The Effects of Income Uncertainty on Liquidity, Default and Prosperity

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1 Introduction

Households face idiosyncratic income uncertainty around business cycle fluctuations which shape their expectations and thus, their future consumption. Such uncertainty is evident from the Great Recession, but particularly more so with the Corona Recession, where masses of laborers have been furloughed as a consequence of the unprecedented spread of COVID-19 and a timeline towards normalization is not easily foreseeable.[1] Households, in combating the increased uncertainty, may lend to prudent behaviors such as precautionary savings, taking positions of greater liquidity, taking on less risky investments and naturally, decreasing levels of consumption.[2] This is well documented — first through the utilization of Bewley models[3] and currently through Heterogeneous Agent New Keynesian (HANK) models, where in addition to the idiosyncratic income-risk and assets with different degrees of liquidity, we have nominal price rigidities.[4] The varying levels of income uncertainty may also push households toward delinquency, whom may default on their debt in order to smooth consumption across states.[5] Precautionary hoarding of liquidity and an increase in defaults may channel their way into the macroeconomy through the decrease of aggregate demand and private investment. It is thus of upmost importance for policymakers to understand, but also quantify the impact of income uncertainty across the economic landscape to find the appropriate fiscal and monetary measures for economic stability and prosperity. This is what this thesis attempts to do.

To that, I first estimate an income process of log earnings on household observables and extract the residuals as the income variation that is idiosyncratic to the household. Coupled with its first and second lag, I assemble the empirical auto-covariance structure of the idiosyncratic component for cohort-quarter cells. It is in the difference between the empirical and theoretical auto-covariances that I extract the sequence of second-moment household income risk shocks via Bayer et al. (2019)'s quasi-maximum likelihood estimator. With that, using Jordà (2005)'s robust local projections (LP) method, I test for empirical evidence of one prudent behavior: flights to liquidity. As households face increased income risk, they will accumulate liquid assets

1. COVID-19 stands for COrona VIrus Disease 2019.
2. E.g., Bayer, Lütticke, Pham-Dao, and Tjaden (2019), Chang, Hong, and Karabarbounis (2018), Carroll (1994)
3. E.g., Aiyagari (1994), Huggett (1993), Bewley (1980)
4. To name a few recent papers e.g., Luetticke (2020) explains the importance of heterogeneity in consumption and investment propensities for the transmission of monetary policy, Bayer et al. (2019) explains the liquidity allocation channel under increased income uncertainty, Den Haan, Rendahl, and Riegler (2018) explains how unemployment fears and deflation induce prudent behaviors.
5. E.g., Livshits (2015), Nakajima and Rıos-Rull (2019), Livshits, MacGee, and Tertilt (2007), Chatterjee, Corbae, Nakajima, and Rios-Rull (2007), Westbrook, Warren, and Sullivan (2000), Barron, Elliehausen, and Staten (2000), Warren, Sullivan, and Jacoby (2000), Domowitz and Sartain (1999)

relative to illiquid to subsidize short-run consumption and be better suited to counter future financial distress. Using portfolio data from the quarterly Flow of Funds, I report on the size and persistence of these time-varying risk shocks on this shift toward liquidity.

A second and equally important part to the thesis are households' treatment of unsecured debt in times of heightened uncertainty. Households may default in the presence of increased income uncertainty, debilitating their commitment to future debt repayment, which limits their ability to smooth consumption *across time*. Bankruptcy, however, grants households an avenue to smooth *across states* as it introduces some contingency into debt contracts. This trade-off is evident given the severity of the Great Recession, where delinquency (informal defaulting) rates reached near 7%, while charge-off rates (formal defaulting) reached above 10%; hinting at the gravity of income uncertainty on whether households exercise the default option despite its long-run effects (Zame (1993)).[6] In spite of these rates, there were no nationwide debt relief efforts (Auclert, Dobbie, and Goldsmith-Pinkham, 2019), when such policy could have been precisely what was needed to prevent the large drop in employment and aggregate demand (Mian and Sufi, 2015).

The current U.S. administration, in response to the economic fallout from the virus for example, has frozen the accrual of interest on student loan debt as well as suspended payments against student loans. Most private creditors have also allowed households to defer payments for some fixed amount of time.[7] This is in recognition of the future labor income uncertainty cast by the virus and possibly the counter cyclical nature of default filings. Thus, I provide justification for such policy by linking household income shocks to default risk à la Jordà (2005), showing the shocks' impact on defaulted balances as well as the credit-risk premium.

Income uncertainty also has its print on overall output and its corresponding components. Recent fiscal efforts to suppress the effects of income uncertainty include the American Recovery and Reinvestment (ARR) Act of 2009 and the Coronavirus Aid, Relief, and Economic Security (CARES) Act of 2020.[8] Both "stimulus" packages pumped large sums of money into the economy to increase liquidity of households to help them insure against future income uncertainty, yet there is little evidence to support that these type of packages indeed "stimulate" private activity. Most estimated government spending multipliers are actually below unity (Ramey and Zubairy, 2018). The reason may come from estimation. Most papers focus on the *average* multiplier. In that, I believe the state of the economy is fundamental in capturing the size of the spending multiplier;

6. Definitions on the rates are discussed in section 3. See credit card loans (unsecured debt), figure 4 and 7 for full time series.

7. More information can be found in the presidential memorandum.

8. For a package breakdown on the CARES Act, see Snell (2020).

thus, I estimate the cumulative multiplier *dependent* on the gravity of income uncertainty; providing evidence as to whether such policy is indeed apropos for economic recovery.

The empirical results conform to general economic canon. Increased income uncertainty signals households to increase their portfolio liquidity today by saving and investing in liquid assets, moving away from illiquid investments and consumption. The change in the liquidity ratio is mostly driven by the demand for liquidity, supported by persistent decreases in nominal rates greater than the decrease in house prices, lending to the increase observed in the liquidity premium. Heightened uncertainty also contests households in their capacity to handle debt. Results show households first dishonor unsecured credit contracts (i.e., credit cards) in trying to smooth consumption compared to collateralized debt. A 1 standard deviation increase in income uncertainty increases defaulted balances by 0.5% by end of year 1. At the beginning of 2020, the amount of credit outstanding from credit cards and other revolving plans constituted 844 billion dollars. This means a 1 standard deviation increase in income uncertainty leads to a 4.22 billion dollar loss in reserves. The increase in the credit-risk premium follows, as banks price consumer risk as a mechanism to protect themselves from income uncertainty.

As aggregate demand decreases from precautionary hoarding and household defaults, the overall economic state suffers. After year 1, GDP declines half a percent from increased uncertainty while total factor productivity one full percent. Half a percent of where GDP stood in 2019 is 106.5 billion dollars and the total loss only accumulates if measures for economic recovery are neglected. In recovering these losses, I show the advantage of expenditure side fiscal policy. The spending multiplier under high income uncertainty is, on average, above 2 and at times, 3. Thus, for every dollar increase in government spending (e.g., in a stimulus package), GDP will increase by a factor greater than 2, backing the brawn of fiscal policy for economic prosperity.

In covering the various channels under income uncertainty, I add to the existing literature by considering the avenues in a mostly empirical setting using an underrepresented specification suggested by Jordà (2005). The income process and liquidity exposition heavily relied on Bayer et al. (2019), with the specification and data extension being the only new additions. The default channel is motivated by Chatterjee et al. (2007), who incorporates income uncertainty in a general equilibrium setting with unsecured consumer credit to connect stylized facts on household debt and default behavior. The use of second-moment persistent income shocks and default outcomes adds to Livshits, MacGee, and Tertilt (2007), where, in a heterogenous agent life-cycle model, they find the variance of the persistent income shock affects the selection of different default regimes. Studying the credit-risk premia in an incomplete markets setting comes from Eaton and Gersovitz (1981), where they show the relationship between interest rates and default probabilities, thereby recognizing that lenders use the rate to compensate themselves in non-default states for losses they suffered in default. Following Ramey and Zubairy (2018), I also add to the state-dependency literature by considering the spending multiplier under the overarching state of income uncertainty.

In Section 2, I motivate the empirical estimations with two partial equilibrium models for the liquidity and default channel. Section 3 presents the portfolio, default and prosperity data. Section 4 presents the corresponding estimation frameworks and results. Section 5 summarizes the findings and provides direction for future research.

2 Theoretical Motivation

Before I present the empirical evidence, I provide two partial equilibrium models to provide economic intuition on the effects of increased income uncertainty on two channels. Taken from Bayer et al. (2019), the first model setup derives the optimal portfolio liquidity allocation given an increase in income uncertainty. For the second model setup, the default channel is explained using a costly state verification model, where we can see the effects of income uncertainty on (1) the credit-risk premium and (2) default probability. The section concludes by summarizing the findings, showing what we should expect in the empirical section of the paper.

2.1 Liquidity Channel

As households face increased future income uncertainty arising from business cycle fluctuations, they will shift their portfolio position towards greater liquidity for better consumption smoothing. To illustrate the precautionary motive, consider the following setup. Suppose households live for three periods. In period 1, all households receive an endowment y with certainty. In period 2, households have a 50% probability of being in a high or low-income state. In the low-income state, households receive $y - \frac{1}{2}\sigma$, where σ denotes income-risk and $y > \sigma > 0$ is income. In the high-income state, households receive $y + \frac{1}{2}\sigma$. They have CRRA-felicity in consumption, with risk aversion parameter set to 1, and do not discount the future, i.e.

$$U(c_1, c_2, c_3) = E_0 \left[\log(c_1) + \log(c_2) + \log(c_3)\right]$$

In period 1, households have the option to consume, c_1, and invest in two assets: (1) an illiquid asset, k_1 or (2) a liquid asset, b_1. They may only invest in the illiquid asset in period 1, which returns $1 < R < 2$ units of the consumption good in period 3.[9] The illiquid asset may not be used as collateral nor sold in period 2. Households may invest in the liquid asset that pays a zero

9. Formally, it should be $1 < R_k < (1 + R^{\frac{\xi-1}{\xi}})_k^{\xi}$. For our example, $\xi = 1$, hence $R^k < 2$

net return in period 2, so it can be interpreted as a storage technology. There is no endowment in period 3. The household problem is:

$$
\begin{aligned}
\max_{c_1, c_2^L, c_2^H, c_3^L, c_3^H} & \left[\log(c_1) + \frac{1}{2}\log(c_2^L) + \frac{1}{2}\log(c_2^H) + \frac{1}{2}\log(c_3^H) + \frac{1}{2}\log(c_3^L)\right] \\
& subject\ to \\
& c_1 \ \leq \ y - k_1 - b_1 \\
& c_2 \ \leq \ b_1 + y - b_2 \\
& c_3 \ \leq \ R^k k_1 + b_2 \\
& b_1 \ \geq \ 0, b_2 \ \geq \ 0, k_1 \ \geq \ 0
\end{aligned}
\tag{1}
$$

where H stands for *high-income*, L stands for *low-income* and the subscripts denote the period $t \in \{1, 2, 3\}$. Period 3 consumption is also denoted with an H or L superscript since income and thus, consumption, will depend on the income-state of period 2. First order conditions are:

$$
\begin{aligned}
\frac{\partial \mathbb{L}}{\partial k_1} &= \frac{-1}{y - k_1^* - b_1^*} + \frac{1}{2}\left(\frac{R^k}{R^k k + b_2^L} + \frac{R^k}{R^k k + b_2^H}\right) = 0 \\
\frac{\partial \mathbb{L}}{\partial b_1} &= \frac{1}{y - k_1^* - b_1^*} + \frac{1}{2(b_1^* + y + \frac{1}{2}\sigma - b_2^H)} + \frac{1}{2(b_1^* + y - \frac{1}{2}\sigma - b_2^L)} = 0
\end{aligned}
\tag{2}
$$

To solve the household problem, we recognize that in period 2, all uncertainty is revealed and the question of self-insurance becomes moot. Households will find the optimal allocation that smooths consumption between period 2 and period 3 if no borrowing constraint binds in period 2 (i.e., $b_2 > 0$). If the constraint binds in period 2, savings entering period 3 will be zero (i.e., $b_2 = 0$). This means households will have consumed all of their income y and liquid assets b_1 in period 2 and are only left to consume out of the illiquid assets in period 3. Under the high-income state, if gross returns on the illiquid asset, R^k, are not too high (as assumed), then, households will not be constrained and will smooth consumption by carrying over savings from period 2 to period 3 (i.e., $b_2 > 0$), equalizing resources across the final periods. For $R^k \neq 1$, households that invest positive amounts of b_1 and k_1 in period 1 imply a binding constraint in period 2 in the low-income state. The last two statements are provided as lemmas and proven in Appendix A.

The optimality conditions are as follows:

$$
\begin{aligned}
\frac{\partial \mathbb{L}}{\partial k_1} &= \frac{-1}{y - k_1^* - b_1^*} + R^k \frac{1}{2}\left(\frac{1}{b_1 + y + \frac{1}{2}\sigma + R^k k_1} + \frac{1}{R^k k_1^*}\right) = 0 \\
\frac{\partial \mathbb{L}}{\partial b_1} &= \frac{-1}{y - k_1^* - b_1^*} + \frac{1}{2}\left(\frac{1}{b_1^* + y + \frac{1}{2}\sigma + R^k k_1} + \frac{1}{b_1^* + y - \frac{1}{2}\sigma}\right) = 0
\end{aligned}
\tag{3}
$$

The remaining derivation I leave to Bayer et al. (2019). Using the implicit function theorem, we solve for $\frac{\partial b_1^*}{\partial \sigma}$ and $\frac{\partial k_1^*}{\partial \sigma}$, establishing that increased income-risk signals households to move toward liquidity (i.e., $\frac{\partial b_1^*}{\partial \sigma} > 0$) and away from illiquid investments (i.e., $\frac{\partial k_1^*}{\partial \sigma} < 0$). To summarize, we considered the following situation:

$$
\begin{aligned}
c_2^H &= \frac{1}{2}(b_1 + y + \frac{1}{2}\sigma + R^k k_1) & c_3^H &= c_2^H \\
c_2^L &= b_1 + y - \frac{1}{2}\sigma & c_3^L &= R^k k_1
\end{aligned}
$$

As income-risk σ increases, c_2^H increases along with c_3^H. In the low-income state, income-risk decreases consumption levels at double the rate relative to the good state and households cannot access their illiquid assets, k_1, to insure against this idiosyncratic risk. Thus, households in period 1 will increase their share of liquid assets, b_1, to smooth consumption overtime.

2.2 Default Channel

To explain the role of income uncertainty on default, I build on the costly state verification (CSV) framework of Townsend (1979).[10] Consider a two-period setup, where you have a unit mass of consumers who borrow to smooth consumption over the two periods and a large, but finite number of lenders. The lenders have large reserves and compete amongst each other in offering unsecured debt contracts to consumers. At the beginning of period 1, the lenders and borrowers come to terms on a debt contract defined by the credit amount $b \geq 0$ and an interest rate I (e.g., a credit card). For simplicity, the borrower can only hold one contract.

Borrowers do not receive an endowment in period 1 nor have a pre-existing stock of wealth/debt, but instead must borrow to consume that period using the recently struck contract. In period 2, borrowers receive an endowment, $y > 0$, subject to income risk, $\sigma > 0$. Specifically, upon the realization of period 2, borrowers may find themselves in one of two states: (1) a low-income state, receiving $y - \sigma$ or (2) a high-income state, receiving $y + \sigma$. Changes in income risk is what will constitute the main theoretical analysis. Consumers have a 50% probability of being in any state and is private information. Once the consumer has observed their period 2 income, they choose their consumption allocation and decide whether they should pay the principal borrowed, b, with interest, I, or default. If the borrower defaults, the borrower must give up a fraction of their endowment, θy, seen as a deadweight cost, for $0 < \theta < 1$.[11]

10. Ideas and structure of the model comes from Townsend (1979), Webb (1992), Boyd and Smith (1994), Tirole (2010), Kovrijnykh and Livshits (2017), Drozd and Serrano-Padial (2017), Duncan and Nolan (2019) and materials from Prof. Dr. Bayer and Prof. Fernandez-Villaverde.

11. For further simplicity, I assume $(1 - \theta)y \geq \sigma$ to secure non-negative consumption in period 2.

Lenders provide a homogeneous debt contract and set prices simultaneously. Thus, rational consumers will seek the product with the lowest price (I assume there are no pecuniary search costs). The competitive Bertrand price equilibrium among lenders results in a Nash equilibrium where price is equal to the marginal cost. This implies that, in addition to offering a contract which maximizes the *ex-ante* utility of borrowers, lenders must also offer a contract that satisfies the zero-profit condition. I say *ex-ante* to emphasize that lenders do not observe the income state faced by each household in period 2 when offering contracts in period 1, and thus must price the default risk from having asymmetric information. Lenders receive an imperfect signal $\hat{d}$ based on what the consumer reports back (i.e., repayment or default) to the lender in period 2. Lenders, thus, decide whether they should incur a cost, C, to verify precisely the state of the borrower's solvency and demand debt where warranted. Debt collection is assumed warranted against borrowers in the high-income state who default, since they had the means to repay and chose not to.

I next describe the lenders and borrowers in more detail with their optimization problems. The result of their interaction is a standard debt contract.[12]

2.2.1 Lenders

At the beginning of period 1, the credit market opens and lenders competitively extend unsecured credit contracts to willing borrowers. The contracts stipulate a credit amount $b \geq 0$ and a nondiscriminatory interest rate, I. For a simple CSV model, costs associated to providing these contracts/funds are normalized to zero. In period 2, lenders receive a signal $\hat{d}$ based on the borrower's default decision. The signal helps lenders decide whether they should pursue debt collection. Let $P(\hat{d})$ be the the probability of verification upon default. $\hat{d}$ is supposed to reflect the public information accessible to all economic agents and d the private signal only observable to the borrower. The private and public information available is summarized by $D = (\hat{d}, d)$ and should be interpreted as capturing the state of world for the borrower.

There are three possible states in the model: (1) the borrower repays and the lender will thus not pursue debt collection. (2) The borrower does not repay and the lender pursues debt collection.

12. A standard debt contract satisfies that following conditions: (1) A contract exists where the contract recipient agrees to borrow from a lender and in return, pay the lender an amount (principal plus interest) that is non-contingent on the state of the world. (2) The state of the world is only observable to the borrower. (3) The state of the world may be *verified* by the lender for some fixed cost. Hence, costly state verification. (4) The investing agent receives an amount and does not verify for high realizations. So above some threshold, contract enforcers do not verify. When the measure of return is below said threshold, bankruptcy measures are taken with probability 1. In other words, state verification is non-stochastic.

(3) The borrower does not repay and the lender does not pursue debt collection.[13] Under Bertrand price competition, the equilibrium contract extended to borrowers that maximizes their ex-ante utility is:

$$U(K, P(\hat{d})) \tag{4}$$

where K is the tuple (b, I) that defines an unsecured debt contract and $P(\hat{d})$ is the probability of verification (henceforth P). In layman's terms, the consumer's utility for consumption is indirectly captured by the contract offered by the lender, K, and his chances of being pursued for debt collection, P. The full utility specification for the borrower is developed in the next section. This is subject to the ex-ante zero-profit condition:

$$\begin{aligned} \sum_{D} \left[\Pi(D, K, P) - C\delta(D, K, P)P(\hat{d}) \right] P(D) &= 0 \\ where & \\ \Pi(D, K, P) &= \begin{cases} I & if\ \delta(D, K, P) = 0 \\ -b & if\ \delta(D, K, P) = 1 \end{cases} \end{aligned} \tag{5}$$

$\sum_D \Pi(D, K, P)$ are lenders' profits which depend on (1) D, the borrower's state of the world defined by the information available (2) K, the contract extended to the borrower, and (3) P, the probability of verification. For the two profit cases: (1) I are profits (interest income) the lender receives if the consumer repays and hence, does not default, $\delta = 0$ and (2) if the borrower defaults, $\delta = 1$, then the lender has a loss of $-b$. $P(D)$ is the discrete probability distribution for the states of the world. Lenders can pay C to verify if borrowers definitively cannot pay their debt by observing their income state. This may be interpreted as a deterministic auditing/credit-monitoring cost.[14]

2.2.2 Consumers

At the beginning of period 1, the consumers accept a single credit contract, for which they borrow b from the lender to subsidize current consumption, c_1. Their consumption in period 1 solely depends on b as they receive no endowment until period 2 and have no other credit lines.

13. In equilibrium, (2) will never occur because high-income households will always choose to pay the principal plus interest rather than having to pay precisely that plus a penalty interest charge. These consumers may have strategically defaulted in period 2 given lenders do not observe their state of the world, but lenders can pay cost C to break information asymmetry and collect debt accordingly. For that reason, D is reduced to two states.

14. The audit is deterministic in that the probability of debt collection after paying cost C is $P(d) \in \{0, 1\}$. Given the borrower has defaulted, this assumption divides the set of feasible period 2 incomes into two regions, Y_0 and Y_1, where Y_0 corresponds to all income endowments that would lead to debt collection ($\hat{Y} > b + I$) and Y_1 are all income endowments that would not ($\hat{Y} < b + I$). Upon paying cost C, all incomes in Y_1 have a probability one of being monitored, while all incomes in Y_0 have probability zero of being monitored.

