Consumption insurance and credit shocks*

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Preliminary - Comments welcome

Abstract

This paper investigates how permanent and transitory credit shocks affect households' consumption smoothing patterns. Using a heterogeneous-agent incomplete-markets model I simulate two different shock specifications as observed in credit panel data; one transitory and one permanent credit shock. I show that consumption insurance drops sharply on impact for both kind of shocks. The permanent shock induces a lower level of consumption insurance in the long run. Moreover, I show that these effects differ by current wealth holdings, with households at the lower end of the wealth distribution experiencing the largest drop. Consumption insurance measures in the data, computed with the new PSID consumption series, suggest that the credit shock induced by the grand financial crisis was transitory in nature. Consumption insurance reaches its trough in 2010, but bounces back to its pre-crisis value by 2016.

Keywords: consumption insurance, credit shocks, incomplete markets

JEL codes: D12, D31, D52, E21, E44

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1 Introduction

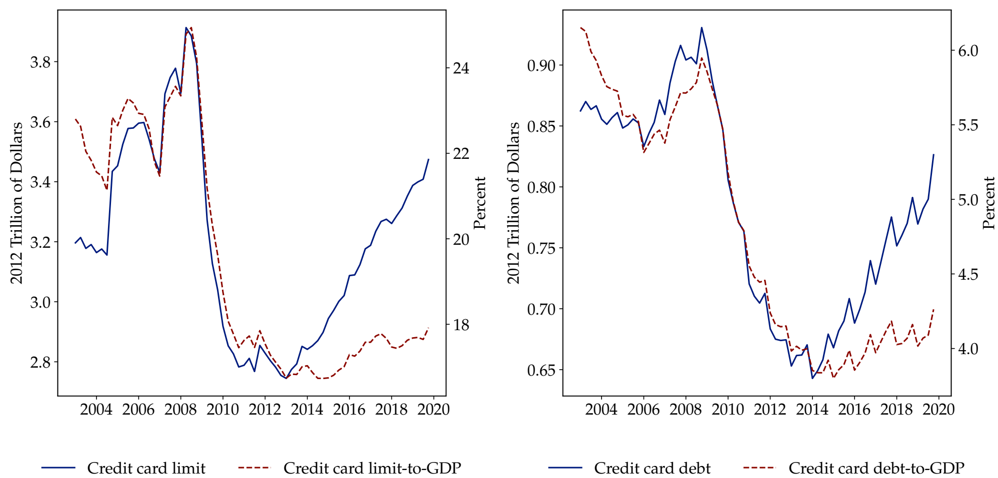
Unsecured borrowing in the form of credit card debt to annual GDP in the United States decreased by around 33% from 6% to 4% during the great financial crisis (GFC) and is still - years later - at this lower level. Aggregate credit card debt, on the other hand, decreased by about 30% during the GFC, but made up almost three quarters of the drop by 2020 (see right panel in Figure 1). Moreover, note that the availability of credit - determined by the credit limit in terms of its absolute values and relative to GDP - shows similar dynamics (see left panel in Figure 1).

In standard incomplete market models, saving and borrowing is one of the main mechanisms for self-insurance (or partial insurance) for agents, that is, to partially smooth consumption fluctuations in the presence of idiosyncratic shocks. In particular, the ability to take up credit - modelled by the credit limit - is an important determinant for the total degree of risk-sharing in an economy (Kaplan and Violante, 2010).

This paper takes the stylized facts from Figure 1 and answers the following question through the lens of a heterogeneous-agent incomplete-markets model: How do permanent and transitory credit shocks affect households' consumption smoothing patterns? In particular, I am interested in the effect of different credit limit dynamics on the amount of consumption insurance present in the economy. To do this, I simulate two economies experiencing a credit crisis - that is, an economy switching from a regime of easy credit to one of tight credit - that differ, however, in the way the credit limit evolves after this aggregate shock.

In general, a credit shock, e.g. a tightened borrowing limit induced by a financial crisis, reduces the availability of credit or loans for households. Credit access allows households to smooth consumption across periods and to absorb adverse transitory shocks to their labor productivity (Deaton, 1991). Tightening this limit brings constrained households further away from their optimal level of intertemporal substitution of consumption and,

Figure 1: Credit card limits and balances in the GFC



Note. The left panel of this figure shows the aggregate credit card limit and the credit limit-to-GDP ratio in the United States. The right panel shows the aggregate credit card debt and the credit card debt-to-GDP ratio in the United States. Credit card data is obtained from the credit card panel of the New York Fed.

additionally, constrains other households that were close to the limit before. This discussion connotes that changing access to credit has important implications for the ability of households to smooth their consumption (Kaplan and Violante, 2010).

Indeed, in my numerical exercise I show that a credit shock - irrespective of its dynamics - reduces the overall level of consumption insurance in the economy. To obtain my quantitative results I simulate two credit shocks that resemble the empirical evidence as in Figure 1. First, the transitory credit shock is modelled to match the drop and mean-reversion of credit debt as observed in the data. Second, the permanent credit shock is modelled to match the drop in credit limit-to-GDP ratio. The drop on impact is about 1% in both specifications. The main difference between the transitory and permanent credit shock lies in their long-run level of risk sharing. Naturally, while the former economy reverts back to is initial level of consumption insurance, the latter economy converges to a steady-state level 0.2% below its initial value.

For my theoretical exercise, I consider an incomplete markets environment with heterogeneous agents. Risk-averse households produce consumption goods, are heterogeneous in terms of their labor productivity and seek insurance against idiosyncratic shocks to this their productivity level. They can trade one period risk-free bonds up to an exogenous (ad-hoc) borrowing limit and pay lump-sum taxes to a government that supplies the risk-free bonds. The credit shock is then modelled by gradually reducing the borrowing limit. The decisive element in this exercise is that I distinguish between a transitory and permanent credit shock. That is, one that reverts back to its initial level and one where the credit limit permanently stays at a lower level. Due to the absence of closed-form solutions in this particular class of models, solutions are obtained using numerical simulations with empirical-based parameterization.

For both shocks, the real interest rate drops and turns negative for two reasons. Households deleverage to move away from the tightened borrowing limit and second, a precautionary savings motive leads to increased savings of households in the permanent specification. (Guerrieri and Lorenzoni, 2017).

These effects have direct implications for consumption smoothing patterns and give rise to heterogeneous responses along the wealth distribution. For households in the 10th wealth percentile the consumption insurance coefficient drops by 40% on impact, for these households are closer to the credit limit and hence, the deleveraging impact is stronger. On the other hand, the insurance coefficient for households in the top 10% increases by 5%, because they decumulate bond holdings which generates additional resources as a buffer. Furthermore, the precautionary savings motive induces unconstrained agents to increase their net asset holdings in the long run. This effect is also stronger for wealth-poor agents, thus their consumption insurance coefficient in the permanent specification decreases.

Moreover, I show that an increase in labor supply is not sufficient to alleviate consumption risk for households in the lower percentiles. Subsequent the credit shock, these households work more hours and thus generate more resources. These resources, however, are used for deleveraging purposes - hence asset accumulation - and to a lesser extent for smoothing consumption fluctuations.

Last, to have an empirical counterpart, I study the empirical degree of consumption insurance making use of the new consumption measure in the Panel Study of Income Dynamics (PSID). I assess the quality of the new PSID consumption series by comparing inequality measures to counterparts from the Consumer Expenditure Survey (CEX). Having confirmed the comparability between the two data sets, I construct consumption insurance coefficients as in Blundell, Pistaferri and Preston (2008) and investigate how they vary over time during the GFC.

The empirical insurance coefficient suggests that the credit shock after the GFC was of transitory nature. Consumption insurance drops by 3% between 2006 and 2010, yet reverts to its 2006 value by 2016. So far, however, the empirical insurance coefficient is very sensitive regarding the DGP when residualizing consumption and income. Further tests have to establish the robustness of the current estimates.

Related literature My paper relates to several works in the literature regarding credit shocks[1] and consumption insurance. My paper brings these two areas together by explicitly modelling different credit limit dynamics.

The theoretical and numerical part of my paper is most closely related to the work of Guerrieri and Lorenzoni (2017) and Kaplan and Violante (2010). Guerrieri and Lorenzoni (2017) study the effects of a credit crunch on aggregate spending and output. For their analysis, they use a heterogeneous-agent incomplete-markets model in which agents are subject to idiosyncratic shocks going back to Bewley (1977), Huggett (1993), and Aiyagari (1994). They document that the credit crunch induces a deleveraging process which depresses interest rates and generates an output drop; moreover, the precautionary savings motive amplifies this mechanism. I adapt their baseline model but focus on the effects on the degree of risk sharing in the economy. Thereby, my main contribution is the explicit distinction between different credit limit dynamics; that is, between a transitory and

[1] Other exemplary papers than the ones mentioned in the main text studying credit shocks are Cúrdia and Woodford (2010); Eggertsson and Krugman (2012); Jones, Midrigan and Philippon (2020)

a permanent credit shock.[2]

In a quantitative study Kaplan and Violante (2010) assess how much insurance agents can obtain with self-insurance in a standard incomplete markets (SIM) life-cycle model and compare it with empirical estimates by Blundell et al. (2008). They conclude that consumption insurance implied by canonical consumption-savings models is too little compared to the data; a conclusion that shared by other papers in the literature (Krueger and Perri, 2006; Broer, 2013).[3] I follow their approach and simulate an artificial panel in the model to construct consumption insurance coefficients as in Blundell et al. (2008). To acknowledge the quantitative shortcomings of the SIM model, however, I focus on the qualitative properties of risk-sharing during the GFC.

Last, I contribute to the empirical literature assessing the evolution of consumption insurance in the data. That is, I compute insurance coefficients from the data in a similar fashion as in the model using the new consumption measure from the PSID. Averages of various categories from new consumption series have been attested to be comparable to the CEX (Li, Schoeni, Danziger and Kerwin Kofi, 2010; Andreski, Li, Samancioglu and Schoeni, 2014). By using this data series, and focussing on the period around the GFC, I avoid estimating (food) demand systems and imputing consumption data across PSID and CEX (Blundell et al., 2008) or within PSID (Attanasio and Pistaferri, 2014). Moreover, I focus on the period during the GFC which has to the best of my knowledge not yet been analyzed.

The rest of the paper proceeds as follows. Section 2 outlines the model and defines the equilibrium in transition. Section 3 presents data, calibration targets and parameterizations. Section 4 contains a comparison of the two steady states and an analysis of the transitional dynamics under different regimes and specifications. Section 5 concludes.

[2] López-Salido, Stein and Zakrajšek (2017) and Nakajima and Rıos-Rull (2019) also document and model mean reversion in credit conditions.

[3] Other studies have since modelled additional channels of insurance to overcome the gap between model and data, such as, advance information (Stoltenberg and Singh, 2020), family labor supply (Blundell, Pistaferri and Saporta-Eksten, 2016), moving back to ones parents (Kaplan, 2012), or social insurance programs (Hubbard, Skinner and Zeldes, 1995), among others.

2 Model

The model mainly follows Guerrieri and Lorenzoni (2017). The main contribution of this paper will be the specification of the evolution of the borrowing limit during transition and the subsequent simulation exercise to determine the extent of insurance during transition.

Households Time is discrete. The economy is populated by a continuum of infinitely-lived households of measure unity. Households receive a utility flow U from consuming $c_{it} > 0$ and leisure, l_{it}. The time endowment of households, which can be allocated between leisure and labor, n_{it}, is normalized to 1. I assume that the utility function $U(c_{it}, n_{it})$ is separable and isoelastic in consumption and leisure; $U : \mathbb{R}_+ \times \mathbb{R}_{[0,1]} \to \mathbb{R}$ is strictly increasing in consumption, strictly decreasing in labor, strictly concave and satisfies the Inada conditions. The future is discounted at rate β:

$$\mathbb{E}\left[\sum_{t=0}^{\infty} \beta^t U(c_{it}, n_{it})\right], \tag{1}$$

where the expectation is taken over realizations of idiosyncratic labor productivity shocks. For now, there is no aggregate risk.

