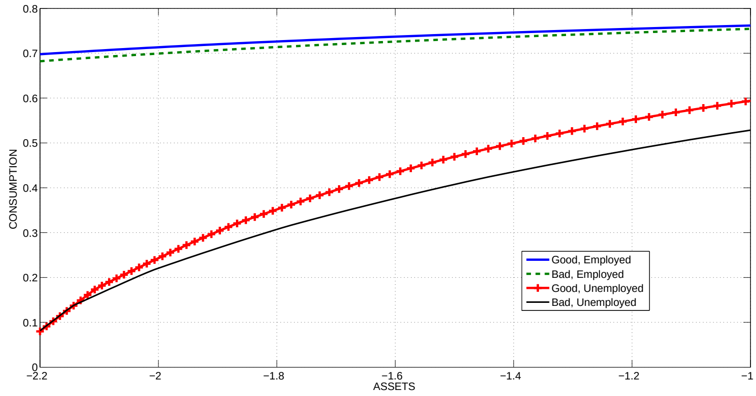
E.1 The results of simulations with the higher intertemporal elasticity of substitution

In the baseline simulations were generated under log-utility, i.e. $\sigma = 1$. Here I increase the value of σ when $\sigma = 5$, which is also a quite commonly used value. Everything else is kept the same as in the simulations of Section 4. Tables A1 and A2 show the results.

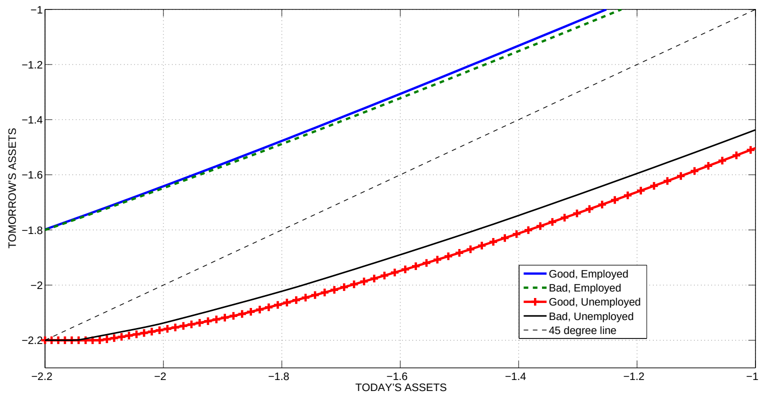
Table A1: The distribution aspects of wealth

Model	Mean K_t	Std. K_t	% of wealth hold by top 1%	20%	60%	Fraction with wealth ≤ 0	Gini coefficient
Benchmark:							
Complete Markets	11.53	0.52					
Incomplete Markets	11.95	0.45	10%	38%	77%	0%	0.29
Credit Shocks	11.95	0.45	10%	38%	77%	0%	0.29
Incomplete Markets II	11.80	0.33	13%	77%	93%	2%	0.71
Credit Shocks II	11.79	0.33	13%	77%	93%	2%	0.72
Stochastic-β:							
Incomplete Markets	12.12	0.44	22%	50%	81%	0%	0.41
Credit Shocks	12.13	0.44	22%	49%	81%	0%	0.42
Incomplete Markets II	12.04	0.33	70%	85%	97%	5%	0.84
Credit Shocks II	12.04	0.33	70%	85%	97%	5%	0.84
Data			35%	82%	99%	10%	0.80