In period 2, the now borrowers have a 50% probability to land in any of the two income states described above and decide on repayment of the debt or default. Borrowers who do not default face the following maximization problem:

$$\begin{aligned} ND &= \max_{c_1, c_2^L, c_2^H, b} \left[(c_1) + \frac{1}{2}(c_2^L) + \frac{1}{2}(c_2^H) \right] \\ & subject\ to \\ & c_1 \leq b \\ & c_2^L \leq y - \sigma - b - I \\ & c_2^H \leq y + \sigma - b - I \\ & b \geq 0 \end{aligned} \tag{6}$$

For simplicity, I do not discount the future. ND stands for *non-default* and is the utility specification for $\delta = 0$ borrowers. This means that in period 2, borrowers were able to repay the amount borrowed b with interest I on that amount. In the case for consumers that have defaulted, the utility function is the following specification:

$$\begin{aligned} DF &= \max_{c_1, c_2^L, c_2^H, b} \left[(c_1) + \frac{1}{2}(c_2^L) + \frac{1}{2}(c_2^H) \right] \\ & subject\ to \\ & c_1 \leq b \\ & c_2^L \leq (1 - \theta)y - \sigma \\ & c_2^H \leq (1 - \theta)y + \sigma - b - \hat{I} \\ & b \geq 0 \end{aligned} \tag{7}$$

where $0 < \theta < 1$ is the cost of defaulting on the balance borrowed. For c_2^H, the constraint says when a borrower defaults, the lender will bear the cost C to verify that the borrower was indeed solvent and as a result, recover $b + \hat{I}$ from the borrower, where $\hat{I} > 0$ is a penalty interest charge. Altogether, the equilibrium contract extended to borrowers will maximize their ex-ante utility subject to the zero-profit condition:

$$\begin{aligned} U(K, P) &= \max_{K,P} \sum_D \left[\delta DF + (1 - \delta) ND \right] P(D) \\ & subject\ to \\ & \sum_D \left[\Pi(D, K, P) - C\delta(D, K, P) P(\hat{d}) \right] P(D) \end{aligned} \tag{8}$$

where the sum of utilities and profits are taken over the distribution of states of the world, $P(D)$. For the maximization problem, $P(D)$ is reduced to two states: (1) the borrower repays or (2) the borrower defaults. In both states, the lender does not pursue debt collection since these consumers truthfully defaulted (i.e., they defaulted when they did not have the means to pay). The third, discounted case, where the borrower falsely defaults and the lender pursues debt collection, occurs with zero probability. Since this is costly, the consumer always prefers to repay.[15] The reason is formulated in Lemma 1.

Lemma 1. *If (1) $b \leq \theta y - I$ and (2) $I \leq \theta y + \hat{I}$, then the consumer always repays.*[16] *(3) If $I > \theta y + \hat{I}$, then the consumer always defaults.*

Stated in (2), those in the high income state will always repay, given repayment will always be cheaper than falsely declaring bankruptcy:[17]

$$\underbrace{b + I}_{\textbf{repayment}} \leq \underbrace{b + \theta y + \hat{I}}_{\textbf{false bankruptcy declaration}}$$

Declaring bankruptcy when having the means to repay warrants successful debt collection upon efforts by the lender. Lenders then collect their debt and at a penalty, $b + \hat{I}$. This is on top of the deadweight loss to households, θy. In general, households will not default if the resources after bankruptcy are less than resources after paying the debt. Thus, for small enough debts and high enough bankruptcy cost, households do not default in and debt collection is not pursued. In this case, in equilibrium, lenders will lend credit at a zero risk-premium ($I = 0$) since neither type of household will default (i.e., they do not pose any risk). These equilibrium contracts are thus *risk-free*. From Lemma 1: $b \leq \theta y - I$ simplifies to $b \leq \theta y$ and given the ex-ante utility specification is increasing in b for $I = 0$, $b = \theta y$ in equilibrium. This is shown in Appendix D.3.1.

If the constraint were slack in the optimal, then the shadow price would be zero and there is no gain from increasing our debt. Given the constraint is binding in the optimal, then the shadow price is positive, indicating gains from incurring more debt. In search for the optimal contract then, I proceed to a debt contract of a medium-range.

Definition 1. A medium-range contract b satisfies the following two conditions: (1) $b > \theta y - I$ and (2) $I \leq \theta y + \hat{I}$.

15. Upon paying verification costs, the lender is able to observe the income state of the consumer and measure solvency. The signal fully informs the lender, thus, strategic default is not possible in this model. In a model where the signals may not be perfect could render a positive probability of strategic default in equilibrium.

16. I assume if the borrower is indifferent between defaulting or not, the borrower does not default.

17. A discussion on higher debt levels is provided later on. Essentially, if a household incurs more debt than any income state can handle, this household is defined to not have the means to pay — hence, they defaulted truthfully.

Lemma 2. *If the consumer is offered a medium-range contract, such a contract would force low-income households to default while high-income households to not.*

In the medium-range, the equilibrium interest rate is increasing in debt and verification costs: $I = b + C$. Thus, compared to the smaller debt contract, there is now a trade-off between the debt one wishes to acquire and the interest rate one has to pay. For that reason, it is not trivial that increasing the debt level will translate to an increase in utility this time. The reason for $I > 0$ arises from the positive probability of default, specifically from low-income households who find the cost of default, θy, to be low enough to be offset by the consumption smoothing benefit from default. In this model, I find that in the medium-range, $\frac{\partial U(K,P)}{\partial b} < 0$. In comparison to the risk-free contracts, medium-debt contract consumers respond even greater to the bankruptcy cost, the penalty charge, and the verification cost. The result is intuitive. Households with debt contracts in the medium-range have a higher risk of default, which makes the associated costs (i.e., the bankruptcy cost, the penalty charge and verification cost) more relevant.

In general, consumers do prefer low verification costs since higher verification costs implies lenders will resort to higher interest rates to protect themselves vs. paying the high cost.[18] Furthermore, consumers prefer a lower penalty charge to make *lying* as cheap as telling the truth. As shown in D.3.1, the ex-ante utility at the equilibrium interest rate is decreasing in b. Thus, the optimal debt level approaches the infimum: $b \downarrow \frac{\theta y - C}{2}$. Yet, the set of risk-free contracts is when $b \leq \theta y$, so the optimal in this range must be $b = \theta y + \varepsilon$, for ε sufficiently small. In this model, the risk-free contract strictly dominates the risk inherent lines.[19]

For completeness, consider a large debt contract. This is any debt level where $b > \theta y + \hat{I} - C$. Given the amount borrowed is *very* large, lenders become highly leveraged and the associated risk premium approaches infinity. This is the case in the model because households who borrow large amounts will always default since at some point, the debt exceeds the available resources for repayment irrespective of the income state. Lenders who make the move to lend will lose $-b$. Thus, lenders aware of the risk will only lend if its at a very high premium (i.e., $R = \infty$) since the risk of default is essentially 100%. In that case, the Nash equilibrium is autarky, since there are no gains from trade in this closed setting. Households have to rely on their incomes to smooth consumption and no one lends.

18. This is implied in the zero-profit constraint, where $I = b + C$. Thus, increases in the verification cost leads to spikes in the interest rates.

19. Under the risk-free contract, for $b = \theta y$ and $I = 0$, utility is equal to: $2y - \frac{\theta y}{2} - \frac{\hat{I}}{2}$. Under the *risky* contract, for $b = \theta y + \varepsilon$ and $I = b + C$, the ex-ante utility is equal to: $y - \frac{3}{4}\theta y - \frac{\hat{I}}{4} - \frac{c}{2} - \frac{1}{4}\varepsilon$. The ex-ante utility under a risky contract is homogeneous of degree zero. Multiplying it by factor 2, it is easy to see $U(K,P)_{risky} < U(K,P)_{risk-free}$.

2.2.3 Role of Income Uncertainty

When a risk-free debt contract is offered, income uncertainty is inconsequential to lenders. Both types of households will consume the same in period 1 and are solvent enough to cover their small debt contracts in period 2. Hence, the risk premium is zero ($I = 0$). As for the consumers, they do not default given their utility functions are strictly increasing in consumption. By defaulting, they are not maximizing consumption and run the inevitability of being pursued for debt collection. This is expressed in Lemma 1, part (2). For medium-range contracts, households confronted with negative uncertainty default to smooth consumption, since covering the debt is more than the cost to declare bankruptcy i.e., $b > \theta y$. In the model, the probability of default is exogenous, since it is 1-to-1 with the discrete distribution of income states, but also because verification reveals full information. If verification revealed an imperfect signal to lenders, some households might default strategically, running the chance they will not be pursued for debt collection. With this additional avenue, the probability of default would increase. In sum, as a greater number of households are stricken with negative uncertainty, the probability of default increases and more so with imperfect verification.

Since I allow for positive and negative income shocks, at a 50% probability of experiencing either, the ex-ante utility specification does not reflect income uncertainty since they are equally opposing forces. If the probability were more than 50% for being in the low-income state, income uncertainty would certainly reflect negatively in the utility specification. Likewise, if the model were posed with a positive probability of households experiencing a negative shock and others no shock, then income uncertainty will always plays a role. As for income uncertainty and interest rates, the focus will be on medium-range contracts. For the small debt contracts i.e., $b \leq \theta y$, consumers do not pose any risk to the lender and are offered a zero-risk premium. For risky contracts i.e., $b > \theta y$, there is a positive probability of default, so the equilibrium interest rate adjusts upward to $I = b + C$. The increased rate reflects the losses expected from the positive default probability and costs the lender has to incur to verify the consumer's solvency.

3 Data

The previous section detailed the economic intuition of uninsurable idiosyncratic risk on two channels: (1) portfolio liquidity-allocation and (2) the default channel. Increased income uncertainty causes households to smooth consumption in order to save for a 'rainy day', shifting their portfolio position toward greater liquidity. Increased uncertainty also contests household's capacity to handle debt, pushing uncertainty stricken households into default in order to smooth consumption across states. I test the theoretical conclusions using the data and estimation strategies discussed below.

3.1 Income Process

To empirically test the relationship between income uncertainty and the portfolio channel, I must first specify an income process to extract the income shock series. For the income process, I employ the Survey of Income and Program Participants (SIPP). The SIPP panel is a nationally representative, individual-level survey known for providing short-term dynamics on employment, earnings, household composition and program participation. I extend the data work of Bayer et al. (2019) with the addition of the 2014 and 2018 SIPP panel. The 2014 and 2018 panels release their waves on an annual basis, running from 2013 to 2017, presenting individual-level monthly data on demographics, family structure, labor market information and government transfers. For the data cleaning, the data is aggregated to the household-level, at quarterly intervals. For the analysis, the data is aggregated to an age-quarter cell.

To capture the labor-market profile, the household heads must be at least 30 and at most 55 years of age. For this age range, included are households with two married adults, supplying more than 260 hours of work per quarter (more than 50% of full time). Each SIPP panel contains a set of households interviewed thrice a year[20] for about four years; however, between SIPP panels we observe a new set of households. This means we are unable to follow a household for the entirety of the SIPP panels. To generate a time-series with the unit of observation spanning the collection of the SIPP panels, 1983Q3 to 2015Q4, we identify an age-quarter cell as our unit of observation. By doing so, we can follow a cohort for the entire span of the SIPP. The cohort is denoted as the quarter when the head of household turned 30.

The idea, developed by Deaton (1985), allows us to treat each cohort as an entity, controlling for anything that is common across households in this age-quarter cell.[21] Loosely speaking, all 30 year old's in 1980 carry to an extent the same national labor market *information*, with some variation at the local level. The important proponent for this level of aggregation is that it also accounts for macroeconomic information for each cohort that occurred *prior* to the construction of the SIPP. For example, consider two groups of 55 year old's: those born in 1928 and those born in 1960. Those born in 1928 are 55 in 1983, for which we have labor-income data. Also, we have data on the 1960 birth cohort from 1990 to the end of the SIPP in 2015.

20. The latest design of the SIPP conducted interviews once a year.
21. This includes average wages, average hours, average taxes, average transfers, etc.

Given the high persistence and counter-cyclical behavior of idiosyncratic risk, we should see higher cross-sectional dispersion among the 1928 cohort than the 1960 cohort. The 1928 cohort might have entered the workforce in their youth, between 1942 and 1946; carrying the war years, the expansionary years following World War II, the civil rights movement and stagflation in the 70s. To summarize, with age-quarter cohorts, we can see variation between the two cohorts because of their different macroeconomic histories. It is at this level of aggregation that we estimate the income and shock variances.[22] Estimation of income risk and derivations are shown in Appendix C and D.

Figure 1 are the estimated series for persistent income risk and income risk shocks. To observe is income uncertainty in booms and recessions. Prior to the onset of a recession, income-risk is distinctively low (with the exception of the second recession) and thereafter spikes. This is particularly so for the Great Recession, where persistent income risk nearly doubles that of all other recessionary periods. For the impulse response functions, I use the sequence of income risk shocks, figure 1 panel (b), to capture exogenous changes in uncertainty.

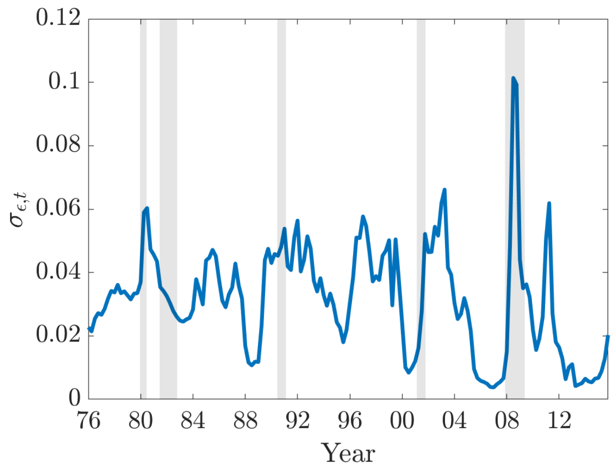
3.2 Liquidity Data

To measure portfolio liquidity, I decompose household portfolios into liquid and illiquid assets. For portfolio composition data, I use the Flow of Funds released by the Federal Reserve. It concerns the Board's quarterly financial accounts of the United States, which details the assets and liabilities of households, businesses, governments, and financial institutions. The data aggregates household data to makeup the balance sheet composition for the household sector. From the data, I construct the main outcome variable for the analysis: the liquidity ratio. This is the ratio of net liquid to net illiquid assets.[23]

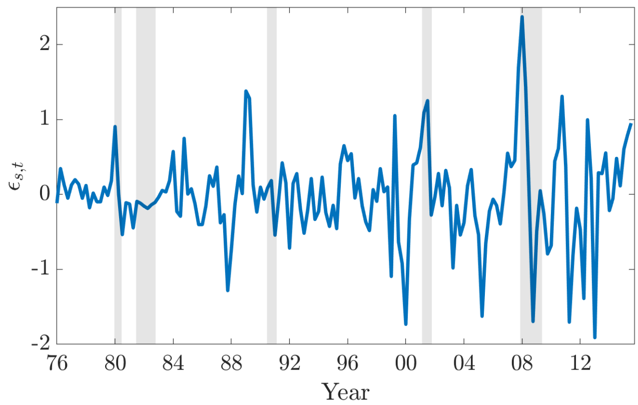
For the analysis, I also consider the liquidity premium. This is the premium paid on risk that arises from investing in an asset that cannot be sold in a timely manner (i.e., illiquid) or rather, the premium you pay for the benefits of liquidity. The difference in the yields is the liquidity

22. Due to the degree of aggregation and government budget cuts, data after 2015Q4 is limited in variation and is disregarded for the estimation.

23. Net liquid assets are net of current liabilities so as to represent pure, residual liquidity. This is to properly reflect the portion of assets in excess that may be used to counter income uncertainty. Net illiquid assets are net of mortgages (the largest household liability). Net liquid assets are defined as total currency and deposits, money market fund shares, various types of debt securities (Treasury, agency- and GSE-backed, municipal, corporate and foreign), loans (as assets), and total miscellaneous assets net of consumer credit, depository institution loans n.e.c., and other loans and advances. Net illiquid wealth is composed of real estate at market value, life insurance reserves, pension entitlements, equipment and non-residential intellectual property products of nonprofit organizations, proprietors' equity in non-corporate business, corporate equities, mutual fund shares subtracting home mortgages as well as commercial mortgages. Definitions for both are taken from Bayer et al. (2019).



(a) Persistent Income Risk



(b) Income Risk Shocks

Figure 1. *Notes:* Panel (a) is the standard deviation of persistent income risk, $\sigma_{\epsilon,t}$, from 1976Q1 to 2015Q4. Panel (b) are shocks to income risk, $\epsilon_{s,t}$. Details on their estimation is in Appendix C. Data for the estimation comes from the SIPP. Gray vertical shadow bands indicate NBER defined recessionary periods.

premium (LP). Following Bayer et al. (2019), I proxy it as:

$$LP_t = \underbrace{\frac{r_{h,t}}{q_t^{house}} + \frac{q_{t+1}^{house}}{q_t^{house}}}_{\textbf{Return on illiquid asset}} - \underbrace{(R_t^b)^{1/4}}_{\textbf{Return on liquid asset}} \tag{9}$$

where the illiquid asset I consider is housing and the liquid asset is the 3-month Treasury bill with secondary market returns, R_t^b (FRED Series: TB3MS). The return on housing is, $\frac{r_{h,t}}{q_t^{house}}$, the rent-to-price ratio at time t plus the quarterly growth rate of house prices, $\frac{q_{t+1}^{house}}{q_t^{house}}$.[24] Essentially, the return on housing is the sum of rents normalized by the price of the house and appreciation.

24. House prices are the Case-Shiller S&P U.S. National Home Price Index provided by FRED (Series: CSUSHPINSA).

Figure 2 plots the liquidity ratio and liquidity premium against persistent income risk from 1983Q1 to 2015Q4.[25] Literature says we should see a rise of liquidity premia occurring during flights to liquidity (Krishnamurthy (2010), Musto, Nini, and Schwarz (2015)). This is precisely what we observe. First notice the behavior of liquidity premium, panel (b) — it *responds* to income risk and is persistent. When income risk increases, the liquidity premium follows with a lag. During the 2007-2009 financial crises, income risk jumped to unforeseen levels, and the liquidity premium followed suit, reaching up to 6%. This is coupled with an increase in the liquidity ratio. Section 4 will discuss what is driving the increase.

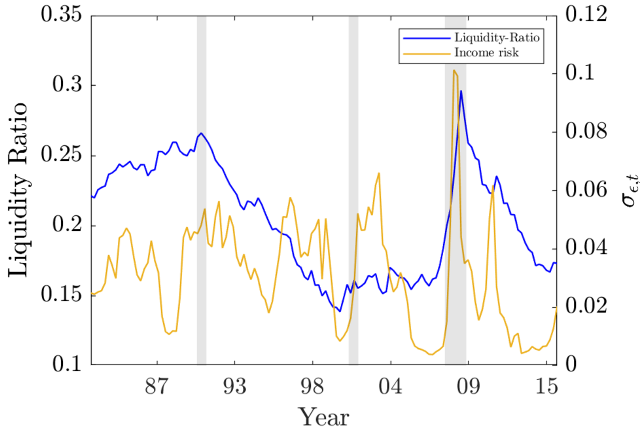
For most of the 80s, we see the ratio on an upward trend, propelled by the decline in net illiquid assets shown in Figure 3. During the latter half of the decade, however, the United States was experiencing an asset expansion, only modestly noticeable here through net liquid assets. Net illiquid assets are net of mortgages, which experienced a large increase in the 1980s.[26] The expansion arose from the deregulation of banks that allowed for a boom in the asset markets, but also from the accumulation of non-monetary liabilities which allowed for increased lending. Towards the end of the 80s and entering the 90s, however, household balance sheets began to weaken from monetary tightening. Liquid assets declined well into the 2000s, but illiquid assets tells us a different story.

Net illiquid assets experienced a decline until the second half of the 90s, when the equity markets experienced a stock market boom. The S&P 500 as well as the Dow Jones Industrial index more than doubled between 1996-2000. Income risk at the time was at its lowest point compared to prior history. Income risk will also jump to its then all-time high after uncertainty arose from the 1997 Asian financial crisis[27], six interest rate hikes from the Fed between 1999-2000, and the ultimate crash of the NASDAQ in March 2000. It would be around 2003-2006 that we witness an all-time low in income-risk followed by the all-time high. Both liquid and illiquid assets grew during this time, hence the rather plateau nature of the liquidity ratio. Growth originated

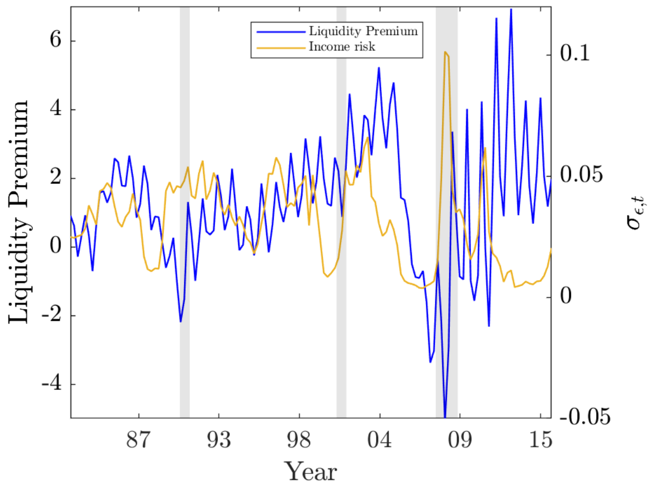
25. This is the post-Volcker disinflation era. Interest rate targeting, at the time the preferred monetary tool, could not mitigate the rampant inflation stemming from the 60s and 70s. In 1979, when Volcker became chairman of the Federal Reserve, he started to focus on money supply in stabilizing the economy. By focusing on this era, I filter out the endogeneity from structurally different monetary regimes.

