Econ 236B : [Spring 2015] Amir Kermani

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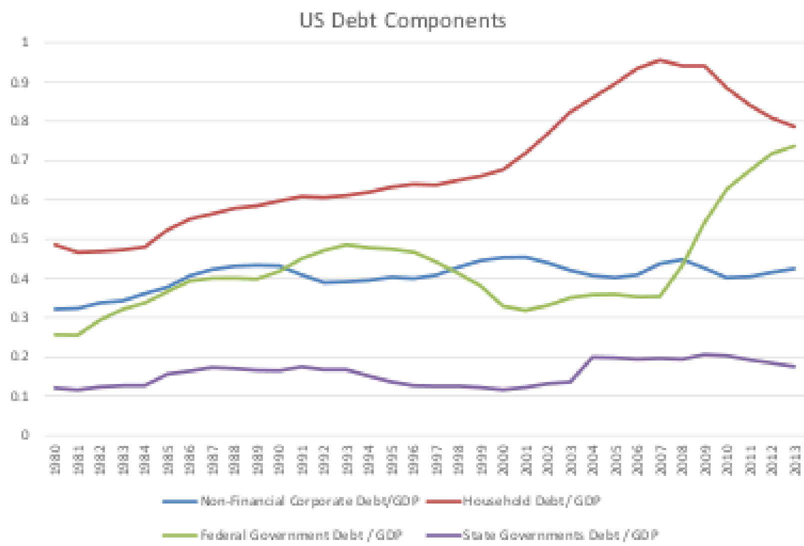
Lecture 1

Households Balance Sheet and Households Income

1.1 Why Household Finance Is Important

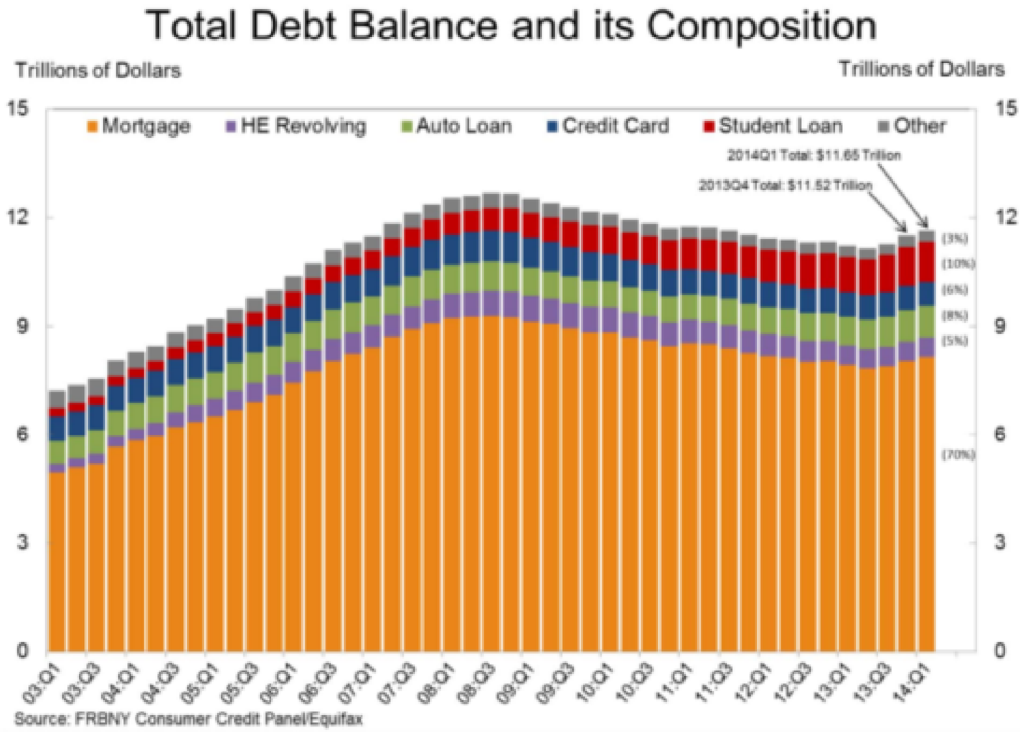
- (FRB, *Flow of Funds Accounts*). Since 1980s, most movement in debt-to-GDP ratios coming from *HH debt* and *Federal Gov't debt*
- Thing to consider: exiting ZLB is a burden on Federal Gov't debt (seen by the surge in Federal debt-to-GDP)
- Corporate debt-to-GDP = boring and doesn't move very much..



1.1.1 HH Debt decomposition:

1.1.1.1 Student Debt:

- Since 2000, *student debt* grew on average 10% per year - concentrated mostly within "young" HH population.
- By far the **fastest growing** component of debt - used to be largely insignificant and almost a non-existent HH balance-sheet liability.
- UNANSWERED QUESTION(S):
  1. What are the implications for *labor market* (*income inequality*)?
  2. What are the implications for *housing market*?
     (a) Taking on too much student debt can hurt creditworthiness - can inhibit you from taking out a mortgage.
     (b) Family formation can be postposed due to too much student debt
  3. What are the implications for the *macroeconomy*?
     (a) If student debt is concentrated within young HH group, which tends to have ***greater MPC*** than the group providing loans (capital owners - ***low MPC***) then too much student debt has implications for aggregate demand.



1.1.1.2 Mortgage Debt

- Mortgage debt is about 70-80% of HH debt; collateralized by home.

1.2 Households' Balancesheet

1.2.1 Campbell (JF, 2006): *Household Finance*

Abstract: The study of household finance is challenging because household behavior is difficult to measure, and households face constraints not captured by textbook models. Evidence on participation, diversification, and mortgage refinancing suggests that many households invest effectively, but a minority make significant mistakes. This minority appears to be poorer and less well educated than the majority of more successful investors. There is some evidence that households understand their own limitations and avoid financial strategies for which they feel unqualified. Some financial products involve a cross-subsidy from naive to sophisticated households, and this can inhibit welfare-improving financial innovation.

- Housing (illiquid asset) is the *most important* asset for about 60% of HHs. HHs hold *very little* liquid (safe) assets - this makes it difficult to smooth consumption if there is a fixed cost that must be paid when "rebalancing" portfolio allocation of housing asset.

- Since most HHs own housing assets relative to equity assets, fluctuations in housing markets have greater implications for real economy than fluctuations in equity markets. In addition, the fact that housing can serve as a collateral asset *amplifie*s these effects.

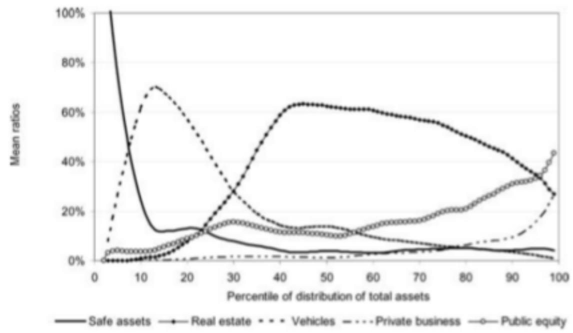


TABLE III

HOUSEHOLD PORTFOLIO COMPOSITION[a]

	Median ($2001)	Mean ($2001)	Fraction Positive	Return (%)
Earnings plus benefits (age 22–59)	41,000	52,745	–	–
Net worth	62,442	150,411	0.90	1.7
Net liquid wealth	2,629	31,001	0.77	−1.5
Cash, checking, saving, MM accounts	2,858	12,642	0.92	−2.2
Directly held MF, stocks, bonds, T-Bills	0	19,920	0.29	1.7
Revolving credit card debt	0	1,575	0.41	–
Net illiquid wealth	54,600	119,409	0.93	2.3
Housing net of mortgages	31,000	72,592	0.68	2.0
Retirement accounts	950	34,455	0.53	3.5
Life insurance	0	7,740	0.27	0.1
Certificates of deposit	0	3,807	0.14	0.9
Saving bonds	0	815	0.17	0.1

[a] Authors' calculations based on the 2001 Survey of Consumer Finances (SCF). The return reported in the last column is the real after-tax risk-adjusted return. MM: money market; MF: mutual funds. See Appendix B.1 for additional details.

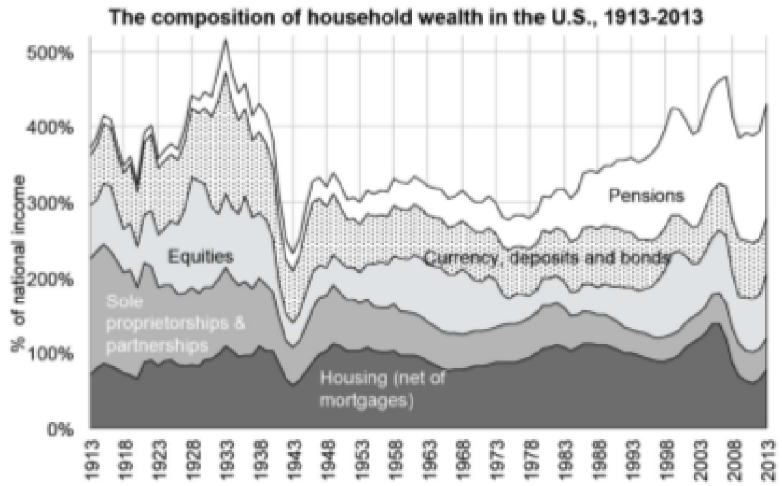
1.3 The Wealth Distribution

1.3.1 Saez and Zucman (R&R QJE, 2014): *Wealth Inequality in the United States since 1913: Evidence from Capitalized Income Tax Data*

Abstract: This paper combines income tax returns with Flow of Funds data to estimate the distribution of household wealth in the United States since 1913. We estimate wealth by capitalizing the incomes reported by individual taxpayers, accounting for assets that do not generate taxable income. We successfully test our capitalization method in three micro datasets where we can observe both income and wealth: the Survey of Consumer Finance, linked estate and income tax returns, and foundations' tax records. Wealth concentration has followed a U-shaped evolution over the last 100 years: It was high in the beginning of the twentieth century, fell from 1929 to 1978, and has continuously increased since then. The rise of wealth inequality is almost entirely due to the rise of the top 0.1% wealth share, from 7% in 1979 to 22% in 2012—a level almost as high as in 1929. The bottom 90% wealth share first increased up to the mid-1980s and then steadily declined. The increase in wealth concentration is due to the surge of top incomes combined with an increase in saving rate inequality. Top wealth-holders are younger today than in the 1960s and earn a higher fraction of total labor income in the economy. We explain how our findings can be reconciled with Survey of Consumer Finances and estate tax data.

1.3.1.1 Interesting Facts

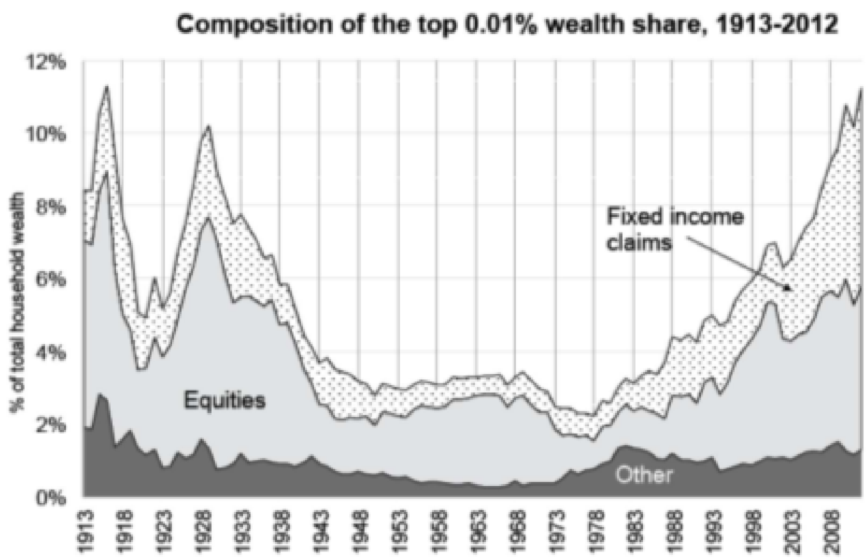
- Looking at figure below, one can see that ***housing (net of morgages)*** is "relatively stable" at ***100% of national income*** since 1913 - with the exception of **(i)** late 1930s-early 1940s and **(ii)** Great Recession
- Pension plans have **INCREASED** substantially since late 1970s due to introduction of *401K*. Before *401K* ... *Defined contribution plans/benefits.*
- ISSUE: The growth in pensions may be an "artificial" fact stemming from not including wealth component tied to *Defined contribution plans/benefits* pre late-1970s.



This figure depicts the evolution of the ratio of total household wealth to national income. This ratio has followed a U-shaped evolution and the composition of wealth has changed markedly since 1913. Source: Appendix Table A1.

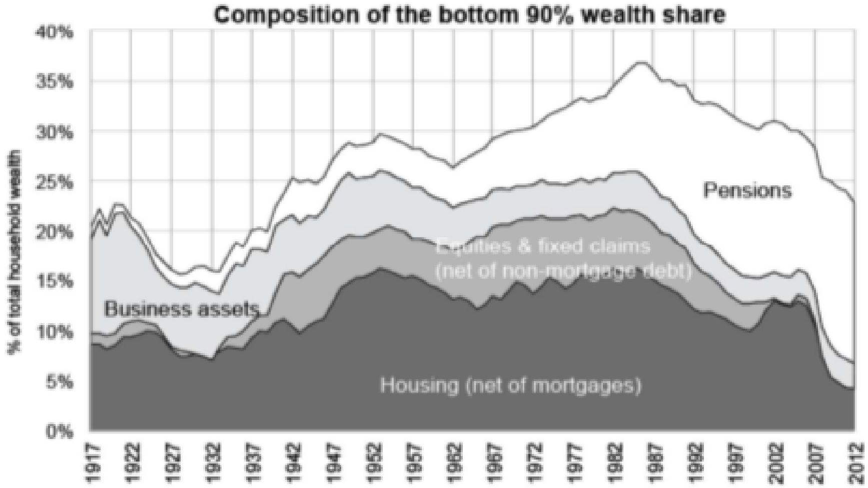
1.3.1.2 The "Wealthiest" Top 0.01% HHs

- Top 0.01% wealth share ≈ 16,000 HHs (hold as of 2013) about 12% of all wealth in the US. Since late 1970s, this increase in the top 0.01% wealth share comes mostly from **Equities** and **Fixed Income** assets
- **Fixed Income assets**: (checkings + savings deposits) + (money market fund shares) + (bond holdings)
- Differences in wealth come from differences in portfolio allocations.



1.3.1.3 Bottom 90% of HHs

- *Defined Contribution Pension Plans* are missing here. The "truth" is WORSE !!!



- ***DECREASING*** interest rates. From late 1990s to 2007, the savings rate of the bottom 90% ***decreased*** and was ***negative*** $\implies$ these HHs were ***net borrowers***. From 2005 to 2007, almost 5% to 9% of consumption was financed by *borrowing* — this was *not sustainable*.
- ***Financial liberalization*** may be a driving force; tied to *financial deregulation* since the late 1970s.