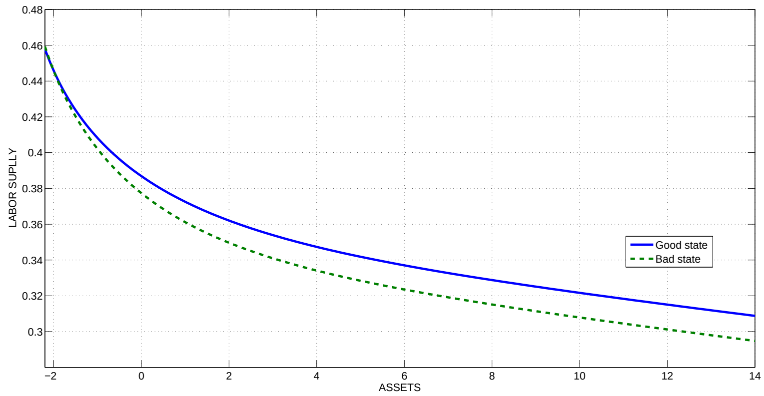
Now agents' utility is lowered more by the fluctuation of consumption than in the case of log-utility. This increases the precautionary saving motive and the aggregate capital stock is higher



(a) Consumption functions

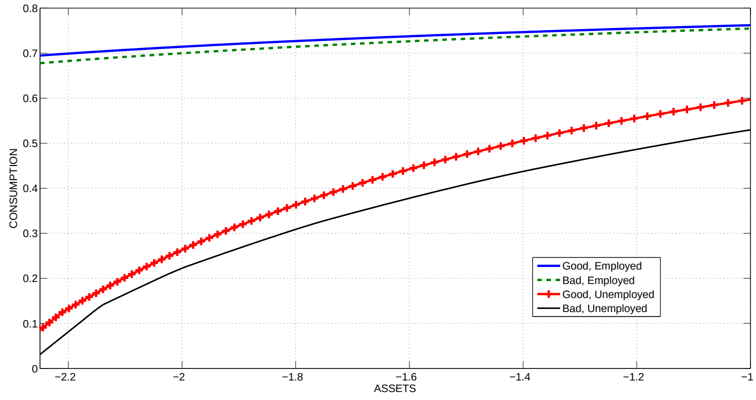


(b) Decision rules

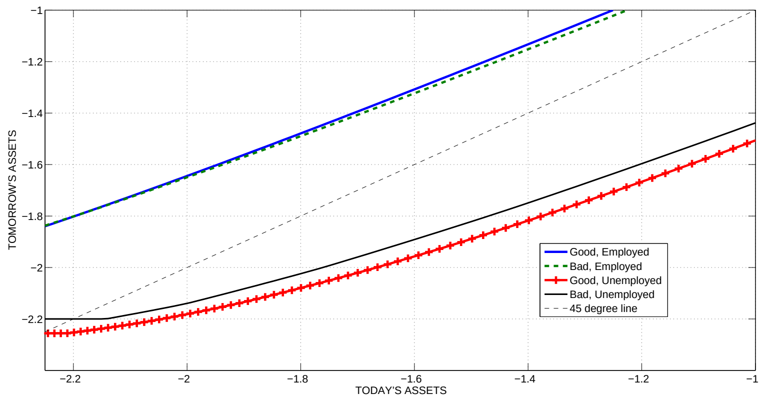


(c) Labor supply functions

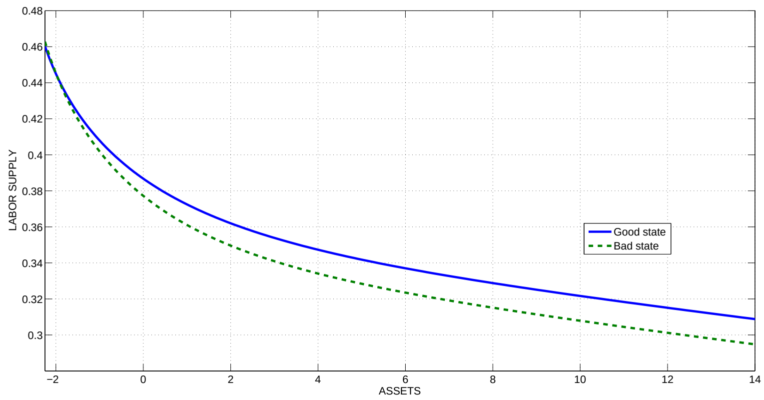
Figure A7: A sample of consumption functions and decision rules in the case of constant liquidity constraint.