Each household i produces the consumption good with the linear technology

$$y_{it} = \theta_{it} n_{it} \tag{2}$$

by choosing labor supply n_{it}. θ_{it} is an idiosyncratic shock to the labor productivity which follows a first-order Markov chain over a finite state space, $\{\theta^1, \ldots, \theta^M\}$.

The only asset traded in this economy is a one-period risk-free bond, b. Hence, household utility maximization is restricted by the following budget constraint:

$$\frac{1}{1+r_t} b_{it+1} + c_{it} \leq b_{it} + y_{it} - \tilde{\tau}_{it},$$

where b_{it} denote bond holdings, r_t is the interest rate, and $\tilde{\tau}_{it}$ is the tax burden net of transfers of household i at time t.

The lowest productivity state, θ^1, is set to zero and interpreted as unemployment. Unemployed households receive a government transfer, or unemployment benefit, ν_t, but all households pay a lump-sum tax τ_t. That is,

$$\tilde{\tau}_{it} = \begin{cases} \tau_{it} & \text{if } \theta_{it} > 0 \\ -v_{it} & \text{if } \theta_{it} = 0. \end{cases}$$

Including unemployment benefits is a stylized way of generating wealth-poor agents in the model. The receipt of government transfers at a productivity level of zero disincentivizes agents to save, as it provides partial insurance to a potential income loss (see, for instance, Krusell and Smith, Jr., 1998). In this sense, unemployment benefits weaken the precautionary motive of saving.

Borrowing is allowed up to an exogenous limit, possibly depending on the productivity state of the household.

$$b_{it+1} \geq -\phi, \tag{3}$$

with $\phi > 0$. I will study the effects of an unexpected one-time shock that reduces this limit.

Recursive formulation of the household program The following formulation as well as the definition of equilibrium below refer to the program during transition since this constitutes the main exercise of the present paper. The equivalent descriptions in a stationary environment are relegated to Appendix C.

A household is characterized by the by the pair $(b_{it} = b, \theta_{it} = \theta)$ — the individual state. Given a sequence of interest rates $\{r_t\}_{t=0}^{\infty}$, a sequence of government policies $\{\tilde{\tau}_t\}_{t=0}^{\infty}$, and a sequence of borrowing limits $\{\phi_t\}_{t=0}^{\infty}$, each household chooses $C_t(b, \theta)$ and $N_t(b, \theta)$ to solve

$$
\begin{aligned}
V_t(b, \theta) = \max & \left[U(c_t(b, \theta), n_t(b, \theta)) + \beta \sum_{\theta_{t+1} \in \Theta} V_{t+1}(b_{t+1}(b, \theta), \theta_{t+1}) \Gamma_{\theta, \theta_{t+1}} \right] \\
& \text{subject to} \\
& \frac{1}{1 + r_t} b_{t+1}(b, \theta) + c_t(b, \theta) \leq b + y_t - \tilde{\tau}_t \\
& b_{t+1} \geq -\phi_t, \quad n_t(b, \theta) \geq 0 \\
& y_t = \theta n_t(b, \theta)
\end{aligned}
\tag{4}
$$

The policy functions $c_t(b, \theta)$ and $n_t(b, \theta)$ are sufficient to determine the transition of bond holdings, as future bond holdings, $b_{t+1}(b, \theta)$, can be derived from the budget constraint.

Denote by Φ_t the distribution of agents over states at time t. This distribution is the *aggregate* state variable. Note that during the transition period, the value function and policies are also a function of time, since the interest rate, the tax schedule and the borrowing limit are time varying: $(r_t, \tilde{\tau}_t, \phi_t)$. Furthermore, the dynamics induced by the credit shock are deterministic, that is, the entire transition path of the borrowing limit is known. As a result, given an initial distribution Φ_0, it is known how $(r_t, \tilde{\tau}_t)$, and Φ_t evolve over time. Therefore, in Equation (4) it is not necessary to make prices and policy functions dependent on the distribution; the time subscript is sufficient.

Government The government budget constraint is

$$B_t + u v_t = \frac{1}{1 + r_t} B_{t+1} + (1 - u) \tau_t,$$

where B_t denotes the aggregate supply of government bonds and u is the fraction of unemployed agents, that is, $Pr(\theta_{it} = 0) = u$. It is assumed, that the government chooses the tax schedule, τ_t, to keep a balanced budget, while keeping bond supply and transfers constant at B and ν.

2.1 Equilibrium

Before defining the equilibrium, it is necessary to define an appropriate measurable space on which the distribution of agents Φ_t is defined. Let $A \equiv [\underline{b}, \overline{b}]$ be the set of possible values for b_{it} with some lower bound $\underline{b}$ and some upper bound $\overline{b}$; it holds that $\underline{b} < -\phi_t \; \forall t$. Define the state space $S \equiv A \times \Theta$ and let the σ-algebra Σ_s be defined as $B_A \otimes P(\Theta)$, where B_A is the Borel σ-algebra on A and $P(\Theta)$ is the power set of Θ. Finally, let $\mathcal{S} = (\mathcal{A} \times \Theta)$ denote a typical subset of Σ_s.

The equilibrium in transition is summarized in the following definition.

Definition 1 *Given an initial distribution Φ_0, and a sequence of borrowing limits $\{\phi_t\}_{t=0}^{\infty}$, a recursive competitive equilibrium is a sequence of value functions $\{V_t\}_{t=0}^{\infty}$, policy functions for households $\{c_t(b,\theta), n_t(b,\theta)\}_{t=0}^{\infty}$, future bond holdings $\{b_{t+1}(b,\theta)\}_{t=0}^{\infty}$, interest rates $\{r_t\}_{t=0}^{\infty}$, government policies $\{\tilde{\tau}_t\}_{t=0}^{\infty}$, and distributions $\{\Phi_t\}_{t=0}^{\infty}$, such that, for all t:*

i) Given r_t and $\tilde{\tau}_t$, the policy functions $c_t(b,\theta)$ and $n_t(b,\theta)$ solve the household's problem (4) and $V_t(b,\theta)$ is the associated value function

ii) The government budget constraint is satisfied

$$(1-u)\tau_t = \nu u + \frac{r_t B}{1+r_t}$$

iii) The asset market clears

$$\int_{(A\times\Theta)} b_{t+1}(b,\theta) d\Phi_t = B$$

iv) For all $\mathcal{S} \in \Sigma_s$, the joint distribution measure Φ_{t+1} satisfies

$$\Phi_{t+1}(\mathcal{S}) = \int_{(A\times\Theta)} Q_t((b,\theta),\mathcal{S})d\Phi_t,$$

where Q_t is the transition function defined as

$$Q_t((b,\theta),\mathcal{S}) = \mathbf{1}_{\{b_{t+1}(b,\theta)\in\mathcal{A}\}} \sum_{\theta_{t+1}\in\Theta} \Gamma_{\theta,\theta_{t+1}}.$$

The goods-market clearing condition is redundant by Walras law and thus omitted.

The optimization problem of the household gives rise to two optimality conditions that are used to construct the sequences of policy functions $c_t(b,\theta)$ and $n_t(b,\theta)$ where I skip the formulation of individual state variables for readability. First, an Euler equation governing optimal intertemporal substitution between consumption today and tomorrow

$$\beta(1+r_t)\mathbb{E}\left[U_c(c_{t+1},n_{t+1})\right] \leq U_c(c_t,n_t); \tag{5}$$

Equation (5) holds with equality if Equation (3) is not binding.

Second, an optimality condition for intratemporal substitution between labor and consumption

$$U_n(c_t,n_t) \leq -\theta U_c(c_t,n_t); \tag{6}$$

Equation (6) holds with equality if $n_t > 0$.

3 Quantitative exercise

3.1 Data and calibration

3.1.1 Data

In the following I will briefly describe the main datasets used in calibration and analysis of the paper regarding productivity, income, consumption, and credit limits.

Productivity, income, and consumption data Data regarding productivity, income and consumption is taken from the Panel Study of Income Dynamics (PSID). The PSID is a longitudinal survey of a representative sample of U.S. individuals and other members of their households. The survey is biennial since 1997 and features low attrition as well as high response rates (Andreski et al., 2014).

I will first discuss how I measure productivity which is needed as an input for the theoretical model. Closely related is the measure of income which is later used for the empirical analysis of consumption insurance. Lastly, I define nondurable consumption in the PSID and show how this measure compares to a similar measure from the Consumer Expenditure Survey (CEX). Note that since consumption is measured on the household level, hence, to achieve a proper mapping from model to data, I will also use productivity and income measures on the household level.

Productivity data I follow Floden and Lindé (2001) and define productivity as an "agent's hourly wage rate relative to all other agents" (p.416). In my case, agent refers to either "head", wife/"wife", or both as indicated in the PSID. An agent's hourly wage is defined as total yearly labor income divided by annual hours worked. Moreover, to be in line with the model I use post-tax wage rates as there are no distortionary taxes present that would affect the labor supply decision of agents. I combine post-tax wage rates within a household to compute productivity levels per household. A more detailed description of the data and the variables can be found in Appendix B.

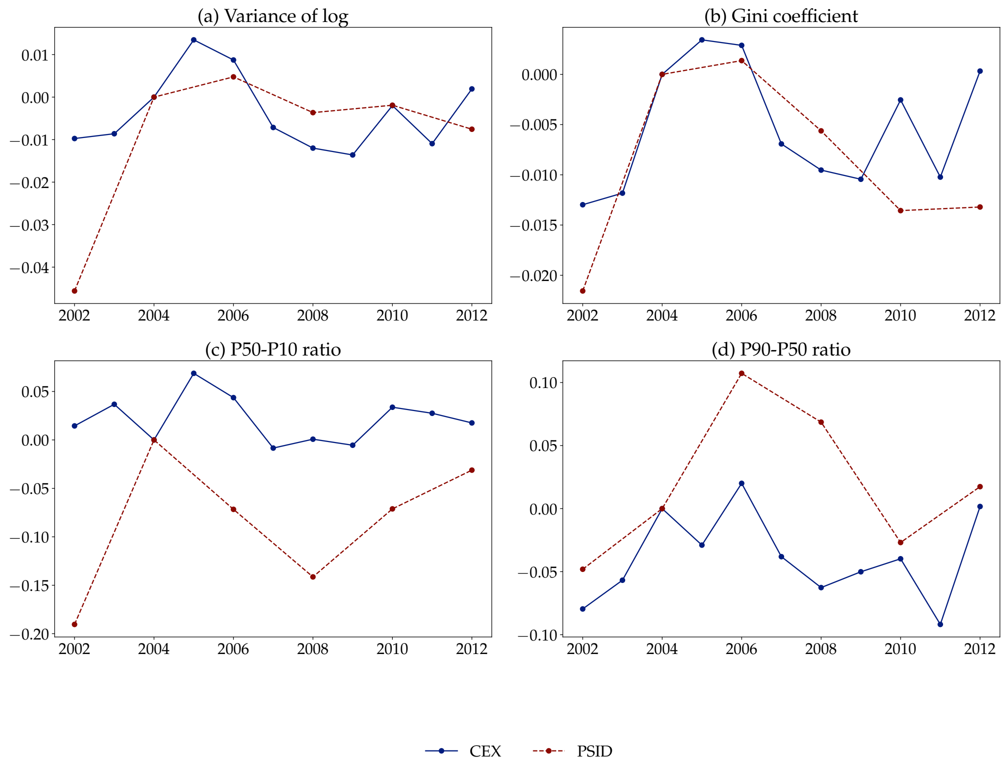
Income data The income measure used in the empirical exercise below should capture the amount of income that households actually have at their disposal. Hence, income is measured as labor income plus transfers and social security income net of taxes. Transfers, which are pre-dominantly important for households at the lower end of the income distribution, are captured by the unemployment benefit in the model. For both productivity and income measures, taxes are computed using NBER's TAXSIM program.