1.3.2 Kopczuk (JEP, 2015): *What Do We Know About Evolution of Top Wealth Shares in the United States?*

Abstract: I discuss available evidence about the evolution of top wealth shares in the United States over the last one hundred years. The three main approaches – Survey of Consumer Finances, estate tax multiplier techniques and capitalization method – generate generally consistent findings until mid-1980s but diverge since then, with capitalization method showing a dramatic increase in wealth concentration and the other two methods showing at best a small increase. I discuss strengths and weaknesses of different approaches. The increase in capitalization estimates since 2000 is driven by a dramatic and surprising increase in fixed income assets. There is evidence that estate tax estimates may not be sufficiently accounting for mortality improvements over time. The non-response and coverage issues in the SCF are a concern. I conclude that changing nature of top incomes and the increased importance of self-made wealth may explain difficulties in implementing each of the methods and account for why the results diverge

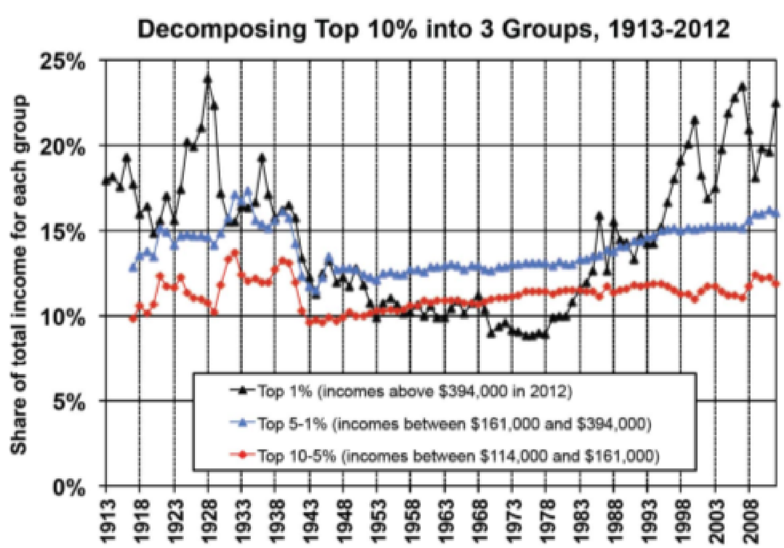
Main issue with estimating wealth directly in the US: ***no tax on wealth.***

- Not all categories of assets generate capital income that appears on tax returns.
  - Defined contribution pension plans (including ss)
  - Capital income on tax returns represents only about one-third of the overall return to capital
- both realized and expected returns to capital vary by asset, but only a very rough division of capital income is available on income tax returns
- The tripling of the fixed income component between 2000 and 2012 is driven by an increase in the underlying capitalization factor from 24 to 96.6

- **Capitalization method:** Almost all the ***INCREASE*** in wealth inequality since 2000 comes from ***INCREASE*** in ***fixed income component.***
- Almost all the ***INCREASE*** in ***fixed income component*** is driven by capitalization factor. *Bottom 90%-Bottom 99.9%* HHs hold fixed income assets in the form of *checkings + savings deposits* while *Top 10%-Top 0.1%* hold fixed income assets in the form of *bonds.* The issue here is that all fixed income assets get clumped up into one group, which is then used to get *one capitalization facto*r.
  - Return on *fixed income assets* across distribution very different: **systematic bias** embedded in the capitalization factor.

1.4 Households' (Labor) Income

Income inequality



Source: Piketty and Saez, 2003 updated to 2012. Series based on pre-tax cash market income including realized capital gains and excluding government transfers. 2012 data based on preliminary statistics.

FACTS:

1. *Labor income* is absent in HH wealth calculations.
2. *Labor income* is more than 2x larger than *capital income.*

QUESTIONS:

1. Why do you need wealth if your labor income is high enough?

2. Does it matter whether you income is *insurable* or *not insurable*?

3. Is there any relation between labor income, saving rates and wealth inequality?

Theory 1: HHs that have ***MUCH riskier labor income*** have a ***GREATER incentive to save***, which in equilibrium affects the interest rate. If ***top income earners*** are the ones that have the ***riskiest*** labor income then their savings behavior may DRIVE UP the interest rate in the aggregate; it can be too low.

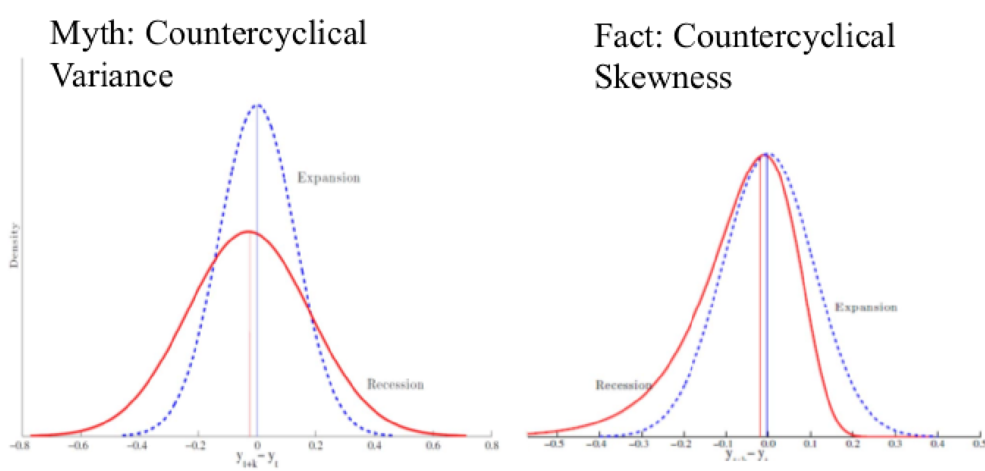
- *INCREASING* σ of top income earners $\implies$ *INCREASING* the "risk" of top income earners' labor income $\implies$ *INCREASING* savings behavior of top income earners $\implies$ *DECREASING* savings rate in equilibrium, which is *too low* for the "middle class" income earners.

Theory 2 (Carroll, 1996): Theory 1 is not correct; top income earners don't save more because of a "precautionary savings" motive. They may simply have an intrinsic value from the wealth itself.

1.4.1 Guvenen, Ozkan, and Song (JPE, 2014): *The Nature of Countercyclical Income Risk*

Abstract: We study business cycle variation in individual earnings risk using a confidential and very large data set from the US Social Security Administration. Contrary to past research, we find that the variance of idiosyncratic shocks is not countercyclical. Instead, it is the left-skewness of shocks that is strongly countercyclical: during recessions, large upward earnings movements become less likely, whereas large drops in earnings become more likely. Second, we find that the fortunes during recessions are predictable by observable characteristics before the recession. Finally, the cyclicality of earnings risk is dramatically different for the top 1 percent compared with the rest of the population.

Labor Income Over the Business Cycle:

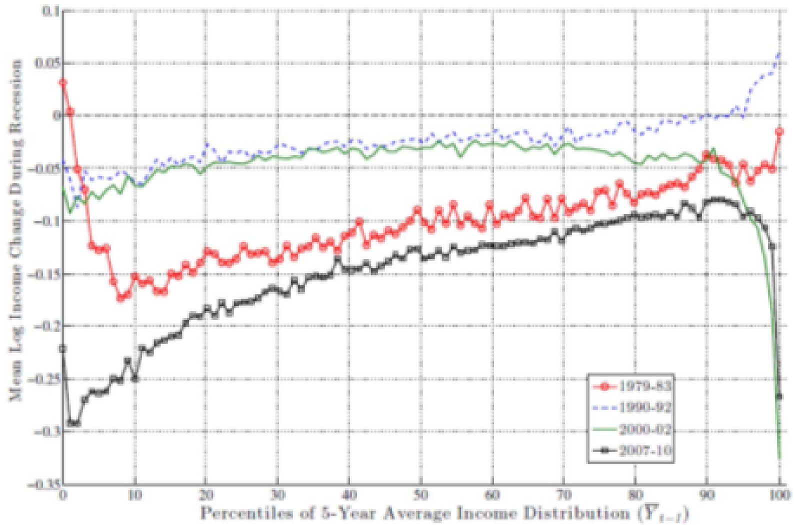


- **Myth:** Normal Distributio with $\mu_{Expansion} > \mu_{Recession}$; $\sigma_{Expansion} < \sigma_{Recession}$

- **Fact:** Normal Distribution during *Expansions*; Non-normal Distribution during Recessions (Left-Skewed) during *Recessions.*

  – ***Skewness*** of individual income shocks becomes ***more negative*** in recessions, whereas the *variance* is *acyclical (i.e. does not vary with the business cycle)*

Who bears the risk of business cycles?



- Age profile: 25-55; employed workers.
- Both tales are ***very risky*** (*low* income HHs + *very high* income HHs). QUESTIONS: Are the consumption consequences the same? Does that matter?
- Low income workers are also more vulnerable to industry-specific shocks (see ***Autor, Dorn, Hanson and Song (QJE 2015)***). Great Recession involved a shock to ***housing market*** so *construction* and *retail sectors* were clearly affected.

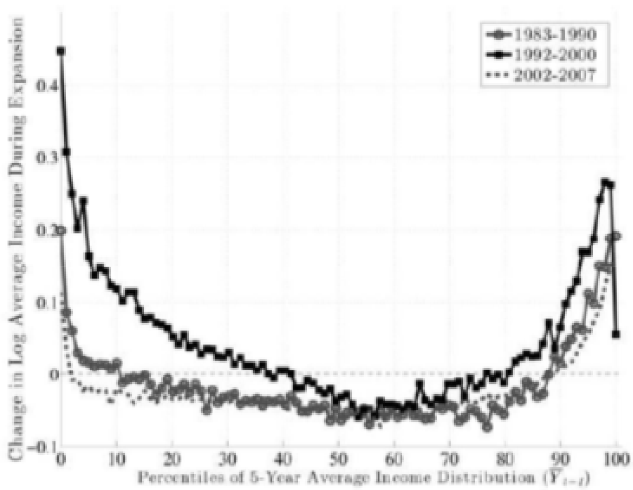


Fig. 14.—Change in log average earnings during expansions, prime-age males

1.4.2 Guvenen, Karahan, Ozkan, and Song (2013): *What Do Data on Millions of U.S. Workers Reveal about Life-Cycle Earnings Risk?*

Abstract: We study the evolution of individual labor earnings over the life cycle using a large panel data set of earnings histories drawn from U.S. administrative records. Using fully nonparametric methods, our analysis reaches two broad conclusions. First, ***labor earnings shocks display substantial deviations from lognormality***—the standard assumption in the incomplete markets literature. In particular, ***labor earnings shocks display strong negative skewness*** and ***extremely high kurtosis*** — as high

as 30 compared with 3 for a Gaussian distribution. The high kurtosis implies that in a given year, most individuals experience very small earnings shocks, and a small but non-negligible number experience very large shocks. Second, these ***statistical properties vary significantly both over the life cycle and with the earnings level of individuals***. We also estimate impulse response functions of earnings shocks and find important asymmetries: positive shocks to high-income individuals are quite transitory, whereas negative shocks are very persistent; the opposite is true for low-income individuals. Finally, we use these rich sets of moments to estimate econometric processes with increasing generality to capture these salient features of earnings dynamics.

What about Labor Income over the *Life Cycle*?

- Labor income is ***much riskier*** than you may think (relative to a Gaussian framework). Most negative shocks are not a "2% loss in income"-income shock but more like "I am losing my job"-type of income shock!
- *Non-normal density* seen here has huge asset pricing implications; can explain ***equity risk premium***.

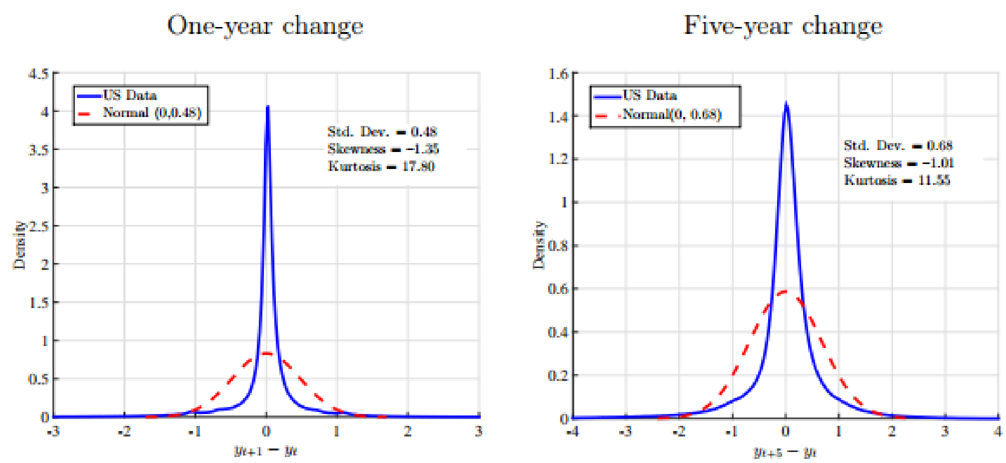
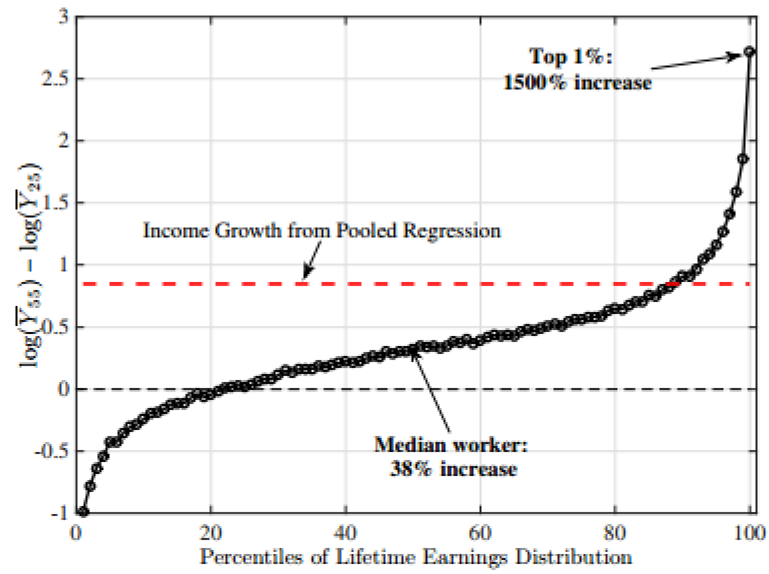


FIGURE 1 – Histogram of Log Earnings Changes. Note: The first year t is 1995, and the data are for all workers in the base sample defined in Section 2.

- The *moments* of labor earnings shocks vary over the life cycle $\implies$ ***non-stationarity***
- The *moments* of labor earnings shocks vary with the ***LEVEL of labor earnings***.
- Interesting question: How can we design a policy such that during recessions, *only HHs that are unemployed* receive help (not the average).

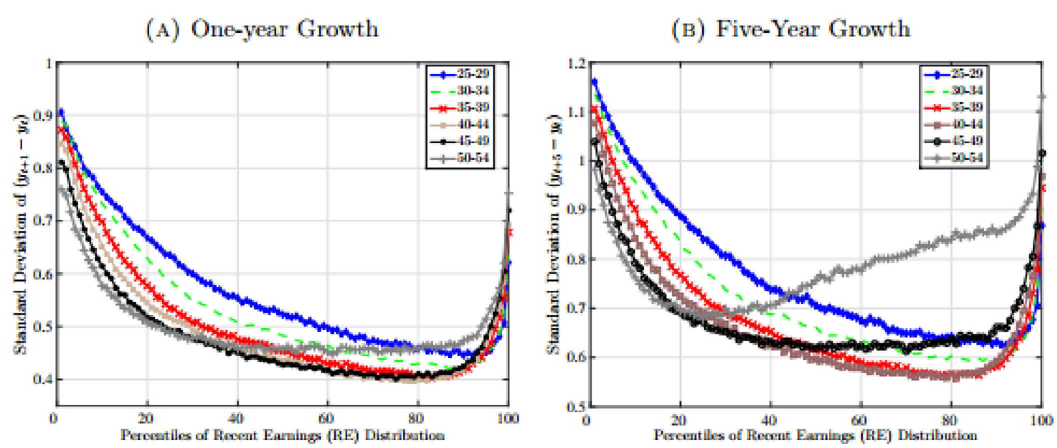
Median Earnings Growth vs. *Average Earning Growth* Over Lifetime

- ***Median income earner*'s** labor income only *increases by 38%* over her lifetime vs. the ***average income earner's*** income, which *increases by about 90%* over her lifetime.
- **ISSUE:** Calibrating a model with the average means you ***overestimate*** the labor income for more than half the population!



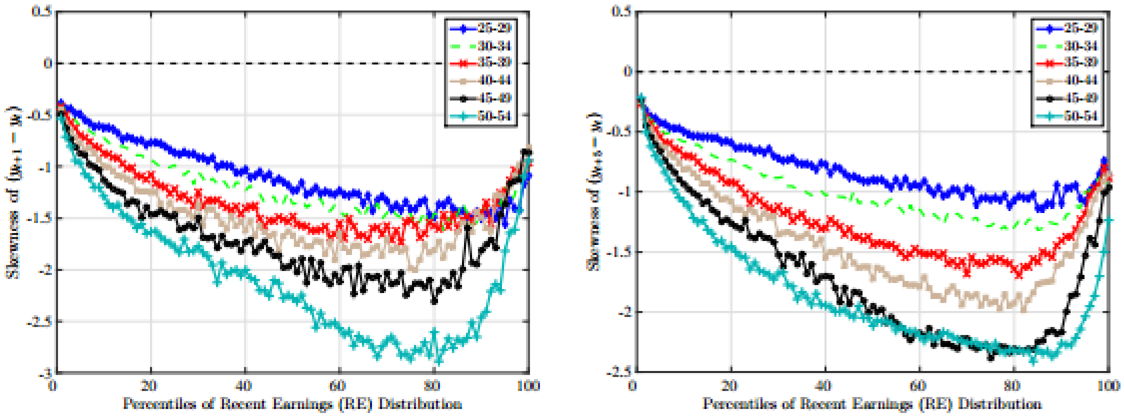
Income Volatility over the Lifetime

- Other than 50-54 year olds, σ_t ***DECREASES*** over time. Except the top 1%, higher income is associated with lower σ_t as well.