26. Mortgage debt rose from 48% of disposable income in 1980 to 65% of disposable income in 1990 (Schinasi and Hargreaves (1993), pg. 4).

27. In 1995-1996, the U.S. dollar strengthened from monetary tightening. The Thai government's currency at the time was tied to the U.S. The immediate effect of the tightening on Thailand is a decrease in exports. As a result, they moved to float the baht and rapid capital outflows immediately started a domino effect across Southeast Asia. Capital outflows imply less demand for the base currency, leading to devaluation in their currencies. As prices weakened across Southeast Asia, foreign real debt increased.



(a) Liquidity Ratio



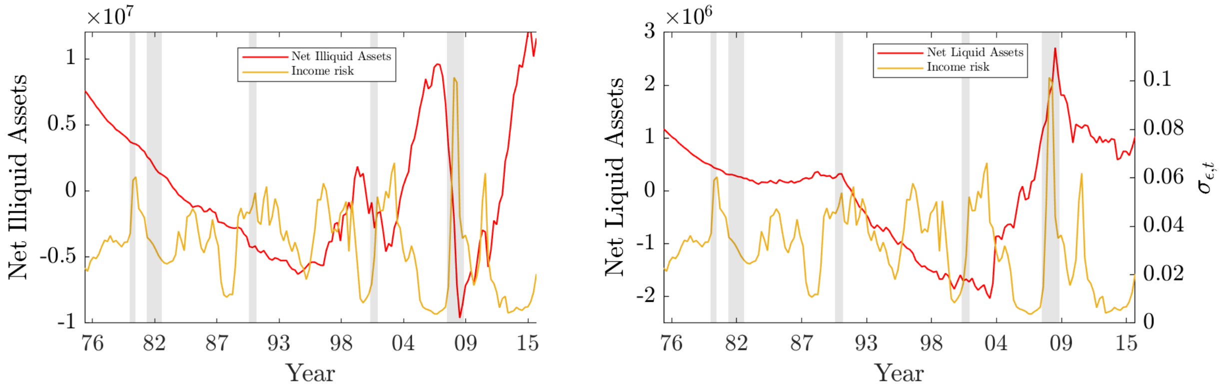
(b) Liquidity Premium

Figure 2. *Notes:* Panel (a) is the household net liquid assets divided by household net illiquid assets from 1983Q1 to 2015Q4. Panel (b) is the Liquidity Premium (%), proxied here as the difference between the return on housing (illiquid asset) and the nominal rate (liquid asset). Details on their estimation is in Appendix C. Data for the liquidity ratio is from the Flow of Funds (Table Z1-B.101) and data for the liquidity premium is from FRED. Gray vertical shadow bands indicate NBER defined recessionary periods.

from excessive lending by banks, the asset price inflation from speculation, and historically low interest rates (Ferguson and Schularick (2007)).

3.3 Default Data

To assess the impact of income risk on the credit-risk premium and default, I use data from the Federal Reserve Bank in St. Louis. Their data service, FRED, has collected data since 1947 for the most common macroeconomic aggregates and has more than 760,000 time series supplied mostly by public sources. To better illustrate the relationship between income uncertainty and



(c) Net Illiquid Assets

(d) Net Liquid Assets

Figure 3. *Notes:* This is (c) Net Illiquid Assets and (d) Net liquid Assets (in red), superimposed on the persistent income-risk series $\sigma_{\epsilon,t}$ (in yellow). Data is from the 1976Q1 to 2015Q4. Asset series are linearly de-trended. Gray vertical shadow bands indicate NBER defined recessionary periods.

default, I show both delinquency and default data from the 1980s-1990s to 2015. This offers a bidimensional outlook in analyzing consumer behavior in times of high income uncertainty.[28]

FRED defines delinquency as being 30 days or more past due on a loan/revolving credit line while still accruing interest on that loan. To capture delinquency, FRED carries delinquency rates for consumer loans, credit card loans, commercial/industrial loans, as well as its aggregation. The rate itself is the ratio of loans that are delinquent to all loans of that specific type.[29] For the default channel, I use the charge-off rate. Charge-offs are the loan balances removed from the books due to default, thus *charged* against their loss reserves. The rate is the defaulted credit-card/loan balances in comparison to the total amount of credit outstanding. FRED presents each series seasonally adjusted, at a quarterly frequency from 1985 to present-day. Although the theoretical section concerned only unsecured debt contracts, I also present here various loan structures for comparison and not as outcome variables for the estimation. Below are the time series for the delinquency rate, charge-off rate, and credit-risk premium.

Figure 4 shows delinquency rates are counter-cyclical — rates noticeably rise during recessions and decrease in booms. Delinquency rates also appear to be noticeably low prior to a crisis and more so approaching a financial crises. From 2000 to 2005, delinquency rates decreased from 4% to 2% and remained there for latter half of the boom. This means delinquent accounts made up 2% of all credit outstanding, which is remarkably low prior to a financial crises. Also

28. For the analysis, I follow the theoretical section in only studying default behavior under varying levels of income uncertainty.
29. For the rate, simply multiply by 100.

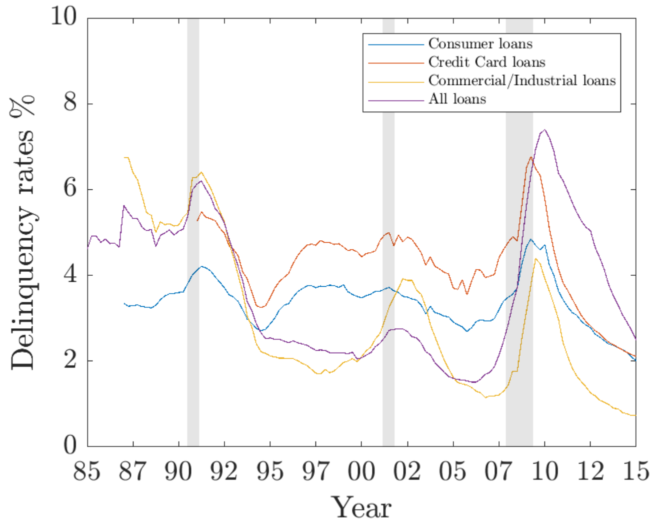


Figure 4. Delinquency Rates

Notes: Delinquency rates are the amount of past due balances relative to loans/credit outstanding. Data comes from FRED with varying start dates, all running until 2015. Consumer, credit card, commercial/industrial and all loans are FRED Series: DR**CL**ACBS, DR**CC**LACBS, DR**BL**ACBS and DR**AL**ACBS. Data is seasonally adjusted, at quarterly frequency. Gray vertical shadow bands indicate NBER defined recessionary periods.

distinctive is the subsequent climb between 2007-2009. Delinquent accounts nearly quadrupled, from 2% to 7%. This is in line with the macro-finance literature on suspiciously "good times" prior to a recession. For example, notably low interest rate environments, consumption and GDP growth (Mian, Sufi, and Verner (2017)), credit expansions (Schularick and Taylor (2012)) as well as bullish market sentiment (López-Salido, Stein, and Zakrajšek (2017)), over-optimism, and positive, extrapolative expectations (Bordalo, Gennaioli, and Shleifer (2018)) all precede financial recessions. Thus, it must be the case that the drop in delinquency rates is driven by these factors, but numerically by expansion in credit.[30] Yet data limitations (and a very sample size of business cycles in general) makes this a preliminary observation.

In times of high income uncertainty, consumers also appear to prefer to delay payments on credit-card accounts vs. consumer, commercial and industrial loans. Given that credit-card accounts are typically unsecured, consumers are willing to take on a penalty charge or a reduction in their credit score vs. foregoing payments on a secured contract, where assets are at stake (Athreya, Sanchez, Tam, and Young (2018)). For this precise reason, consumers sometimes become delinquent or *informally* default to smooth consumption. Delinquent consumers will

30. Between 2000 and 2005, in credit cards and other revolving plans, credit outstanding jumped 100 billion U.S. dollars.

then eventually adhere with payments and continue reducing their debt. In other cases, after 120 days of being delinquent, the consumer's balance may be *charged-off*.

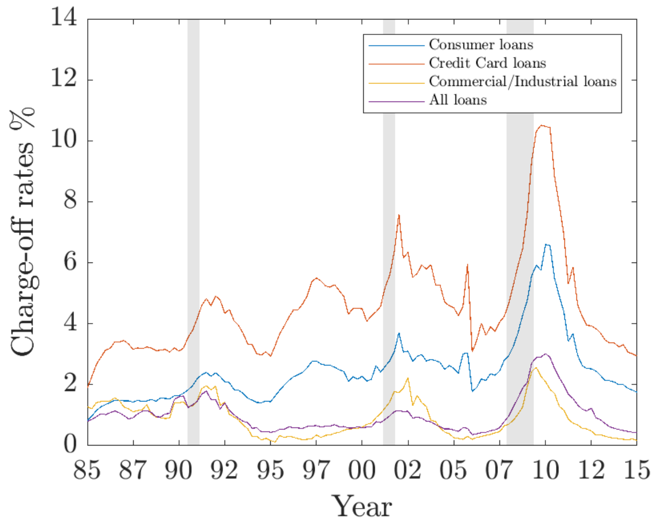


Figure 5. Charge-off Rates

Notes: Charge-off rates are the amount of defaulted balances relative to loans/credit outstanding. Data comes from FRED and begins 1985Q1, running until 2015. Consumer, credit card, commercial/industrial and all loans are FRED Series: COR**C**ACBS, COR**CC**T100S, COR**BL**ACBS and COR**AL**ACBN. Data is seasonally adjusted, at quarterly frequency. Gray vertical shadow bands indicate NBER defined recessionary periods.

Figure 5 presents the time series data on charge-off rates from 1985 to 2015. Unsurprisingly, it varies identically with delinquency rates. Defaulted balances rise during recessions and decline after. For credit-cards, rates reached as high as 10% during and slightly after the Great Recession. Commercial and industrial loans experience dampened swings compared to the high-variability of defaulted credit-card balances. This is again evidence for credit-cards being the "first to go" in trying to smooth consumption during a crisis. To note is also the fact that, at times, the charge-off rate is greater than the delinquency rate, which implies that although delinquent accounts may lead to defaulted accounts, giving the interpretation of defaulted accounts being a subset of delinquent accounts, you may also have borrowers who legally default on all accounts, even non-delinquent ones. There's also a double-whammy effect for charge-off rates where if defaulted balances increase (numerator), credit outstanding decreases (denominator) since banks charged-off the balance.

Figure 6 plots persistent income risk over the charge-off and delinquency rates for credit card loans. Prior to the two recessions, 1998-2000 and 2004-2006, income risk are low and persistently-unvarying while the *difference* between the delinquency rate and charge off rate is statistically insignificant. The direction of the difference is also important to note. In these two time periods, delinquency rates hover just over the charge-off rate. As soon as income risk spikes, for example for 2001-2003 and 2007-2009, there appears to be decoupling of the two

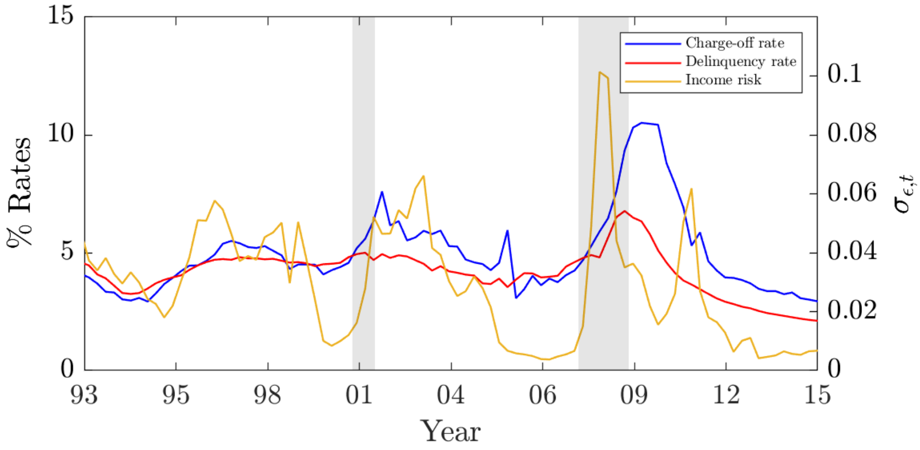


Figure 6. Default under Income Uncertainty

Notes: See figure 4 and 5 for details. Rates are subset to credit-card loans. Income risk (yellow) is the estimated standard deviation of persistent income risk. Data for the estimation of income risk comes from the SIPP.

rates with defaults surpassing delinquent balances; widening the gap between the charge-off and delinquency rate. This means as households face greater income uncertainty, some households plunge their delinquent accounts towards default or directly default to lessen the dissipation of their consumption. Below is the full correlation matrix of the variables. The Pearson correlation between income risk and the difference in rates becomes larger over time. For the length of the time series, the correlation is 0.0085, but for post-2000, the correlation is 0.24.[31] As theory has shown, default rates and delinquency rates share positive correlations with income risk and of comparable magnitudes, while the difference weakly so.

Table 1. Default Correlation Matrix

Variables	Income Risk (1)	Charge-off Rate Rate (2)	Delinquency Rate (3)	Rate Difference (4)
Income Risk	1	.45	.50	.24
Default Rate	—	1	.77	.83
Delinquency Rate	—	—	1	.27
Rate Difference	—	—	—	1

Notes: Coefficients shown are Pearson's correlations for a linear relationship. Income risk is the estimated standard deviation of persistent income risk. Charge-off rates are the amount of defaulted balances relative to loans/credit outstanding. Delinquency rates are the amount of past due balances relative to loans/credit outstanding. Data for the estimation of income risk comes from the SIPP. Charge-off and delinquency rates come from FRED. Only data from post-2000 is considered.

31. For the length of the time series, the row 1 correlations are $1, 0.33, 0.54, 0.0085$.

Figure 7 reports the average nominal credit-card interest rate offered by banks and the risk premium from 1995-2015. The risk premium is the difference between the interest rate offered to consumers and the risk-free rate exercised between financial intermediaries. Essentially, the risk premium is the price banks charge to accept consumer risk. Thus, it is only to be expected that when income risk is low, risk premium is also low and that is what is precisely shown for figure 7. Income risk and thus, the risk premium are low during economic booms and the opposite is also true for recessions. Currently, because of the historically low interest rate levels, rates charged to consumers are quite low, despite the risk premium being at an all-time high.

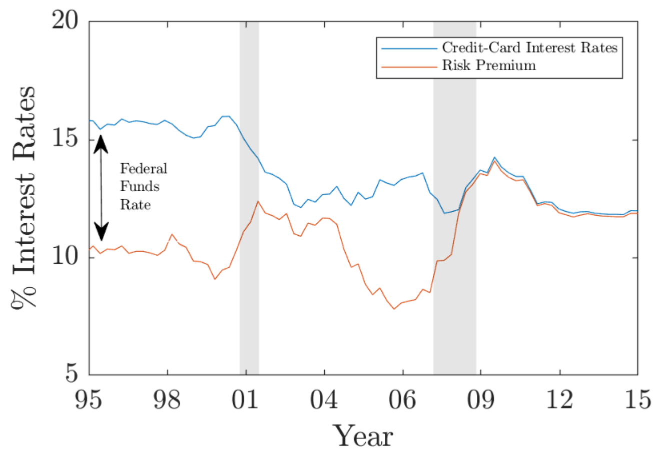


Figure 7. Credit-risk Premium

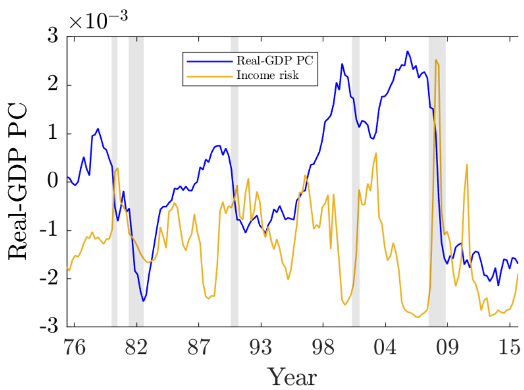
Notes: Credit-card interest rates are commercial bank rates offered on credit-card plans (FRED Series: TERMCBCCALLNS). Data comes from FRED and begins 1994Q4, running until 2015. Data is not seasonally adjusted, at quarterly frequency. Risk Premium is the difference between the rates banks offer to consumers on unsecured debt and the risk-free rate measured by the Federal Funds rate. Gray vertical shadow bands indicate NBER defined recessionary periods.

3.4 Prosperity Data

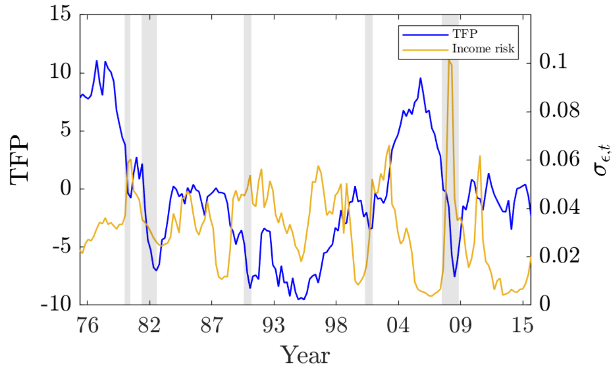
To measure the impact of income uncertainty on prosperity, I consider the standard macroeconomic aggregates: (1) GDP (2) Consumption (3) Investment and (4) Total Factor Productivitiy (TFP) plus (5) the spending multiplier. For (1)-(3), I take macroeconomic time series data from FRED and for (4), I use Fernald (2014)'s TFP series.[32] For (5), I rely on data from Ramey and Zubairy (2018). This includes government purchases and the extended military news shock series needed to construct the multiplier. The reason for the selection of measures is to decompose the movements in GDP. It is important to understand how income uncertainty permeates through

32. FRED provides quarterly seasonally adjusted annual series from 1947 onward for most aggregates. Seasonal adjustments correct for seasonal variation in aggregate variables, but it's based on some fixed correction versus actual recognition of contemporary events (non-seasonal). Refer to Blanchard and Perotti (2002) for more details.

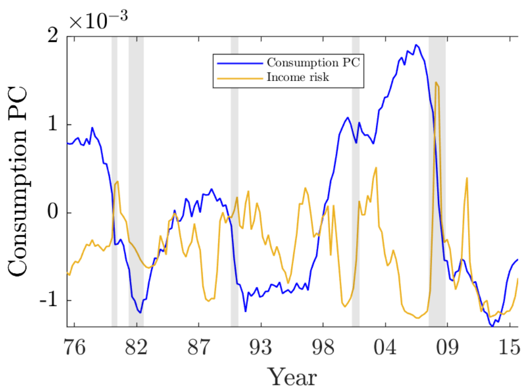
consumption, investment and/or TFP and how that translates to GDP fluctuations. That way, policy makers can be precise in their policy implementations in re-stabilizing the economy. In re-stabilizing the economy for example, the government may attempt to stimulate the economy through increased government spending; for instance, with stimulus packages. It is typically in these times that households internalize income uncertainty in their consumption and investment decisions. Hence, it is also important to understand how varying levels of income uncertainty affect economic recovery and whether these stimulus packages are indeed the correct response. Below are plots of the macroeconomic aggregates and the raw TFP series:



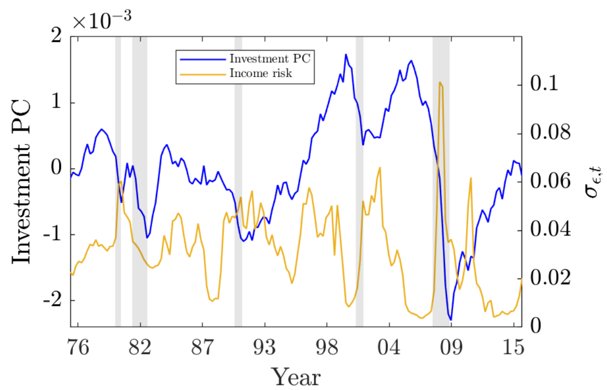
(a) Real-GDP PC



(b) TFP



(c) Consumption PC



(d) Private Investment PC

Figure 8. *Notes:* Real-GDP PC, Consumption PC, Investment PC and TFP are de-trended for the time period considered. Real-GDP PC, Consumption PC and Investment PC are FRED Series: GDPC1, PCECC96, and GPDIC1 respectively, divided by the U.S. population. TFP is raw total factor productivity from Fernald (2014). Income risk is shown in yellow.

For the government spending multiplier, I use the RZ shocks and BP innovations to capture the exogenous variation in government spending. The military shock series from Ramey (2011b) (shown below) heavily relied on *Business Week*, which has forecasts/predictions on future economic outcomes since its debut in 1929. It is "an estimate of changes in the expected present value of government spending." Because changes in government spending are often anticipated long before government spending actually changes, the present value is taken, discounted at the 3-year Treasury bond rate prevailing at the time and the long-term government bond rate before the 1950s.[33] As part of the identification assumption, the spending shocks must be military in nature because they do not respond to forces determining macroeconomic aggregates such as GDP or consumption, but from geopolitical events.