Consumption data Historically only some consumption categories were captured in the PSID; in particular food and housing. In 1999, however, new questions were added to the survey to collect information regarding expenditures on healthcare, education, childcare, transportation, and utilities. The sum of these categories captured around 70% of the expenditures collected in the Consumer Expenditure Survey (CEX) (Li et al., 2010) and in the U.S. National Income and Product Accounts (NIPA) (Blundell et al., 2016). Beyond that, expenditures for clothing, trips & vacations, recreation & entertainment, telecommunication, home repairs & maintenance, and household furnishings & equipment were added in 2005. As a result, the PSID now captures almost all categories of the CEX, albeit at a less aggregated level (Andreski et al., 2014).

To compute the empirical consumption insurance measures below, I define nondurable consumption as the sum of food expenditures, rent, home insurance, utilities, car insurance, gasoline, parking, bus fares, taxi fares, other transportation related expenditure, school expenditure including tuition, childcare, health insurance, other health expenditure, clothing, vacation, and entertainment. The latter three categories are included once they are available in the PSID.

Sample selection My sample comprises all PSID waves from 1999 to 2018. I include a head and/or spouse of a family who are between 20 and 59 years old, have information on non-imputed labor income with a hourly wage above half the minimum wage, and work positive, but not more than 5840 hours. Lastly, I exclude families whose equivalized food

Figure 2: Consumption inequality in the PSID and CEX



Note. This figure shows different measures of dispersion for nondurable consumption in the PSID and CEX, respectively. Panel (a) shows the variance of the log of nondurable consumption. Panel (b) shows the gini coefficient. Panel (c) shows the P50-P10 ratio. Panel (d) shows the P90-P50 ratio. All time series are normalized to 0 in 2004. Note that the two measures in the left panel are more sensitive to the bottom of the consumption distribution, while the measures in the right panel are more sensitive to the top.

consumption is below 400 dollars per year, whose food expenditures exceed half of total family income, and whose nondurable consumption (as defined above) is negative.

To assess the goodness of the PSID consumption measure I compare it to a corresponding consumption measure from the CEX from 2002 until 2012. The sample selection and the definition of nondurable consumption in the CEX follow as close as possible the strategy used in the PSID. Moreover, I exclude households who are classified as incomplete income respondents. This variable is only available until 2012, hence my comparison stops at that year.

As mentioned above, there has been considerable effort to gauge the similarity between consumption in these datasets regarding first moments. Since consumption insurance, by definition, regards to what extent the variance of income *shocks* translates to consumption growth I focus on second moments and other inequality measures.[4] Figure 2 compares various measures of inequality for the consumption measures in the PSID and CEX, respectively, where consumption has been equivalized using the OECD equivalence scale. I normalize all values to the pre-crisis value in 2004.

Panel (a) and (b) show the variance of log consumption and the gini coefficient from 2002 until 2012, respectively. In 2002, the two measures in the PSID are considerable below the CEX counterpart. After 2004, however, when all consumption categories are included in the PSID, the two measures follow each other quite well. Panel (c) shows the 50th–10th percentile ratio. While the value of this measure differs considerably between the two datasets, both exhibit a U-shape with the trough being around 2008. Similarly, the 90th–50th percentile ratio in Panel (d) show a discrepancy in levels between the PSID and CEX, however, both capture the decrease during the financial crisis between 2006 and 2010.

Overall, the comparison here confirms the view that the new PSID consumption measure goes a long way in capturing consumption patterns in the United States. While the CEX has been, and probably still is, the preferred data source to measure consumption expenditures, the PSID provides a reasonable substitute with other, crucial benefits. One obvious benefit is the panel structure of the PSID which I will exploit below when computing the amount of consumption insurance in the economy.

Credit data I employ two different credit data sources. Firstly, the credit limit data is from the 2020 Q2 Household Debt and Credit Report (HDCR) via the FRBNY Consumer Credit Panel (CCP).[5] The CCP is a longitudinal database which comprises information on consumer debt and credit via Equifax credit reports. The sampling procedure makes use of the randomness in the last 4 digits of the social security numbers to create a nationally representative random sample of individuals who have a credit report. The information

[4] Table 3 shows a comparison in equivalized consumption means.

[5] The microdata can only be accessed by researchers of the Federal Reserve System, hence, I rely on aggregate data which is published with recent reports; in my case this report is the HCDR. See questions on Data Requests here

from credit reports on individual accounts is then further limited to accounts that have been updated within the last three months.

In particular, the credit limit in the HDCR refers to the limit on *bankcard accounts* (or credit card accounts) which are revolving accounts for banks, bankcard companies, national credit card companies, credit unions and savings & loan associations (Lee and van der Klaauw, 2010). Credit limits via home equity revolving accounts are considered separately and are not captured here.

The second data source is the consumer credit time series from the Federal Reserve Board Flow of Funds (FoF). Particularly, I am interested in the *evolution* of credit card debt as a fraction of GDP. Note that this is the same dataset which is used to calibrate the net supply of bonds, B; that is, the datapoints in 2006 are used as a benchmark to calibrate the initial steady state, whereas I make use of the whole time series of consumer credit to calibrate my transitional dynamics.

Lastly, note that even though I use two different data sets in my calibration exercise below, consumer credit is one of the components in the FoF which can be directly compared to debt measures in the HDCR (CCP). The report states that the numbers obtained in the third quarter of 2009 for consumer credit from both datasets are very similar in magnitude. ($2.6 trillion in the CCP vs $2.5 trillion in the FoF; see HCDR).[6]

The following section describes first how the initial steady-state - the starting point of the quantitative exercise - of the model is calibrated, and second how I use the information in the credit datasets to discipline my simulated transitional dynamics. Thereby, I distinguish between calibration on a transitory and a permanent credit shock.

3.1.2 Steady-state calibration

In the following I will describe the calibration strategy for the initial steady state. The strategy aims to capture economic conditions, especially at the household level, prior to

[6] A small part of the remaining difference, for instance, can be explained by debt holdings from individuals without a social security number; these individuals are captured only in the FoF.

the GFC in 2006 and before. Table 1 summarizes the calibration.

Model functional forms and parameters

Preferences I assume preferences are additively separable and isoelastic in consumption and labor:

$$U(c,n) = \frac{c^{1-\gamma}}{1-\gamma} + \psi\frac{(1-n)^{1-\eta}}{1-\eta},$$

where I already normalized time endowment for leisure and labor to 1, $l + n = 1$. The time period is a quarter.

The discount factor β is set to match an annual interest rate of 2.5% in the initial steady state. The elasticity of intertemporal substitution (EIS), $\frac{1}{\gamma}$, is set to a quarter. The parameters governing the curvature of utility from leisure and the utility weight of leisure, η and ψ, are set to match an average Frisch elasticity of 1 and average hours worked for employed agents of 0.4, respectively. The latter is supported by evidence from Nekarda and Ramey (2010)[7].

Labor productivity process Following Guerrieri and Lorenzoni (2017), I assume that when positive, θ follows an AR(1) process in logs:

$$\theta_{it} = \rho\theta_{it-1} + \epsilon_{it}, \tag{7}$$

where ϵ_{it} is assumed to be drawn from a normal distribution with mean zero and variance σ_ϵ^2. Theoretical variance and covariance moments of the stochastic wage process in Equation (7) are matched to empirical moments constructed using data from the 2002-2006 PSID waves. In other words, the parameters from the quarterly AR(1) process are such that they match the estimates of an autocorrelation of 0.9368 and conditional variance of 0.0294 for annual relative wages of households. I choose this time horizon to be consistent with

[7] This reference refers to an older version of their working paper, meanwhile titled "The Cyclical Behavior of the Price-Cost Markup". For the evidence considered here, see Figure 10 in the 2010 version

my overall calibration strategy to target the pre-crisis conditions. A detailed description of the estimation procedure can be found in Appendix B. The continuous wage process is then transformed into a 12-state Markov chain using Tauchen (1986)'s method. The mean of θ under the stationary distribution is normalized to 1.

Employment Turning to transition probabilities between employment and unemployment states, and to unemployment benefits, I follow Guerrieri and Lorenzoni (2017) and Shimer (2005). The latter uses data from the Current Population Survey (CPS) to infer the monthly job finding and separation rate in the United States. While a consistent calibration using the PSID would be desirable, the lack of annual data on unemployment duration or spells therein would require additional assumptions. Hence, I draw on these external estimates. At a quarterly frequency, the transition probability to the unemployment state is set to 0.057 and the transition probability to the employed state is set to 0.882. Conditional on transferring from the unemployed to the employed state, the agent draws θ from its unconditional distribution. The unemployment benefit, ν, is 40% of average labor income (Guerrieri and Lorenzoni, 2017).

Asset supply Parameters regarding the asset supply are jointly matched to reconstruct pre-crisis characteristics of households' balance sheets. Using data from the 2006 Federal Reserve Flow of Funds, I target a liquid asset to GDP ratio of 1.78. Particularly, liquid asset include Deposits, Treasury Securities, Agency- and GSE- backed securities, Municipal Securities, Corporate Foreign Bonds, Mutual Fund Shares, and Security Credit[8]. The net supply of Bonds, B, is defined to be equal to liquid assets ratio minus credit card debt holdings of households, all expressed in terms of annual output. Thus, given a credit card debt-to-GDP ratio, B is then adjusted to match the liquid asset to GDP ratio. Thus, the borrowing capacities in the model mirror unsecured revolving credit. ϕ is also used to, in addition, match the credit card debt-to-GDP ratio prior to the GFC.

[8] Data is taken from Table B.100 which can be found here

Table 1: Calibrated parameters

Parameter		Value	Target/Source
Discount factor	$\boldsymbol{\beta}$	0.9680	Annual interest rate of 2.5%
Curvature of utility from leisure	η	1.50	Average frisch elasitcity = 1
Coefficient on leisure in utility	$\boldsymbol{\psi}$	24.20	Average hours of endowment worked = 0.4
Elast. of intertemp. substitution	$\frac{1}{\gamma}$	0.25	Guerrieri and Lorenzoni (2017)
Persistence productivity process	ρ	0.976	PSID
Variance productivity process	σ_ϵ^2	0.012	PSID
Transition to unemployment	π_{eu}	0.057	Shimer (2005)
Transition to employment	π_{ue}	0.882	Shimer (2005)
Unemployment benefits	$\boldsymbol{\nu}$	0.147	40% of average labour income
Net bond supply (to annual GDP)	$\frac{\mathbf{B}}{Y_A}$	1.6	Flow of Funds liquid assets
Borrowing limit (to annual GDP)	$\frac{\boldsymbol{\phi}}{Y_A}$	0.417	Credit card debt-to-GDP

Note. This table summarizes the calibrated and baseline parameters of the benchmark model. Variables and parameters in bold indicate that these have been calibrated to match simulated moments. See main text for details.

3.2 Credit shocks

In both specifications, the shock to the credit limit is not expected by the agents and hits the economy in the initial steady state. To abstract from households defaulting on their one-period bonds,[9] I follow Guerrieri and Lorenzoni (2017) and assume that the credit shock lasts for six periods and follows a linear path. In this way, households are able to incrementally adjust their portfolios without paying back unrealistically large amounts of debt within a single period. The complete path of the credit limit towards the terminal steady state is fully known to households.