- Looking at *second moments as measures of "riskiness"* is not correct since ***higher order moments*** (skewness, kurtosis) matter! Labor income risk may actually *INCREASE over time* (as given here by the skewness)

(A) One-Year Change (B) Five-Year Change



Lecture 2

Financial Frictions and Households: Empirical Evidence I

2.1 Evidence on violation of *Permanent Income Hypotheses* (PIH)

2.1.1 PIH: Review

PIH: *anticipated (predicted) income shocks* and *consumption smoothing*

2.1.2 Recent Literature

Gelman, Kariv, D. Shapiro, Silverman, Tadelis (2015): *How Individuals Smooth Spending: Evidence from the 2013 Government Shutdown Using Account Data*

Abstract: Using comprehensive account records, this paper examines how individuals respond to a temporary drop in income following the 2013 U.S. Federal Government shutdown. Affected employees saw their income decline by 40% on average, which was recovered within two weeks. Despite having no effect on lifetime earnings, spending dropped sharply, implying a naïve estimate of the marginal propensity to spend of 0.57. This estimate overstates how consumption responded. To smooth consumption, individuals adjusted by delaying recurring payments such as mortgages and credit card balances. Those with the least liquidity struggled most to smooth spending and were left holding more debt months after the shutdown.

2.1.2 Johnson, Parker and Souleles (AER, 2006): *Household Expenditure and the Income Tax Rebates of 2001*

Abstract: Using questions expressly added to the Consumer Expenditure Survey, we estimate the change in consumption expenditures caused by the 2001 federal income tax rebates and test the permanent income hypothesis. We exploit the unique, randomized timing of rebate receipt across households. Households spent 20 to 40 percent of their rebates on nondurable goods during the three-month period in which their rebates arrived, and roughly two-thirds of their rebates cumulatively during this period and the subsequent three-month period. The implied effects on aggregate consumption demand are substantial. Consistent with liquidity constraints, responses are larger for households with low liquid wealth or low income.

The Economic Growth and Tax Relief Reconciliation Act of 2001 sent tax rebates:

- typically \$300 or \$600 in value, to most U.S. households over a ten-week period from late July to the end of September 2001.
- the timing of the mailing of each rebate was based on the second to-last digit of the Social Security number (SSN)

Main Regression: $C_{i,t+1} - C_{i,t} = \mathbf{\Sigma}\beta_{0s} \cdot month_{s,i} + \beta_1 X_{i,t} + \beta_2 R_{i,t+1} + u_{i,t+1}$

- $R_{i,t+1}$ = ESP variable which can be the dollar value $Rebate_{i,t+1}$ or an indicator variable for payment received $\mathbf{1}_{\{Rebate_{i,t+1}\}}$

Main Result: HHs spent ***20-40%*** of their rebates on ***nondurable goods*** during the 3-month period in which their rebates arrived. HHs' consumption does react significantly upon arrival of their rebate, despite the fact it was anticipated.

Table 2—The Contemporaneous Response of Expenditures to the Tax Rebate

	Panel A. Dependent variable: dollar change in expenditures on:					
	Food	Strictly nondurable goods	Nondurable goods	Food	Strictly nondurable goods	Nondurable goods
Estimation method	OLS	OLS	OLS	OLS	OLS	OLS
Rebate	0.109	0.239	0.373			
	(0.056)	(0.115)	(0.135)			
I(*Rebate* > 0)				51.5	96.2	178.8
				(27.6)	(53.6)	(65.0)
Age	0.570	0.449	1.165	0.552	0.391	1.106
	(0.320)	(0.550)	(0.673)	(0.318)	(0.548)	(0.670)
Change in adults	130.3	285.8	415.8	131.1	287.7	418.6
	(57.8)	(90.0)	(102.8)	(57.8)	(90.2)	(102.9)
Change in children	73.7	98.3	178.4	74.0	98.7	179.2
	(45.3)	(82.4)	(98.3)	(45.3)	(82.5)	(98.3)
RMSE	934	1680	2047	934	1680	2047
R^2 (percent)	0.6	0.6	0.6	0.6	0.6	0.6

2.1.3 Parker, Souleles, Johnson, and McClelland (AER, 2013): *Consumer Spending and the Economic Stimulus Payments of 2008*

Abstract: We measure the change in household spending caused by receipt of the economic stimulus payments of 2008, using questions added to the Consumer Expenditure Survey and variation from the randomized timing of disbursement. Households spent 12-30 percent (depending on specification) of their payments on nondurable goods during the three-month period of payment receipt, and a significant amount more on durable goods, primarily vehicles, bringing the total response to 50-90 percent of the payments. The responses are substantial and significant for older, lower-income, and home-owning households. Spending does not vary significantly with the method of disbursement (check versus electronic transfer).

Table 2—The Contemporaneous Response of Expenditures to ESP Receipt among All Households

	Food OLS	Strictly nondurables OLS	Nondurable spending OLS	All CE goods and services OLS	Food OLS	Strictly nondurables OLS	Nondurable spending OLS	All CE goods and services OLS
Panel A. Dollar change in spending								
ESP	0.016	0.079	0.121	0.516				
	(0.027)	(0.046)	(0.055)	(0.179)				
I(*ESP*)					10.9	74.8	121.5	494.5
					(31.7)	(56.6)	(67.2)	(207.2)

The *size of the payment* is almost ***twice the size*** of 2001 Tax rebate

Main Regression: similar to ***Parker et al. (2006)***

Main Results:

1. ***size of the ESP*** matters with regards to the ***MPC out of the ESP***.

2. HHs spent about ***12-30 %*** of their stimulus payments on ***nondurable goods*** during the 3-month period in which the payments were received;
3. significant effect on the purchase of *durable goods* and related services, primarily the purchase of vehicles;
4. *total consumption expenditure (CE)*: 50-90% of the payments during the 3-month period of receipt

Interaction with HH Characteristics

TABLE 6—THE PROPENSITY TO SPEND ACROSS DIFFERENT HOUSEHOLDS

Interaction:	*Panel A. By age*		*Panel B. By income*		*Panel C. By liquid assets*		*Panel D. By housing status*	
Dependent variable:	Dollar change in		Dollar change in		Dollar change in		Dollar change in	
	Non-durable spending	All CE goods and services	Non-durable spending	All CE goods and services	Non-durable spending	All CE goods and services	Non-durable spending	All CE goods and services
	Age Low: ≤ 40 High: > 58		Income Low: ≤ 32,000 High: > 74,677		Liquid assets Low: ≤ 500 High: > 7,000		Housing status Low: own with mortgage High: own without	
ESP	0.345	0.952	0.215	0.568	0.275	0.851	0.213	0.431
	(0.133)	(0.398)	(0.124)	(0.442)	(0.164)	(0.558)	(0.153)	(0.455)
ESP × *Low*	−0.150	−0.461	0.024	0.715	−0.253	−0.844	0.043	0.543
(group difference)	(0.124)	(0.399)	(0.155)	(0.500)	(0.184)	(0.527)	(0.131)	(0.394)
ESP × *High*	0.044	0.414	−0.009	0.205	−0.075	0.083	0.260	0.800
(group difference)	(0.151)	(0.472)	(0.139)	(0.466)	(0.186)	(0.631)	(0.169)	(0.514)
Observations	10,488	10,488	8,592	8,592	5,071	5,071	10,380	10,380
Implied total spending								
Low group	0.195	0.491	0.239	1.283	0.022	0.007	0.256	0.974
	(0.114)	(0.394)	(0.180)	(0.564)	(0.205)	(0.566)	(0.112)	(0.364)
High group	0.389	1.366	0.206	0.773	0.200	0.934	0.473	1.231
	(0.168)	(0.498)	(0.133)	(0.463)	(0.202)	(0.677)	(0.175)	(0.508)

- 3 groups: *low, middle, and high*
- "All CE goods and services" = ***durable spending***
- HHs with ***low liquid assets*** don't respond as much.
- Financial frictions can DECREASE fiscal multiplier since HHs demanding a leverage purchased can't do so. Fiscal multipliers from 2001 may be larger relative to those from 2008 due to the presence of financial frictions and HHs damaged balance-sheets.

2.1.4 Bertrand and Morse (AER P&P, 2009): *What do High-Interest Borrowers Do with their Tax Rebate*

Abstract: Building on prior literature that constrained individuals consume the most out of a tax rebate, we study the tradeoffs high interest borrowers face when they received their 2008 tax stimulus checks. We find a persistent decline in payday borrowing in the pay cycles that follow the receipt of the tax rebate. The reduction in borrowing is a significant fraction of the mean outstanding loan (12%) and appears fairly persistent over the time, but is moderate in dollar magnitude (about $35) relative to the size of the rebate check ($600 per person). In trying to reconcile this finding with the cost of not retiring expensive payday debt, we find substantial heterogeneity across borrowers. Among individuals that we classify as temptation spenders (e.g. those that use 400% APR loans to buy electronic goods or go on vacation), we find no reduction in payday borrowing after the tax rebate is issued, but this group represents only a small fraction of payday borrowers. A second group for which we find no debt retirement post-check is the set of borrowers that appear to use what should be short-term payday loans as a long-term financing solution. We infer that the marginal use of the tax rebate for this group was to deal with regular monthly obligations, such as paying down late utility bills or making rent payments.

They look at ***low income***, ***low liquidity*** **HHs** and find that rebates are used to pay utility bills, pay lenders, credit cards, etc.

2.1.5 Broda and Johnson (2012): Tax Rebates

- Authors use data on HHs in the ***Nielsen Consumer Panel***, which were surveyed about their 2008 Economic Stimulus Payment; higher quality and higher frequency data

Table 7: Differences in average spending response by previous income

	Panel A: Using all variation in time of receipt					
	Dollars spent on indicator of ESP (dollars spent)			Dollars spent on average group ESP/100 (MPC percent)		
	Income <35,000	35,000< Income <70,000	70,000< Income	Income <35,000	35,000< Income <70,000	70,000< Income
Month before	7.3	7.5	-1.2	1.12	0.90	-0.03
	(8.9)	(9.5)	(13.4)	(1.54)	(1.01)	(1.22)
Contemporaneous month	41.9	46.9	33.9	7.16	4.96	3.17
	(11.2)	(13.1)	(17.5)	(1.96)	(1.38)	(1.59)
First month after	13.1	8.4	22.0	2.58	0.90	2.03
	(14.1)	(16.9)	(22.0)	(2.48)	(1.78)	(1.99)
Second month after	13.8	2.0	36.2	2.88	0.02	3.61
	(16.7)	(21.2)	(26.6)	(2.92)	(2.23)	(2.41)
Three month cumulative dollar increase or cumulative MPC	68.8	57.4	92.1	12.64	5.88	8.80
	(39.7)	(47.8)	(62.0)	(6.96)	(5.04)	(5.60)
Number of households	6,172	6,537	4,881	6,078	6,409	4,792

- No effect on the announcement date

Table 6: The average household spending response to learning about getting an ESP

	Panel A: All households					
	Using all variation in time of receipt			Using only variation in timing within each method of receip		
	Dollars spent on indicator of ESP ($ spent)	Spending as pct of 2008Q1 spending on indicator of ESP (% chg in spending)	Dollars spent on average ESP/100 (MPC, in %)	Dollars spent on indicator of ESP ($ spent)	Spending as pct of 2008Q1 spending on indicator of ESP (% chg in spending)	Dollars spent on average ESP/100 (MPC, in %)
Month before	10.0	2.2	1.10	9.4	2.2	0.94
	(7.8)	(1.3)	(0.85)	(7.8)	(1.3)	(0.86)
Contemporaneous month	0.2	0.7	0.12	-0.3	0.8	-0.11
	(6.6)	(1.2)	(0.71)	(6.5)	(1.2)	(0.72)
First month after	2.6	0.3	0.26	3.0	0.6	0.12
	(6.8)	(1.3)	(0.74)	(6.9)	(1.3)	(0.76)
Second month after	-2.4	0.5	-0.06	-2.1	0.7	-0.10
	(7.0)	(1.4)	(0.76)	(7.0)	(1.4)	(0.77)
Three month cumulative dollar increase or cumulative MPC	0.3		0.33	0.6		-0.10
	13.1		(1.42)	13.1		(1.46)
Three month average percent increase in spending		0.5			0.7	
		(0.8)			(0.8)	

- ** DISCLAIMER: Heterogeneity in consumption responses is not enough to show ***low income*** HHs have ***higher MPC*** since we don't observe all consumption behavior; CEX data is probably the best data that contains most of the consumption behavior of HHs; PSID data is very limited. **

	Time dummes								
	Dollars spent on indicator of ESP (dollars spent)			Spending as percent of pretreatment spending on indicator of ESP (percent change in spending)			Dollars spent on average ESP/100 (MPC percent)		
	Income <35,000	35,000< Income <70,000	70,000< Income	Income <35,000	35,000< Income <70,000	70,000< Income	Income <35,000	35,000< Income <70,000	70,000< Income
Week before	0.7 (2.4)	2.4 (2.7)	-0.8 (3.7)	-1.9 (2.2)	-0.4 (2.0)	-0.5 (2.8)	0.12 (0.40)	0.25 (0.27)	-0.08 (0.32)
Contemporaneous week	**21.7** **(3.3)**	**15.7** **(3.2)**	**6.3** **(3.9)**	**16.0** **(2.7)**	**10.6** **(2.4)**	**1.9** **(2.9)**	**3.55** **(0.55)**	**1.56** **(0.33)**	**0.53** **(0.34)**
First week after	17.2 (2.7)	13.0 (2.9)	7.3 (4.1)	13.5 (2.5)	7.4 (2.3)	4.9 (2.8)	2.78 (0.44)	1.29 (0.30)	0.70 (0.36)
Seven week cumulative dollar increase, average pct. increase, and cumulative MPC in pct.	**65.7** **(10.7)**	**47.2** **(10.9)**	**23.8** **(15.9)**	**6.8** **(1.6)**	**3.6** **(1.3)**	**1.8** **(1.6)**	**10.90** **(1.76)**	**4.68** **(1.11)**	**2.16** **(1.41)**
Share answering	0.34	0.58	0.08	0.34	0.58	0.08	0.34	0.58	0.08

Heterogeneity in liquid assets

In case of an unexpected decline in income or increase in expenses, do you have at least two months of income available in cash, bank accounts, or easily accessible funds?

	Time dummes					
	Dollars spent on indicator of ESP ($ spent)		Spending as pct of pre-treatment spending on indicator of ESP (pct. chg in spending)		Dollars spent on avgerage ESP/100 (MPC %)	
Answer:	*Yes*	*No*	*Yes*	*No*	*Yes*	*No*
Month before	-0.3 (1.6)	2.6 (2.1)	-2.9 (1.3)	-0.7 (1.8)	0.00 (0.18)	0.29 (0.23)
Contemporaneous month	**5.1** **(2.1)**	**19.4** **(2.9)**	**0.6** **(1.8)**	**11.5** **(2.9)**	**0.58** **(0.24)**	**2.13** **(0.32)**
First month after	1.8 (2.6)	4.3 (3.7)	-1.6 (2.3)	1.6 (3.6)	0.20 (0.29)	0.54 (0.40)
Five month cumulative dollar increase, average pct. increase, and cumulative MPC in pct.	**19.7** **(15.7)**	**28.4** **(21.2)**	**-0.1** **0.4**	**0.4** **(0.6)**	**2.22** **(1.75)**	**3.63** **(2.32)**

- Liquidity constraint HHs have much ***higher MPCs***.

2.1.6 Behavioral Explanations

Rational Inattention: The idea is that decision-makers have a limited amount of attention and have to decide how to allocate it.

- ***Implications:*** Rules-of-Thumb, Quasi-optimization. For *small rebate*s, costs of optimization may not exceed benefit so a rule-of-thumb may be better. For *large rebates*, full optimization may be more beneficial on the margin.