For the estimations, the RZ shocks are scaled by lagged nominal GDP. For the BP innovations, Blanchard and Perotti (2002) identify them using a VAR multivariate system that includes a tax measure, GDP and government spending.[34] To recover the reduced form residuals, I regress government spending on four lags of government spending, GDP, and federal tax receipts — all in log-real terms — and extracting the residuals as my innovation.[35]

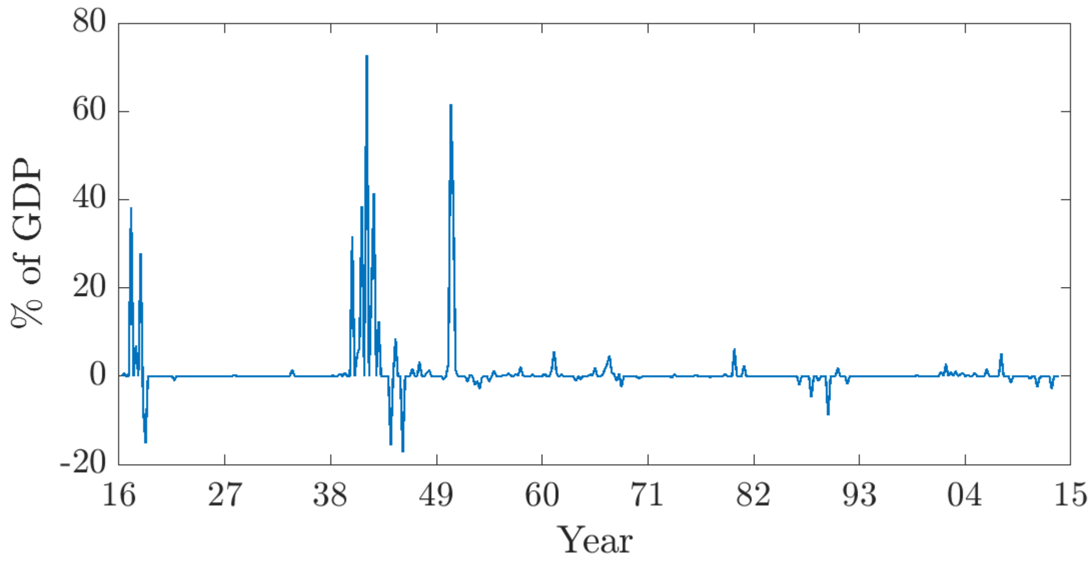


Figure 9. Military Shock Series from Ramey (2011b)

Notes: The military shock series represents the present discounted value of military spending news, in percentage terms of lag GDP. The shock series and GDP are both in billions. Data comes from Ramey (2011b).

33. I provide the first stage Kleibergen Paap F-statistic for evidence of a weak instrument. As the horizon h increases, the exogenous variation captured by the shock *today* dampens.

34. Bernardini and Peersman (2018) mentions that VAR estimated innovations are predictable and built from systems of time-invariant parameters. Given the length of the data, it is more appropriate to pose the parameters as time-varying to mitigate the volatility observed in the shocks.

35. Results are also robust to 4 and 12 lags. A quadratic time trend is also included in the structural equation.

4 Estimation

4.1 Estimation Framework

To estimate the impulse response functions for the various channels, I take the estimated sequence of shocks to household income risk and formulate an LP model. This avoids the need to specify some underlying multivariate system and to exploit its simplicity in estimation and inference.[36] The model will take the general form of:

$$\Upsilon_{t+h} \;=\; \gamma_h + \theta_h \epsilon_t^s + X_{t-1} + \nu_{t+h} + \mathbf{1}_{h>0}\nu_{t+h-1} \tag{10}$$

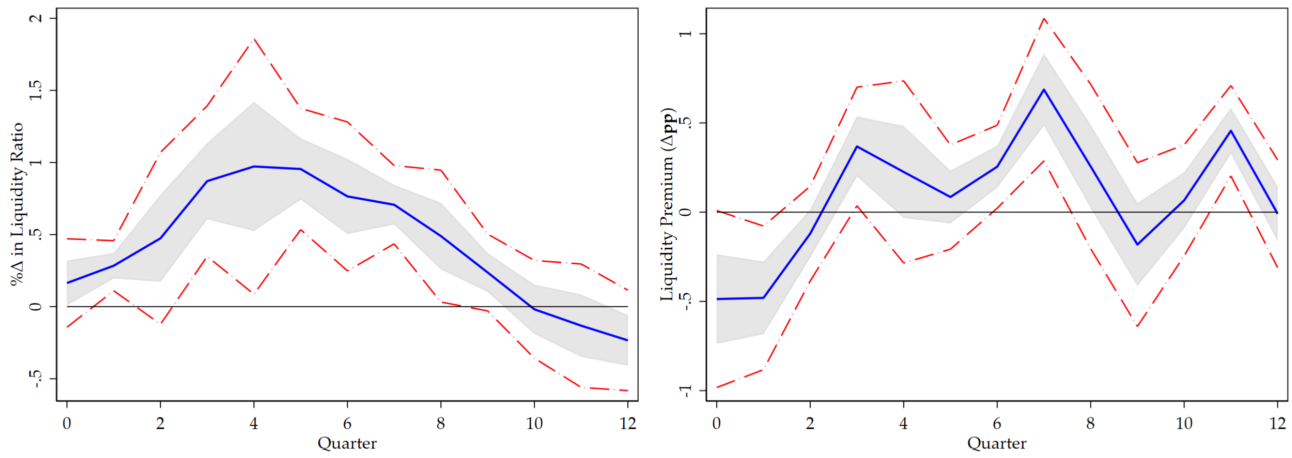
where Υ is the set of liquidity, default and prosperity outcome variables, ϵ_t^s is the sequence of shocks to household income risk, and X_{t-1} is a vector of controls.[37] Although this is a shock series and by definition, exogenous, the additional controls reduce the likelihood that these shocks were economically motivated. Following a recommendation from Jordà (2005), I also include the $h-1$ residual from the h^{th} regression for $h > 0$. This is to increase efficiency of the estimates by reducing noise, but also accounting for lagged endogeneity not captured by the set of controls. Standard errors are measured with a Newey-West window estimator for heteroskedastic and auto-correlation consistent errors. Results follow.

4.2 Liquidity Results

Panel (a) of Figure 10 shows an increase in income uncertainty increases the liquidity ratio. A 1 standard deviation effect increases the ratio gradually at first, before seeing a jump at the end of the first year, from 0.5% in quarter 2 to 1%($t - stat = 2.17$) in quarter 4. The second year shows an unhurried decline in the ratio, from 0.95% ($t - stat_{q5} = 4.50$) to 0.71% ($t - stat_{q7} = 5.16$), before dissipating in year 3. The increase arises from changes in demand for liquid and illiquid assets. As households expect greater income uncertainty, they will accumulate liquid assets

36. By running local projections as a series of regressions vs. VARs, the impulse response function is not restricted to some shape. Also, LHS variables make be expressed differently than RHS variables, which is not possible under VAR estimations. Essentially, it is more robust to misspecification. The estimates, however, are noisy at times (compared to SVAR which is known for its efficiency), particularly so at longer time horizons, where it is susceptible to greater imprecision. I provide a discussion on this in Appendix E.

37. Controls include returns on 3-month T-bills and the GDP share of the government deficit as well as the log of (1) real-GDP (2) real-consumption (3) real-investment (4) TFP and (5) real wages. 1 lag is considered since for each lag, 7 additional variables must be considered. This may be too demanding given the small sample size, thus I rely on the fact that I do have exogenous variation, but also conservatively include the previous residual for possible lagged endogeneity. Given (1), (2), and (3) are highly correlated, I ran results without (2) and (3) for a more parsimonious specification. Results are robust. Although adding more lags compromises full rank of the regressors, results are not very much different.



(a) Liquidity Ratio

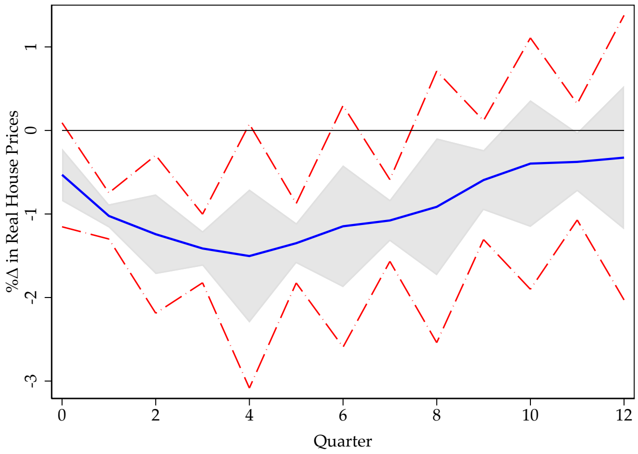
(b) Liquidity Premium

Figure 10. *Notes:* This is the effect of a 1 standard deviation increase in income uncertainty on (a) the liquidity ratio and (b) the liquidity premium. The blue line reports θ_h for $h = 0, 1, \ldots 12$. Data is from 1983Q1 to 2015Q4. Δ **pp** is the change in percentage points. $\%\Delta$ is the percent change. Newey-West standard errors are shown in gray. 95% confidence intervals are the red dashed lines.

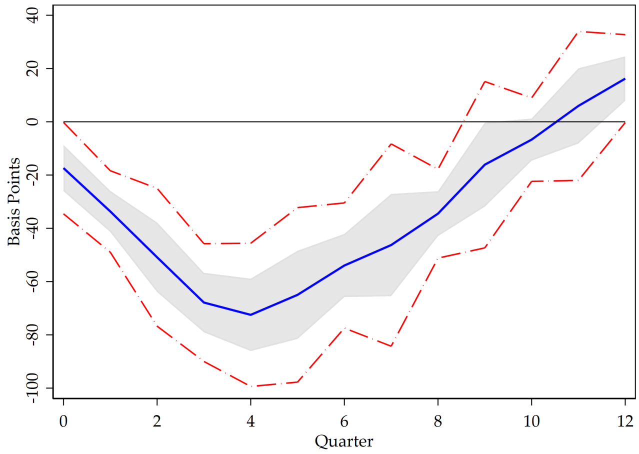
relative to illiquid for short-run consumption and also in case of financial distress. This is reinforced by Figure 3, panel (b) of Figure 10 and Figure 11.

The liquidity premium increases sharply after quarter 1— a shock to income risk increased the liquidity premium at the turn of quarter 1 by nearly 100 basis point jump, from $\theta_1 = -0.50\%$ $(t - stat = -2.36)$ to $\theta_3 = .40\%$ $(t - stat = 2.19)$, with the apex reaching $0.70\% (t - stat = 3.41)$. General economic theory tells us this occurs when the demand for liquid assets increases, driving the return on liquid assets downward. This is what is observed for panel (a) of Figure 3 and Panel (b) of Figure 11: a stark solo flight to liquidity compared to the descent of net illiquid assets, net housing assets and non-housing illiquid assets and a drop in rates of about 73 basis points after year 1 ($\theta_4 = -72.49,\ t - stat = -5.34$).

An increase in the return premium may also, however, arise from increased rents and/or decreasing house prices. Panel (b) of Figure 11 shows a drop in real house prices of 140 basis points ($\theta_4 = -1.41\%,\ t - stat = -6.82$) after 1 year. This means the rise in the liquidity premium is mostly driven by the collapse of house prices vs. demand for liquidity as rates do not fall equally as large. As a robustness check, given the small sample size of the data and the nature of the Great Recession, I ran results without the Great Recession (see Appendix G.3). This flips the interpretation. Housing prices now show a much mitigated decrease, but so does the liquidity ratio. Yet, the change in house prices is positive after the first year, while the liquidity ratio remains positive and growing in year 2. Panel (d) of Figure G.1 confirms that the demand for liquidity is responsible for the persistent increase. The nominal rate is strongly negative, especially during that second year and larger in magnitude than the full-sample result.[38] This confirms how econometrically influential the Great Recession is.



(a) Real House Prices



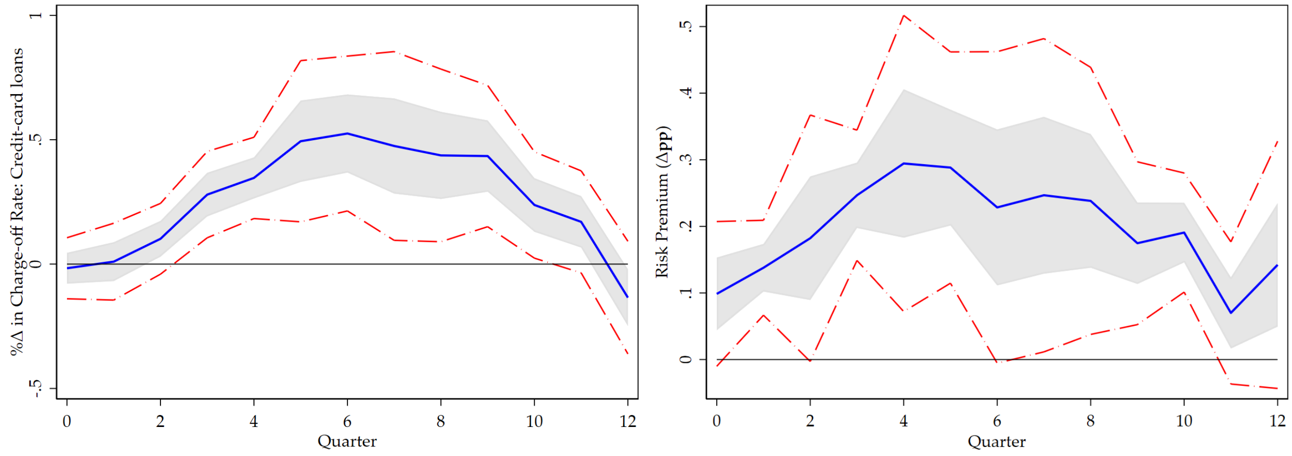
(b) Nominal Rate

Figure 11. *Notes:* This is the effect of a 1 standard deviation increase in income uncertainty on (a) house prices (FRED Series: CSUSHPINSA) divided by the all-items CPI (FRED Series: CPIAUCSL). and (b) the 3-month T-bill secondary rate (FRED Series: TB3MS). Data is from the 1980s to 2015Q4. The blue line reports θ_h for $h = 0, 1, \ldots 12$. 100 basis points is equal to 1%. Newey-West standard errors are shown in gray. 95% confidence intervals are the red dashed lines.

4.3 Default Results

Figure 12 plots the impulse response functions for charge-off rates and the credit-risk premium. A shock to income risk causes households to default in order to smooth consumption across states, seeing an increase in the charge-off rate upon impact. The effect is persistent and plateaus for year 2 and the beginning of year 3 before re-stabilizing. The change in default rates increases to 0.35% ($t - stat = 4.30$) after quarter 4, 0.53% ($t - stat = 3.35$) after quarter 6, and 0.43% ($t - stat = 3.03$) after quarter 9. The credit-risk premium also mostly follows the same shape as the change in default rates. The risk premium of consumer credit over the federal funds rate doubles over the first year, from $\theta_1 = 0.14\%$ ($t - stat = 3.86$) to $\theta_4 = 0.29\%$ ($t - stat = 2.64$). The effect persists, with a 0.19%*** increase in quarter 10. Thus, as households are more exposed to income risk, banks swiftly price the increased risk to compensate for the potential losses reasonably expected, as shown in panel (a) of Figure 12.

38. The difference in magnitudes in the nominal rate may have risen from the nature of the Great Recession being coupled by the liquidity trap.



(a) Charge-off Rates

(b) Risk Premium

Figure 12. *Notes:* This is the effect of a 1 standard deviation increase in income uncertainty on (a) the charge-off rate on credit card loans (FRED Series: CORCCACBS) and (b) the risk premium, θ_h. For panel (a), data is from the 1985Q1 to 2015Q4 and for panel (b), data is from 1994Q4 to 2015Q4. The blue line reports θ_h for $h = 0, 1, \ldots 12$. Δ **pp** is the change in percentage points. Newey-West standard errors are shown in gray. 95% confidence intervals are the red dashed lines.

4.4 Prosperity Results

4.4.1 Macroeconomic Aggregates

Figure 13 reports the effect of a 1 standard deviation increase in income risk on macroeconomic aggregates. Output, consumption and investment fall on impact and do not rebound until the end of year 3. For output, the effect is persistently negative, hovering around -0.50% between quarter 3 and quarter 9, before recovering over year 3. The largest component in the GDP equation comes from consumption[39], so it is no surprise output takes a dip. As households face increased income uncertainty, they are more reluctant to consume out of uncertain income, birthing the precautionary savings motive commonly hypothesized and tested in the precautionary savings literature.

The decline in consumption is stark, reaching a percent change of -0.72% ($t - stat = -4.39$) in quarter 7. The effect of income risk on consumption is also persistent, hovering around -0.60%. The second largest component in GDP's composition is investment. Its reaction to a shock in income risk takes on the same convex curvature as GDP and consumption, but of a greater magnitude. By the first quarter, the drop in new investment is nearly triple size of the trough of consumption and GDP, with a percent change of -1.51% ($t - stat =$

39. Consumption today constitutes 70% of GDP today (De Nardi, French, and Benson (2012)).

-5.13). By quarter 3, it quintuples and by the end of year 1, it is almost eight times greater (-4.51% ($t - stat = -4.24$)).[40]

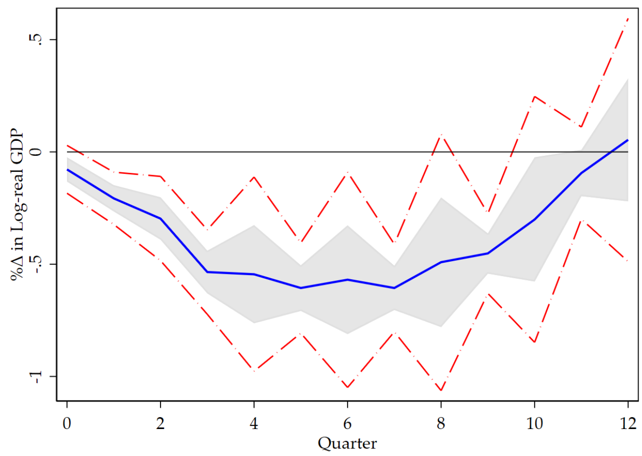
During times of high uncertainty, due to the demand for liquid assets, the accumulation of savings, and simply monetary activism, interest rates decline. This is noted in figure 11. This makes the cost of borrowing cheaper and should entice investment; this could be in the form of new construction, new fixed investment, new private inventory and other capital formations. However, there may be factors inhibiting this opportunity for investment, flipping the accelerator effect. For example, the drop in aggregate demand from precautionary savings may contribute to a slump in business investment (e.g., drop in new inventories). As sales and profits decrease from the change in consumer expectations (De Nardi, French, and Benson (2012)), demand for new capacity/facilities as well business confidence topples; thus, fixed investments become unattractive.

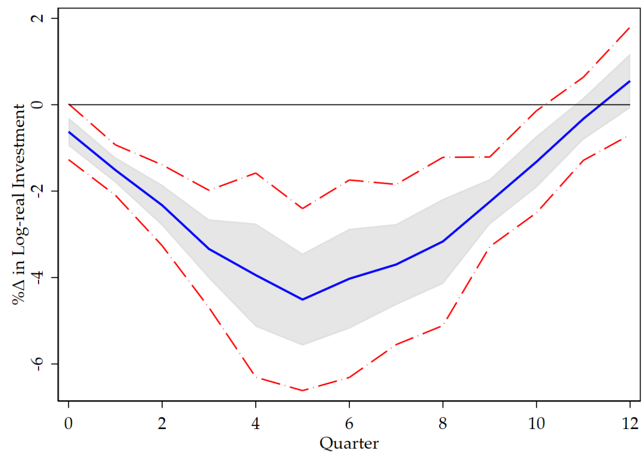
Residential investment may also play a large role. During the Great Recession for example, residential investment plummeted from the rise and fall of house prices. Housing a few years prior was an attractive asset for its appreciation. This eventually caused an excess supply of housing, evident by home-ownership,[41] and the decline of new residential investment during the Great Recession. Interest rates at the time were unable to entice other forms of investment given the liquidity trap.

Financial frictions were also present as financial intermediaries limited their lending capacity in order to mitigate their exposure to default risk — *a credit crunch*. Balance sheet effects and the decline in aggregate demand moved businesses to cut production, lending to layoffs and so on. This rise in economic slack from unemployment and under-utilization of capital resources is evident in panel (b) of Figure 13. Total factor productivity (TFP) or the Solow Residual declined 0.41% on impact from a shock to income risk, nearly tripling by quarter 3 ($\theta_3 = -1.13$, $t - stat = -2.96$). TFP does recover quickly; stabilizing and back on trend by quarter 7. In sum, the lack of private activity caused by income uncertainty has to be countered to alleviate recessionary woes. In the next section, I describe the spending multiplier and how effective this may be in times of varying income-uncertainty.