Transitory The transitory credit shock tries to capture the mean-reverting notion of the aggregate credit card statistics as observed in Figure 1. Since I look at transitional dynamics starting from a steady state, I have to extract the stationary component in the time series. In order to do so, I decompose the credit card balance into a trend and cyclical component

[9] Note, however, that default or delayed payment can be a channel of insurance by itself. Gelman, Kariv, Shapiro, Silverman and Tadelis (2020) provide evidence that during the 2013 US government shutdown, many affected employees delayed recurring payments, for instance, for credit cards to smooth consumption.

using the Hodrick-Prescott filter. Thereafter, I estimate the autocorrelation of the cyclical component using a simple AR(1). This estimate captures the mean-reversion which is rectified from any trend component and thus the one I use to calibrate my transitory credit shock.

In particular, the estimated AR(1) coefficient equals 0.873. The path of the credit limit after the shock will be specified in such a way, that the autocorrelation of the model implied aggregate debt balance during transition will match the this estimate from the data. Moreover, since the calibration of the initial steady state is aimed to reconstruct pre-crisis characteristics of households' balance sheets in 2006, the size of the credit shock (i.e. the drop in the credit limit) is chosen to match the trough in credit card debt-to-GDP ratio after the onset of the grand financial crisis.

To summarize, the shock in the first 6 periods follows the linear specification

$$\phi_{t+1} = \bar{\phi} - \frac{(1-\chi)\bar{\phi}}{6} \cdot t \quad \text{for } t \leq 6,$$

where χ governs the size of the shock. Subsequent the shock I specify the evolution of the credit limit as

$$\phi_{t+1} = \varrho\bar{\phi} + (1-\varrho)\phi_t \quad \text{for } t > 6,$$

where ϱ governs the speed of mean-reversion of the borrowing limit and $\bar{\phi}$ denotes the long-run average, that is, the value from Table 1 in the initial steady state. The parameters ϱ and χ are then *jointly* determined in order to match both the empirical size of the credit shock and the autocorrelation of the credit card balance along the transition path.

Permanent The permanent credit shock, on the other hand, tries to match the downward shift in credit card variables once they are scaled with GDP as observed in Figure 1. This exercise is similar to the one conducted in the benchmark case of Guerrieri and Lorenzoni

(2017) as the shock boils down to a permanent drop in the credit limit.[10] The difference, however, is the fact that I can observe this limit from the data. Since it is, unfortunately, not possible with the current model to match both the credit balance-to-GDP ratio as well as the credit limit-to-GDP ratio - and I target the latter in my initial steady state - I choose to match the percentage change in the credit limit-to-GDP ratio. This change amounts to a drop of 30 percent (see Figure 1).

Table 2: Calibrated parameters and moments - Credit shocks

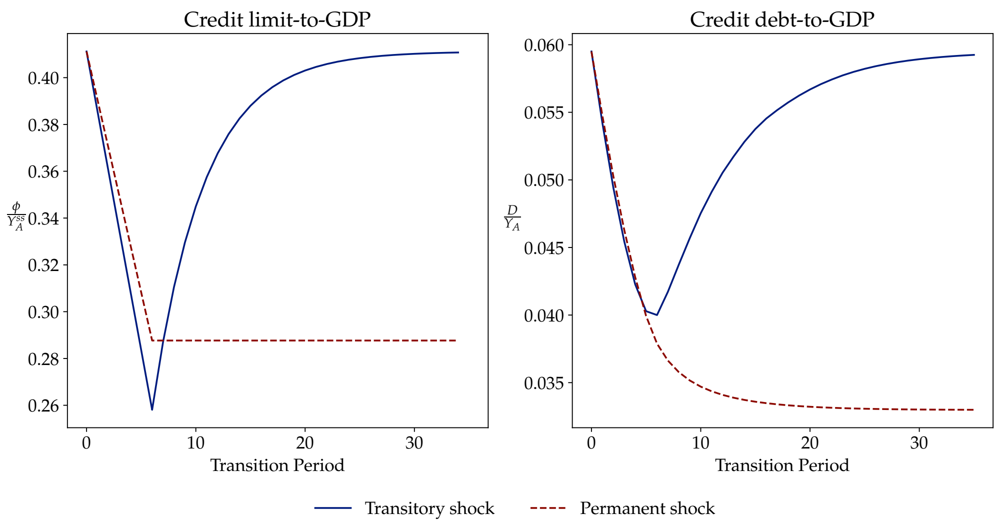
a) Parameters				
			Model values	
Explanation			Transitory	Permanent
Credit shock size	$1\text{-}\chi$		0.372	-
Mean-reversion	$1\text{-}\varrho$		0.826	-
Borrowing limit (to annual GDP)	$\frac{\phi}{Y_A}$		-	0.289
b) Moments				
Target		Data		
Trough credit card debt-to-GDP		0.04	0.04	-
Autocorr. credit card debt		0.8731	0.8731	-
Δ Credit limit-to-GDP		30%	-	30%

Note. This table summarizes the calibrated parameters to match the transition of the credit shocks in the model to empirical moments. See main text for details.

Table 2 summarizes the calibrated parameters and targeted moments during transition. The mean-reversion parameter is similar in size to the matched autocorrelation of the credit debt-to-GDP ratio. The intuition for this results resembles the precautionary behavior subsequent credit shocks as documented, for instance, by Guerrieri and Lorenzoni (2017). When the shock hits the economy in the initial steady state, agents accumulate wealth to stay away from the borrowing limit. As the path for the credit limit is fully known to them, they can align deleveraging and leveraging phases with the dynamics of the limit. This perfect foresight behavior can also be seen from Figure 3 which shows the dynamics of the credit limit-to-GDP and the credit card debt-to-GDP ratios, respectively, under the

[10] Guerrieri and Lorenzoni (2017) also simulate a transitory credit shock in an economy with durable goods and a credit spread. This shock is modelled as a transitory increase in the credit spread, which affects agents over the whole wealth distribution and not mainly the ones near the credit limit.

Figure 3: Transitory and permanent credit shocks



Note. The left panel of this figure shows the path of the credit limit under the transitory and permanent credit shock, respectively. The right panel shows the model implied credit debt-to-GDP ratio under both shock scenarios. Both panels show the first 35 periods of the transition.

different shock specifications. Even though the size of the transitory shock is larger than the permanent shock, in the former case the credit debt-to-GDP ratio is smaller after 6 periods as agents realize that the credit limit will be loosened from then on. In the latter case, however, agents keep deleveraging to stay away from the credit limit (Guerrieri and Lorenzoni, 2017).

3.3 Consumption insurance measure

To evaluate the extent of risk-sharing and consumption insurance I compute insurance coefficients as introduced by Blundell et al. (2008) and further examined by Kaplan and Violante (2010). To set the scene, let us quickly revise the notion of insurance in this framework. The insurance coefficient for a shock x_{it} to logged income or productivity is defined as

$$\varphi^x = 1 - \frac{cov(\Delta c_{it}, x_{it})}{var(x_{it})},$$

where Δc_{it} denotes the first difference in logged (residual) consumption, and the second moments are taken over the entire cross-section of households. The intuition is best captured by Kaplan and Violante (2010): the insurance coefficient is "the share of the variance of the x shock that does *not* translate into consumption growth" (p.57).

Coming back to the setup here, recall that productivity process follows an AR(1): $\theta_t = \rho\theta_{t-1} + \epsilon_t$. The measure introduced here relies on knowledge of the realizations of the idiosyncratic shocks ϵ. To compute this measure from the model perspective is straightforward, as I actually simulate the shocks when constructing the artificial panel. To infer the shocks from the data, however, I can deploy the assumptions made about the stochastic income process. I now briefly discuss both in detail.

Model The insurance coefficient from the model reads

$$\varphi^{\epsilon}_{model} \equiv 1 - \frac{cov(\Delta c_{it}, \epsilon_{it})}{var(\epsilon_{it})}.$$

I compute this statistic directly from simulated data using the quasi-difference operator. Recall that the ρ as calibrated in Section 3.1.2 was conditional on positive realizations of θ. Hence, to account for the additional unemployment state I simulate the earnings process and estimate the autocorrelation of the full productivity process, denoted ρ^{unemp}. I can then recover the shocks ϵ_t by applying the quasi difference defined by $\tilde{\Delta}\theta_t \equiv \theta_t - \rho^{unemp}\theta_{t-1} = \epsilon_t$ to the simulated values of θ.

Data To compute consumption insurance coefficients from the data, I look at total post-tax labor and asset income plus transfers of head and spouse of a family, for this is the income which is disposable for consumption. I denote this income measure by z. Looking at labor productivity by using the hourly wage rate, as we did when calibrating, would not capture income changes due to untaxed transfers which are a big part of the insurance mechanism for households.

To be in line with the stochastic structure of the theoretical model, I model log post-tax income as

$$z_{it} = f(\mathbf{X}_{it}, \beta) + \rho_z z_{it-1} + \lambda_{it},$$

where $\mathbf{X}_{it}$ is a set of observable control variables, ρ_z is a persistence parameter, and λ_{it} is a transitory income shock with $NID \sim (0, \sigma_\lambda^2)$.

I residualize log income by partialling out the effect of the observable control variables, $z_{it}^{res} \equiv z_{it} - f(\mathbf{X}_{it}, \hat{\beta})$, which contain a second-order age polynomial and dummies for education, race, household size, occupation, and employment status. Moreover, I include state dummies and self-reported house value to capture geographical differences. With the residuals in hand, I can compute the insurance coefficient

$$\varphi_{data}^{\lambda} \equiv 1 - \frac{cov(\Delta c_{it}, \tilde{\Delta} z_{it}^{res})}{var(\tilde{\Delta} z_{it}^{res})} = 1 - \frac{cov(\Delta c_{it}, \lambda_{it})}{var(\lambda_{it})}, \tag{8}$$

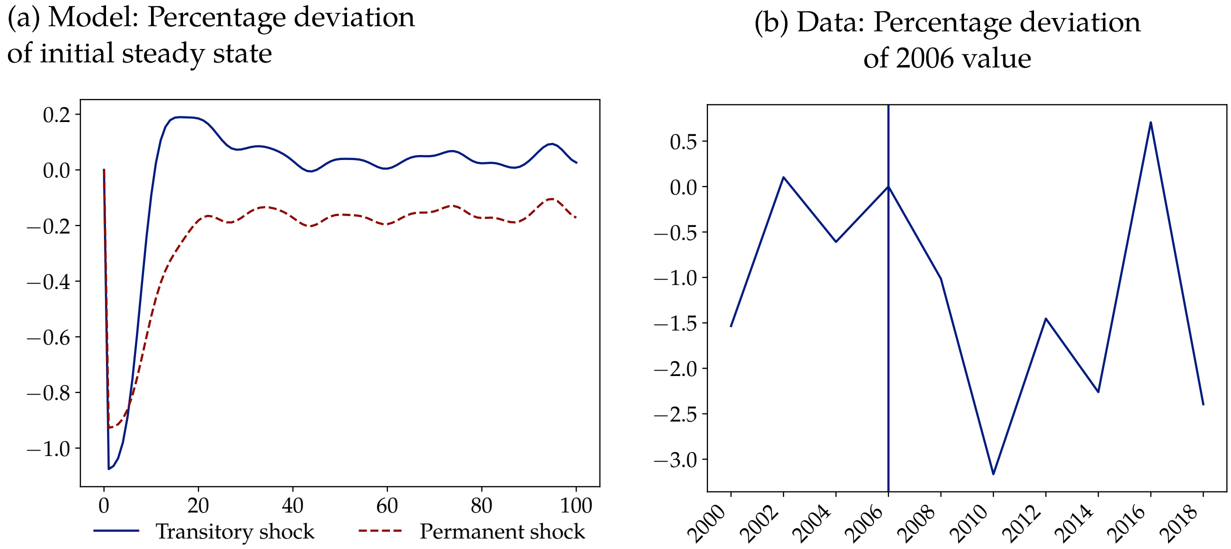
where $\tilde{\Delta}$ again denotes the partial difference operator, hence, $\tilde{\Delta} z_{it}^{res} = z_{it}^{res} - z_{it-1}^{res}$. The persistence parameter ρ^z is estimated on the residualized income data by minimizing the distance between empirical and theorical covariances.