2.1.7 Gross and Souleles (QJE, 2002): *Do Liquidity Constraints And Interest Rates Matter For Consumer Behavior? Evidence From Credit Card Data*

Abstract: This paper utilizes a unique dataset of credit card accounts to analyze how people respond to *changes in credit supply*. The data consist of a panel of thousands of individual credit card accounts from several different card issuers, with associated credit bureau data. We estimate both MPCs out of liquidity and interest-rate elasticities. We also evaluate the ability of different models of consumption to rationalize our results, distinguishing the PIH, liquidity constraints, precautionary saving, and behavioral models. We find that increases in credit limits generate an immediate and significant rise in debt, counter to the PIH. The average "MPC out of liquidity" (dDebt/dLimit) ranges between 10%-14%. The MPC is much larger for people starting near their limits, consistent with binding liquidity constraints. However, the MPC is significant even for people starting well below their limit. We show this response is consistent with buffer-stock models of precautionary saving. Nonetheless there are other results that conventional models cannot easily explain, e.g. why so many people are borrowing on their credit cards, and simultaneously holding low yielding assets. Unlike most other studies, we also find strong effects from changes in account-specific interest rates. The long-run elasticity of debt to the interest rate is approximately -1.3. Less than half of this elasticity represents balance-shifting across cards, with most reflecting net changes in total borrowing. The elasticity is larger for decreases in interest rates than for increases, which can explain the widespread use of temporary promotional rates. The elasticity is smaller for people starting near their credit limits, again consistent with liquidity constraints.

Motivation: The canonical Permanent-Income Hypothesis (PIH) assumes that consumers have certainty-equivalent preferences and *don't face any liquidity constraints*. Under these assumptions the marginal propensity to consume (MPC) out of liquid wealth depends on model parameters, but generally averages less than 0.1. The ***MPC out of predictable income*** or ***"liquidity" (e.g. increases in credit limits)***, which do not entail wealth effects, ***should be zero***.

The ***leading alternative view*** of the world is that *liquidity constraints are pervasive*. Even when they do not currently bind they can be reinforced by precautionary motives concerning the possibility that they bind in the future. Under this view the MPC out of liquidity can equal one over a range of levels for "cash-on-hand," defined to include available credit [Deaton 1991, Carroll 1992, and Ludvigson 1999].

To test whether *liquidity constraints* and *interest rates* really matter in practice, this paper uses a unique new data set containing a panel of thousands of individual credit card accounts from several different card issuers. In particular it *separately records* **credit limits** and **credit balances**, allowing us to ***distinguish credit supply and demand***, as well as account-specific interest rates. These data allow the authors to analyze the *response of debt to changes* in *credit limits* and thereby estimate the MPC out of liquidity, both on average and across different types of consumers. Because *bankcards* are the *marginal source of credit for most household*s, they can be used to measure the ***pervasiveness of liquidity constraints***.

The Credit-supply Function: Endogeneity is a generic problem in studies of the effects of credit supply, including monetary policy [Christiano, Eichenbaum, and Evans 1996, Kashyap and Stein 1995]. In their case there could be a problem if *credit card issuer*s INCREASE *credit supply* when they EXPECT *credit demand* to $\uparrow$. Then part of the observed response in debt could be the result of a ***demand shock***, not just a response to supply. However, their data allows them to go further than most previous studies to address the endogeneity of both credit limits and interest rates.

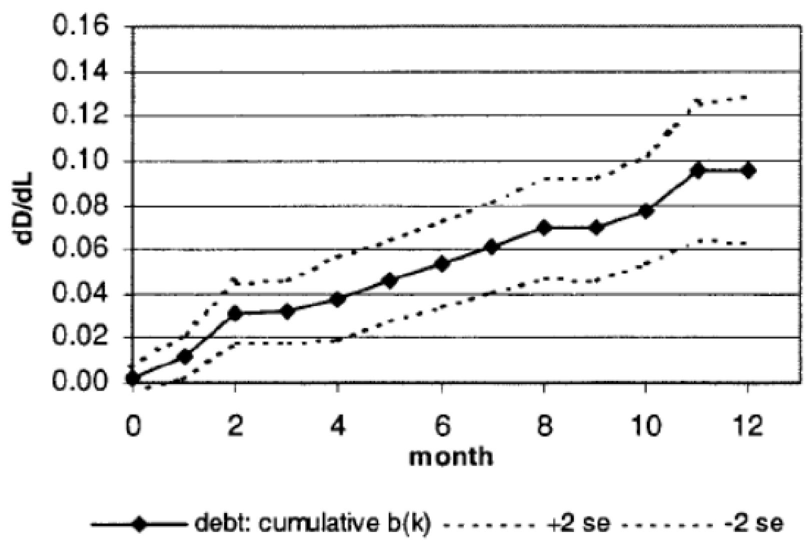
- Empirical Strategy: They follow two strategies:

  1. They use an unusually rich set of *control variables* to capture the endogenous part of credit-supply changes.

2. They use *IVs* to isolate exogenous changes in credit supply. In particular they exploit exogenous "***timing rules***" built into the credit-supply functions.
   - e.g. Many issuers will not consider (or are less likely to consider) an account for a *line change* if it has been less than 6 months or less than 1 year since the last line change. Hence for a given account the probability of a change is exogenously higher in certain months than in others. Consider, for example, two accounts *opened at the same time* that currently have the *same credit scores* but are on different timing cycles for exogenous reasons. Suppose one account had its latest line increase 12 months ago, the other had it 11 months ago. Because of the timing rules the first account is more likely to have its line go up this month, even though there is no fundamental difference between the accounts.
   - They handle ***interest rates analogously***. In particular credit card issuers also use exogenous timing rules for changing interest rates, which the authors exploit as instruments.

Results: Changes in Credit Limits

The figure below gives the "impulse response" to liquidity, specifically the cumulative response of debt to "automatic" increases in the credit line, per dollar of extra line. Debt rises sharply and significantly over the first 2 months after a line increase, and then smoothly asymptotes to b_{12}= *cumulative increase in debt after 12 months*.

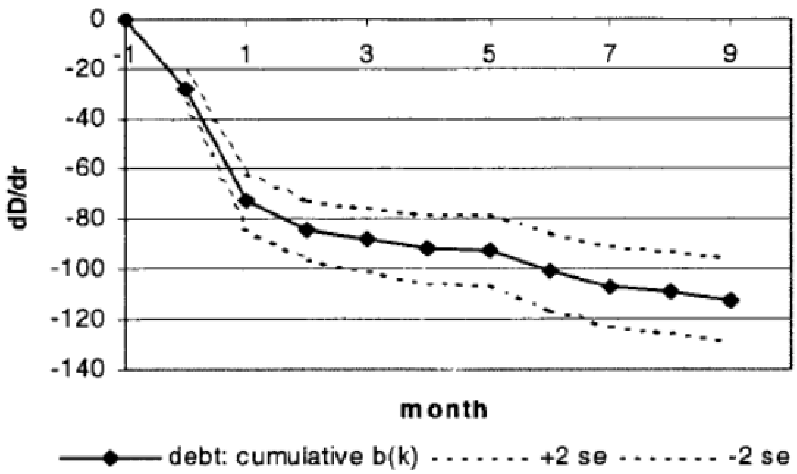


Results: Changes in Interest Rates

The figure below gives the "impulse response" to interest rates, specifically the cumulative response of debt to increases in the interest rate, per percentage point. It shows that debt responds immediately, *declining* by about $70 in the first two months after a rate change.

- Each percentage point INCREASE in the interest rate leads to a $110 DECREASE in debt on *average*, within 9 months $\Longrightarrow$ interest rates $\uparrow$ lead to substantially less borrowing – people are in fact *sensitive to interest rates.*

But it is not only the debt limit that matters, interest rates matters as well



The authors also investigate the *heterogeneity in people's responses*. Their goal is to identify what models of consumption explain these responses and credit card usage more generally. In the figure below, ***Panel A*** analyzes the effects of credit line changes, while ***Panel B*** analyzes the effects of interest rate changes

UTILIZATION RATES AND LIQUIDITY CONSTRAINTS

Row	b_{Tot}	*S.e.*	# obs
A. Credit limit changes			
(1) *dD/dL*			143511
utilization < .50	0.068	0.018	
utilization .50–.90	0.158	0.060	
utilization > .90	0.452	0.125	
(2) *d*(utilization)/*dL*			143511
utilization < .50	−0.012	0.004	
utilization .50–.90	0.013	0.015	
utilization > .90	0.012	0.026	
B. Interest rate changes			
(3) *dD/dr*			182317
increase *r*			
utilization < .50	−65.0	11.4	
utilization .50–.90	−129.5	20.5	
utilization > .90	−85.5	21.4	
decrease *r*			
utilization < .50	−296.9	99.7	
utilization .50–.90	−429.3	120.2	
utilization > .90	−151.9	63.7	

- initial utilization rate $= \frac{\text{initial debt balance}}{\text{initial credit limit}}$
- Individuals that are not close to their *prior credit limit* also respond to changes in *new credit limit.* What kind of model do we need to explain this? ***Precautionary savings: The evidence is potentially consistent with the interaction of precautionary motives and the possibility that liquidity constraints bind in the future, as in buffer-stock models***
- When analyzing the effects of *d*interest rates, the authors distinguishing between *increases* and *decreas*es in interest rates. The estimated coefficients vary *non-monotonically* with utilization, for both increases and decreases in rates. This non-monotonicity of interest-rate elasticities is again consistent with liquidity constraints.

The table below examines other dimensions of heterogeneity in credit card usage.

TABLE V
HETEROGENEITY IN CREDIT-CARD USAGE

Row	(1) % with utilization > .90	(2) Credit limit MPCs ΔD/ΔL b_{Tot}	S.e.	(3) Interest rate sensitivities Δ(D/L)/Δr b_{Tot}	S.e.
(1) Credit Limit					
small (≤ $5000)	16.9	0.081	0.035	-0.016	0.002
large (> $5000)	9.2	0.100	0.023	-0.017	0.002
p-value		0.675		0.512	
N		145429		185151	
(2) Credit Score					
low (≤ .5)	25.8	0.125	0.026	-0.016	0.002
high (> .5)	1.8	0.070	0.020	-0.020	0.002
p-value		0.066		0.059	
N		132121		169234	
(3) Income					
low (≤ $31000)	14.0	0.122	0.049	-0.015	0.002
high (> $31000)	12.6	0.114	0.019	-0.018	0.009
p-value		0.876		0.103	
N		116542		141675	
(4) Age of account-holder					
young (≤ 43)	17.7	0.123	0.033	-0.020	0.002
old (> 43)	11.5	0.068	0.027	-0.017	0.002
p-value		0.182		0.196	
N		91832		132243	
(5) Age of account (years since booking)					
new (≤ 4)	14.7	0.103	0.018	-0.017	0.001
old (> 4)	12.9	0.067	0.029	-0.015	0.002
p-value		0.259		0.365	
N		145429		185151	
sample average	13.8				

This table contrasts the response of debt to credit supply (b_{Tot}) across accounts of different characteristics. In column (2) the dependent variable is the change in debt ΔD and the independent variables are changes in the credit limit ΔL (equation (1)). In column (3) the dependent variable is the change in debt normalized by the line and the independent variables are changes in interest rates Δr (equation (2)). Each row in column (2) and in column (3) represents a separate regression. Column (1) reports the fraction of accounts with utilization rates above 90 percent. Each row

- Something we observe in housing market is that DEMAND of *prime (good) borrowers* is ***much more sensitive*** to interest rates than that of *sub-prime borrowers*.
- In ***row (2)*** the MPC for people with *low credit scores* is substantially larger than for people with *high scores*, significantly so at the 7% level. This bolsters the previous evidence that low credit scores reinforce liquidity constraints. ***Row (3)*** shows that low income people have a larger MPC on average, though not significantly so. In ***row (4)*** young people have a much larger MPC than older people, about double in magnitude though not significantly different. (The result is similar for the youngest quartile of account-holders.) This is again consistent with liquidity constraints. Similarly in ***row (5)***, newer accounts have somewhat larger MPCs on average.
- Overall, these results suggest that *liquidity constraints are pervasive and vary across the population*, disproportionately affecting *low income* and, in particular, *young people.* They also highlight the importance of the credit scores in gaining access to credit.

2.1.8 Kreiner, Lassen and Leth-Petersen (WP 2014): *Consumption Responses to Fiscal Stimulus Policy and the Household Price of Liquidity*

Abstract: Consumption theory predicts that the cost of liquidity determines spending responses to a stimulus. We test this hypothesis directly using administrative records of individual-level loan and deposit accounts in combination with a Danish fiscal stimulus reform transforming illiquid pension wealth into liquid wealth. The data reveal substantial variation in the cost of liquidity across households, and this cost robustly predicts the propensity to spend. We find that the heterogeneity across households cannot be explained by short-lived shocks appearing within the duration of a typical business cycle but show that it is consistent with liquidity constraints being self-imposed by impatient types.

Motivation: The authots set up a basic consumption model and show that a *HH's marginal cost of liquidity* is a ***robust predictor*** of the *HH's consumption response to a fiscal stimulus*. We proceed to test this hypothesis directly using a novel and unique Danish data set on *HH marginal interest rates*, computed from third-party reported administrative records of individual-level loan and deposit accounts.

**** *Note about Scandinavian Data*: We can observe full balance-sheet of HHs and can hence can obtain *marginal interest rate* of each HH ****

More evidence on the relation between cost of liquidity and consumption.

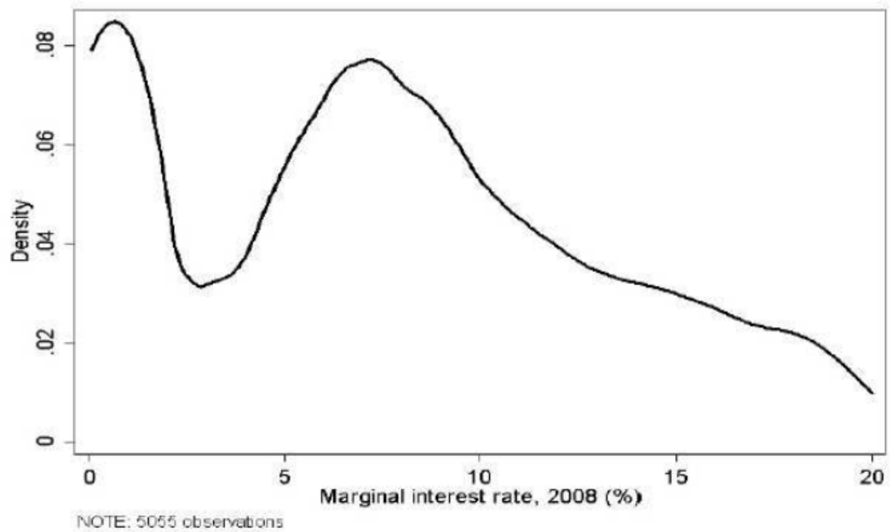
- Q: Is the HH price of liquidity (= marginal interest rate = credit constraints) a *robust predictor* of consumption responses to fiscal stimulus policy?
- Very interesting quasi natural experiment: "The Special Pension Savings Pay Out" in 2009 as part of "fiscal stimulus"
- Average per person after tax: 9,536 DKK (~1,900 USD) . No wealth effect, just change in the liquidity.

Bimodal Distribution of marginal interest rates

The figure below shows that the *distribution of marginal interest rates is bimodal*. The area around the lower modal point is dominated by *HHs that have only deposit accounts*, while the area around the upper modal point is dominated by *HHs that have loan accounts*. The distribution suggests that there is a significant amount of heterogeneity in the marginal interest rates in their sample.