40. The decline is less rash when I remove quarters associated with the Great Recession, yet still quantitatively large. See Appendix G.8

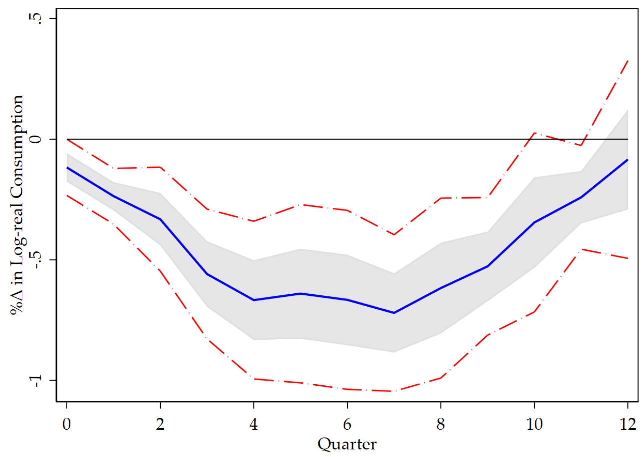
41. Home-ownership was 65% in 1996, 69% in 2006 and again 65% in 2014. It dropped to 63% in 2017, but is now back on a rise similar to that of pre-Great Recession, with home ownership at 68% as of 2020Q2 (Quarterly Residential Vacancies and Home ownership, Second Quarter 2020, release number: CB20-107).

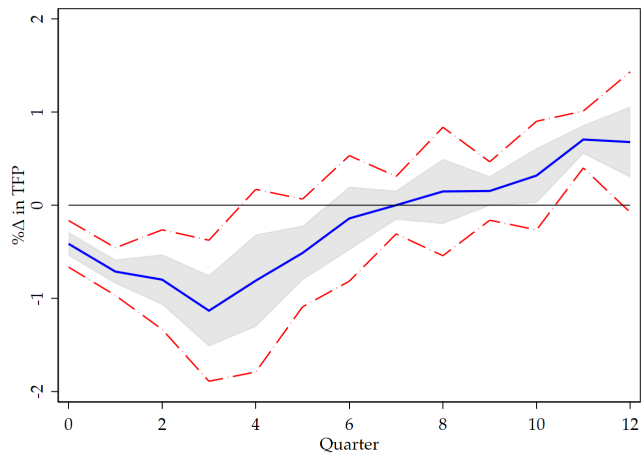




(a) GDP

(b) Investment





(c) Consumption

(d) Solow Residual

Figure 13. *Notes:* This is the effect of a 1 standard deviation increase in income uncertainty on (a) Real GDP (FRED Series: GDPC1) (b) Real Investment (FRED Series: GPDIC1) (c) Real Consumption (FRED Series: PCECC96) and (d) the Solow Residual. Data is from 1976Q1 to 2015Q4. The blue line reports θ_h for $h = 0, 1, \ldots 12$. Newey-West standard errors are shown in gray. 95% confidence intervals are the red dashed lines.

4.4.2 State Dependent Multiplier under Income Uncertainty

The state of the economy is fundamental in capturing the size of the spending multiplier. At any point in history, you cannot disassociate output and government purchases from some state of the economy, whether in times of slack, operating at the zero lower bound, recessions or institutional characteristics such as political affiliation and exchange rate regimes. This paper considers the significance of income uncertainty for expenditure side fiscal policy. As above, I estimate the impulse responses using Jordà (2005)'s local projections (LP) method. First, for comparison, I estimate the "average" cumulative multiplier by running $h = 16$ LP-IV regressions, instrumenting the variation in cumulative changes in government purchases using the defense news series constructed and extended by Ramey (2011b) (RZ) and government spending innovations as identified by Blanchard and Perotti (2002) (BP). The cumulative multiplier, m_h, is derived from the following equation[42]:

$$\sum_{j=0}^{h} \Delta^j y_{t+j} \;=\; \gamma_h + \sum_{j=1}^{8} \Theta_h Z_{t-j} + m_h \sum_{j=0}^{h} \Delta^j g_{t+j} + \Phi_h T_t + \varepsilon_{t+j} \tag{11}$$

where $m_h = \frac{\sum_{j=0}^{h} \Delta y_{t+j}}{\sum_{j=0}^{h} \Delta g_{t+j}}$, y_t is log-real GDP, g_t is log-real government spending, Z_{t-j} is the set of pre-treatment controls[43], and T_t is a quartic time trend to capture low-frequency demographics.[44] For inference on the time series, I weigh the variance-covariance matrix with a Newey-West window estimator for heteroskedastic and auto-correlation consistent errors.[45] The controls specified follow Blanchard and Perotti (2002), Ramey (2011b), Ramey and Zubairy (2018), and Ferriere and Navarro (2018). The data spans nearly a century — 1916Q1 to 2014Q4. Samples of 160 observations have been shown to perform impressively so under the LP method with respect to magnitude and direction. The sample I use is just under 400— more than enough for reliability and proper inference.

Historically, of varying identification strategies, observed fiscal activism reports a multiplier effect between 0.6 and slightly above 2 (Hall (2009), Gordon and Krenn (2010), Ramey (2011a), Auerbach and Gorodnichenko (2013), Ramey and Zubairy (2018) to name a few studies).[46] The estimated cumulative multiplier here after the first four quarters grows from 0.70 to 1.13 ($t - stat_{q5} = 2.96$, $t - stat_{q16} = 5.40$), in line with previous studies.

The main question is, however, whether the cumulative multiplier is statistically different under varying levels of income uncertainty. This has important policy implications given the role

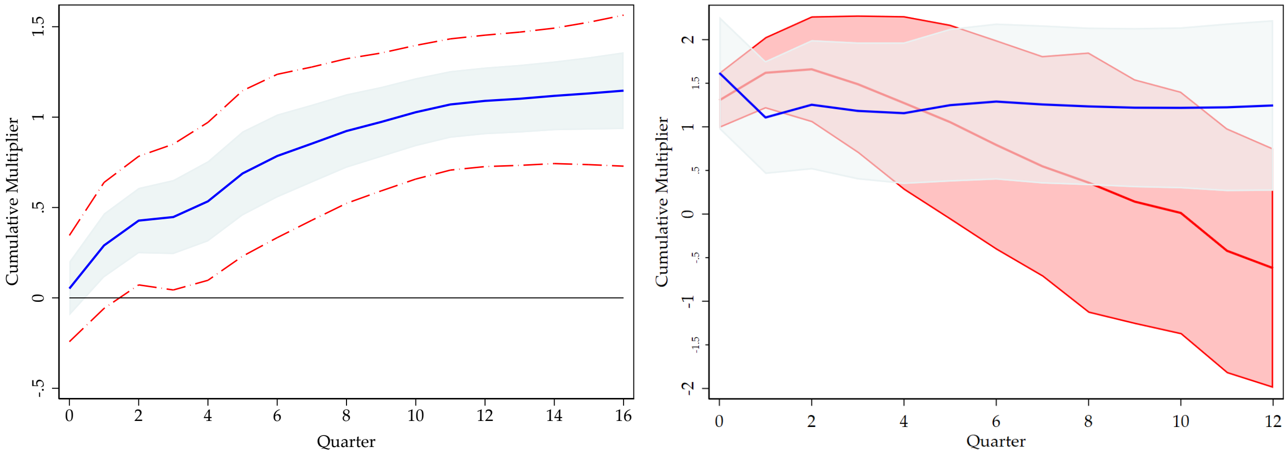
42. The cumulative multiplier is also considered one of the more appropriate measures, as it considers the growing (shrinking) of the cumulative changes over time. You may also consider other measures, such as the impact multiplier $\frac{\Delta Y_t}{\Delta G_t}$, the multiplier at some horizon $\frac{\Delta Y_{t+h}}{\Delta G_t}$, and the peak multiplier $\max_N \frac{\Delta Y_{t+h}}{\Delta G_t}$ (Spilimbergo, Schindler, and Symansky (2009)).

43. The controls for equation 11, Z_{t-j}, are eight lags, j, of log-real GDP, log-real government spending, and the average marginal tax rate (AMTR). Following Ferriere and Navarro (2018), the AMTR, given it varies annually, is repeated across quarters annually to be in line with the quarterly frequency, which is essential to estimate fiscal shocks. Blanchard and Perotti (2002) provides a discussion on the importance of quarterly data for estimating fiscal shocks. Seasonal patterns lend to fluctuations in taxes derived from quarterly economic activity; however, our tax data only fluctuates at the annual level. Alternatives are not discussed in Ferriere and Navarro (2018).

44. By definition, a trend is a slowly evolving change. Ramey and Zubairy (2018) suggests a quartic trend given pre- and post-WWII data — quadratic trend for post WWII data. The trend would capture demographic variations such as the Baby Boom.

45. As reflected in the code, I make sure to use small sample statistics to request the degrees-of-freedom adjustment $N/(N-k)$ be made to the variance-covariance matrix of parameters and that small-sample F and t statistics be reported, where N is the sample size and k is the number of parameters estimated. By default, no degrees-of-freedom adjustment is made, and Wald and z statistics are reported. For $h > 0$, the estimator essentially corrects for large shifts in the dependent variable, the improvement/deterioration of measurements, systemic variation in quarterly data, auto-correlation in the residuals from successive leading of the dependent variable, etc.

46. More studies are listed on Ramey (2011a) and Ramey and Zubairy (2018).



(a) Average Cumulative Multiplier

(b) M1

Figure 14. *Notes:* This is the cumulative multiplier (a) as an average of all economic states and (b) under varying levels of income uncertainty dichotimized by average (**M1**). For panel (a): data is from 1916Q1 to 2015Q4. The blue line reports the cumulative multiplier, m_h, for $h = 0, 1, \ldots 12$. Newey-West standard errors are shown in gray. 95% confidence intervals are the red dashed lines. For panel (b): data is from the 1976q2 to 2015Q4. The blue line reports the cumulative multiplier under high income uncertainty. The red line reports the cumulative multiplier under low income uncertainty. The light-blue and red shade are Newey-West standard errors bands.

of consumption and investment on aggregate output. To estimate, I take ideas from Auerbach and Gorodnichenko (2013) and Ramey and Zubairy (2018) and specify the following model:

$$\begin{aligned}\sum_{j=0}^{h} \Delta^j y_{t+j} =& I_{t-1}\left[\gamma_{HI,h} + \sum_{j=1}^{4} \Theta_{HI,h} Z_{t-j} + m_{HI,h} \sum_{j=0}^{h} \Delta^j g_{t+j}\right] \\ &+ (1 - I_{t-1})\left[\gamma_{L,h} + \sum_{j=1}^{4} \Theta_{L,h} Z_{t-j} + m_{L,h} \sum_{j=0}^{h} \Delta^j g_{t+j}\right] + \Phi_h T_t + \varepsilon_{t+j}\end{aligned} \tag{12}$$

where the subscript HI denotes a high uncertainty quarter and L a low uncertainty quarter. Again, I instrument for variation in $\Delta^j g_{t+j}$ using the RZ shocks and BP innovations, this time interacted with the high and low income uncertainty at quarter $t-1$.[47] To identify points of high and low income uncertainty, I consider two definitions and one alteration.

The first definition (**M1**) uses the average income risk as a cutoff point, where all quarters above this cutoff are classified as carrying high income uncertainty and all quarters below are classified as carrying low income uncertainty. Although simple to implement and seen in the literature, it ignores the variation over time. For example, the Great Recession will naturally

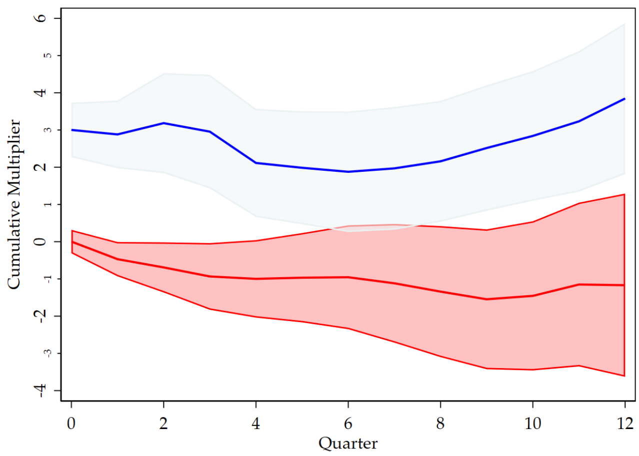
47. This implies four instruments: (1-2) a low and high uncertainty RZ shock and (3-4) a low and high uncertainty BP innovation at time $t = 0$. The specification only considers 4 lags as opposed to 8 above due to sample size limitations brought upon by the length of income risk and only a quadratic trend.

increase the overall average of income risk, making it more likely to misclassify a high income uncertainty quarter as a low one. To correct for this, I consider Harding and Pagan (2002)'s BBQ algorithm (**M2**) for identifying peaks and troughs in a time series. This is an improvement on the Bry and Boschan (BB) algorithm (Bry and Boschan (1971)) since it identifies business cycle peaks and troughs based on quarterly data (Q).

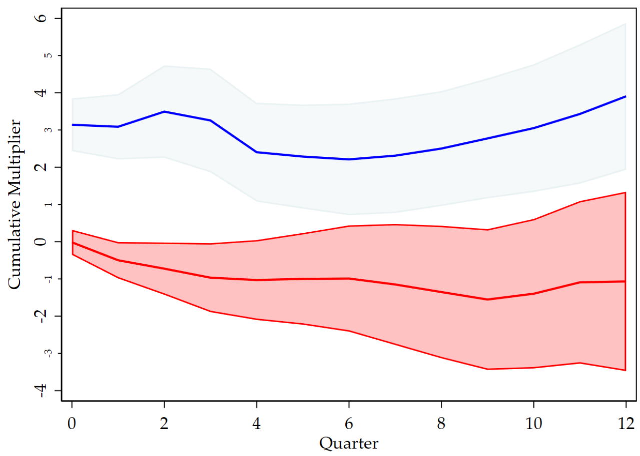
The algorithm determines the local minima or maxima using the following condition: A candidate peak is an observation j for which $\sigma_{j-1} < \sigma_j > \sigma_{j+1}$, where σ is income risk. A candidate trough is an observation j for which $\sigma_{j-1} > \sigma_j < \sigma_{j+1}$. Given that the algorithm uses the lag and following quarter in identifying the peak, I also classify these supporting quarters inline with their candidate point. This is to better capture the definition of a state rather than defining uncertainty over one quarter. This second definition does run into the problem that three observations do overlap. For these three observations, precisely 1984q3, 2004q3, and 2014q2, I used two criteria to redefine them (**M3**). First, I compare magnitudes of income risk to the average income risk under low and high uncertainty. Second, I consider the direction of the income shock. If it is closer to the low uncertainty average and has a positive income shock, it is defined as low uncertainty. The opposite holds for redefining high uncertainty. For **M2** and **M3**, the specification is identical to equation 12, except I_{t-1} and $(1 - I_{t-1})$ become HI and L respectively, as these indicator functions are no longer complements.

Results for **M1** are shown in Figure 14, panel (b), while results for **M2** and **M3** are shown in Figure 15. Under **M1**, we clearly see the role of income uncertainty on the spending multiplier. High income uncertainty produces a rather constant multiplier around 1.2, similar to that of the average multiplier. Under low income uncertainty, the multiplier is on a steady decline after quarter 2, breaking unity at quarter 7 and becoming negative by quarter 12. Although there are visible differences, p-values for equality of coefficients report no statistical difference in their paths, given parameters are noisily estimated. **M2** and **M3** show a different story. Using Harding and Pagan (2002)'s algorithm, the spending multiplier paths are much more distinguished. Under low income uncertainty, the multiplier is consistently negative. An increase in government spending by \$1 here will not stimulate private activity and will actually decrease output by an average factor of 1. Under high income uncertainty, the multiplier is quite large, being consistently above 2 and at times, 3. Removing variation from the Great Depression increases the multiplier to an average of 4.4.

This means in times of high income uncertainty, government spending is indeed the correct response to stimulate private activity to re-stabilize the economy. The p-values for equality of coefficients in the first year are < 0.03, suggesting spending is statistically different for varying levels of income uncertainty.[48]



(a) M2



(b) M3

Figure 15. *Notes:* This is the state-dependent cumulative multiplier (a) using the BBQ algorithm and (b) after redefining some observations as discussed in the text. See figure 14 for details.

5 Conclusion

The thesis lays out the breath and depth of income uncertainty on the U.S. economy. By identifying a sequence of income risk shocks via quasi-maximum likelihood estimation, we can measure its effects on default risk, liquidity ratios as well as their corresponding premiums. As households face increased income risk, they will accumulate liquid assets relative to illiquid to subsidize short-run consumption and be better suited to counter future financial distress. Increased uncertainty also shows to amplify default risk as households move to save and resort to non-payment on unsecured debt contracts to further smooth consumption across states at the expense of smoothing across time. The associated return premium for liquid assets and credit-risk premium are appropriately priced in accordance with these two results.

The two results also channel their way into the macroeconomy. As households partake in precautionary hoarding of liquidity, aggregate demand decreases. Businesses respond by not investing in new inventories and/or other capital formations such as buildings and technologies. The decrease in aggregate demand and investment inhibit economic prosperity. After year 1, increased income risk on households decreases real-GDP by half a percent while total factor

48. The remaining p-values are above and below 0.10, but I believe this is due to the small sample size operating on a demanding specification vs. truly the presence of null effects. **M3** brought on increased efficiency across all quarters.

productivity decreases one full percent. As income uncertainty permeates between economic actors, governments and policy makers have to respond to mitigate the damage. To boost aggregate consumption and investment, I show governments can partake in expenditure side fiscal policy by pushing stimulus packages. The government spending multiplier is on average above 2 in times of high income uncertainty. Thus, doubling every dollar spent for GDP growth.

A natural extension can be the effects of income uncertainty on *secured* debt, where foreclosures and repossessions instead of bankruptcies are considered. It would also be interesting to study the consumption sequences before and after a default for evidence of a default trap, where delinquent consumers remain on the brink of default. Further research may look into prediction models on predicting variability of income risk. Due to the counter-cyclical relationship of income uncertainty and recessions, papers establishing the determinants of crises already provide some insight. This would help in creating a dictionary of signals by which institutions can adhere to in initializing their own automatic stabilizers to fight future income uncertainty.

Appendix A Proofs on Liquidity Channel

Lemma 1. *In the high income state in period 2, the borrowing constraint never binds if* $R^k < \left(1 + R^{k\frac{\xi-1}{\xi}}\right)^{\xi}$.

Proof. Suppose the borrowing constraint *does* bind in period 2 for the high income state. This means households will consume $b_1 + y + \frac{1}{2}\sigma$ and leave no savings for the next period (i.e., $b_2 = 0$), leaving only to consume the illiquid asset, $R^k k_1$, in period 3. This requires $c_2^H < R^k k_1$ since otherwise, with $c_2^H > R^k k_1$, we can smooth consumption by reducing consumption in period 2 and have $b_2 > 0$. Substituting $b_2^L = b_2^H = 0$ in equation 2, we have the optimality condition that:

$$\frac{1}{y - k_1 - b_1} = \frac{1}{k_1} \longrightarrow k_1^* = c_1$$

Plugging this equality into the budget constraint of period 3, we have $c_3^* = R^k c_1$. The consumption allocation for period 1 and period 3 would be $c_1^* = y - b_1 - k_1^* = \frac{y-b_1}{2}$ and $c_3^* = R^k \frac{y-b_1}{2}$; however, here, $c_2^H > c_3^*$, since as $R^k \to 2$, we arrive at $y - b_1$ for c_3^*, which is less than $c_2^H = y + b_1 + \sigma$. This contradicts the initial optimality condition we made in period 2 (i.e., $b_2 = 0$), that — $c_2^H < R^k k_1$. Thus, the borrowing constraint in period 2 can never bind for a sufficiently low return on the illiquid asset. Households in the high state, with $R^k < 2$, will consume $\frac{1}{2}(b_1 + y + \frac{1}{2}\sigma + R^k k_1)$ in period 2 and the other half in period 3 — $c_2^H = c_3^H$. □

Lemma 2. *If the household holds positive amounts of both assets in period 1 and* $R^k \neq 1$, *then the borrowing constraint binds in period 2 in the low-income state.*

Proof. Households invest in liquid assets b_1 and illiquid assets k_1 to curb uncertainty in the low-income state in period 2 and enable consumption in period 3. By carrying positive amounts of both assets, it is not borrowing constrained in period 1 and hence, $u'(c_1) = \mathbb{E}u'(c_2)$ and by optimality of period 1 found above, we know $k_1^* = c_1 \longrightarrow u'(c_1) = R^k E u'(c_3)$. If again, the household is not borrowing constrained in period 2, then she will try to smooth consumption across the final periods i.e., $c_2^{H,L} = c_3^{H,L}$. This means $\mathbb{E}u'(c_3) = \mathbb{E}u'(c_2) = R^k \mathbb{E}u'(c_3)$. This implies $R^k = 1$, which is false by assumption. □

Appendix B Proofs on Default Channel

For the proofs, the notation is the following: Consumption is $c_t(D, b, \delta)$, where $D \in \{0, 1\}$ is the state of the world, b is the debt level, $\delta \in \{0, 1\}$ is the default decision and $t \in \{1, 2\}$ is the time period; whether period 1 or 2. If $D = 0$, then the consumer is in the high income state;

$D = 1$ for consumers in the low-income state. If $\delta = 1$, then the consumer has defaulted; $\delta = 0$ if the consumer repaid.

Lemma 1. *If (1) $b \leq \theta y - I$ and (2) $I \leq \theta y + \hat{I}$, then the consumer always repays. (3) If $I > \theta y + \hat{I}$, then the consumer always defaults.*

Proof. To prove the first statement, I have to show that the utility under repayment is greater than utility under default. $I \leq \theta y + \hat{I}$ and $b \leq \theta y - I$ imply $c_1(D, b, \delta = 1) = c_1(D, b, \delta = 0)$ and $c_2(D, b, \delta = 1) < c_2(D, b, \delta = 0)$. Since b is bounded from above and utility is strictly increasing in consumption, both types of consumers in period 1 will borrow up to the bound. In period 2, those consumers that default will have to pay the debt at a penalty i.e., $b + I \leq b + \theta y + \hat{I}$. When the inequality is slack, defaulting leads to less consumption; precisely $(\theta y + \hat{I}) - I$ less. Under equality, I have assumed the consumer does not default. Thus, summing the corresponding consumption allocations, utility under non-default is greater than under default (i.e., $ND > DF$).