To ensure a proper comparison between the quantitative exercise in the model and the computations from the data, I discard observations who have received financial help from relatives or friends, or report taxable income from other family members. Both channels of insurance are not modelled in the theoretical part, hence, accounting for them in the data could push the observed insurance coefficient upward. Eventually, I have an unbalanced panel of 10,848 from which I can compute both $cov(\Delta c_{it}, \tilde{\Delta} z_{it}^{res})$ and $var(\tilde{\Delta} z_{it}^{res})$.

4 Quantitative results

In the following subsection, I will analyze how the transitory and permanent credit shocks affect consumption insurance patterns of households.

Figure 4: Insurance coefficients over time



Note. The left panel shows the path of the insurance coefficient under the transitory and permanent credit shock, respectively. The values depict percentage deviations of the initial steady state and are filtered using a 1-D gaussian filter with standard deviation (smoothing parameter) of 3. The right panel shows the empirical insurance coefficient during the grand financial crisis. The empirical value is normalized to zero in 2006.

4.1 Transitional dynamics

Figure 4 shows the transition dynamics of the insurance coefficients for both the model and the data. Figure 4a compares the dynamics for both calibrated credit limit-to-GDP ratios as described above (cf. Figure 3). We see that the path for both shocks is very similar with the level being the only difference[11]. The drop on impact is, in absolute terms, 16% larger for the transitory shock, however, this is mainly mechanical since the drop in the credit limit-to-GDP ratio implied by the calibration is also 11% larger. The reason for the big drop subsequent the aggregate shock it that households with debt have to start deleverage their portfolios, thereby reducing their nondurable consumption irrespective of their idiosyncratic shocks (see also Guerrieri and Lorenzoni (2017)). As we will see below, the drop on impact is driven by households in the lower percentiles of the wealth distribution that are closer to the borrowing limit. This decomposition on impact holds for

[11] The little swings in both lines are due to the fact that I use the same seed when simulating the artificial data. Hence, the simulated markov chain for the idiosyncratic shocks is the same to warrant comparability between the simulations and to exclude any effect induced by simulation uncertainty.

both specification of shocks.

The crucial difference is that the long-term value for the consumption insurance is lower in the permanent specification. In the terminal steady state, the insurance coefficient is approximately 2% lower than with the mean-reverting shock.

This result can be explained by two factors. First, the level of output in both steady states is very similar. Hence, to achieve a lower credit-limit to GDP ratio, the credit limit has to be tighter in the permanent specification. The tighter credit limit in turn further prohibits agents to borrow resources to smooth labor productivity shocks. The result here can be seen as an intermediate case of the results in Kaplan and Violante (2010) who look at two extreme versions of the borrowing limit. That is, natural debt limit and the zero borrowing limit (no-borrowing). They also show that a tighter borrowing limit is accompanied by lower insurance, in their case for both transitory and permanent income shocks.

Second, the desired level of precautionary savings is higher if the borrowing constraint is tighter. Unconstrained agents accumulate assets to stay away from the borrowing limit. With a fixed supply of government bonds, a permanently lower interest rate in the terminal steady state of the permanent specification is the result of this heightened precautionary demand. Furthermore, this effect is stronger for wealth-poor agents, and their consumption insurance coefficient in the permanent specification decreases, driving down the overall level of insurance in the long run.

Figure 4b shows the evolution of the consumption insurance in the economy during the GFC according to Equation (8). The data series is normalized to 0 in 2006, i.e. the last year in the PSID before the financial crisis hit, which is indicated by the black verical line. We see that the insurance coefficient reaches a trough in 2010 implying a 3% drop over 4 years. Subsequently, it bounces back to a bit above its 2006 value in 2016, but decreasing substantially again in 2018. While the initial reduction is in line with the prediction of the theoretical model, the high volatility of the insurance coefficient, especially regarding the later years in the PSID, points to certain known issues when trying to compute insurance coefficients from the data.

First, Deaton (1997) argues that the variety of possible insurance mechanisms[12] makes it difficult to identify single channels and that it is better to look at total consumption smoothing achieved by households. The omission of observations that received financial help from family or friends above, for instance, partially addressed this concern. The "Deaton critique" (Heathcote, Storesletten and Violante (2014)), however, implies that there could be other important insurance mechanisms present that affect the results and are not controlled for.

Second, the empirical insurance coefficients are very sensitive to the specification used to compute the residuals z^{res}, sometimes even uncoupling the computed path from any clear direction during the GFC. To see this more clearly, note that the covariance ratio in Equation (8) essentially amounts to the coefficient of a Mace (1991)-regression once consumption and income have been residualized. A simple application of the Frisch-Waugh-Lovell theorem then shows that a full regression of log consumption growth on log income growth and controls would yield the same coefficient. Hence, any endogeneity issue, omitted variables, measurement error, or advance information, for instance, are sources of concern regarding the estimation of the insurance coefficient.

Last, an alternative as, for instance, implemented by Blundell, Low and Preston (2004) or Blundell et al. (2008), is to approximate the solution to a consumption-saving life-cycle optimization problem in which agents have CRRA utility and use the solution as a data-generating process for the consumption decisions of households.[13] A difficulty - while not impossible - when using this approach, however, would be identification of the insurance coefficients if one allows both the insurance coefficient and the variance of the shock to be time-varying. Even quasi-maximum likelihood estimation, which is in this case more precise than minimum distance estimation (Chatterjee, Morley and Singh, 2021), would

[12] See the paragraph "related literature" in the introduction for examples.

[13] As long as preferences are separable in consumption and leisure, the effect of leisure in this approximation is absent, since the Euler equation is not affected.

not resolve this issue.

4.2 Exploring the mechanism

This subsection further explores the mechanisms behind the results obtained above by zooming into different parts of the wealth distribution.

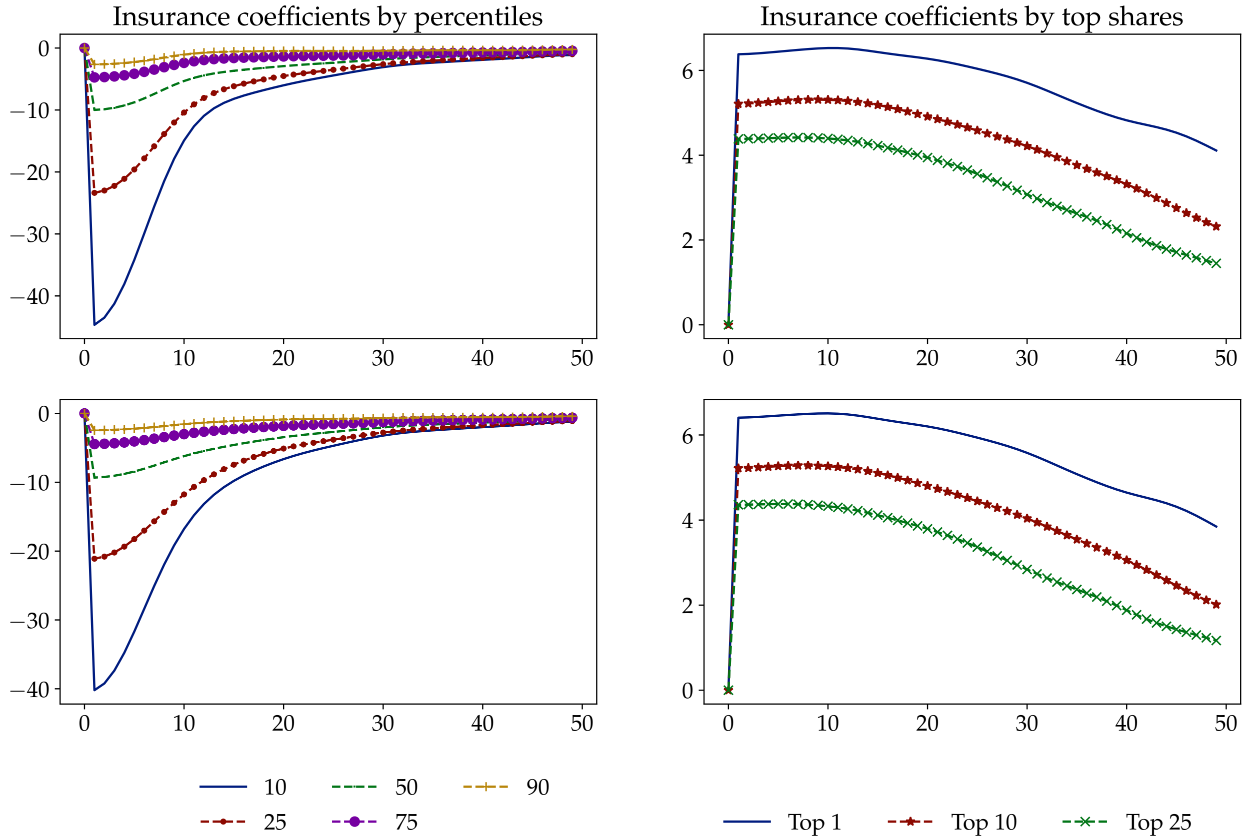
Decomposition Figure 5 shows the show the transitional dynamics of the insurance coefficient by percentile (left panels) and top wealth shares (right panels), respectively. As mentioned above, the decomposition by percentiles shows that the drop is most pronounced for households close to the borrowing constraint. These households have to accumulate bonds and deleverage to move away from the borrowing limit, thereby forgoing consumption. For instance, the insurance coefficient for household within the 10th percentile drop by roughly 40% in both specifications.

Consumption insurance of agents at the top, on the other hand, increases by about 6%. Since the total amount of bonds is unchanged during transition, the deleveraging episode of net borrowers induces net lenders at the top to sell some of their bond holdings; that is, these agents decumulate assets. The additional resources facilitate consumption insurance and the value increases. This is a common finding in the literature, that agents close to constraints (or close to kinks in their budget constraints) drive aggregate behavior after shocks (Kaplan and Violante, 2014; Guerrieri and Lorenzoni, 2017).

Labor supply as insurance Instead of looking at the amount of consumption insurance with respect to shocks, an alternative is to look at *innovations*, ι - defined as the difference between realized and expected income.[14] The main drawback of the innovation measure is that it is very difficult to construct a data counterpart. One would have to know agents' expectations regarding their future income, which is, at least within the PSID, not feasible.

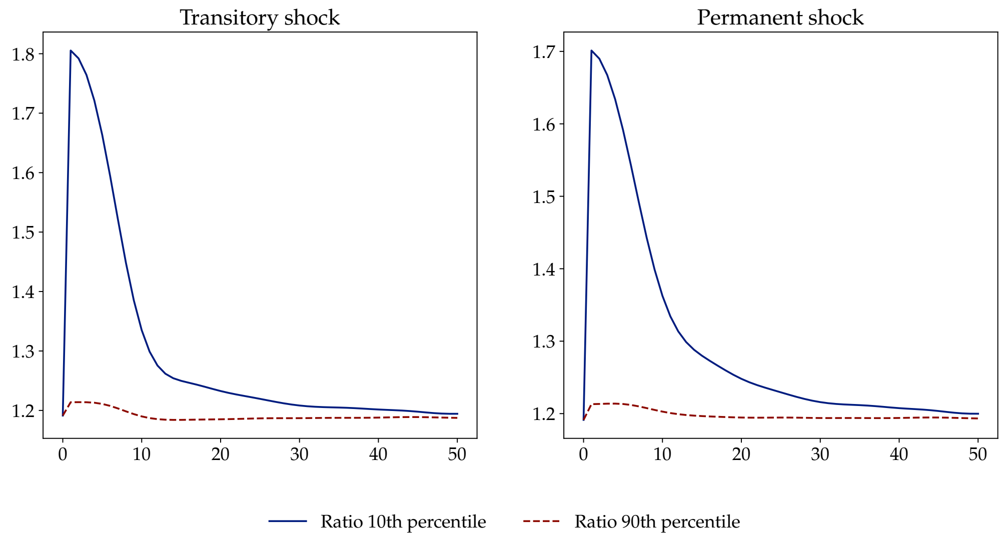
[14] Appendix E discusses innovations and their computation in more detail. The overall qualitative results when looking at innovations were always in line with the ones considered so far.