(a) Consumption functions



(b) Decision rules



(c) Labor supply functions

Figure A8: A sample of consumption functions and decision rules with time-varying liquidity constraint

Table A2: Time series properties of aggregate consumption

Model	The relative std. of C_t to the std. of Y_t	Autocorrelation of C_t with C_{t-1}	C_{t-2}	C_{t-3}	Cross-correlation of C_t with Y_t	Y_{t-1}	Y_{t-2}
Benchmark:							
Complete Markets	31%	0.99	0.52	0.32	0.74	0.72	0.72
Incomplete Markets	35%	0.86	0.83	0.81	0.81	0.72	0.69
Credit Shocks	35%	0.86	0.83	0.81	0.81	0.72	0.69
Incomplete Markets II	44%	0.78	0.69	0.62	0.96	0.75	0.65
Credit Shocks II	44%	0.78	0.69	0.62	0.96	0.75	0.65
Stochastic-β:							
Incomplete Markets	35%	0.84	0.82	0.79	0.81	0.72	0.68
Credit Shocks	35%	0.84	0.82	0.79	0.81	0.72	0.68
Incomplete Markets II	45%	0.74	0.66	0.59	0.94	0.73	0.63
Credit Shocks II	45%	0.74	0.66	0.59	0.94	0.73	0.63

than in the baseline case with log-utility. However, credit shocks do not matter in this case either since models with credit shocks deliver the same key statistics as model without credit shocks. Hence, the conclusion made in Section 4 holds here as well.

E.2 The results of simulations when the leisure is valued

Now I let leisure be valued. Let $\sigma = 1$ and $\phi_0 = 0.1$ and the rest of parameters are the same as in Section 4. Tables A3 and A4 show the results.

The approximate aggregation does not hold as well here as it did in the baseline model where the leisure was not valued. R^2-statistics were 0.98 and 0.97 for the forecasting function of aggregate labor supply, i.e. for equations (A16). The behavior of aggregate labor supply is almost similar in complete markets model (standard RBC-model) and in the incomplete markets model. However, the capital holdings are reduced significantly in the incomplete markets model. The poor people supply more labor when their assets are at the low level, which implies that they have quite a good insurance against fluctuations in income. If we set $\phi_0 = 0$, the mean K_t is almost the same

Table A3: The distribution aspects of wealth

Model	Mean K_t	Std. K_t	% of wealth hold by top 1%	20%	60%	Fraction with wealth ≤ 0	Gini coefficient
Complete Markets	11.48	0.13					
Incomplete Markets	11.15	0.25	7%	44%	80%	0%	0.36
Credit Shocks	11.15	0.25	7%	44%	80%	0%	0.36
Data			35%	82%	99%	10%	0.80

Table A4: Time series properties of aggregate consumption

Model	The relative std. of C_t to the std. of Y_t	Autocorrelation of C_t with C_{t-1}	C_{t-2}	C_{t-3}	Cross-correlation of C_t with Y_t	Y_{t-1}	Y_{t-2}
Complete Markets	31%	0.98	0.96	0.93	0.63	0.64	0.65
Incomplete Markets	32%	0.94	0.92	0.90	0.63	0.63	0.64
Credit Shocks	32%	0.94	0.92	0.90	0.63	0.63	0.64

as in the case of complete markets. Thus, the importance of ϕ_0 is emphasized when the leisure is valued, but credit shocks do not matter in this case since models with credit shocks deliver the same key statistics as model without credit shocks. Hence, conclusion made in Section 4 holds here as well.