For $I > \theta y + \hat{I}$, consumers face a high interest rate. In that case, both consumers will still borrow the same amount to maximize consumption in period 1. In period 2, consumers will maximize consumption by defaulting since it is cheaper than repayment i.e., $b + \theta y + \hat{I} < b + I$. Thus, utility under non-default is less than under default (i.e., $ND < DF$). □

Lemma 2. *If the consumer is offered a medium-range contract, such a contract would force low-income households to default while high-income households to not.*

Proof. Suppose the consumer is offered a medium-range contract. This means $b > \theta y - I$ and $I \leq \theta y + \hat{I}$. By assumption, low-income households do not have the means to repay, so $c_2(D, b, \delta = 0) < c_2(D, b, \delta = 1)$ since $b + I > \theta y$. For equal period 1 consumption allocations, low-income households maximize consumption under default, so $DF > ND$. High-income households have been assumed to have the capacity to cover up to $b + \theta y + \hat{I}$. Since strategic defaulting is punished i.e., $I \leq \theta y + \hat{I}$, and consumption is maximized under repayment, high-income households utility under repayment is greater than utility under default, $ND > DF$. □

Appendix C Estimating Income-Risk

The income process is modeled as:

$$
\begin{aligned}
\log y_{it} &= f(o_{it}) + \tau_{it} + h_{it} + \mu_i \\
\tau_{it} &= \varepsilon_{it}^{\tau} + \rho_\tau \varepsilon_{it-1}^{\tau} \\
h_{it} &= \sum_{s=c}^{t} \rho_h^{t-s} \varepsilon_{is}^{h} \\
\varepsilon_{it}^{\tau} \sim \mathcal{N}(0,\, \sigma_{\tau,d}^2) \quad & \varepsilon_{it}^{h} \sim \mathcal{N}(0,\, \sigma_{\varepsilon,t}^2) \quad \mu_i \sim \mathcal{N}(0,\, \sigma_{\mu,d}^2)
\end{aligned}
\tag{C.1}
$$

where y_{it} is labor income after taxes[49] and transfers[50] for household i at quarter t. $f(o_{it})$ is the predictable variation of income from observables. These observables include a quadratic function for age, a linear-quadratic term in age for each education level, quarterly-time fixed-effects, number of dependent children and ethnicity. τ_{it} is the transitory shock to income, represented as an moving-average of order 1. h_{it} is the highly-persistent component of income and μ_i are household fixed effects. The permanent/transitory decomposition takes the insights of Friedman (1957).[51] As oppose to positing homoskedasticity for the transitory and fixed effect component, variances for these components depend on the newly designed SIPP, illustrated by d.[52] Shocks ε_{it}^{h} still vary over the life-cycle.

To measure the risk process, let $\sigma_{\varepsilon,t}^2$ be the variance parameter of shocks ε_{it}^{h} to the persistent income component h_{it}. Mathematically, it is persistent income-risk, $\overline{\sigma}_{\varepsilon}^2$, multiplied by the exponential of a log AR(1) process around a quadratic time-trend:

$$
\begin{aligned}
\sigma_{\varepsilon,t}^2 &= \overline{\sigma}_{\varepsilon}^2 \exp(s_t + t\theta_1 + t^2\theta_2) \\
s_{t+1} &= \rho_s s_t + \varepsilon_t^s \\
\varepsilon_t^s &\sim \mathcal{N}\left(-\frac{\sigma_s^2}{2(1+\rho_s)}, \sigma_s^2\right)
\end{aligned}
\tag{C.2}
$$

49. Taxes are imputed using TAXSIM9 for pre-2016 data. TAXSIM32 is used for post-2016.

50. Transfers are bifurcated into (1) means-tested and (2) non-means tested benefits. (1) includes Temporary Assistance for Needy Families (TANF) (succeeded AFDC in July 1997), Supplemental Security Income (SSI), pass-through child supp., general assistance (GA) and/or general relief. (2) includes Veterans affairs benefits, workers' compensation, unemployment compensation, and/or social security. As opposed to previous years, the SIPP stopped reporting amounts for these non-cash benefits: medicaid, home energy assistance, free or reduced price school lunches/breakfast, and public or subsidized rental housing. Monthly amounts for the Supplemental Nutrition Assistance Program (SNAP) and Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) are still reported and are also considered means tested. For more information, see the 2014 panel documentation. Also, we focus on government transfers and not transfers between households such as child support, alimony, bequests, other court-ordered payments, etc.

51. Where consumption behavior of agents depends primarily on the first moment of the discounted value of their endowment sequence (permanent income) and secondarily on transitory (unexpected) changes in income.

52. More details on the new design and what we change for our estimation in the appendix.

where ε_t^s is a shock to household income-risk for time t and σ_s^2 is the variability of income-risk, s.

For the income process, I first estimate the predictable variation of income, $f(o_{it})$, using weighted least squares and in the following, I work with the time-series properties of the residuals, composed of $\tau_{it} + h_{it} + \mu_i$.[53] The residual component represents the random component of a household's income that is idiosyncratic to them. Coupled with its first and second lag, they assemble the auto-covariance structure of residual income for cohort-quarter cells, denoted as c and t. The cohort is defined as the quarter for which the household head turned 30. Together, they construct independent three-year panels, aggregated to the cohort level in the subsequent step. The auto-covariance structure will help identify the parameters of interest (ρ_h, ρ_s, ρ_τ, $\overline{\sigma}_\epsilon^2$, σ_τ^2, σ_μ^2, σ_s). More on this in the next section.

Let $\omega_{0,j}^2(c,t)$ for $j = 0, 1, 2$ be the theoretical auto-covariances of the residuals.[54] They are:

$$
\begin{aligned}
\omega_{0,0}^2(c,t) &= (1+\rho_\tau^2)\sigma_{\tau,d}^2 + \sigma_{\mu,c,d}^2 + \sigma_h^2(c,t) && \textit{Theoretical variance} \\
\omega_{0,1}^2(c,t) &= \rho_\tau\sigma_{\tau,d}^2 + \sigma_{\mu,c,d}^2 + \rho_h\sigma_h^2(c,t-1) && \textit{Auto-covariance, } j = 1 \\
\omega_{0,2}^2(c,t) &= \sigma_{\mu,c,d}^2 + \rho_h^2\sigma_h^2(c,t-2) && \textit{Auto-covariance, } j = 2
\end{aligned}
\tag{C.3}
$$

where $\sigma_{\tau,d}^2$, $\sigma_{\mu,c,d}^2$, and σ_h^2 are the variances for the transitory, fixed-effect and permanent component. They are equal to their empirical counterparts, $ac_{0,j}(c,t)$, up to some sampling error. It is precisely in this sampling error that I extract the shock series. σ_h^2 accumulates permanent income-risk shocks with respect to:

$$
\begin{aligned}
h_{it} &= \sum_{j=c}^{t} \rho_h^{t-j}\varepsilon_{ij}^h && \textit{permanent income component} \\
\sigma_h^2 &= Var(h_{it}) = \sum_{j=c}^{t} \rho_h^{2(t-j)}\sigma_{\varepsilon,j}^2 && \textit{variance of the permanent income component} \\
&= \overline{\sigma}_\varepsilon^2 \sum_{j=c}^{t} \rho_h^{2(t-j)} \exp(s_j + j\theta_1 + j^2\theta_2)
\end{aligned}
\tag{C.4}
$$

53. The top and bottom 0.5% of the residuals are removed to mitigate outlier/influential effects. The SIPP provides probability weights.

54. Two lags is sufficient for the identification of the parameters. Auto-covariances decline in absolute value, present no clear pattern between them, and may be as much positive as negative in direction. After the second lag, magnitudes are typically statistically no different than zero. See G. Violante, "Income Process" and *Handbook of Labor Economics*, Vol. 4b, Ch. 9., pg. 797 for a list of studies that support this claim. There is also fear of imprecision from higher lags, simply from the loss of observations

To identify the income shock series and estimate the parameters of interest, I follow Bayer et al. (2019) by formulating the following quasi-maximum likelihood estimator:[55]

$$-2\log L = \sum_{(c,t)\in S} \psi(c,t)'\Sigma(c,t)^{-1}\psi(c,t) + \sum_{j\in T} \frac{(\varepsilon_j^s)^2}{\sigma_s^2} + \#T\log\sigma_s^2 \tag{C.5}$$

where

$$\psi(c,t) = \begin{pmatrix} ac_{0,0}(c,t) - \omega_{0,0}(c,t) \\ ac_{0,1}(c,t) - \omega_{0,1}(c,t) \\ ac_{0,2}(c,t) - \omega_{0,2}(c,t) \end{pmatrix} \tag{C.6}$$

is the difference between the empirically derived auto-covariances and the theoretical auto-covariances. The estimator assumes a multivariate Gaussian distribution for this sampling noise. S is the set of all cohort-quarter pairs observed between 1983Q3 and 2015Q4 and T is the set of quarters for which we estimate shocks, i.e., 1976Q1 to 2015Q4. The variance-covariance matrix of the error differences is $\Sigma(c,t)$, which is estimated at the cohort-quarter cell. Each cell is an independent cluster of observations that may carry similar macroeconomic histories, so cluster-bootstrapping is necessary to withhold that structure and produce the correct variance-covariance matrix.[56]

Appendix D Derivations

D.1 Auto-covariance Derivations

For illustration, we derive $\omega^2_{0,0}(c,t)$, $\omega^2_{0,1}(c,t-1)$, and $\omega^2_{0,2}(c,t-2)$:

$$\begin{aligned} Var(\varepsilon^*_{ct}) &= Var(\tau_{ct} + h_{ct} + \mu_c) && \textit{Taking the variance of the residuals} \\ \omega^2_{0,0}(c,t) &= Var(\varepsilon^\tau_{ct} + \rho_\tau\varepsilon^\tau_{ct-1} + h_{ct} + \mu_c) && \textit{Substituting AR(1) transitory shock process} \\ \omega^2_{0,0}(c,t) &= (1+\rho_\tau^2)\sigma_\tau^2 + \sigma^2_{\mu,c} + \sigma^2_h(c,t) && \textit{Theoretical variance} \end{aligned} \tag{D.1}$$

$$\begin{aligned} \omega^2_{0,1}(c,t) &= E_{ct}\left[\tau_{ct} + h_{ct} + \mu_c\right] E_{c,t-1}\left[\tau_{c,t-1} + h_{c,t-1} + \mu_c\right] \\ &= \underbrace{E_{ct}\left[\varepsilon^\tau_{ct} + \rho_\tau\varepsilon^\tau_{ct-1} + \sum_{j=c}^{t}\rho_h^{t-j}\varepsilon^h_{cj} + \mu_c\right] E_{c,t-1}\left[\varepsilon^\tau_{c,t-1} + \rho_\tau\varepsilon^\tau_{c,t-2} + \sum_{j=c}^{t-1}\rho_h^{t-j}\varepsilon^h_{cj} + \mu_c\right]}_{\textit{Substituting permanent and transitory shock processes}} \\ &= \rho_\tau\sigma_\tau^2 + \sigma^2_{\mu,c} + \rho_h\sigma^2_h(c,t-1) \quad \textit{Auto-covariance, } j = 1 \end{aligned} \tag{D.2}$$

55. The estimator's construction is shown in the appendix.
56. By confining ourselves to a larger independent unit, I am exposed to noise from lack of variation. Such exposure is only exacerbated with the new 2014 and 2018 SIPP panels being half the size of the 2008 SIPP.

$$
\begin{aligned}
\omega^2_{0,2}(c,t) &= E_{ct}\left[\tau_{ct} + h_{ct} + \mu_c\right] E_{c,t-2}\left[\tau_{c,t-2} + h_{c,t-2} + \mu_c\right] \\
&= E_{ct}\left[\varepsilon^{\tau}_{ct} + \rho_\tau \varepsilon^{\tau}_{ct-1} + \sum_{j=c}^{t} \rho_h^{t-j} \varepsilon^h_{cj} + \mu_c\right] E_{c,t-2}\left[\varepsilon^{\tau}_{c,t-2} + \rho_\tau \varepsilon^{\tau}_{c,t-3} + \sum_{j=c}^{t-2} \rho_h^{t-j} \varepsilon^h_{cj} + \mu_c\right] \\
&= \sigma^2_{\mu,c} + \rho_h^2 \sigma_h^2(c, t-2) \quad \textit{Auto-covariance, } j = 2
\end{aligned}
\tag{D.3}
$$

D.2 Derivation of the Quasi-Maximum Likelihood Estimator

For the derivation, I construct auto-covariance structures following Deaton (1985) and compare them to their theoretical counterparts. Each structure contains the auto-covariance of residual income for up to two lags and is treated as our unit of observation. I am interested in the difference between the empirically derived auto-covariances and the theoretical values since the difference is a function of the model parameters and sequence of income-risk shocks, for which I wish to estimate. The structure with the differences is shown below:

$$
\psi(c,t) = \begin{pmatrix} ac_{0,0}(c,t) - \omega_{0,0}(c,t) \\ ac_{0,1}(c,t) - \omega_{0,1}(c,t) \\ ac_{0,2}(c,t) - \omega_{0,2}(c,t) \end{pmatrix} = \begin{pmatrix} e_{0,0} \\ e_{0,1} \\ e_{0,2} \end{pmatrix} \tag{D.4}
$$

The resulting estimation generates the parameter vector for the laws of motion for income-risk and variance of the persistent component of income that minimize the negative likelihood function. Shown below are exactly these laws of motion, which includes the persistence of income-risk, ρ_s, shocks to income-risk, ε^s_j, time trend parameters θ_1 and θ_2, persistence of income, ρ_h, and mean of the income shock variance, $\overline{\sigma}^2_\epsilon$. Estimating $\psi(c,t)$ also helps construct the other parameters of interest: $\sigma^2_s, \sigma^2_\tau, \sigma^2_\mu, \rho_\tau$.

$$
\begin{aligned}
\sigma_h^2 &= \overline{\sigma}^2_\varepsilon \sum_{j=c}^{t} \rho_h^{2(t-j)} \exp(s_j + j\theta_1 + j^2\theta_2) \\
s_{j+1} &= \rho_s s_j + \varepsilon^s_j
\end{aligned}
\tag{D.5}
$$

The estimation begins by identifying the sampling noise, $\psi(c,t)$, as an order S vector-valued Gaussian distribution with covariance matrix $\Sigma \in D^S_{++}$.[57] Below is the corresponding probability density function for ψ — a multivariate Gaussian distribution, while the income-risk process

57. There are S many age-quarter cohorts. Thus, D^S_{++} means the covariance matrix is in the space of symmetric, positive definite SxS matrices. Thus, for any matrix A, $A = A^T$, and $x^T A x > 0 \; \forall x \in \mathbb{R}^n$ such that $x \neq 0$. $\Sigma = \mathbb{E}\left[(\boldsymbol{ac} - \omega)(\boldsymbol{ac} - \omega)^T\right]$.

consists of univariate normal density functions. The product of densities is considered at the cohort level, S, for our data-generated auto-covariance structure $\boldsymbol{ac(c,t)}$:

$$\prod_{s=1}^{S} f(\boldsymbol{ac(c,t)}|\boldsymbol{\theta}) = \left(\frac{1}{(2\pi)^S|\boldsymbol{\Sigma}|}\right)^{1/2} \exp\left\{-\frac{\sum_{(c,t)\in S}(\psi(c,t)'\boldsymbol{\Sigma}^{-1}\psi(c,t))}{2}\right\} \tag{D.6}$$

where $\boldsymbol{\theta}$ is the parameter set of interest. This is numerically demanding to compute, thus I work with the natural logarithm of the likelihood function.[58]

$$\log L = \frac{1}{2}\left(\log(1) - \log((2\pi)^S|\boldsymbol{\Sigma}|)\right) - \frac{1}{2}\sum_{(c,t)\in S}\psi(c,t)\boldsymbol{\Sigma}^{-1}\psi(c,t) \tag{D.7}$$

Removing terms not containing any parameters of interest and adding the shock component leads to the quasi-maximum likelihood estimator[59]:

$$-2\log L = \sum_{(c,t)\in S}\psi(c,t,)\boldsymbol{\Sigma}^{-1}\psi(c,t) + \underbrace{T\log(\sigma_s^2) + \sum_{j\in T}\frac{(\varepsilon_j^s)^2}{\sigma_s^2}}_{\text{the jointly-normal income-risk shocks component}} \tag{D.8}$$

D.3 Utility Representation of the Default Channel

The unsecured debt contract offered to consumers that maximizes their ex-ante utility is subject to the the lender's zero profit constraint. The specification is the following:

$$\begin{aligned} U(K,P) &= \max_{K,P}\sum_{D}\left[\delta DF + (1-\delta)ND\right]P(D) \\ &\quad subject\ to \\ &\quad \sum_{D}\left[\Pi(D,K,P) - C\delta(D,K,P)P(\hat{d})\right]P(D) \end{aligned} \tag{D.9}$$

where $U(K,P)$ is the utility representation dependent on the contract offered K and probability of verification P. δ is the dichotomous representation for the default decision. DF is the utility representation for defaulted borrowers, ND is the utility representation for non-defaulted borrowers and $P(D)$ is the probability of being in the three states of the world. The zero profit condition ensures profits Π less verification costs C are zero. $P(\hat{d})$ is the probability of being verified after default.

58. Since the logarithm is a monotonic function, the same parameter estimates that maximizes the likelihood will also maximize the *log*-likelihood. To check for convergence, depending on the software package you are using, check the outputted Jacobian matrix to ensure $\frac{\partial l}{\partial \theta_k} = 0$ for $k \in \Theta$.

59. The reason it is a *quasi* estimation comes from possible misspecification of the distribution. Meaning, the sampling error vector $\psi(c,t)$ may not be multivariate-normal.

D.3.1 Comparative Statics

First I test a small debt level where default does not occur in any state, so $P(D_0) = 100\%$ and $P(D_1) = 0\%$. I then see if this debt level is optimal at equality or slack. The utility specification is:

$$\begin{aligned} U(K,P) &= \left[b + \frac{1}{2}[(1-\theta)y - \sigma] + \frac{1}{2}[(1-\theta)y + \sigma - b - \hat{I}]\right] \\ &+ \left[b + \frac{1}{2}[y - \sigma - b - I] + \frac{1}{2}[y + \sigma - b - I]\right] \end{aligned} \tag{D.10}$$

Simplifying $U(K,P)$:

$$\begin{aligned} U(K,P) &= \frac{1}{2}b + 2y - \theta y - \frac{\hat{I}}{2} \\ & subject\ to \\ I &= 0 \\ b &\leq \theta y \end{aligned} \tag{D.11}$$

The lenders *can* observe the possible states of the world, but not the distribution of those in the low and high income state. As such, when offering small debt contracts, they know the likelihood of default is zero. In that, they offer the equilibrium interest rate $I = 0$.[60] The ex-ante utility indicates that for risk-free lines, the utility is increasing in b, thus $b = \theta y$ is optimal. Suppose now a medium-range debt contract is offered (recall the definition in section 2). The probability of default increases now to 50%: $P(D_0) = 50\%$ and $P(D_1) = 50\%$.

$$\begin{aligned} U(K,P) &= \frac{1}{2}\left[b + \frac{1}{2}[(1-\theta)y - \sigma] + \frac{1}{2}[(1-\theta)y + \sigma - b - \hat{I}]\right] \\ &+ \frac{1}{2}\left[b + \frac{1}{2}[y - \sigma - b - I] + \frac{1}{2}[y + \sigma - b - I]\right] \end{aligned} \tag{D.12}$$

Simplifying $U(K,P)$:

$$\begin{aligned} U(K,P) &= \frac{1}{4}b + y - \frac{\theta y}{2} - \frac{\hat{I}}{4} - \frac{I}{2} \\ & subject\ to \\ I - b - C &= 0 \\ b &\leq \theta y - C + \hat{I} \end{aligned} \tag{D.13}$$

60. This can be derived by knowing the probability of default is zero, so repayment occurs 100% of the time. Thus, using the zero-profit condition, we arrive at the interest rate equaling the cost of funds, which in the model, has been normalized to zero.

I consider three debt levels within this range:

$$\begin{aligned}(1)\ b &= \theta y - C \\ (2)\ b &= \theta y - C + \frac{\hat{I}}{2} \\ (3)\ b &= \theta y - C + \hat{I}\end{aligned} \tag{D.14}$$

where (3) is the upper bound level for medium-range contracts. All contracts satisfy: $b > \theta y - I$. For contract (1), $I > C$ arises from the equilibrium interest rate equation, $I = b + C$, so (1) is greater than $\theta y - I$. Substituting that into equation D.13 , the resulting utilities are:

$$\begin{aligned}&(1) y - \frac{3}{4}\theta - \frac{1}{4}\hat{I} - \frac{C}{4} \\ &(2) y - \frac{3}{4}\theta - \frac{2}{4}\hat{I} - \frac{C}{4} \\ &(3) y - \frac{3}{4}\theta - \frac{3}{4}\hat{I} - \frac{C}{4}\end{aligned} \tag{D.15}$$

Since the ex-ante utility is decreasing in b, then at this equilibrium interest rate, the optimal debt level approaches the infimum:

$$\begin{aligned}b\ &\downarrow \frac{\theta y - C}{2} \\ &since \\ b &> \theta y - I \\ b &> \theta y - b - C \\ b &> \frac{\theta y - C}{2}\end{aligned} \tag{D.16}$$

Yet, the set of risk free contracts is when $b \le \theta y$, thus for this medium range, the optimal approaches $b = \theta y + \varepsilon$, for ε suffciently small.