Figure 5: Insurance coefficients during transition - Decomposition



Note. The top left panel shows the path of the insurance coefficient under the transitory credit shock for the 10th, 25th, median, 75th and 90th percentile respectively. The bottom left shows the same for the permanent credit shock. shows the path of the insurance coefficient under the transitory credit shock for the top 1%, top 10% and top 25% wealth share. The bottom right shows the same for the permanent credit shock. The values depict percentage deviations of the initial steady state and are filtered using a 1-D gaussian filter with standard deviation (smoothing parameter) of 3.

Figure 6: Insurance coefficients with respect to shocks relative to innovations



Note. The left panel shows the ratio of the insurance coefficient with respect to labor productivity shocks to the ones with respect to innovations for the 10th percentile. The right panel shows the same ratio for the 90th percentile. The values are filtered using a 1-D gaussian filter with standard deviation (smoothing parameter) of 3.

Naturally, however, it is possible to construct innovations within the model and they can be used to assess to what extent labor supply serves as an insurance mechanism against fluctuations in productivity (Low, 2005; Pijoan-Mas, 2006).[15] Intuitively, it is always possible for agents to work more once they receive a negative productivity shock. When computing the innovation, it is already captured how much agents expect to work next period. Hence, a comparison between insurance coefficients with respect to shocks and innovations, respectively, can be informative about the amount of labor supply used for insurance.

Figure 6 shows the ratio of the insurance coefficient with respect to shocks relative to the insurance coefficient with respect to innovations, $\varphi^{\epsilon}/\varphi^{\iota}$ for both the 10th and 90th percentile. As Guerrieri and Lorenzoni (2017) document, after a credit shock aggregate

[15] Note that the effect of a wage change on hours worked is mainly determined by the parameter for risk aversion, γ. Chetty (2006) shows that for no initial wealth and separable preferences in consumption and labor, if $\gamma > 1$, the income effect of a wage increase dominates and hours worked incrase. In this case, the parameter for the Frisch elasticity is a determinant of the strength of the precautionary savings motive, as labor supply can be increased in presence of a negative shock (see also Heathcote et al. (2014)).

productivity falls as less productive agents who are closer to the credit limit increase their labor supply to generate resources to deleverage. What this figure shows is that these additional resources are also used to smooth consumption as well. The ratio for households in the 10th percentile increases by more than for households in the 90th percentile, implying a stronger response of φ^{ι} relative to φ^{ϵ} at the lower end of the income distribution. This stronger response of φ^{ι} is due to the fact that labor supply responses - as described above - now play a bigger role in cushioning productivty fluctuations. In other words, the insurance measure that does not take into account labor supply responses, φ^{ι}, is affected to a larger extent. The response for households in the 90th percentile is dampened, as wealthier households actually reduce their hours worked. That is, the ratio actually declines for households at the top.

5 Conclusion

In this paper, I have studied the evolution of consumption insurance patterns in the economy after unexpected credit shocks. I focused on two different shock specifications as observed in the data: a transitory credit shock following aggregate credit debt levels, and a permanent credit shock following credit debt-to-GDP ratios in the data. I have shown that the evolution of consumption insurance after both kind of shocks is similar as insurance levels decrease sharply on impact. The permanent shock induces a lower level of consumption insurance in the long run. These effects differ largely by present wealth holdings, with households at the lower end of the wealth distribution experiencing the brunt of the drop. The corresponding risk-sharing measure in the data suggests that the credit shock induced by the GFC was transitory in nature. Consumption insurance reaches its trough in 2010, but bounces back to its 2006 value by 2016.

I want to mention at least two potential areas for future research related to this topic. First, this paper remains largely silent regarding other channels for insurance that are present in the data. While the sample selection for the empirical exercise tried to account for this, especially public insurance via taxes and transfers were still implicit in the model. A model that explicitly models the tax structure in the United States as, for instance, Heathcote, Storesletten and Violante (2017), would allow for a normative analysis whether a more progressive taxation would have been welfare improving; especially for agents at the lower end of the wealth distribution.

Second, my calibration only considers unsecured credit card debt. A richer model with secured debt, such as mortgages, could investigate the implication of decreasing collateral value for consumption insurance. For instance, modelling secured credit based on a second illiquid asset (housing) as in Kaplan and Violante (2014) or Kaplan, Mitman and Violante (2020) would endogenously give rise to a larger share of hand-to-mouth consumers consistent with the data (Kaplan, Violante and Weidner, 2014), potentially amplifying the aggregate responses. Moreover, in this model one would have to distinguish further between the type of credit that is affected by the shock.

Appendix

A Data

Table 3: Equivalized quartlery expenditure in PSID and CEX

	PSID	CEX
Food	833.11	814.90
Rent	1256.78	1454.25
Home insurance	63.13	34.70
Utilities	243.72	242.38
Car insurance	177.46	122.43
Car repair	136.99	99.05
Car fuel	247.83	203.40
Parking	6.57	4.87
Busfare	6.30	9.31
Taxifare	3.52	1.94
Other transport	14.86	17.98
School	224.45	171.69
Childcare	67.94	39.43
Health insurance	131.83	106.76
Nurse	41.91	13.03
Doctor	57.84	63.46
Prescription	30.17	39.75
Clothing	158.90	203.87
Vacation	208.26	136.26
Entertainment	107.03	209.33

B Estimation of the productivity process

In the calibration section of the paper, I propose a persistent stochastic process of productivity for household i at time t:

$$\theta_{i,t} = \rho\theta_{i,t-1} + \epsilon_{i,t},$$

where ϵ_i is a temporary shock i.i.d. normally distributed with zero mean and variance σ_ϵ^2. I now describe the strategy to estimate the relevant parameters ρ and σ_ϵ^2 from wage residuals. The exposition largely follows Floden and Lindé (2001) who use a head's hourly wage relative to all other heads as the measure for productivity.

Data I use the Panel Study of Income Dynamics (PSID) data from 2003 to 2007 to estimate the parameters of interest. I choose this time horizon to be consistent with my overall calibration strategy to target the pre-crisis conditions. The PSID is a longitudinal survey of a representative sample of U.S. individuals and other members of their households. Since the PSID changed to a biennial frequency in 1997, I am effectively using the three survey waves from 2003, 2005, and 2006. In general, the questions on labor income and hours are retrospective. That is, survey questions from 2005 refer to the year 2004 etc. In addition to these standard questions, however, respondents are also asked to provide information about income and labor supply two years before. Collecting this information makes it possible to construct an *annual* panel of labor income and hours worked.

Until 2015, the PSID referred to the husband in a married couple as the Head of the household, irrespective of employment status and labor income. To capture the full labor productivity of a household, I include both Head and Wife/"Wife"[16] (if present) when estimating the stochastic process. This is a better measure to use as it better describes the increase in resources a household has if either of its members increases their labor supply.

Sample selection I only look at households whose head or spouse follow the following criteria. The individual (i) is from the main Survey Research Center (SRC) sample, (ii) is between 25 and 59 years old, (iii) provides information on years of education (iv) has positive working hours with a maximum of 5840 (maximum possible value in the survey), (v) has an hourly wage rate more than half the minimum wage (in 2002 dollars), (vi) does

[16] Until 2015, the PSID uses the term Wife for married females and "Wife" for a cohabiting female. Starting with the 2015 wave, it changed its terminology to *reference person* for the head, and *spouse* or *partner* for the Wife and "Wife", respectively. Going forward, I will use head and spouse.

not have unreasonable income swings between two years, and (vii) is observed in every year. Note that my sample selection applies these criteria individually to both head and spouse within a family. That is, if some of these criteria do not apply for the head, but do apply for the spouse, the latter is excluded in the sample, while the former is included. Starting from the individual heads and spouses in the SRC sample, Table 4 shows how the selection process affects the total number of observations.

Table 4: Sample selection in PSID

	# dropped	# remain
Initial sample (head and spouse)	...	31,161
Age between 25 and 59	4,924	26,237
No Education information	2,505	23,732
Hours worked ≤ 0 or > 5840	79	23,653
Hourly wage < 0.5 min wage (2002$)	392	23,261
Wage fluctuations	876	22,385
Balanced panel	7850	14,535

Note. The initial sample already excludes the latino, the immigration as well as the SEO subsample. I look at PSID from 2002-2006, hence the final number of 14,535 amounts to 2,907 individuals observed over the entire time horizon. In total, I observe 10,865 families.

Variable definitions

Annual labor income The notion of labor income used for estimation includes wages and salaries, bonuses, overtime, tips, commissions, professional practice or trade, market gardening, farm income, and unincorporated business income. All variables refer to pre-tax values. Post-tax values are obtained by subtracting (labor income) taxes which are estimated with NBER's TAXSIM program.

Annual labor hours Total annual hours worked refers to self-reported hours worked in all jobs, including overtime. Due to missing data for the years 2003 and 2005, I cannot add time spent in unemployment or time spent away from work due to illness of the respondent or others to this variable. Results in Floden and Lindé (2001) suggest, however, that the parameter estimates are largely unaffected by this omission.

Hourly earnings Hourly post-tax earnings (or post-tax hourly wage) are computed by dividing post-tax annual labor income by annual labor hours.

Table 5 provides summary statistics of the hourly wage rate and yearly labor earnings of the final sample.

Table 5: Summary statistics for the primary sample, PSID 2002-2006

Year	Mean age	Mean wage	Median wage	Var of log(wage)	Mean age	Mean wage	Median wage	Var of log(wage)
	Head				Spouse			
2002	40.93	20.28	16.19	0.35	29.58	15.83	13.64	0.27
2003	41.89	19.89	15.92	0.31	30.65	15.22	13.08	0.27
2004	42.89	21.44	17.00	0.33	31.40	16.76	14.48	0.27
2005	43.94	20.78	16.38	0.32	32.42	15.54	13.29	0.28
2006	44.93	22.45	17.58	0.34	33.19	17.48	14.80	0.28

Note. Wage variables are in 2002 dollars.

Statistical Model The full process to be estimated separately for head and spouse is

$$\begin{aligned} \ln w_{m,t} &= \psi_m + \theta_{m,t} + \xi_{m,t}, \\ \theta_{m,t} &= \rho\theta_{m,t-1} + \epsilon_{m,t}, \end{aligned} \tag{9}$$

where $w_{m,t}$ denotes the hourly wage of family member $m \in \{head, spouse\}$ at year t relative to the average hourly wage of all individuals at year t. This observed relative wage rate is the sum of an individual permanent component ψ_m, a temporary component $\theta_{m,t}$, and potential measurement error $\xi_m \sim NID(0, \sigma^2_{\xi_m})$. As Floden and Lindé (2001), I refrain from modelling individual-specific intercepts to capture the permanent component. Instead, it is assumed that permanent wage differences can be captured by observed individual characteristics in 2002. These characteristics include age, completed education, occupation, sex, and race.[17] That is, I estimate the following linear model using OLS:

[17] Education refers to years of completed schooling in 2002. The occupation variable captures 3-digit occupation codes from the 2000 BLS census of population and housing. In total, 24 categories are then constructed based on all major occupation profiles: https://www.bls.gov/oes/current/oes_stru.htm.

$$\ln w_{m,2002} = \beta_0 + \beta_1 age_m + \beta_2 age_m^2 + \beta_3 sex_m + \beta_4 educ_m + \beta_5 \vec{occ}_m + \nu_{m,2002}, \qquad (10)$$

where age denotes the individual's age, sex_m is a dummy variable for the individual's gender, $educ_m$ is years of completed education, and $\vec{occ}_m$ is a vector of 24 occupation dummies. The estimation results are shown in Table 6.