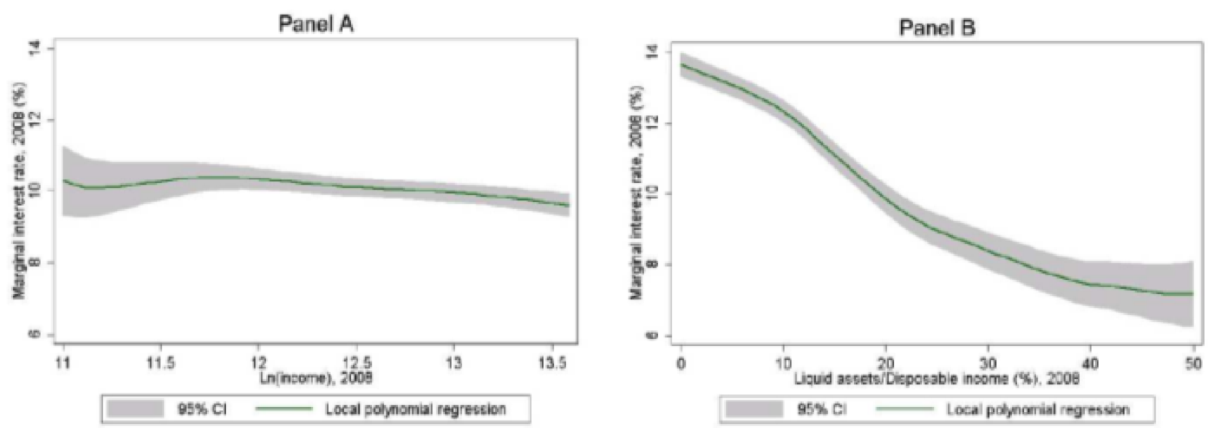
By imputing the interest rates they potentially introduce a measurement error. However, their detailed account data includes a subset of accounts with information about the actual interest rate and this enables them to directly compare the calculated interest rates with an actual interest rate to get an impression of the accuracy of their imputation.

Figure 5: Distribution of marginal interest rates across households



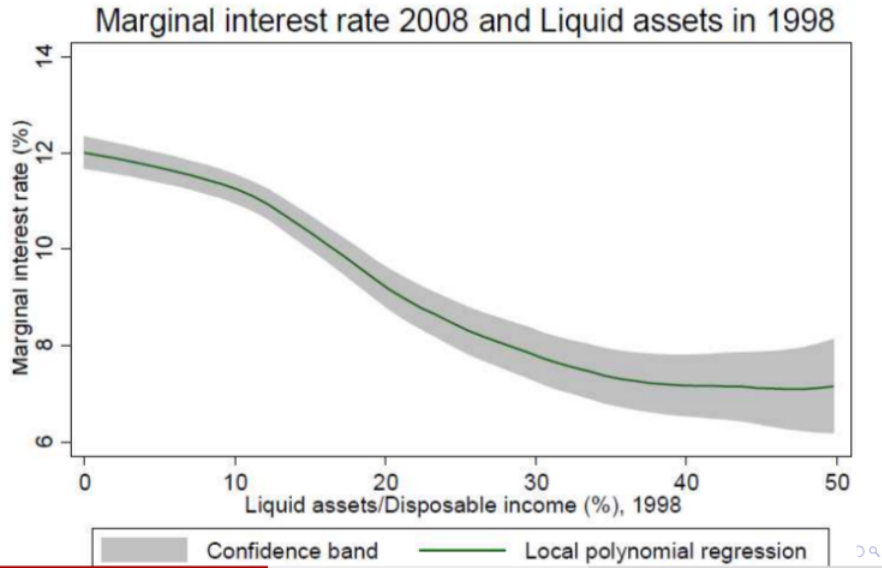
- This property in the density is related to earlier findings of Campbell and Mankiw (1989): 50% of HHs hand-to-mouth, 50% full optimizers. Drivers of this property:

Figure 7: Marginal interest rate and ln(income) (A) and liquid assets (B)



In the left panel of the figure above (i.e. Figure 7) they show a local polynomial smooth of the *marginal interest rate* against the *log(income)*. The correlation between these two measures is very weak and suggest that ***income is not a good proxy for credit market imperfections***, consistent with the empirical findings of Shapiro and Slemrod and recent theoretical work by Kaplan and Violante (2011). In the right panel of the figure above (i.e. Figure 7), they also plot a local polynomial smooth of the *marginal interest rate* and the *level of liquid assets by the end of 2008 relative to disposable income during 2008*. The picture shows a ***clear negative relation between the marginal interest rate and liquid asset holdings***.

- This observed behavior in MPC may ***not be completely*** driven by the marginal interest rate, which is related to the Euler equation (i.e. $\beta < r$ implies you want to front-load your consumption).
- In this paper, consumption behavior obtained from ***survey data.*** Other method is the ***residual method***: consumption is the "*residual*" of net balance-sheet inflows and outflows.



2.2 Incomplete Markets I: Buffer-Stock (Huggett/Deaton) Model

** See Demian Pouzo's notes for Econ 202B **

2.3 Incomplete Markets II: Aiygari Model

** See Demian Pouzo's notes for Econ 202B **

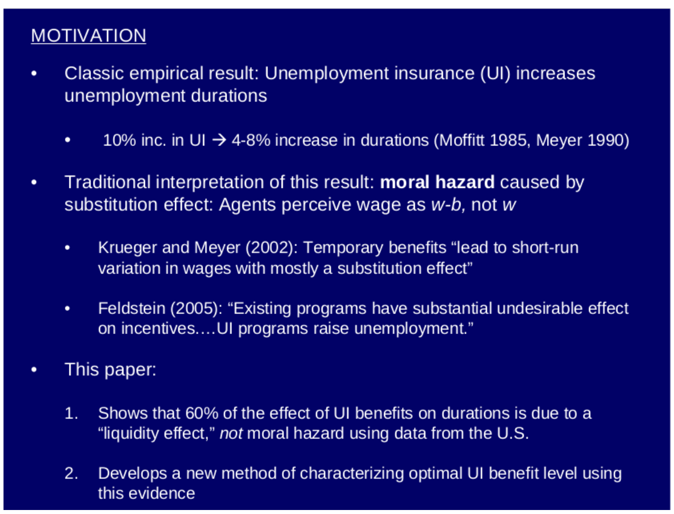
Lecture 3

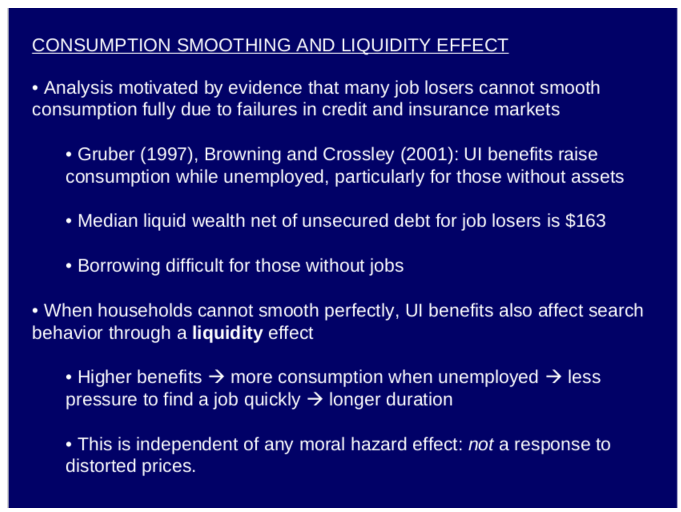
Liquidity Constraints and Consumption

3.1 Chetty (JPE, 2008): *Moral Hazard vs. Liquidity and Optimal Unemployment Insurance*

Abstract: This paper presents new evidence on why unemployment insurance (UI) benefits affect search behavior and develops a simple method of calculating the welfare gains from UI using this evidence. I show that 60 percent of the increase in unemployment durations caused by UI benefits is due to a "liquidity effect" rather than distortions on marginal incentives to search ("moral hazard") by combining two empirical strategies. First, I find that increases in benefits have much larger effects on durations for liquidity-constrained households. Second, lump-sum severance payments increase durations substantially among constrained households. I derive a formula for the optimal benefit level that depends only on the reduced-form liquidity and moral hazard elasticities. The formula implies that the optimal UI benefit level exceeds 50 percent of the wage. The "exact identification" approach to welfare analysis proposed here yields robust optimal policy results because it does not require structural estimation of primitives.

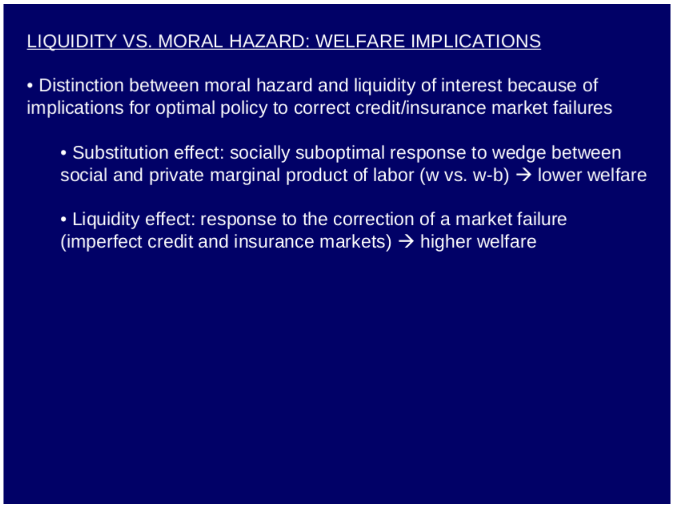
3.1.1 Motivation

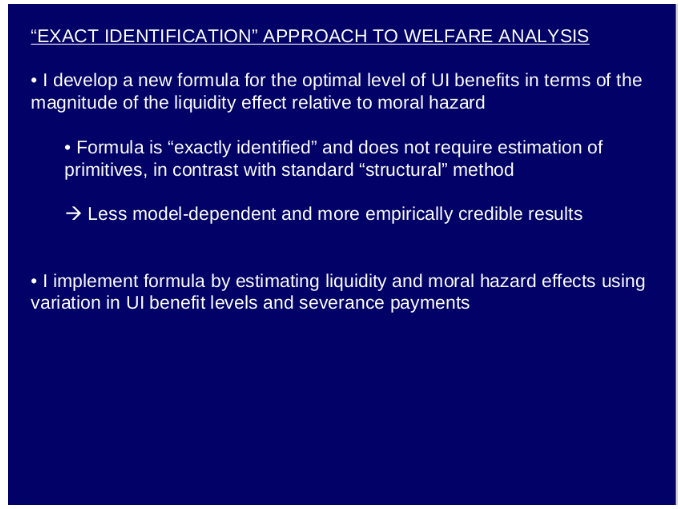




Gruber (1997): upon unemployment, the consumption of individuals DROP $\implies$ no "perfect" consumption smoothing. Also, individuals in states with MORE GENEROUS UI benefits, hold *MORE liquid assets* $\implies$ ***precautionary savings***.

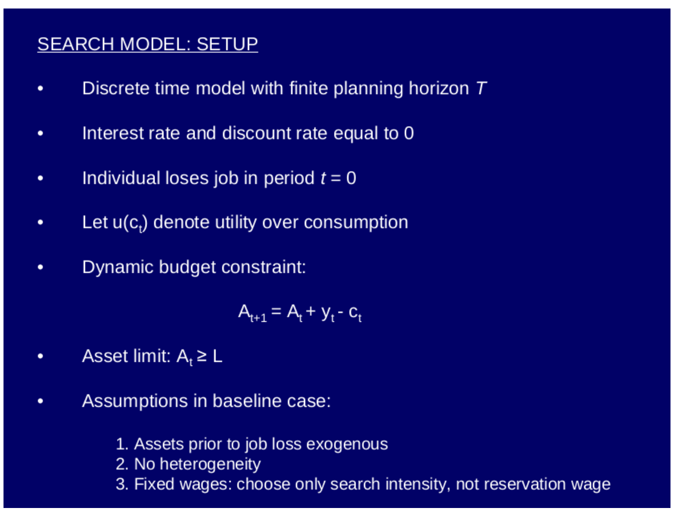
HHs with a *mortgage* see their consumption $\downarrow$ MORE when they are unemployed and get UI benefits. Intuition: **(1)** *first effect* is the liability that must be met each month (mortgage payment) that forces the HH to forego SOME consumption. **(2)** *second effect* is a precautionary savings motive; HH knows it may be unemployed for an extended period of time and hence must save to have liquid assets.

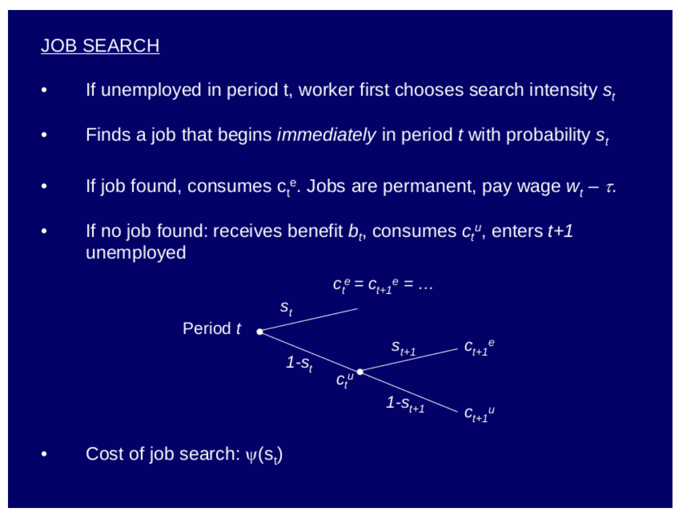




3.1.2 Labor Search Model

The model features (partial) failures in *credit* and *insurance markets*, creating a potential role for government intervention via an insurance program. He first distinguishes the ***moral hazard*** and ***liquidity effects*** of UI and then derive a formula for the welfare gain from UI in terms of these *elasticities*.





Assumption 3: Once you are employed, your wage is FIXED.

In the model:

- We can see that agents DO NOT derive *dis-utility from labor*, only *dis-utility from job search* $\psi(s_t)$
- $y_t = \begin{cases} w_t & = \text{fixed pre-tax wage, if EMPLOYED} \\ b_t & = \text{unemployment benefit if UNEMPLOYED} \end{cases}$
- $\tau =$ tax used to finance the UI benefit
- A_0 is EXOGENOUS in the *baseline model* and then extended to be endogenously determined by b, which also allows for *endogenous private insurance.*

- Value function for agent who finds a job in period t:

$$V_t(A_t) = \max_{A_{t+1}\geq L} v(A_t - A_{t+1} + w_t - \tau) + V_{t+1}(A_{t+1})$$

- Value function for agent who does not find a job in period t:

$$U_t(A_t) = \max_{A_{t+1}\geq L} u(A_t - A_{t+1} + b_t) + J_{t+1}(A_{t+1})$$

where $J(A_{t+1})$ is value of entering next period unemployed.