F Comparison between the data and models

In these comparisons each model is simulated 1000 times with each simulation being 200 periods long to match the number of observations underlying the statistics reported from data. The data and simulated data were in logarithms and filtered by Hodrick-Prescott filter to give us the representation of the business cycles. Table A5 shows the results from models given in Section 4. Table A6 gives result generated by models described by Section E.1 and Table A7 considers the valued leisure case, i.e. it considers models presented in Section E.2.

Table A5: Time series properties of aggregate consumption: Comparison against the data with the baseline calibration

Model	The relative std. of C_t to the std. of Y_t	Autocorrelation of C_t with			Cross-correlation of C_t with		
		C_{t-1}	C_{t-2}	C_{t-3}	Y_t	Y_{t-1}	Y_{t-2}
Benchmark:							
Complete Markets	20%	0.83	0.64	0.44	0.66	0.66	0.60
Incomplete Markets	26%	0.66	0.41	0.22	0.80	0.64	0.48
Credit Shocks	28%	0.65	0.40	0.21	0.80	0.63	0.48
Incomplete Markets II	48%	0.61	0.33	0.13	0.97	0.63	0.38
Credit Shocks II	48%	0.61	0.33	0.13	0.97	0.63	0.38
Stochastic-β:							
Incomplete Markets	34%	0.66	0.40	0.21	0.86	0.66	0.48
Credit Shocks	34%	0.66	0.40	0.21	0.86	0.66	0.48
Incomplete Markets II	54%	0.62	0.34	0.13	0.98	0.64	0.39
Credit Shocks II	54%	0.62	0.34	0.13	0.98	0.64	0.38
Data	77%	0.84	0.65	0.42	0.89	0.76	0.56

Table A6: Time series properties of aggregate consumption: Comparison against the data with the higher intertemporal elasticity of substitution

Model	The relative std. of C_t to the std. of Y_t	Autocorrelation of C_t with C_{t-1}	C_{t-2}	C_{t-3}	Cross-correlation of C_t with Y_t	Y_{t-1}	Y_{t-2}
Benchmark:							
Complete Markets	12%	0.75	0.52	0.32	0.80	0.67	0.54
Incomplete Markets	22%	0.57	0.29	0.11	0.85	0.58	0.38
Credit Shocks	22%	0.57	0.29	0.11	0.85	0.58	0.38
Incomplete Markets II	47%	0.59	0.29	0.09	0.99	0.60	0.32
Credit Shocks II	48%	0.58	0.29	0.09	0.99	0.60	0.32
Stochastic-β:							
Incomplete Markets	23%	0.57	0.29	0.10	0.86	0.58	0.37
Credit Shocks	23%	0.57	0.29	0.10	0.86	0.58	0.37
Incomplete Markets II	48%	0.58	0.29	0.09	0.99	0.60	0.32
Credit Shocks II	48%	0.58	0.29	0.09	0.99	0.60	0.32
Data	77%	0.84	0.65	0.42	0.89	0.76	0.56

In all models the standard RBC-model generates way too low cross-correlation between consumption and GDP. However, the RBC-model can generate quite realistic autocorrelation function for consumption. Incomplete markets model do not generate enough autocorrelation for consumption, but cross-correlation with GDP is quite close the one observed from the data. Generally, in all the models consumption is too smooth, i.e. the relative standard deviation of consumption to the standard deviation of GDP is too small, when it is compared against the values implied by data.

Table A7: Time series properties of aggregate consumption: Comparison against the data when the leisure is valued

Model	The relative std. of C_t to the std. of Y_t	Autocorrelation of C_t with			Cross-correlation of C_t with		
		C_{t-1}	C_{t-2}	C_{t-3}	Y_t	Y_{t-1}	Y_{t-2}
Complete Markets	20%	0.84	0.65	0.45	0.63	0.65	0.61
Incomplete Markets	35%	0.97	0.93	0.89	0.62	0.66	0.67
Credit Shocks	35%	0.97	0.93	0.89	0.62	0.66	0.67
Data	77%	0.84	0.65	0.42	0.89	0.76	0.56

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