Table 6: OLS estimation for permanent relative wage component

	Heads	Spouses
age	0.067***	0.006
	(0.013)	(0.017)
$\frac{age^2}{100}$	−0.068***	−0.003
	(0.018)	(0.021)
sex	0.152***	–
	(0.039)	
$educ$	0.074***	0.077***
	(0.007)	
constant	−2.625***	−1.636***
	(0.365)	(0.570)
F-test	0.000	0.000
Adj R^2	0.235	0.284
N	1,919	988

Note. $^{*} p < 0.1$; $^{**} p < 0.05$; $^{***} p < 0.01$. Occupation dummies are included in the regression, but are not presented here. The sex variable is omitted in the specification for spouses as all observations are female.

The predicted wage $\ln \hat{w}_{m,2002} \equiv \hat{\psi}_m$ is then used as an estimate for the permanent wage component for all years $t \in \{2002, 2003, 2004, 2005, 2006\}$ for head and spouse, respectively.

To isolate the residual within a household i, I sum the predicted values for all wage earners within a family and subtract it from the observed total family wage, that is,

$$w_{i,t}^{res} = \ln w_{head,t} + \ln w_{spouse,t} - (\hat{\psi}^{head} + \hat{\psi}^{spouse}).$$

The residual is essentially the stochastic part (due to innovations in θ) which captures all remaining productivity risk once observable permanent components have been removed. With the family wage residuals at hand, I can estimate the parameters ρ, σ_ϵ^2, and σ_ξ^2 from the following variance moment conditions for all t.[18]

$$\begin{aligned} var\left(w_{i,t}^{res}\right) - var(\theta_{i,t}) - var(\xi_{i,t}) &= 0 \\ var\left(w_{i,t}^{res}\right) - \frac{\sigma_\epsilon^2}{1-\rho^2} - \sigma_\xi^2 &= 0, \end{aligned} \tag{11}$$

where the second line follows from stationarity of θ_t. And from the following covariance moment conditions for all $t > s$:

$$\begin{aligned} cov\left(w_{i,t}^{res}, w_{i,s}^{res}\right) - cov(\theta_{i,t}, \theta_{i,s}) &= 0 \\ cov\left(w_{i,t}^{res}, w_{i,s}^{res}\right) - \rho^{t-s}\frac{\sigma_{\tilde{\epsilon}}^2}{1-\rho^2} &= 0, \end{aligned} \tag{12}$$

where the first line already excludes covariance terms with $\xi_{i,t}$ due to the independence

[18] Note that when using family residuals to estimate the parameters, I implicitly assume that both head and spouse have the same ρ and that their idiosyncratic shocks are independent:

$$\begin{aligned} \ln w_{spouse,t} + \ln w_{head,t} - \psi^{spouse} - \psi^{head} &= \theta_{spouse,t} + \theta_{head,t} + \xi_{spouse,t} + \xi_{head,t} \\ w_{it}^{res} &= \theta_{i,t} + \xi_{i,t} \end{aligned}$$

with $\xi \sim NID(0, \sigma_{\xi_{head}}^2 + \sigma_{\xi_{spouse}}^2)$.

Moreover,

$$\begin{aligned} \theta_{spouse,t} + \theta_{head,t} &= \rho(\theta_{spouse,t-1} + \theta_{head,t-1}) + \epsilon_{spouse,t} + \epsilon_{head,t} \\ \theta_{i,t} &= \rho\theta_{i,t-1} + \epsilon_{i,t} \end{aligned}$$

with $\epsilon \sim NID(0, \sigma_{\epsilon_{head}}^2 + \sigma_{\epsilon_{spouse}}^2)$.

assumption.

In total I can construct 15 moments (five variance moments and ten covariance moments) to estimate three parameters; that is, the system is overidentified. Therefore, I use the generalized method of moments (GMM) to minimize the equally weighted distance[19] between model and data determined by the theoretical moment conditions in Equation (11) and Equation (12), and their empirical counterparts.

Table 7: GMM estimation results for the stochastic process

Parameter	Estimate	Standard Error
ρ	0.9368	0.0092
$\sigma^2_{\tilde{\epsilon}}$	0.0294	0.0045
$\sigma^2_{\tilde{\xi}}$	0.0670	0.0044

Note. Ecker-White heteroskedasticity consistent standard errors.

The GMM estimation results are shown in Table 7.

Quarterly process To match the parameters from the quarterly AR(1) process to the annual moments, I use the expression for the variance and autocovariance of the *yearly average* of a quarterly AR(1) process. To illustrate this, take the following process z to represent a standard AR(1) process in quarterly terms, where t denotes the 4th quarter and $t-3$ is the 1st quarter of a given year:

$$z_s = \rho z_{s-1} + \varepsilon_s \quad \forall s \in \{t, t-1, t-2, t-3\},$$

where I omit a constant as it does not affect either the variance or the covariance and ε is assumed to be identically and independently distributed with variance σ^2_ε. Furthermore, I assume that the process is weakly stationary. Thus, the yearly average is given by $\overline{z}$ =

[19] Equal weights are motivated by the results of Altonji and Segal (1996) who show that in small samples the equally weighted minimum distance estimator dominates the optimal distance estimator, especially when using higher than first-order moments.

$\frac{1}{4}(z_t + z_{t-1} + z_{t-2} + z_{t-3})$. Given a zero mean and using that the unconditional variance of the AR(1) process is given by $\frac{\sigma_\varepsilon^2}{1-\rho^2}$, I can write the variance as

$$\begin{aligned}
\mathrm{Var}(\overline{z}) = E[\overline{z}^2] &= \frac{1}{4^2}(z_t + z_{t-1} + z_{t-2} + z_{t-3})^2 \\
&= \frac{1}{4^2}(E[z_t^2] + E[z_t z_{t-1}] + E[z_t z_{t-2}] + E[z_t z_{t-3}] \\
&+ E[z_{t-1}^2] + E[z_t z_{t-1}] + E[z_{t-1} z_{t-2}] + E[z_{t-1} z_{t-3}] \\
&+ E[z_{t-2}^2] + E[z_t z_{t-2}] + E[z_{t-1} z_{t-2}] + E[z_{t-2} z_{t-3}] \\
&+ E[z_{t-3}^2] + E[z_t z_{t-3}] + E[z_{t-1} z_{t-3}] + E[z_{t-2} z_{t-3}]) \\
&= \frac{1}{4^2}(4\frac{\sigma_\varepsilon^2}{1-\rho^2} + 6\rho\frac{\sigma_\varepsilon^2}{1-\rho^2} + 4\rho^2\frac{\sigma_\varepsilon^2}{1-\rho^2} + 2\rho^3\frac{\sigma_\varepsilon^2}{1-\rho^2}) \\
&= \frac{1}{4^2}(4 + 6\rho + 4\rho^2 + 2\rho^3)\frac{\sigma_\varepsilon^2}{1-\rho^2}
\end{aligned} \tag{13}$$

where I used that

$$\begin{aligned}
E[z_t z_{t-h}] &= \rho^h E[z_{t-h}^2] \quad \forall h \in \{1, 2, 3\} \\
E[\varepsilon_t z_s] &= 0 \quad \text{for} \quad s \leq t
\end{aligned}$$

By analogy, the autocovariance between two yearly averages, $\overline{z}_{\tilde{t}}$ and $\overline{z}_{\tilde{t}+1}$, is

$$\mathrm{Cov}(\overline{z}_{\tilde{t}}\overline{z}_{\tilde{t}+1}) = \frac{1}{4^2}(\rho + 2\rho^2 + 3\rho^3 + 4\rho^4 + 3\rho^5 + 2\rho^6 + \rho^7)\frac{\sigma_\varepsilon^2}{1-\rho^2} \tag{14}$$

The yearly estimates from Table 7 are 0.9368 for the autocorrelation and 0.0294 for the conditional variance. Hence, I choose the quarterly parameters (see Table 1) to match the yearly unconditional variance, $\frac{0.0294}{1-0.9368^2}$, for Equation (13) and the yearly autocovariance, $0.9368 \cdot \frac{0.0294}{1-0.9368^2}$, for Equation (14).

C Steady state optimization and stationary recursive equilibrium

In this section, I first state the household problem in the steady states in recursive form. Second, I define the stationary recursive competitive equilibrium. The main difference to the transitional equilibrium definition in the main text is that the value function, policy functions, the interest rate and government policies are not indexed by Φ; recall that the time subscript implicitly took care of this in Definition 1. The reason is that all conditions have to be satisfied only for the equilibrium measure Φ, which reproduces itself — it is stationary.

Recursive Problem

$$
\begin{aligned}
V(b,\theta;\Phi) &= \max_{c,n,b'} \left[U(c,n) + \beta \mathbb{E}[V(b',\theta';\Phi')] \right] \\
&\text{s.t.} \\
q(\Phi)b' + c &\leq b + y - \tilde{\tau}(\Phi) \\
b' &\geq -\phi \\
\Phi' &= H(\Phi),
\end{aligned} \tag{15}
$$

where $H(\Phi)$ is the law of motion generated by the Markov process governed by Γ and the optimal policy functions of the household.

Denote the set of all probability measures on the measurable space (S, Σ_s) by $\mathcal{M}$. The stationary recursive equilibrium is summarized in the following definition.

Definition 2 *A **stationary recursive competitive equilibrium** is a value function $V : S \to \mathbb{R}$, policy functions for the household $C : S \to \mathbb{R}$ and $N : S \to \mathbb{R}$, future bond holdings b', an interest rate r, government policies $\tilde{\tau}$ and a measure $\Phi \in \mathcal{M}$ such that*

i) V, C, N are measurable with respect to Σ_s, V satisfies the optimization problem of the household, Equation (15), and C, N are the associated policy functions, given r and $\tilde{\tau}$.

ii) The government budget constraint is satisfied

$$(1-u)\tau = \nu u + \frac{rB}{1+r}$$

iii) The asset market clears

$$\int_{(A\times\Theta)} b'(b,\theta)d\Phi = B$$

iv) For all $\mathcal{S} \in \Sigma_s$

$$\Phi(\mathcal{S}) = \int_{(A\times\Theta)} Q((b,\theta),\mathcal{S})d\Phi,$$

that is, the probability measure reproduces itself.

Again, the goods-market clearing condition is redundant by Walras law and thus omitted.

D Computational Details

D.1 Numerical Algorithm - Steady State

I describe now how I compute the policy functions and the invariant distribution for the initial and terminal steady states.

Policy Functions To obtain the policy functions, I employ the endogenous grid method by Carroll (2006).

1. I construct a grid on (b,θ) where $b \in G_b = \{b_1, \ldots, -\phi, \ldots, 0, \ldots, b_N\}$ and $\theta \in \Theta = \{\theta^1, \ldots, \theta^{13}\}$

2. I guess an initial policy function $\hat{C}_0(b_i, \theta_j) = \max\{c_{min}, r \cdot b_i\}$ where c_{min} is a pre-specified minimum consumption level.