Appendix E Discussion on LP vs. SVAR

Impulse response functions (IRFs) are one the most important tools in modern empirical macroeconomics, giving us input on the dynamics surrounding business cycles and interrelationships between economic aggregates. For that reason, such a tool needs to be theoretically and empirically assessed to disclose and correct potential drawbacks. IRFs have been largely estimated via specifying some underlying multivariate system and running a structural vector auto regression (SVAR) (Sims (1980)), but now has been overtaken by the 'new kid on the block': the local projections (LP) method, introduced by Jordà (2005). The LP method has become the popular method for its simplicity in estimation and inference, but which one is correct? Ramey (2016) has added to the discussion while considering various identification and estimation strategies and more recently, Plagborg-Møller and Wolf (2019).

To begin, once the shocks have been identified, whether through a Cholesky decomposition or narratively, you can estimate an IRF using SVAR (i.e., an iterative forecast approach) or LP (i.e., a direct forecast approach). SVAR is superior to LP *only if* the data generation process is perfectly captured; however, in the case of a mispecified model (e.g., specifying the incorrect time trend, settling for a parsimonious model in spite of observing an important state variable) specification errors will amalgamate the errors at each iteration. Although literature, research and time go into specifying the correct model, SVAR may be too sensitive and thus, costly to misspecification. Jordà (2005), thus, provides a method that is less vulnerable to misspecification and flexible in terms of including other variables and of various transformations. Further, the IRF does not need to adhere to a certain shape, which lends to its first con — it is sometimes imprecise and presents oscillations at the longer time horizons.

These are the quintessential comments regarding the two estimation strategies, but where is the evidence? I consider three studies on the topic to present the discussion: (1) Meier (2005) (2) Kilian and Kim (2011) (3) Brugnolini (2018). One of the first to fully test their differences across various specifications is Meier (2005). Using simulated data from Smet-Wouters (2003), he tests the VAR and LP frameworks according to three different shocks: a (1) monetary shock (2) labor supply shock and a (3) technology shock. In a first test, he considers a 7-variable setup with four lags at varying sample sizes: (1) 80 observations (2) 160 observations and (3) 5000 observations. No comment was provided on the selection of these sample sizes.

For the monetary shock, the VAR, compared to the LP, outperforms at just about every observation count. At the 5000 mark, however, it is identical to the LP. Relative to the true IRF, both the LP and VAR methods take a reasonable shape by 160 observations, but lack the persistence. Comparing the methods at 160 observation for a three variable system instead (approximating the same IRF as before), they find that the average mean-squared deviations of the estimates from the true responses is cut in half in comparison to the 7-variable system. This holds true at 4 and 8 lags. This is not trivial. Essentially there are opposing forces at work — they are omitting important state variables, which may contribute to the bias, but by its omission, they obtain a more parsimonious specification with greater degrees of freedom for that sample. Essentially, for larger datasets, this not important since the intuition is that you cannot demand such a large multivariate system with a small sample size.

For the monetary shock, it also appears that more lags has the same effect as specifying more variables. With the 7-variable setup, the 4 lags performs better than the 8 lags in every case for both methods. For the technology and labor supply shock, the results hold for the 160 observation sample — 4 lags better than 8 lags and 3 variables better than 7. Although the VAR outperforms the LP in just about every case, they both reflect fairly well the shape of the true

IRF and the differences between them are minuscule and non-existent for larger samples, but this is simply a visual interpretation as no tests were made to test for equality of coefficients. Any expert on the field, however, can see that the visual similarity in shape does not require a statistical verification. Kilian and Kim (2011) discusses the same idea, but also whether, as empirical researchers, the method of inference should be asymptotic or bootstrap. First, they find that even for large samples, there are not apparent advantages to the LP method. The estimates are accurate, but the *length* of the confidence intervals are on average much larger than the bias-corrected bootstrapped VAR. When the LPs are block-bootstrapped and bias-corrected, the length shortens, but still lacks the coverage accuracy in finite samples.[61] This lends to the conclusion that we should abandon the LP altogether.

Brugnolini (2018), however, criticizes this conclusion. Precisely that their results are driven by the lag-length selection criterion (AIC vs. BIC used in Jordà (2005)), delivering an unfair comparison between LP and VAR IRFs. Brugnolini extends the Monte Carlo simulation presented by Kilian and Kim by focusing on a VAR(12) data generation process in a 4 variable model and a LP1, LP5, LP10 and LP20 model.[62] The sample size is about 460 observations (excluding the 300 burn-in observations for the MC) and is taken from Christiano et al. (1999). Optimal lag-length for VAR and LP, **p** and **x** respectively, is chosen via AIC and BIC information criteria and VAR(p)/LP(x) are then fit on the simulated data. Using the AIC criteria for lag-length selection, the MC simulation chooses $p = 12$ each time for the VAR model, which is the correct lag-length based on the data generation process. When picking the lag-length at $h = [1, 5, 10, 20]$, the MC simulation selects 12, 8, 6, 4 as optimal lag-lengths, which lends to a comparison of a perfectly-specified VAR and a mispecified local projection model for $h = [5, 10, 20]$.[63].

This also brings up a second important issue. Jordà (2005) mentions that in the series of regressions, you *may* have different lag-specifications for each horizon h, which complicates its performance assessment. Thus, instead of trying to find a scalar lag-length as in a VAR structure, LPs need a $H \times 1$ vector of optimal lag-lengths. This is important since lag-length affects the magnitude and direction of the IRF at each horizon, yet there's no published approach on this, just three suggestions: (1) selecting the lag-length *for each* projection using an information

61. Coverage accuracy is defined as the proportion of the time in which the interval contains the true value of the IRF for each horizon h. Precisely, $\frac{1}{M}\sum_{m=1}^{M} I(IRF_{true}(h) \in \left[IRF_L^{(m)}(h), IRF_H^{(m)}(h)\right], \quad h = 1, \ldots H$, where M is the number of repetitions in the Monte Carlo Simulation (MC) and I is an indicator function. The rate heavily relies on the alpha level of significance, α. The closer the rate is to $1 - \alpha$, the better.

62. The number signifies the horizon at which we select the lag-length.

63. When lag-length selection takes place at $h = 1$, it correctly picks the optimal lag-length of 12. This has been described and tested in Jordà (2005)

criteria like AIC, BIC, HQC, AICC (2) selecting the lag-length at $h = 1$ using an information criteria, what's called the *first step ahead* and using it for the H horizons (Jordà (2005)) and (3) selecting one lag-length for all h regressions. (2) does remarkably well, as tested by Jordà (2005) and Brugnolini (2018) and (3) is commonly used. To even the playing field, Brugnolini (2018) continues the experiment by performing an MC simulation with a controlled form of misspecification, thus comparing both methodologies when the models have been misspecified.

Results show the LP's confidence intervals capture the true value on average 80% of the confidence bands, but it's mostly due to large confidence intervals bands at growing horizons. The VAR captures 40%, having just one-third the size of the LP confidence intervals. Under misspecification, the LP estimates, nonetheless, are much closer to the true IRF than for VAR. The paper concludes by making a few suggestions: (1) Consider different methodologies for estimating the variance-covariance matrix for the LP method in an effort to attenuate confidence intervals bands created by the Newey-West estimator (2) Jordà (2005) recommends including residual h in estimation $h + 1$ to dampen the estimation uncertainty (3) Work with various information criteria in deciding the optimal lag-length. I put (2) into practice for the thesis and will leave (3) for future research.

Appendix F 2014 SIPP Design

Bayer et al. (2019) formulates the auto-covariance structure of residuals for cohort-quarter cells, with transitory shocks and fixed effects to be homoskedastic; however, to reflect the new design of the 2014 SIPP, the variance of the fixed effect and variance of the transitory component are now functions of the sample design. The auto-covariance structure is now posed in the following:

$$\begin{aligned}
\omega^2_{0,0}(c,t,d) &= (1+\rho^2_\tau)\sigma^2_{\tau,d} + \sigma^2_{\mu,c,d} + \sigma^2_h(c,t) && \textit{Theoretical variance} \\
\omega^2_{0,1}(c,t,d) &= \rho_\tau\sigma^2_{\tau,d} + \sigma^2_{\mu,c,d} + \rho_h\sigma^2_h(c,t-1) && \textit{Auto-covariance, } j = 1 \\
\omega^2_{0,2}(c,t,d) &= \sigma^2_{\mu,c,d} + \rho^2_h\sigma^2_h(c,t-2) && \textit{Auto-covariance, } j = 2
\end{aligned} \tag{F.1}$$

where d is for design.[64] The posited non-constant variance comes from the U.S. Census Bureau re-engineering the 2014 SIPP. In the SIPP user guide, they report:

> *'The reengineering set out to reduce respondent burden and costs, to improve data quality and timeliness, and to modernize the instrument and processing'*

First, as opposed to interviewing individuals thrice a year and asking them to reference information for the prior four months, they now only interview households once a year — asking them

64. To illustrate, $\sigma^2_{\tau,d} = \sigma^2_{\tau,pre-2014} + \sigma^2_{\tau,post-2014}$.

to recall/collect information from the past year.[65] The reduction in interviews makes the SIPP, as well as other longitudinal studies, less susceptible to 'seam bias'.[66] Seam bias is the occurrence of too few transitions within a reference period, but much deviation between reference periods. This is important for duration models, where timing between events is paramount. The short-term dynamics that the SIPP previously offered was plagued by this 'heaping', large movements regarding program participation simply based on the end of reference periods versus when they actually ended.[67]

Second, although the new design tackles seam bias, it is susceptible to recall bias. Suppose it is May 2014 and I am interviewing a respondent for 2013 employment data. If I ask the respondent, five months after the end of the reference period, when did she switch employment, if ever, their accuracy is in question because the event may have happened in the early months of 2013. For some additive measurement error, this attenuates estimates. In an attempt to improve recall in a cost effective manner, the 2014 SIPP thus includes an event history calendar (EHC), asking the respondent to recall and log events that occurred in their lives. The SIPP believes the EHC improves measurement by associating life events with economic events. For example, your employment change may have been associated with a new address.[68] Still, having interviews conducted one to five months after the end of the reference period makes me concerned with the quality of the estimates.[69]

To assess the quality of the estimates, the National Academies of Sciences, Medicine, et al. (2018) used the final year (final three waves) of the 2008 SIPP for comparison given it overlaps with wave 1 of the 2014 SIPP. The overlapping period provides a means for comparison in the aggregate numbers, means, and quantiles.[70] For the sake of the estimations, I am only concerned about the quality of the estimates for income, government transfers and household demographics. There is general consensus that surveys tend to underestimate benchmark estimates of aggregate income, thus, the Academies of Science rely on the "more is better" principle for assessment.[71]

65. For more information on the sample design for statistical inference such as primary sampling units and strata used for the 2014 SIPP, see page 4 of the SIPP user guide.

66. Page 2, footnote 2 of Ham, Li, and Shore-Sheppard (2016) lists the longitudinal surveys exposed to seam bias as well as suggesting studies for further analysis. Moore (2008) also provides a more in-depth explanation of seam bias in the SIPP and provides studies that assess the bias itself.

67. See National Academies of Sciences, Medicine, et al. (2018), pg.138-139 for more information on 'seam bias'.

68. In Council et al. (2009), pg. 105, the council did not see how the EHC could offset the trademark thrice a year interview design

69. A natural idea would be to think earlier months in the reference period carry a reduced quality than months closer to the interview date, but Bureau. (2013) does not find evidence of 'reverse telescoping'.

70. This section will briefly summarize chapter 7 of National Academies of Sciences, Medicine, et al. (2018). Refer to the book for more details.

71. For comparison, the aggregate numbers came from the National Income Product Accounts (NIPA).

First, income estimates are higher for the first wave of the 2014 SIPP than the last year of the 2008 panel, yet the study panel finds the distribution of income is statistically different. National Academies of Sciences, Medicine, et al. (2018) reads:

> *Compared to the 2008 panel, the 2014 SIPP panel captures less income at the very bottom of the income distribution, as reflected in higher estimates of the monthly percentage of the population in families below 50 percent of the federal poverty threshold. Above that threshold and up to 200 percent of the poverty threshold, the 2014 panel finds a smaller percentage of the population than the 2008 panel, although the poverty rate (percentage of population below the threshold) in the 2014 panel remains higher than the poverty rate in the 2008 panel.* [72]

Second, social security income, supplemental security income, and general family assistance were lower in the 2014 SIPP wave 1 than the 2008 SIPP final year.[73] This is evidence for the weakening in measurement of low-income households. This is alarming considering Chief of the Demographical Statistical Methods Division, James B. Treat, in his accuracy statement for the 2014 SIPP wave 1, says:

> *Households were classified into two strata, such that one stratum had a higher concentration of low income households than the other. We oversampled the low income stratum by 24 percent to increase the accuracy of estimates for statistics of low income households and program participation. Analysts are strongly encouraged to use the SIPP weights when creating estimates since households are not selected with equal probability (Mahdi Sundukchi and Nwaoha-Brown (2017)).*

Thus, despite the efforts to consciously improve estimates of low-income households, they did not par. When comparing the aggregate numbers of the 2014 SIPP to the NIPA, family assistance is underestimated, but income fares very well.[74] Overall, the observed differences in design, questionnaire, sample dynamics, and reference period will impact findings if unchecked, justifying the use of our proposed design-dependent variances.

72. See pg. 157 for a complete breakdown of the distribution.

73. Differences in means for these transfers are statistically significant at the 5% level. For a broader inspection, see National Academies of Sciences, Medicine, et al. (2018), pg.118-120.

74. In a SIPP-to$_{N}$ $IPAratio, familyassistanceis0.220andwages/salariesis0.95.PleaseseeNational Academiesof Sciences, Medicine, Et\ al.(2018), pg.123formoreinformation.$

Appendix G Results and Robustness Checks

G.1 Liquidity Results and Robustness Checks

Table G.1. Liquidity Ratio

Statistics:	θ_h (1)	s.e. (2)	C.I. Lower Bound (3)	C.I. Upper Bound (4)
		Full Sample		
quarter 0	.164	.155	-.143	.471
quarter 4	.972	.447	.086	1.858
quarter 8	.489	.231	.032	.947
quarter 12	-.234	.176	-.582	.114
		Without Great Recession		
quarter 0	.014	.089	-.163	.191
quarter 4	.079	.143	-.205	.363
quarter 8	.144	.193	-.238	.527
quarter 12	-.37	.149	-.665	-.074

Notes: Table results are estimated via OLS. θ_h is the effect of a 1 standard deviation increase in income uncertainty at horizon, h. s.e. is the Newey-West standard error. C.I. Lower Bound is the confidence interval lower bound assuming a normal distribution. C.I. Upper Bound is the confidence interval upper bound assuming a normal distribution. For information on the variable, see section 3.2. Estimates are in percentage changes.

Table G.2. Liquidity Premium

Statistics:	θ_h (1)	s.e. (2)	C.I. Lower Bound (3)	C.I. Upper Bound (4)
		Full Sample		
quarter 0	-.487	.25	-.982	.009
quarter 4	.225	.258	-.285	.736
quarter 8	.256	.232	-.205	.717
quarter 12	-.009	.152	-.311	.293
		Without Great Recession		
quarter 0	-.428	.295	-1.013	.156
quarter 4	.161	.215	-.264	.586
quarter 8	.3	.219	-.134	.734
quarter 12	-.028	.179	-.382	.327

Notes: See Table G.1 for details. Estimates are changes in percentage points.

Table G.3. Real House Prices

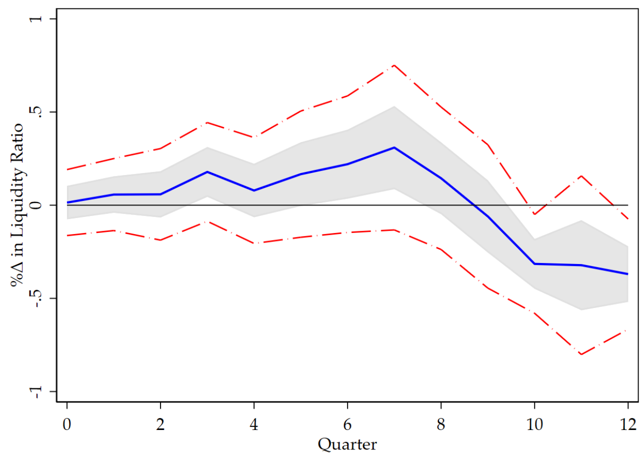
Statistics:	θ_h (1)	s.e. (2)	C.I. Lower Bound (3)	C.I. Upper Bound (4)
		Full Sample		
quarter 0	-.531	.314	-1.153	.092
quarter 4	-1.503	.798	-3.084	.077
quarter 8	-.914	.82	-2.54	.711
quarter 12	-.325	.859	-2.029	1.378
		Without the Great Recession		
quarter 0	-.209	.208	-.622	.204
quarter 4	-.211	.394	-.992	.57
quarter 8	.732	.384	-.029	1.494
quarter 12	1.944	.413	1.123	2.764

Notes: See Table G.1 for details. Estimates are changes in percent.

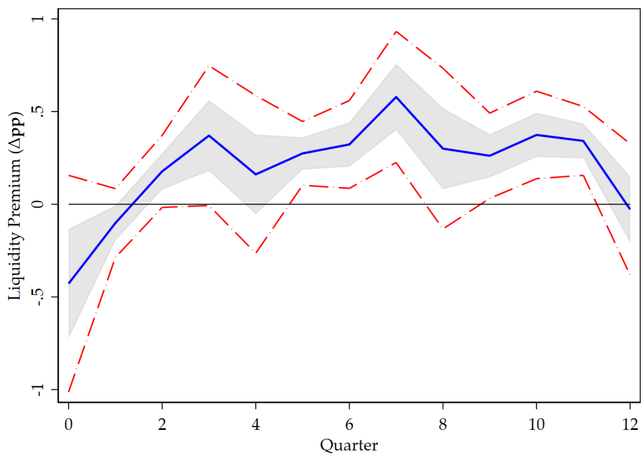
Table G.4. 3-month T-bill Interest Rate

Statistics:	θ_h (1)	s.e. (2)	C.I. Lower Bound (3)	C.I. Upper Bound (4)
		Full Sample		
quarter 0	-17.375	8.679	-34.549	-.202
quarter 4	-72.49	13.583	-99.376	-45.603
quarter 8	-34.499	8.424	-51.18	-17.819
quarter 12	16.205	8.332	-.299	32.709
		Without the Great Recession		
quarter 0	-10.485	11.037	-32.338	11.367
quarter 4	-69.153	17.371	-103.56	-34.747
quarter 8	-48.918	7.958	-64.686	-33.151
quarter 12	20.26	8.822	2.774	37.747

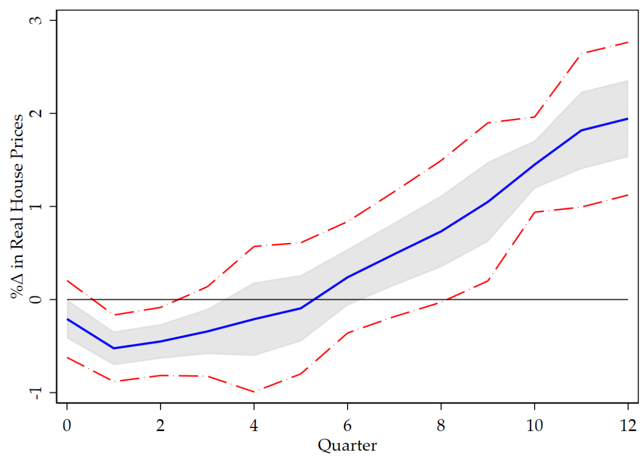
Notes: See Table G.1 for details. Estimates are changes in basis points.



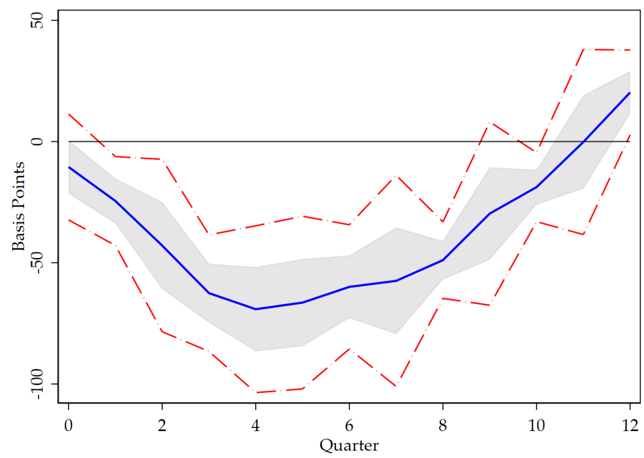
(a) Liquidity Ratio



(b) Liquidity Premium



(c) Housing Prices



(d) Nominal Rate

Figure G.1. *Notes:* These are results filtering out the quarters associated with the Great Recession. Results are estimated via a series of OLS regressions. This is the effect of a 1 standard deviation increase in income uncertainty on (a) the liquidity ratio (b) the liquidity premium (c) house prices and (d) nominal rate. Data is from 1983Q1 to 2015Q4, but does not include the Great Recession. The blue line reports θ_h for $h = 0, 1, \ldots 12$. Newey-West standard errors are shown in gray. 95% confidence intervals are the red dashed lines.