- Agent chooses s_t to maximize expected utility:

$$J(A_t) = \max_{s_t} s_t V_t(A_t) + (1 - s_t)U_t(A_t) - \psi(s_t)$$

- First order condition for optimal search intensity:

$$\psi'(s_t^*) = V_t(A_t) - U_t(A_t)$$

MORAL HAZARD VS. LIQUIDITY

- Effect of benefits on durations:

$$\partial s_t/\partial b_t = -u'(c_t^u)/\psi''(s_t)$$

- Benefit effect can be decomposed into two conceptually distinct terms:

$$\partial s_t/\partial A_t = \{v'(c_t^e) - u'(c_t^u)\}/\psi''(s_t) \leq 0$$

$$\partial s_t/\partial w_t = v'(c_t^e)/\psi''(s_t) > 0$$

$$\Rightarrow \quad \partial s_t/\partial b_t = \underbrace{\partial s_t/\partial A_t}_{\text{Liquidity}} - \underbrace{\partial s_t/\partial w_t}_{\text{Moral Hazard (subst. effect)}}$$

- No liq. effect for agents who smooth perfectly; negligible liq. effect for those who are not credit constrained because unemp. shocks small
- Liquidity and total benefit effects large for agents who cannot smooth relative to permanent income (e.g. low asset, credit constrained)

In the model:

- $v(\cdot)$ is the *utility flow from consumption* while $V(\cdot)$ is the *continuation value function*
- Agent that *finds a job*: $c_t = A_t - A_{t+1} + \underbrace{w_t}_{=y_t} - \tau$
- Agent that *can't fina a job*: $c_t = A_t - A_{t+1} + \underbrace{b_t}_{=y_t}$

Intuition: s_t is chosen to equate the ***marginal cost of search effort*** with its ***marginal value***, which is given by the *difference between the optimized values of employment and unemployment*: $\underbrace{\psi'(s_t^*)}_{\text{marginal cost of job search}} = \underbrace{V_t(A_t) - U_t(A_t)}_{\text{marginal benefit of job search}}$

- s_t is also **Prob** [finding a job]

Comparative Static: Moral Hazard vs. Liquidity: To understand the channels through which UI benefits affect job search behavior consider the following:

- effect of a \$1 $\uparrow$ in the *UI benefit level* b_t on *job search intensity* s_t in period t:

$$\frac{\partial s_t}{\partial b_t} = -\frac{u'(c_t^u)}{\psi''(s_t)}$$

- effect of a \$1 $\uparrow$ in *liquid assets* A_t on *job search intensity* s_t in period t:

$$\frac{\partial s_t}{\partial A_t} = \frac{\left\{v'(c_t^e) - u'(c_t^u)\right\}}{\psi''(s_t)} \leq 0$$

  - Intuition: The effect of a cash grant on *job search intensity* depends on the *difference in marginal utilities between **employed** and **unemployed** states.* This is because an INCREASE in cash on hand DECREASES the marginal return to search to the extent that it raises the *value of being unemployed relative to being employed.*

- effect of a \$1 $\uparrow$ in the *wage* w_t on *job search intensity* s_t in period t:

$$\frac{\partial s_t}{\partial w_t} = \frac{v^{'}\left(c_t^e\right)}{\psi^{''}\left(s_t\right)} > 0$$

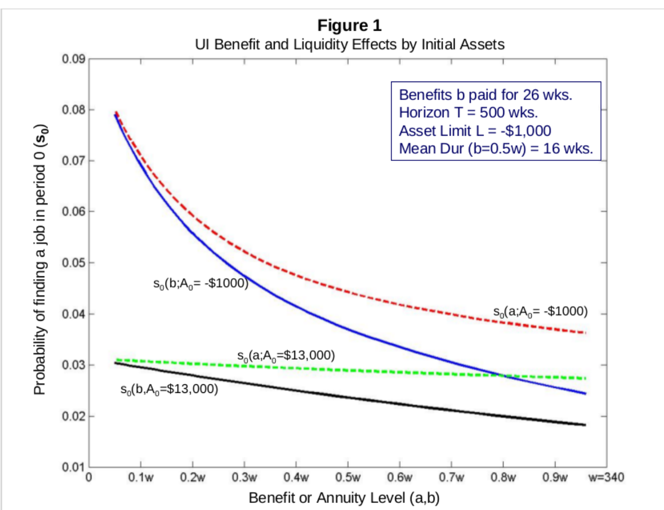
  - Intuition: The effect of an INCREASE in $w_t \propto v^{'}\left(c_t^e\right)$ because a *higher wage* increases the marginal return to search to the extent that it raises the *value of being employed.*

We get the decomposition: $\frac{\partial s_t}{\partial b_t} = -\frac{u^{'}(c_t^u)}{\psi^{''}(s_t)} = \frac{v^{'}(c_t^e)-u^{'}(c_t^u)}{\psi^{''}(s_t)} - \frac{v^{'}(c_t^e)}{\psi^{''}(s_t)} = \underbrace{\frac{\partial s_t}{\partial A_t}}_{\text{liquidity effect}} - \underbrace{\frac{\partial s_t}{\partial w_t}}_{\text{moral hazard}}$, which applies to a *one-period increase* in the UI benefit level.

- The 1^{st} channel is the ***liquidity effect***: UI benefit $\uparrow \Longrightarrow$ the agent's cash-on-hand $\Longrightarrow$ agent is able to maintain a HIGHER level of consumption *while unemployed* and it reduces the pressure to find a *new job quickly.*

- The 2^{nd} channel is the ***moral hazard effect***: UI benefit $\uparrow \Longrightarrow$ net wage $(w_t - \tau - b_t) \downarrow \Longrightarrow$ DECREASING the incentive to search though a *substitution effect*

If we have PERFECT consumption smoothing: $v^{'}(\cdot) = u^{'}(\cdot) \Longrightarrow \underbrace{\frac{\partial s_t}{\partial A_t}}_{\textbf{liquidity effect}} = 0$



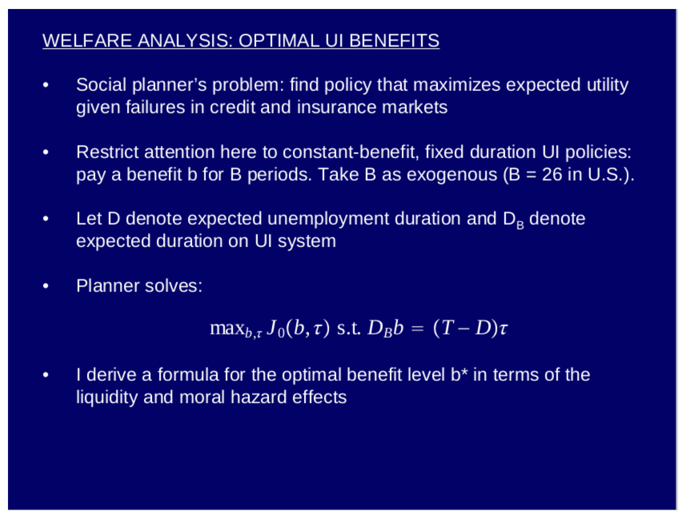


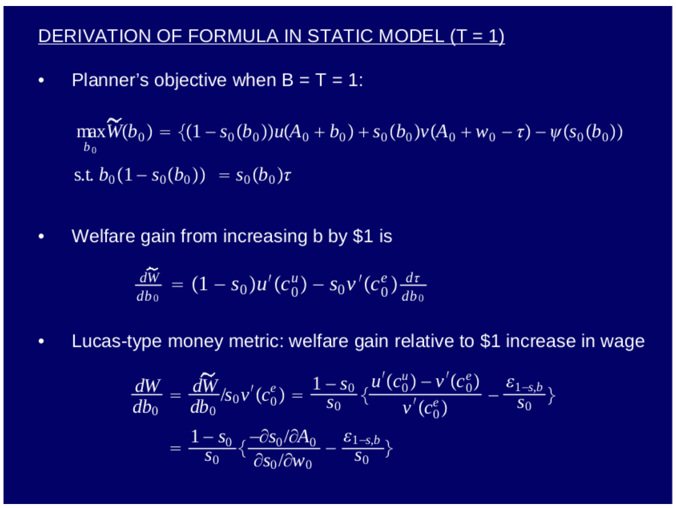
Figure 1: The **solid curves** plot *job search intensity* in period 0, (s_0) vs. the UI benefit level b for agents with $A_0 = -\$1000$ and $A_0 = \$13,000$, the 25th and 75th percentiles of the *initial asset distribution of the job losers* observed in the data.

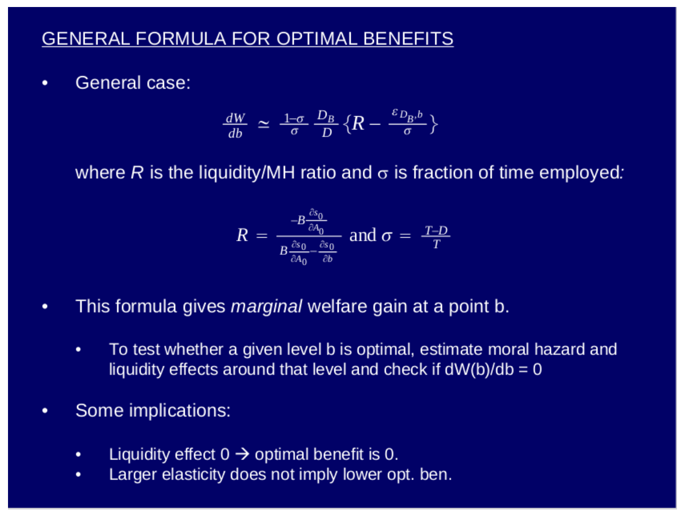
- As predicted, the *effect of UI benefits on job search intensity* $\downarrow$ *with assets*: raising the wage replacement rate from $b = 0.05w$ to the actual rate of $b = 0.5w$ REDUCES search intensity by approximately 55% for the *low-asset group* $(A_0 = -\$1000)$ compared to 22% for the *high-asset group* $(A_0 = \$13,000)$.

- Intuition: The reason for the difference in the benefit effects is that the ***liquidity effect is much larger for the low-asset agent***.

Letting a denote the *increment in a* **pure lump-sum transfer** *annuity payment* when $t \leq 25$, the **dashed lines** plot *job search intensity* in period 0, (s_0) vs. a FIXING the UI benefit b at 0. This experiment involves giving the agent a *lump-sum transfer* a in period 0 instead of a UI benefit payment b_t in each period $\implies$ doesn't induce a substitution effect.

- If an agent becomes EMPLOYED, she still receives a, while she would not receive b under the UI benefit payment structure.
- Increasing the annuity payment from $a = 0.05w$ to $a = 0.5w$ reduces search intensity by 45% for the *low-asset group* ($A_0 = -\$1000$), compared to 7% for the *high-asset group* ($A_0 = \$13,000$).
- Intuition: The ***liquidity effect*** thus accounts for the majority of the UI benefit effect for the *low-asset agent*, whereas ***moral hazard*** accounts for the majority of the benefit effect for the *high-asset agent*.
- The *liquidity effects* are large for agents with low A_0 since they reduce c_t^u quite sharply *early in the spell*, either because of binding borrowing constraints or as a precaution against a protracted spell of joblessness (as in ***Carroll 1997***). Once agents have a moderate buffer stock of assets (e.g. $A_0 > \$10,000$) to *smooth temporary income fluctuations*, liquidity effects become negligible even though insurance markets are incomplete.





Chetty first simplifies the exposition and begins by characterizing the welfare gain from UI for a *static **"one-shot"** search model* ($B = T = 1$). He then considers the general problem, where UI benefits are paid at a constant level b for $B \leq T$ periods.

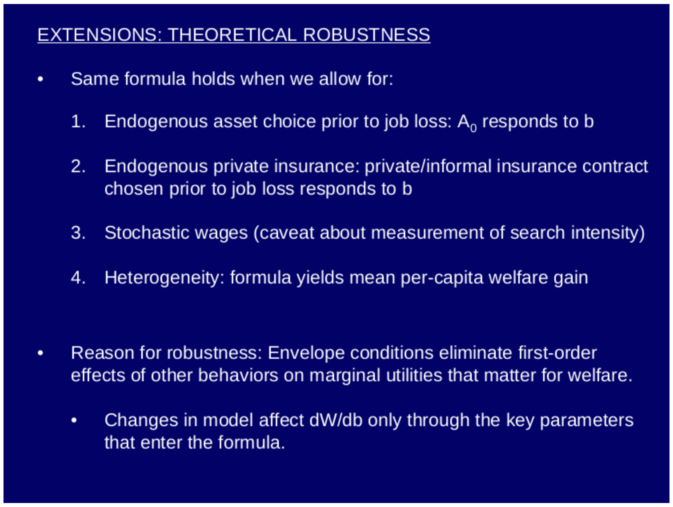
General Formula for Optimal Benefits: Chetty's *Corollary 1* is important.

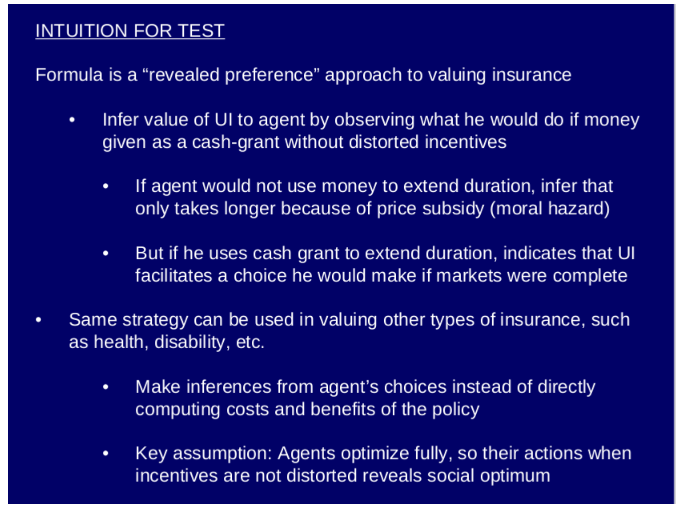
Corollary 1: *Under the approximations that (i) c_t^e does not vary with t, (ii) $\varepsilon_{D,b} = \varepsilon_{D_B,b}$ and (iii) the borrowing constraint is slack before period B, the welfare gain from raising b is*

$$\frac{dW}{db} = \frac{1-\sigma}{\sigma}\frac{D_B}{D}\left\{R - \frac{\varepsilon_{D_B,b}}{\sigma}\right\}$$

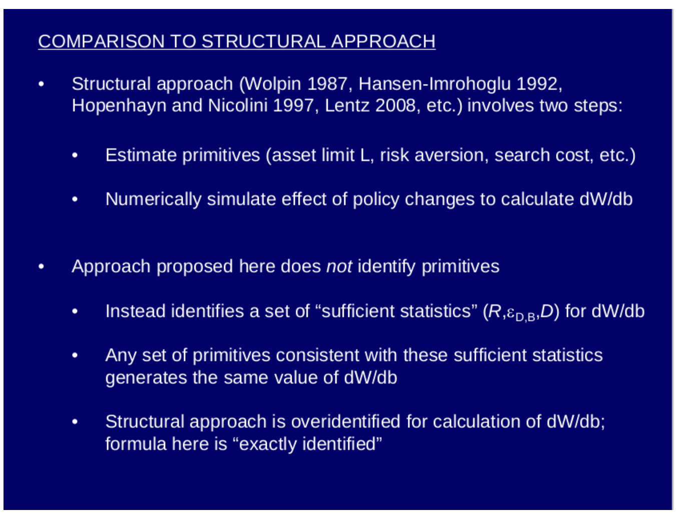
- $R \equiv \dfrac{\left.\frac{\partial s_0}{\partial a}\right|_B}{\left.\frac{\partial s_0}{\partial a}\right|_B - \frac{\partial s_0}{\partial b}} = \dfrac{-B\frac{\partial s_0}{\partial A_0}}{B\frac{\partial s_0}{\partial A_0} - \frac{\partial s_0}{\partial b}} =$ liquidity-to-moral hazard ratio. Intuition: the MORE important is the *liquidity effect (moral hazard effect)* $\implies$ the MORE important is to increase (decrease) the UI benefit level b.
- $\varepsilon_{D_B,b} = \frac{b}{D_B}\frac{dD_B}{db} =$ elasticity of total ***UI-compensated*** duration w.r.t UI benefit level

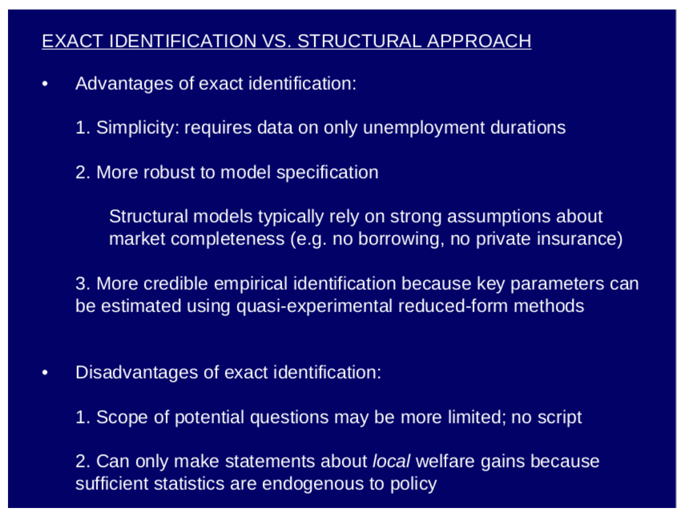
- $\varepsilon_{D,b} = \frac{b}{D}\frac{dD}{db}$ = elasticity of total ***unemployment*** duration w.r.t UI benefit level
- $\sigma = \frac{T-D}{T}$ = fraction of his life the agent is employed.





3.1.3 Empirical Implementation I: Role of Liquidity Constraints in UI Benefit-Duration Link

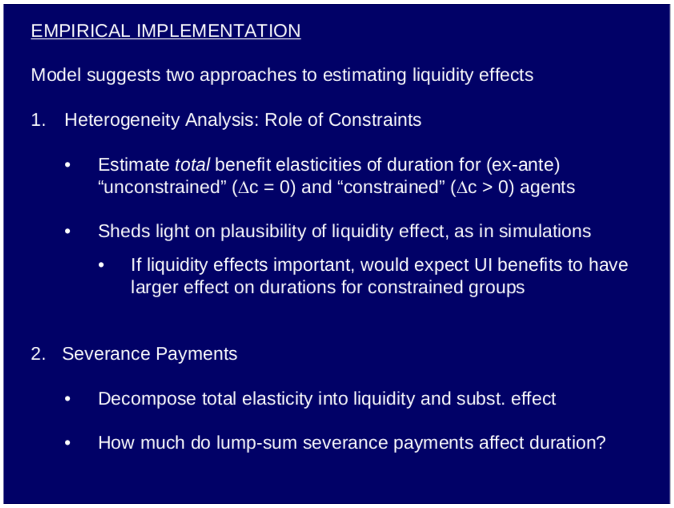




**** This paper is one of the first big papers using a “sufficient statistics” approach ****

Sufficient Statistic: All the parameters of the model (i.e. the primitives) don’t need to be known in order to know the *optimal UI transfer*. The sufficient statistic is estimated through some *identification*. The identification involves using *moments of the data* that tie down the liquidity effect and the moral hazard effect separately.