3. Iterate over pairs $\{b_i', \theta_j\}$ in this and the next step. Fix θ_j and iterate over all grid values of b_i'. For any pair $\{b_i', \theta_j\}$ on the mesh $G_b \times \Theta$ where the borrowing limit is not binding, construct

$$\tilde{C}(b_i', \theta_j) = \left[\beta(1+r) \sum_{\theta' \in \Theta} \pi(\theta'|\theta_j) \hat{C}_0(b_i', \theta')^{-\gamma}\right]^{-\frac{1}{\gamma}},$$

which is the Euler equation solved for consumption using my utility specification. $\pi(\theta'|\theta_j)$ denotes the probability of being type θ' tomorrow conditional on being θ_j today. Similarly, I solve for optimal labor supply and construct

$$\tilde{N}(b_i', \theta_j) = \max\left\{0, 1 - \left[\frac{\theta_j \tilde{C}(b_i', \theta_j)^{-\gamma}}{\psi}\right]^{-\frac{1}{\eta}}\right\}$$

where I use the consumption level from the consumption policy function above. If the borrowing limit is binding, I cannot use the Euler equation as it is not binding. Hence, I set the consumption level to c_{min} to calculate optimal labor supply n_{min} from the condition above. Using n_{min}, I compute the level of consumption, c^*, that solves

$$0 = -\phi - \frac{-\phi}{1+r} - c^* + \theta_j n_{min} - \tilde{\tau}.$$

This is the lowest consumption level that is generated by the consumption policy function. The consumption area between this level and the lowest consumption level where the constraint is not binding, is then generated by computing an evenly sized grid between these two points. Subsequently, labor supply for constrained households is computed identically as above, using the newly obtained consumption levels. Do this for all $\theta_j \in \Theta$.

These two approaches combined yield the policy function for consumption and labor supply, respectively, in any given iteration.

4. From the budget constraint, I solve for the value of assets today, $b^{\dagger}(b_i', \theta_j)$. For unconstrained agents, this is

$$b^{\dagger}(b_i', \theta_j) = \frac{b_i'}{1+r} + \tilde{C}(b_i', \theta_j) - \theta_j \cdot \tilde{N}(b_i', \theta_j) + \tilde{\tau}.$$

   For constrained agents, I replace b_i' with $-\phi$. This implies that asset holdings of $b^{\dagger}(b_i', \theta_j)$ and an idiosyncratic shock of θ_j today would lead the agent to hold b_i' assets tomorrow. The function $b^{\dagger}(b_i', \theta_j)$ is not defined on the grid G_b and changes every iteration, i.e. endogenous grid. This is also important when I compute the invariant distribution.

5. Update the guess of the consumption policy function. To obtain a new guess $\hat{C}_1(b_i, \theta_j)$ I linearly inter-and extrapolate the values for $\{\tilde{C}(b_n^{\dagger}, \theta_j), \tilde{C}(b_{n+1}^{\dagger}, \theta_j)\}$ on the two most adjacent values $\{b_n^{\dagger}, b_{n+1}^{\dagger}\}$ that enclose the given grid point b_i. If some grid point values b_i are beyond $b_N^{\dagger}$, I extrapolate to obtain the new guess. After I obtained all new guesses, I impose the lower bound of c_{min}.

6. I declare convergence when

$$\max_{i,j} |\hat{C}_{n+1}(b_i, \theta_j) - \hat{C}_n(b_i, \theta_j)| < \varepsilon,$$

   for some small ε and where $\hat{C}_n(b_i, \theta_j)$ denotes the consumption policy in the n'th iteration. If convergence has not been achieved, repeat steps 3-5 using the latest guess of the consumption policy function and check convergence again.

Invariant Distribution

1. Assign weights for all possible bond holding values generated by the policy functions above that are proportional to the distance of the two most adjacent grid point values.

For instance, let the current bond holdings be $b^\dagger$ and let $\{b_{n-1}, b_n\}$ be the two most adjacent grid point values that enclose these bond holdings. The weight $\zeta^\dagger$ is then computed as

$$\zeta^\dagger = \frac{b^\dagger - b_{n-1}}{b_n - b_{n-1}}.$$

If current bond holdings are above (below) the highest (lowest) grid point value, set the weight for the highest (lowest) grid point equal to 1.

2. The initial guess for the initial distribution $\Phi_{(0)}(b|\theta)$ is the uniform distribution.

3. Fix θ_j and and compute the distribution as follows:

$$\Phi_{(1)}(b_{n-1}|\theta_j) = \sum_{\theta' \in \Theta} (1-\zeta)\pi(\theta'|\theta_j)\Phi_{(0)}(b_{n-1}|\theta_j)$$
$$\Phi_{(1)}(b_n|\theta_j) = \sum_{\theta' \in \Theta} \zeta\pi(\theta'|\theta_j)\Phi_{(0)}(b_n|\theta_j),$$

where ζ denotes the particular weight for the bond holding that is enclosed by the grid points $\{b_{n-1}, b_n\}$. The weights adjust for the transition of off-grid values to values on the grid: when bond holdings are close to, say, b_n, the distribution $\Phi_{(1)}(b_n|\theta)$ gets a higher weight. Furthermore, the distribution $\Phi_{(k)}(b_n|\theta_j)$ is affected by the probability of being type θ' tomorrow conditional on being θ_j today, denoted by $\pi(\theta'|\theta_j)$, and the current mass at particular bond holdings conditional on being type θ_j, $\Phi_{(k-1)}(b_n|\theta_j)$.

Repeat this for all $\theta_j \in \Theta$, $b_n \in G_b$ and sum the distributions to get $\Phi_{(k)}(b|\theta)$.

4. I check convergence by computing

$$|\Phi_{(k)}(b|\theta) - \Phi_{(k-1)}(b|\theta)| < \epsilon,$$

for some small ϵ and where $\Phi_{(k)}(b|\theta)$ denotes the distribution in the k'th iteration.

If convergence has not been achieved, repeat step 3 using the latest guess of the distribution and check convergence again.

D.2 Numerical Algorithm - Transition

I describe now how I compute the transition path for interest rates. Essentially, the algorithm iterates backward over the policy functions starting from the terminal steady state to obtain a sequence of policy functions. Subsequently, with the sequence of policy functions at hand, iterate the distributions forward starting from the stationary distribution in the initial steady state. This backward-forward iteration to obtain general equilibrium time paths of aggregate prices (and variables) has been employed by several recent articles, for instance, Guerrieri and Lorenzoni (2017) or Auclert and Rognlie (2020)

The economy at $t = 0$ is at the steady state with stationary distribution Φ over assets and productivity types. At the end of period $t = 0$, an unexpected credit crunch hits the economy that reduces the borrowing limit ϕ_t. I assume that the economy converges to the new terminal steady state after T periods, for T arbitrarily large but finite. The assumption on T allows us to solve the household problem by backward induction. To compute the equilibrium interest rate path, I follow these steps:

1. I set T = 100.

2. I specify the sequence of borrowing limits $\{\phi_t\}_{t=1}^{T}$ where the borrowing limit from the terminal steady state is obtained after 6 periods.

3. I compute the policy functions of the initial and terminal steady state using the algorithm in Appendix D.1

4. I guess an initial interest rate path of length T such that $r_t = r_T \quad \forall t > 1$, i.e. the sequence of interest rates equals the interest rate in the terminal steady state.

5. Since $\hat{C}_T(b, \theta)$ equals the consumption policy function from the terminal steady state,

I can solve the household problem by backward induction and derive $\{\hat{C}_t(b,\theta)\}_{t=1}^{T-1}$ and $\{\hat{N}_t(b,\theta)\}_{t=1}^{T-1}$ using the endogenous grid method as outlined above. For every t, I use the corresponding interest rate and borrowing limit from the specified sequences. Again, bond holdings can be computed via the budget constraint.

6. Iterate the bond distribution forward starting from the initial steady state distribution at $t = 1$. Compute the aggregates, i.e. output, consumption, labor supply, and household bond demand, at time t, using the time t policy functions from the previous step.

7. For every iteration, I check bond market clearing for convergence:

$$\sqrt{\frac{\langle (B_{dem} - B), (B_{dem} - B) \rangle}{T}} < \epsilon, \tag{16}$$

for a small ϵ and where B_{dem} denotes the aggregate bond demand vector of length T, B denotes the bond supply vector of length T, and $\langle \cdot, \cdot \rangle$ denotes the inner product.

8. If inequality Equation (16) is not satisfied for any iteration k, I update the interest rate path for next iteration, $r^{(k+1)}$, based on bond market clearing with the following linear updating rule

$$r^{(k+1)} = r^k - \varepsilon (B_{dem}^{(k)} - B),$$

where B_{dem}^k denotes aggregate bond demand at iteration k and B denotes bond supply. ε are exponentially decaying weights, i.e. divergences in the bond markets at time periods closer to the credit crunch get a higher weight. Note that $r^{(k+1)}$, r^k, ε, $B_{dem}^{(k)}$, and B are vectors of length T representing the whole path. Repeat steps 5-8 using the new interest rate path until convergence is achieved.

E Consumption insurance: Innovations

Let y_{it} be logged income and c_{it} logged consumption. Moreover, denote the innovation to income for each household by ι:

$$\iota_{it} = y_{it} - \mathbb{E}[y_{it}|y_{it-1}] = \theta_{it}n_{it} - \mathbb{E}[\theta_{it}n_{it}|\theta_{it-1}n_{it-1}] = \theta_{it}n_{it} - \mathbb{E}[\theta_{it}n_{it}|(b_{it-1}, \theta_{it-1})] \quad (17)$$

Then the innovation insurance coefficient is defined as

$$\varphi^{\iota} \equiv 1 - \frac{cov(\Delta c_{it}, \iota_{it})}{var(\iota_{it})}, \quad (18)$$

where $var(\cdot)$ and $cov(\cdot)$ denote the cross-sectional variance and covariance at time t, respectively. This measure makes use of the artificial panel which is simulated to construct the model implied aggregates.

Note that the measure considered here is different compared to Kaplan and Violante (2010) to the extent it captures the share of the variance of the *innovation* to income which is not affecting consumption growth and hence can be insured. Kaplan and Violante (2010) consider the magnitude of persistent shocks where income follows a standard persistent-transitory process.

The reason for this deviation is because the persistent shock in this framework affects the labor productivity -rather than the income - of the agent, which together with the endogenous labor supply decision yields the income (see Equation (2)). Hence, the coefficient in Equation (18) captures insurance possibilities through endogenous labor supply adjustments. The key for this observation is the construction of the expectation operator in Equation (17); it combines both the expected labor productivity and the expected labor supply next period.

How is the expectation in Equation (17) computed? Make use of the transition function Q on the state space $S \equiv A \times \Theta$ described above. Recall that the transition function is completely described by the exogenous law of motion for the state and the decision rules regarding the state in the next period. In this framework, these objects refer to the exogenous markov chain for the productivity process and the saving decision rule, b'. Hence, for all possible grid points $(b_{i'}, \theta_{j'})$ on the discretized state space, I can compute:

$$Pr(b_{t+1} = b_{i'}, \theta_{t+1} = \theta_{j'} | b_t = b_i, \theta_t = \theta_j) \equiv P_{i'j'|ij}$$

Equipped with these probabilities I can compute the expected income, for every current state (b_j, θ_i), as

$$\begin{aligned} E[y_{t+1} | b_t = b_i, \theta_t = \theta_j] &= E[\theta_{t+1} n(b_{t+1}, \theta_{t+1}) | b_t = b_i, \theta_t = \theta_j] \\ &= P_{11|ij} \theta_1 n(b_1, \theta_1) + P_{12|ij} \theta_2 n(b_1, \theta_2) + \cdots \\ &= \sum_{j'}^{|\Theta|} \sum_{i'}^{|A|} P_{i'j'|ij} \; \theta_{j'} n(b_{i'}, \theta_{j'}) \end{aligned}$$

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