G.2 Prosperity Results and Robustness Checks

Table G.5. GDP

Statistics:	θ_h (1)	s.e. (2)	C.I. Lower Bound (3)	C.I. Upper Bound (4)
		Full Sample		
quarter 0	-.078	.054	-.184	.029
quarter 4	-.545	.218	-.977	-.112
quarter 8	-.491	.289	-1.063	.08
quarter 12	.054	.273	-.488	.595
		Without the Great Recession		
quarter 0	-.06	.093	-.244	.125
quarter 4	-.3	.175	-.646	.046
quarter 8	-.474	.316	-1.1	.152
quarter 12	.401	.258	-.11	.911

Notes: See Table G.1 for details. For more information on the variable, see section 3.4. Estimates are in percentage changes.

Table G.6. TFP

Statistics:	θ_h (1)	s.e. (2)	C.I. Lower Bound (3)	C.I. Upper Bound (4)
		Full Sample		
quarter 0	-.415	.126	-.665	-.165
quarter 4	-.81	.495	-1.79	.17
quarter 8	.148	.348	-.542	.837
quarter 12	.677	.38	-.076	1.431
		Without the Great Recession		
quarter 0	-.301	.172	-.642	.04
quarter 4	.001	.252	-.498	.499
quarter 8	.283	.432	-.573	1.14
quarter 12	1.2	.36	.485	1.914

Notes: See Table G.1 for details. For more information on the variable, see section 3.4. Estimates are in percentage changes.

Table G.7. Consumption

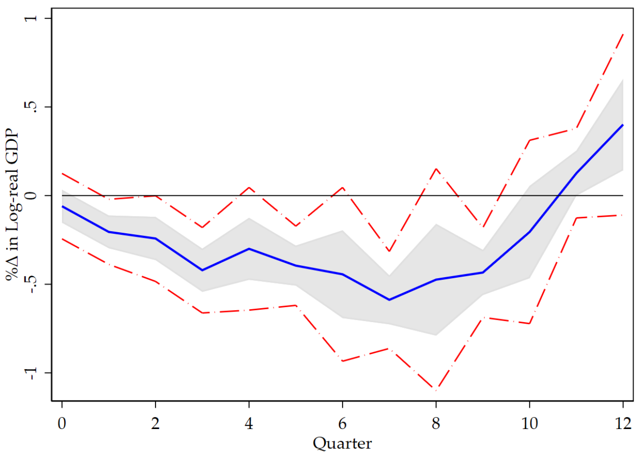
Statistics:	θ_h	s.e.	C.I. Lower Bound	C.I. Upper Bound
	(1)	(2)	(3)	(4)
			Full Sample	
quarter 0	-.117	.059	-.233	0
quarter 4	-.667	.165	-.994	-.34
quarter 8	-.617	.188	-.99	-.244
quarter 12	-.084	.207	-.494	.326
			Without the Great Recession	
quarter 0	-.12	.08	-.277	.038
quarter 4	-.445	.134	-.711	-.179
quarter 8	-.463	.194	-.848	-.078
quarter 12	.187	.246	-.301	.675

Notes: See Table G.1 for details. For more information on the variable, see section 3.4. Estimates are in percentage changes.

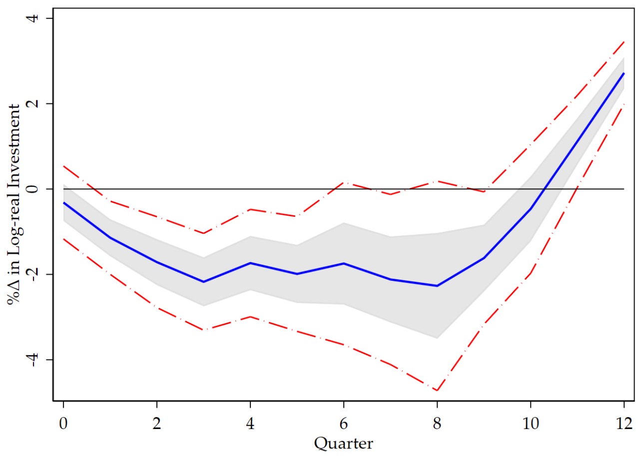
Table G.8. Investment

Statistics:	θ_h	s.e.	C.I. Lower Bound	C.I. Upper Bound
	(1)	(2)	(3)	(4)
			Full Sample	
quarter 0	-.626	.326	-1.271	.02
quarter 4	-3.944	1.194	-6.307	-1.581
quarter 8	-3.164	.983	-5.111	-1.217
quarter 12	.552	.629	-.694	1.799
			Without the Great Recession	
quarter 0	-.315	.431	-1.169	.539
quarter 4	-1.735	.635	-2.993	-.477
quarter 8	-2.269	1.238	-4.723	.185
quarter 12	2.722	.368	1.992	3.452

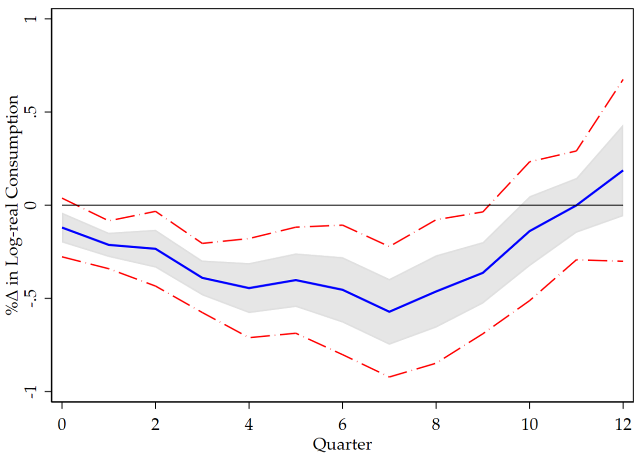
Notes: See Table G.1 for details. For more information on the variable, see section 3.4. Estimates are in percentage changes.



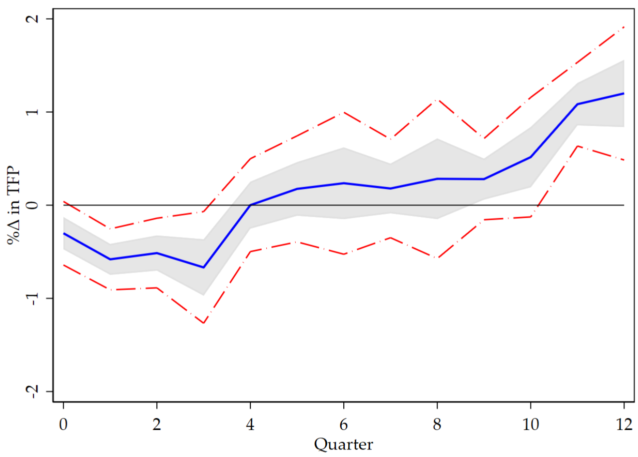
(a) GDP



(b) Investment



(c) Consumption



(d) Solow Residual

Figure G.2. *Notes:* These are results filtering out the quarters associated with the Great Recession. See figure 13 for remaining details.

G.3 Default Results and Robustness Checks

Table G.9. Charge-off Rate

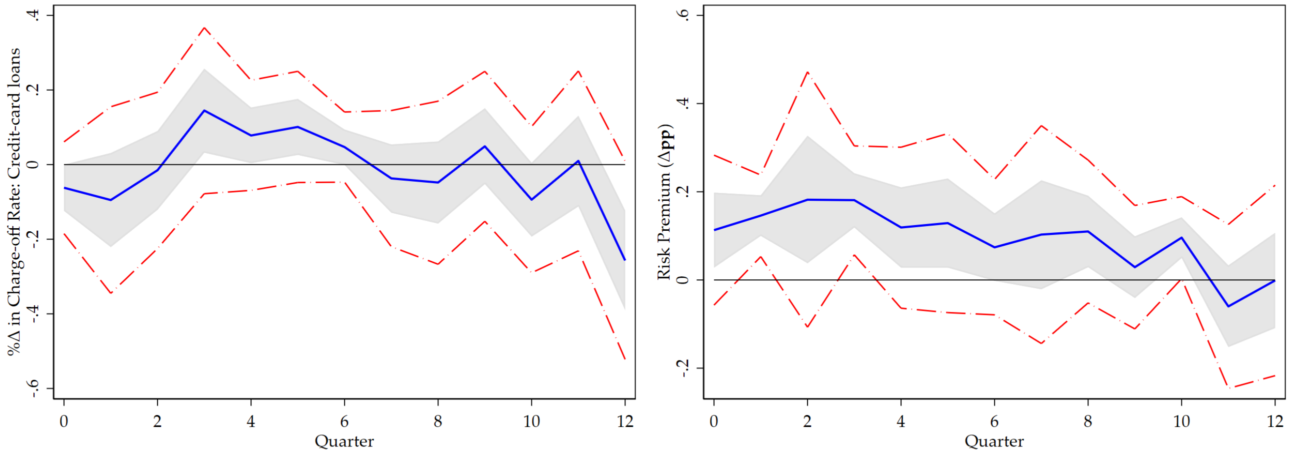
Statistics:	θ_h (1)	s.e. (2)	C.I. Lower Bound (3)	C.I. Upper Bound (4)
		Full Sample		
quarter 0	-.017	.062	-.139	.106
quarter 4	.347	.082	.183	.51
quarter 8	.437	.175	.09	.784
quarter 12	-.135	.114	-.361	.092
		Without the Great Recession		
quarter 0	-.062	.062	-.185	.061
quarter 4	.078	.074	-.069	.226
quarter 8	-.048	.11	-.267	.17
quarter 12	-.257	.134	-.522	.009

Notes: See Table G.1 for details. For more information on the variable, see section 3.3. Estimates are in percentage changes.

Table G.10. Credit-risk Premium

Statistics:	θ_h (1)	s.e. (2)	C.I. Lower Bound (3)	C.I. Upper Bound (4)
		Full Sample		
quarter 0	.099	.054	-.01	.207
quarter 4	.294	.111	.072	.517
quarter 8	.238	.1	.038	.439
quarter 12	.142	.093	-.043	.328
		Without the Great Recession		
quarter 0	.113	.085	-.057	.283
quarter 4	.119	.091	-.064	.301
quarter 8	.11	.081	-.052	.272
quarter 12	-.001	.108	-.217	.215

Notes: See Table G.1 for details. For more information on the variable, see section 3.3. Estimates are changes in percentage points.



(a) Charge-off Rate

(b) Credit-risk Premium

Figure G.3. *Notes:* These are results filtering out the quarters associated with the Great Recession. See figure 12 for remaining details.

G.4 Multiplier Results and Robustness Checks

Table G.11. Cumulative Multiplier

Statistics:	m_h (1)	s.e. (2)	C.I. Lower Bound (3)	C.I. Upper Bound (4)	Kleibergen-paap Wald F-stat (5)
quarter 0	.052	.148	-.239	.343	35.912
quarter 4	.534	.241	.061	1.008	11.42
quarter 8	.923	.197	.535	1.311	14.978
quarter 12	1.09	.171	.754	1.426	14.034
quarter 16	1.146	.199	.754	1.539	7.752

Notes: Table results are estimated via 16 LP-IV regressions. m_h is the multiplier parameter. s.e. is the Newey West standard error. C.I. Lower Bound is the confidence interval lower bound assuming a normal distribution. C.I. Upper Bound is the confidence interval upper bound assuming a normal distribution. The Kleibergen-paap Wald F-stat is the statistical test for weak instruments. p-value is the p-value statistic from a equality of coefficients Chow Test.

Table G.12. State Dependent Cumulative Multiplier: **M1**

Statistics:	m_h (1)	s.e. (2)	C.I. Lower Bound (3)	C.I. Upper Bound (4)	Kleibergen-paap Wald F-stat (5)	p-value (6)
			Low Income Uncertainty			
quarter 0	1.304	.318	.674	1.935	84.899	.58
quarter 4	1.273	.997	-.703	3.25	37.089	.914
quarter 8	.36	1.493	-2.6	3.321	12.329	.521
quarter 12	-.62	1.374	-3.347	2.106	15.228	.143
			High Income Uncertainty			
quarter 0	1.618	.645	.34	2.896	84.899	.58
quarter 4	1.157	.812	-.453	2.767	37.089	.914
quarter 8	1.234	.903	-.557	3.026	12.329	.521
quarter 12	1.245	.978	-.695	3.186	15.228	.143

Notes: See Table G.11 and G.12 for remaining details. **M1** is defining low and high income uncertainty based on whether they were below or above average income risk.

Table G.13. State Dependent Cumulative Multiplier: **M2**

Statistics:	m_h (1)	s.e. (2)	C.I. Lower Bound (3)	C.I. Upper Bound (4)	Kleibergen-paap Wald F-stat (5)	p-value (6)
			Low Income Uncertainty			
quarter 0	.003	.317	-.626	.631	22.171	0
quarter 4	-.998	1.041	-3.062	1.066	5.884	.074
quarter 8	-1.341	1.76	-4.832	2.15	3.251	.12
quarter 12	-1.169	2.461	-6.052	3.715	1.231	.147
			High Income Uncertainty			
quarter 0	3.002	.731	1.552	4.453	22.171	0
quarter 4	2.115	1.452	-.763	4.994	5.884	.074
quarter 8	2.16	1.623	-1.059	5.378	3.251	.12
quarter 12	3.846	2.028	-.177	7.87	1.231	.147

Notes: See Table G.11 and G.12 for remaining details. **M2** is defining low and high income uncertainty based on an alternative Bry and Boschan Algorithm.

Table G.14. State Dependent Cumulative Multiplier: **M3**

Statistics:	m_h (1)	s.e. (2)	C.I. Lower Bound (3)	C.I. Upper Bound (4)	Kleibergen-paap Wald F-stat (5)	p-value (6)
				Low Income Uncertainty		
quarter 0	-.017	.338	-.687	.652	27.097	0
quarter 4	-1.029	1.073	-3.158	1.099	5.336	.045
quarter 8	-1.353	1.781	-4.884	2.179	2.96	.089
quarter 12	-1.067	2.41	-5.849	3.714	1.209	.124
				High Income Uncertainty		
quarter 0	3.141	.709	1.735	4.547	27.097	0
quarter 4	2.404	1.328	-.229	5.037	5.336	.045
quarter 8	2.502	1.543	-.558	5.562	2.96	.089
quarter 12	3.906	1.974	-.01	7.821	1.209	.124

Notes: See Table G.11 and G.12 for remaining details. **M3** is defining low and high income uncertainty based on an alternative Bry and Boschan Algorithm and income shock directions.

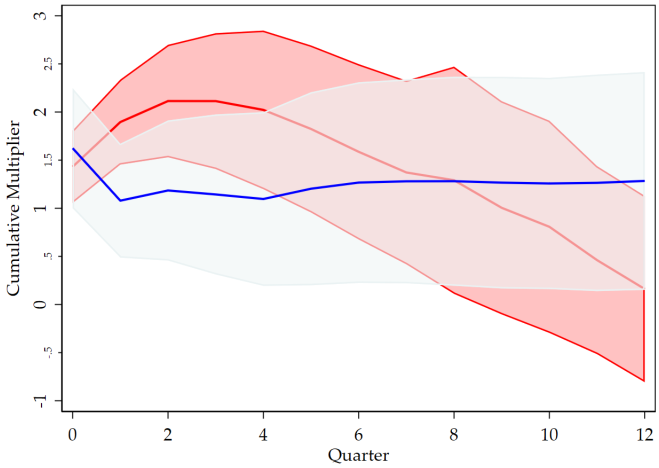


Figure G.4. Without the Great Recession: **M1**

Notes: Results exclude the Great Recession. The blue line reports the cumulative multiplier under high income uncertainty. The red line reports the cumulative multiplier under low income uncertainty. The light-blue and red shade are Newey-West standard errors bands.

Table G.15. Without the Great Recession: **M1**

Statistics:	m_h (1)	s.e. (2)	C.I. Lower Bound (3)	C.I. Upper Bound (4)	Kleibergen-paap Wald F-stat (5)	p-value (6)
			Low Income Uncertainty			
quarter 0	1.431	.377	.683	2.179	65.23	.728
quarter 4	2.022	.824	.387	3.657	29.952	.382
quarter 8	1.291	1.181	-1.052	3.634	11.172	.993
quarter 12	.161	.969	-1.763	2.085	18.097	.252
			High Income Uncertainty			
quarter 0	1.624	.624	.385	2.863	65.23	.728
quarter 4	1.096	.903	-.695	2.888	29.952	.382
quarter 8	1.281	1.086	-.875	3.437	11.172	.993
quarter 12	1.284	1.132	-.964	3.532	18.097	.252

Notes: Results exclude the Great Recession. See Table G.11 and G.12 for remaining details. **M1** is defining low and high income uncertainty based on whether they were below or above average income risk.

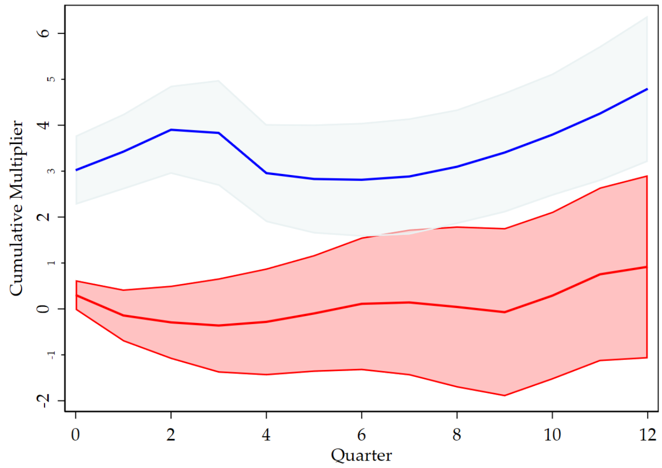


Figure G.5. Without the Great Recession: **M2**

Notes: See Figure G.4 for details.

Table G.16. Without the Great Recession: **M2**

Statistics:	m_h (1)	s.e. (2)	C.I. Lower Bound (3)	C.I. Upper Bound (4)	Kleibergen-paap Wald F-stat (5)	p-value (6)
			Low Income Uncertainty			
quarter 0	.303	.324	-.341	.947	30.541	.001
quarter 4	-.282	1.165	-2.594	2.03	4.617	.072
quarter 8	.042	1.755	-3.441	3.526	2.419	.201
quarter 12	.918	1.996	-3.045	4.88	1.253	.23
			High Income Uncertainty			
quarter 0	3.021	.753	1.527	4.514	30.541	.001
quarter 4	2.957	1.066	.841	5.073	4.617	.072
quarter 8	3.097	1.246	.623	5.57	2.419	.201
quarter 12	4.794	1.589	1.638	7.95	1.253	.23

Notes: Results exclude the Great Recession. See Table G.11 and G.12 for remaining details. **M2** is defining low and high income uncertainty based on an alternative Bry and Boschan Algorithm.

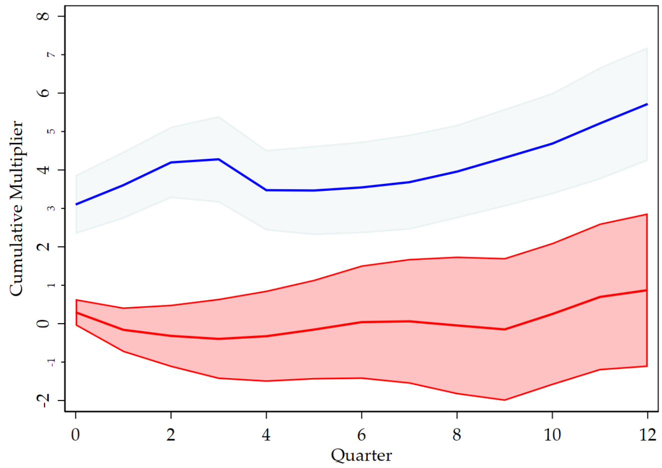


Figure G.6. Without the Great Recession: **M3**

Notes: See Figure G.4 for details.

Table G.17. Without the Great Recession: **M3**

Statistics:	m_h (1)	s.e. (2)	C.I. Lower Bound (3)	C.I. Upper Bound (4)	Kleibergen-paap Wald F-stat (5)	p-value (6)
			Low Income Uncertainty			
quarter 0	.296	.345	-.388	.98	30.59	.002
quarter 4	-.326	1.187	-2.681	2.029	4.679	.039
quarter 8	-.047	1.792	-3.604	3.511	2.829	.087
quarter 12	.873	1.998	-3.095	4.841	1.447	.094
			High Income Uncertainty			
quarter 0	3.101	.766	1.58	4.621	30.59	.002
quarter 4	3.473	1.048	1.394	5.552	4.679	.039
quarter 8	3.958	1.216	1.545	6.371	2.829	.087
quarter 12	5.718	1.475	2.788	8.648	1.447	.094

Notes: Results exclude the Great Recession. See Table G.11 and G.12 for remaining details. **M3** is defining low and high income uncertainty based on an alternative Bry and Boschan Algorithm and income shock directions.

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Statement of Authorship

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15. November 2020

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