- ISSUES: Inference is only ***local*** since you only look at some sub-sample or population group - not everyone. The identification is coming from some *local variation*. Usually, one has to assume the *local effect* generalizes to a *global (population) effect*.



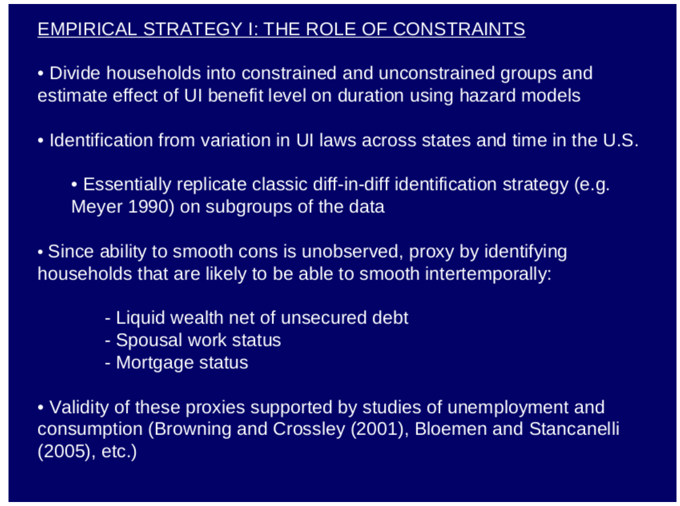
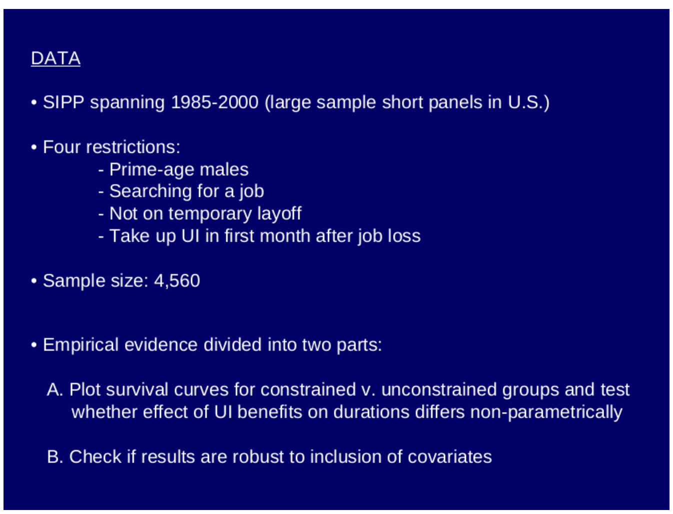


Table 1: The main difference between the ***quartiles*** lies in the ***median home equity***.

3.1.4 Empirical Implementation I: Data



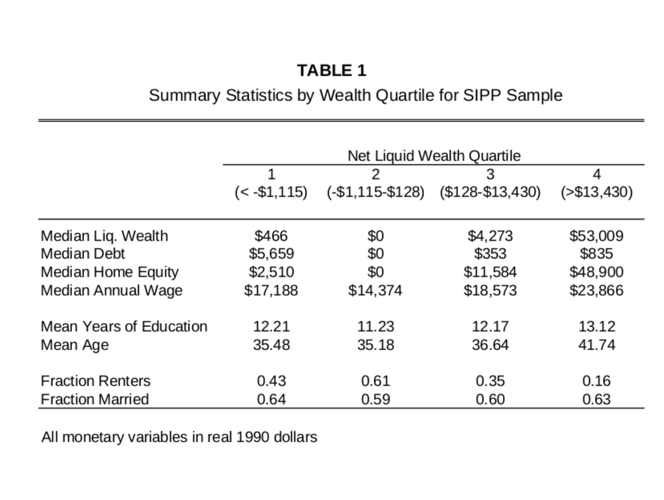


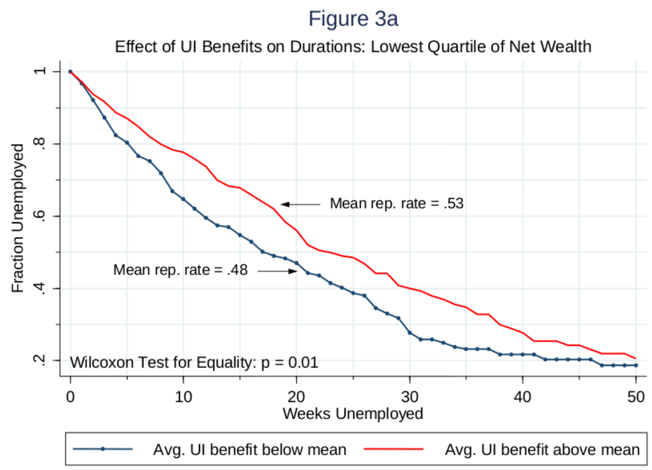
TABLE 1
Summary Statistics by Wealth Quartile for SIPP Sample

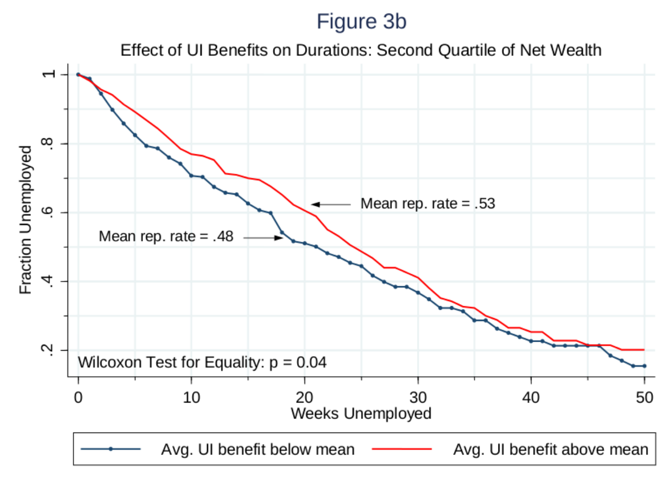
	Net Liquid Wealth Quartile			
	1 (< -$1,115)	2 (-$1,115-$128)	3 ($128-$13,430)	4 (>$13,430)
Median Liq. Wealth	$466	$0	$4,273	$53,009
Median Debt	$5,659	$0	$353	$835
Median Home Equity	$2,510	$0	$11,584	$48,900
Median Annual Wage	$17,188	$14,374	$18,573	$23,866
Mean Years of Education	12.21	11.23	12.17	13.12
Mean Age	35.48	35.18	36.64	41.74
Fraction Renters	0.43	0.61	0.35	0.16
Fraction Married	0.64	0.59	0.60	0.63

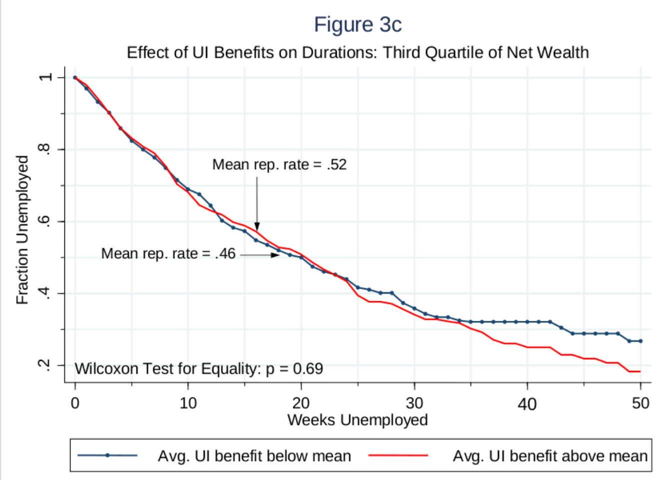
All monetary variables in real 1990 dollars

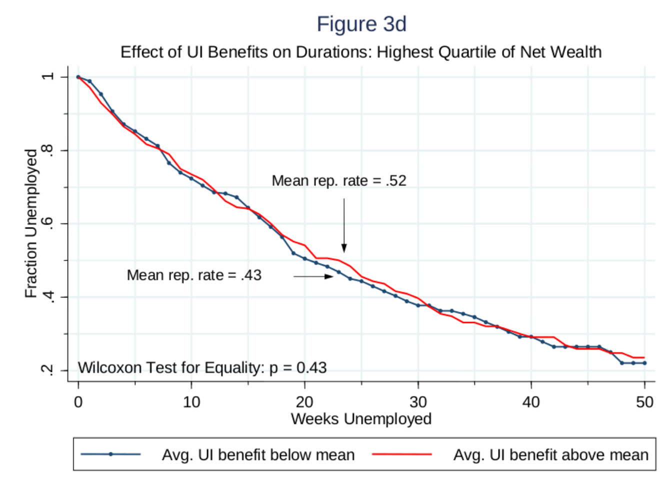
3.1.5 Effect of UI Benefits on Durations: Figures

Chetty's main way of differentiating the effect of UI benefit level b on job search intensity is by using a type of differences-in-differences (D-D) approach *within* each quartile. He constructs the figures by first *dividing the full sample of UI claimants into two categories*: those that are in **(state, year)** pairs that have average weekly benefit amounts ***above the sample median*** and those ***below the samplemedian***. He then plot Kaplan-Meier survival curves for these two groups using the HHs in the relevant net wealth quartile. Note that the differences in average individual replacement rates between the low and high-benefit are fairly similar in the four quartiles.









Figures 3a-d show the ***effect of UI benefits on job-finding rates*** for HHs in the each of the ***four quartiles*** of the net wealth distribution.

- ***Figure 3a***: UI benefits $\uparrow \implies$ much lower job-finding rates for individuals in the *lowest wealth quartile*. **e.g.** 15 weeks after job loss, 55% of individuals in low-benefit state/years are still unemployed, compared with 68% of individuals in high-benefit state/years: HHs with *less generous* UI benefit levels (below mean) find a job MUCH FASTER than HHs with *more generous* UI benefit levels (above mean)

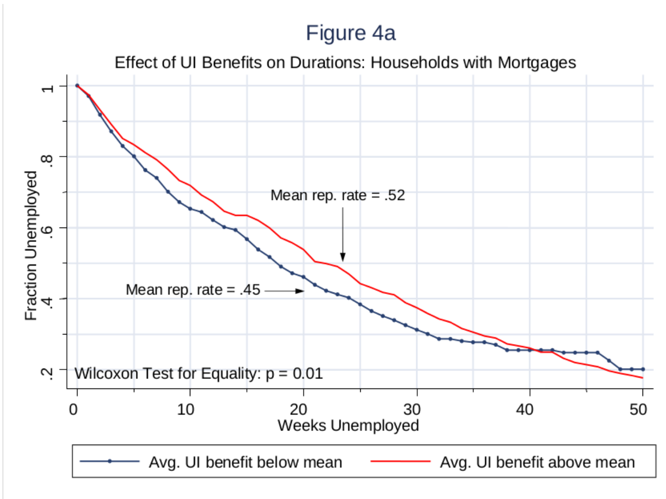
- ***Figure 3b:*** constructs the same survival curves for the *second wealth quartile*. UI benefits have a smaller effect on durations in this group.

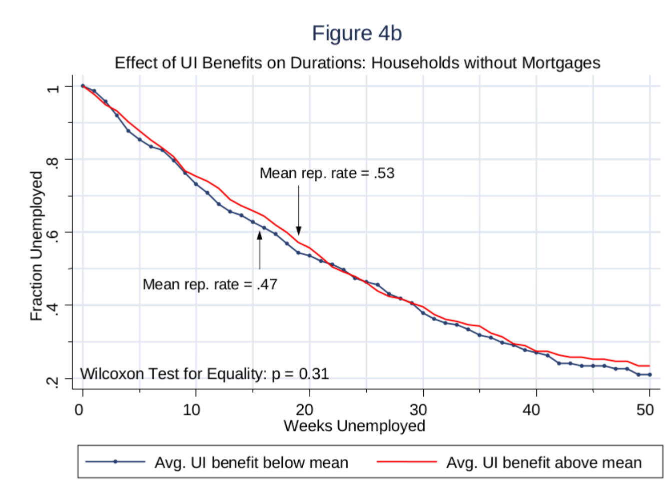
- ***Figures 3c and 3d***: effect of UI on durations virtually disappears in the *third and fourth quartiles of the wealth distribution*. Intuition: The fact that UI has little effect on durations in the unconstrained groups suggests that it induces little moral hazard among these HHs

Figures 4a-b show the ***effect of UI benefits on job-finding rates*** for HHs *with* and *without* home mortgages.

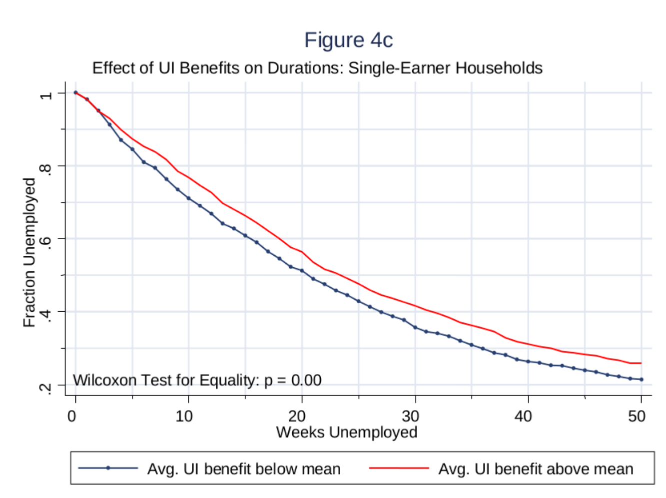
- Figure 4a: UI benefits have a clear (statistically significant) effect on job finding rates among HHs that are *paying of mortgages prior to job loss* $\implies$ *more constrained.*

- Figure 4b: effect is smaller for HHs that are *not paying of mortgages* $\implies$ *less constrained.*





Figures 4c-d show the ***effect of UI benefits on job-finding rates*** for HHs that are *single-earner* or *dual-earner*. Results are similar for the spousal work proxy: UI benefits have a MUCH LARGER effect on job finding hazards for single-earner families than dual-earner families (see Figure 2 in ***Chetty (2005)***).



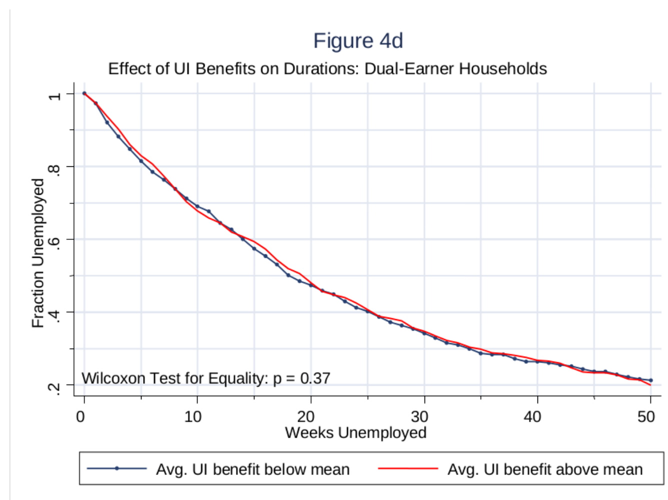
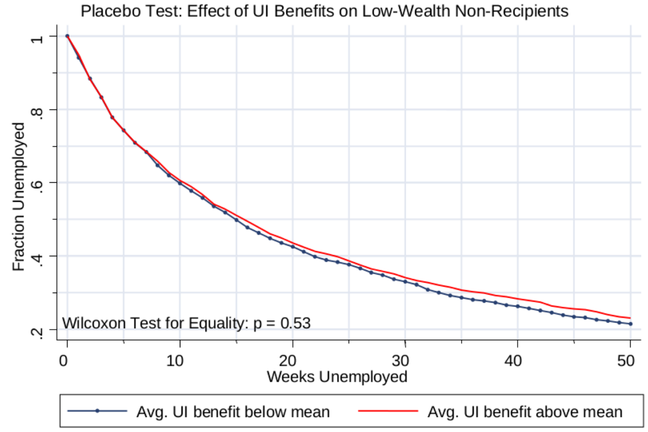


Figure 4e

Placebo Test: Effect of UI Benefits on Low-Wealth Non-Recipients



3.1.6 Hazard Model

HAZARD MODEL ESTIMATION

- Now examine whether these results are robust to controls
- Estimate Cox hazard models stratified by asset quartile (Q):

$$\log h_{itj} = \alpha_{t,j} + \beta_1^j Q_{i,j} \log b_i + \beta_3 X_{itj}$$

- β_1^j is elasticity of hazard rate. w.r.t. UI benefit in quartile j of asset distribn.
- Similar models estimated for spousal and mortgage proxies
- Covariate set (X):
  - 10 piece log wage spline, log total wealth
  - industry, occupation, state, and year dummies
  - education, age, seam dummy, marital status, spouse work status

TABLE 2

Effect of UI Benefits: Cox Hazard Model Estimates

	(1)	(2)	(3)	(4)	(5)
	Pooled	Stratified	Stratified with Full Controls		
	Full cntrls	No cntrls	Avg WBA	Max WBA	Ind. WBA
log UI ben	**-0.527**				
	(0.267)				
Q1 x log UI ben		**-0.721**	**-0.978**	**-0.727**	**-0.642**
		(0.304)	(0.398)	(0.302)	(0.241)
Q2 x log UI ben		**-0.699**	**-0.725**	**-0.388**	**-0.765**
		(0.484)	(0.420)	(0.303)	(0.219)
Q3 x log UI ben		**-0.368**	**-0.476**	**-0.091**	**-0.561**
		(0.309)	(0.358)	(0.370)	(0.156)
Q4 x log UI ben		**0.234**	**0.103**	**0.304**	**0.016**
		(0.369)	(0.470)	(0.339)	(0.259)
Q1=Q4 p-val		0.039	0.013	0.001	0.090
Q1+Q2=Q3+Q4 p-val		0.012	0.008	0.002	0.062
Number of Spells	4529	4337	4054	4054	4054

Chetty evaluates the robustness of the graphical results by estimating a set of *Cox hazard models* in Table 2 above. Column 1 reports the results from the ***Cox regression***, which uses the *full sample,* to identify the *unconditional effect of UI* on the hazard rate.

$$log\left(h_{i,t,j}\right) = \alpha_t + \beta_1^j log\left(b_i\right) + \beta_2^j t \times log\left(b_i\right) + \beta_3 X_{i,t,j}$$

- β_1 = *elasticity of the hazard rate with respect to UI benefits at the beginning of the spell* $(t = 0)$ because the interaction term $t \times log\left(b_i\right)$captures any *time-varying effect* of UI benefits on hazards.

The estimate in *Column 1* of Table 2 indicates that a 10% $\uparrow$ in the UI benefit rate $\implies$ hazard rate $\downarrow$ by 5.3% in the pooled full sample, consistent with the estimates of prior studies.

Columns 2-5 report the results from the following ***stratified Cox regression***, which examines the heterogeneity of the UI effect by estimating *separate coefficients for each of the four quartiles of the net wealth distribution*.

$$log\left(h_{i,t,j}\right) = \alpha_{t,j} + \beta_1^j Q_{i,j} log\left(b_i\right) + \beta_2^j Q_{i,j} t \times log\left(b_i\right) + \beta_3 X_{i,t,j}$$

- $h_{i,t}$ = ***probability of finding a job*** = *unemployment exit hazard rate* for individual i in week t of an unemployment spell

- α_t = baseline hazard rate in week t
- b_i = *the unemployment benefit level* for individual i
- $X_{i,t}$ = set of controls
- $Q_{i.j}$ = indicator variable equal to 1 if agent i belongs to *quartile* j of the wealth distribution
- Columns 2-5 of Table 2 report estimates of $\left\{\beta_1^j\right\}_{j=1,2,3,4}$

Specification (2) of Table 2 reports estimates of the ***stratified Cox regression*** with no controls (no X).

- The effect of UI benefits *declines monotonically* with net wealth. Among HHs in the lowest quartile of net wealth, a 10% $\uparrow$in UI benefits $\implies$ hazard rate $\downarrow$ by 7.2%

Specification (3) replicates Specification (2) with the full set of controls used in column (1), including state and year fixed effects so that the coefficients are identified from changes in UI laws within states rather than cross-state comparisons.

In specifications (4) and (5), he explores robustness to changes in the definition of b_i . Both of these specifications *include the control set* used in (3). Column (4) uses the ***maximum UI benefit*** level in individual $i's$ state/year and column (5) uses the ***simulated UI benefit*** for each individual i using the two-stage procedure described in the paper.

3.1.7 Empirical Implementation II: Severance Pay and Durations and Data

The ideal way to estimate the *liquidity effect* would be a randomized experiment where some job losers are given *lump-sum grants* or *annuity payments* while others are not. Lacking such an experiment, I exploit variation in severance pay policies across firms in the US. Severance payments are made either as lump-sum grants at the time of job loss or in the form of salary continuation (short-duration annuities). All severance packages are unconditional payments that do not distort marginal incentives to search for a new job. Thus, any causal e§ect of severance pay on unemployment durations reáects a *pure liquidity effect*.

EMPIRICAL STRATEGY II: SEVERANCE PAY AND DURATIONS

• Preceding evidence shows that effect of UI benefits on durations comes primarily from behavioral responses by constrained agents

• But does not tell us whether response in constrained group is due to a liquidity or substitution effect

- unless one assumes that substitution effects are similar in constrained and unconstrained groups (i.e., identical preferences).

• Now estimate liquidity effect directly by using variation in severance payments, which are lump-sum grants at time of job loss

• Estimate hazard models analogous to those above; key independent var is now a dummy for receipt of severance pay

• Identification assumption: Receipt of severance pay orthogonal to other determinants of durations

• I evaluate this assumption after showing basic results

SEVERANCE PAY: BACKGROUND AND DATA

• Approximately 20% of job losers in the U.S. receive severance pay

• Considerable cross-firm variation in packages, but little individual discretion

• Conditional on job tenure, receipt of severance pay is determined almost entirely by which firm you work for and not individual characteristics

• Since tenure is highly correlated with durations, I use only cross-firm variation in severance packages by controlling for tenure throughout

• Data from two Mathematica surveys matched to administrative data from UI system, with same sample restrictions as above

• Pooled sample size: 2,730

Chetty estimates the effect of severance pay using hazard models similar to those used in the previous sections.

$$log\left(h_{i,t}\right) = \alpha_t + \theta_1 sev_i + \theta_2 sev_t \times t + \gamma X_{i,t}$$

- sev_i = indicator for *receipt of severance pay*

- $X_{i,t}$ = same controls as in previous regressions.
- θ_1 = identifies the effect of cash grants on job finding hazards at the beginning of the spell if receipt of severance pay is orthogonal to other determinants of durations.

Table 3 shows summary statistics for **severance pay** *recipients* and *non-recipients*. The sample generally looks quite similar on observables to the SIPP sample used above. Given the minimum tenure eligibility requirement, it is not surprising that severance pay recipients have much higher median job tenures than non-recipients. Correspondingly, *severance pay recipients* are older and HIGHER in observable characteristics (i.e. education, marriage status) than non-recipients $\implies$ sorting effect.

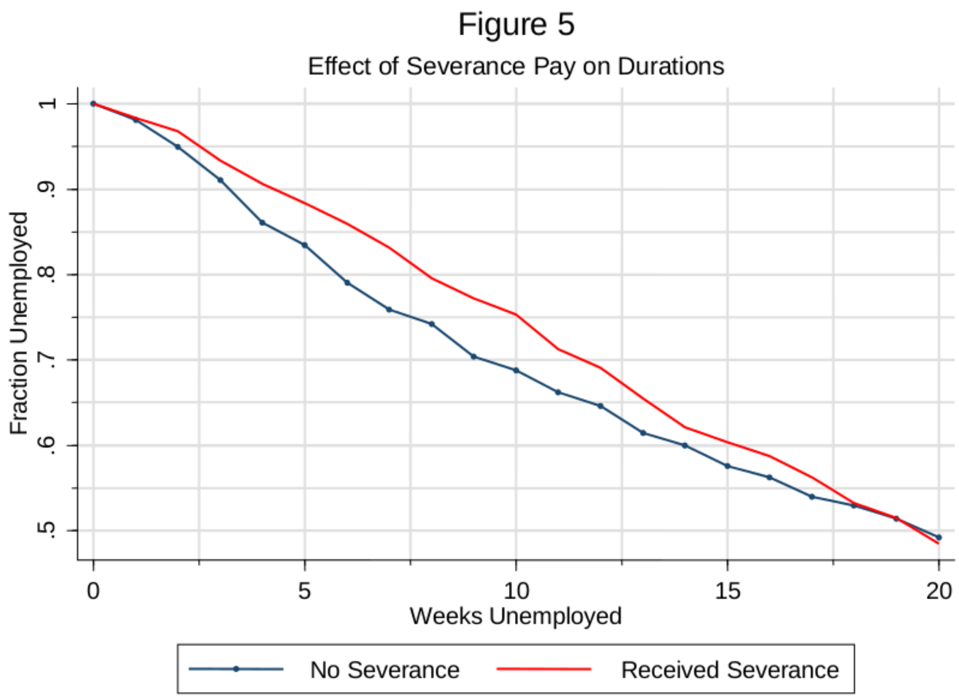
TABLE 3

Summary Statistics for Mathematica Data

	Pooled	No Severance (0.83)	Severance (0.17)
Percent dropouts	14%	15%	6%
Percent college grads	17%	13%	34%
Percent married	58%	56%	68%
Mean age	36.2	35.2	40.6
Median pre-unemp annual wage	$20,848	$19,347	$30,693
Median job tenure (years)	1.9	1.5	4.8

Figure 5 shows Kaplan-Meier survival curves for two groups of individuals: those who received severance pay and those who did not. Since pre-unemployment job tenure is an important determinant of severance pay and is also highly positively correlated with durations, he controls for it throughout the analysis.

- These survival curves have been adjusted for tenure by fitting a Cox model with tenure as the only regressor and recovering the baseline hazards for each group.
- ***Severance pay recipients have significantly lower job finding hazards***: 75% of individuals who received severance pay remain unemployed after 10 weeks, compared with 68% among those who received no severance payment.



ISSUE: An obvious concern in interpreting above result as *evidence of a liquidity effect* is that it may reflect correlation rather than causality because severance pay recipients differ from non-recipients.

- For instance, firms that offer severance packages might do so because their workers have accumulated more specific human capital and are likely to take a long time to find a suitable new job. This would induce a *spurious correlation* between severance pay and durations in the cross-section.

IS SEVERANCE PAY CAUSAL?

- Obvious concern: Receipt of severance pay correlated with other factors that affect durations
  - Ex: Firms where finding a new job is difficult may pay severance
- Three approaches to address this concern:
  1. Test if severance pay affects durations more in constrained groups
     - Asset data unavailable here, so predict assets using age, income, education, and marital status (using SIPP data)
  2. Check if inclusion of a rich set of controls affects key coefficient.
  3. Do individuals who receive larger severance packages take longer to find a job (intensive margin test)?
     - Implement by testing whether effect of severance pay is larger among high-tenure individuals

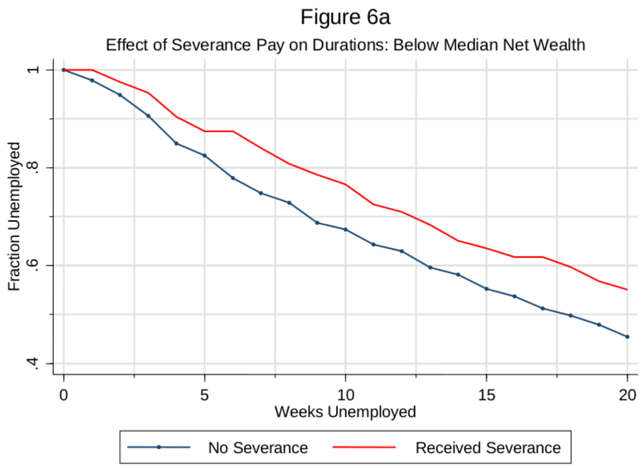
Chetty divides HHs into constrained and unconstrained groups. Unfortunately, the Mathematica surveys do not contain data on assets and the other proxies for *constraint status* used in the SIPP data. To overcome this problem, he predict assets for each HH with an equation estimated using OLS on the SIPP sample. The *prediction equation* is a linear function of age, wage, education, and marital status.

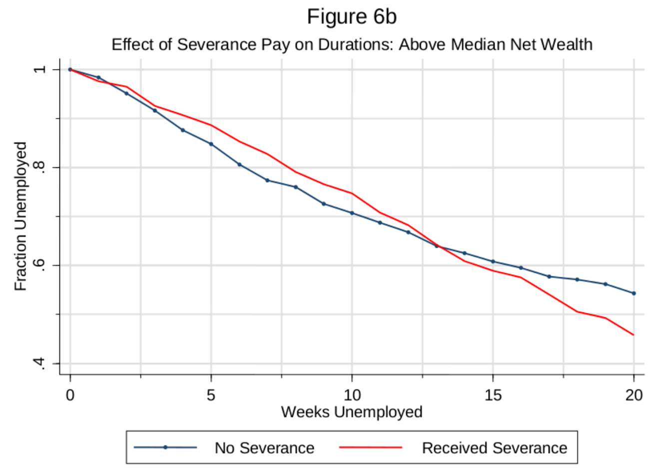
- He then divide HHs into two groups: *above* and *below the median level of predicted assets.*

Figures 6a-b below replicate Figure 5 for the two groups.

- Figure 6a: receipt of severance pay is associated with a large INCREASE in survival probabilities for *constrained* (low asset) HHs.
- Figure 6b: severance pay has a much smaller effect on search behavior for HHs that are likely to be wealthier i.e. *unconstrained* (high asset) HHs

These results are similar if HHs are split into *constrained* and *unconstrained* groups on the ***basis of age or income alone***. Results are also unaffected by changes in the functional form of the asset prediction equation, prediction via quantile regression instead of OLS, or trimming of outliers.





As a second approach to examining the *causality of severance pay*, he also assesses the *sensitivity of the severance pay effect* to controlling for observed heterogeneity. He estimates variants of the Cox model

$$log\left(h_{i,t}\right) = \alpha_t + \theta_1 sev_i + \theta_2 sev_t \times t + \gamma X_{i,t}$$

censoring all durations at 50 weeks as in the SIPP data. He first estimates a model with *only a linear tenure control* and a the time-varying interaction of severance pay with weeks unemployed. He then estimates the model with the *following control set*: ten piece linear splines for log pre-unemployment wage and job tenure; dummies for prior industry, occupation, and year; and controls for age, marital status, and education (using a dummy for dropout status and college graduation). Table 4 reports the results that use *full-control specifications*.

- Column (1) of Table 4 shows that receipt of severance pay is estimated to LOWER the job-finding hazard at the beginning of the spell by $\theta_1 = -23\%$
- Column (2) of Table 4 shows the results from estimating separate severance pay coefficients for constrained (*below-median predicted assets*) and unconstrained (*above-median*) HHs. The baseline hazards are stratified by predicted wealth group (*above/below* median) and the wage spline and industry/occupation dummies are interacted with the predicted wealth dummy, as in the SIPP specifications. Consistent with Figure 6, the estimates indicate that severance pay reduces initial job finding hazards in the ***low-wealth group by 46%***, but has little or no effect ***(less than 1%) in the high-wealth group.***
- Column (3) of Table 4 replicate specifications 2, stratifying the baseline hazards by a *short job tenure indicator* and interacting it with the *severance pay indicato*r. For individuals who have ***short job tenure, receipt of severance pay reduces initial job finding hazards by 14.3%***, ***compared with 34% for the long tenure group***

TABLE 4
Effect of Severance Pay: Cox Hazard Model Estimates

	Pooled	By Liquid Wealth	By Sev. Amt.
Severance Pay	**-0.233**		
	(0.071)		
(Netliq < Median) x Sev Pay		**-0.457**	
		(0.099)	
(Netliq > Median) x Sev Pay		**-0.088**	
		(0.081)	
(Tenure < Median) x Sev Pay			**-0.143**
			(0.055)
(Tenure > Median) x Sev Pay			**-0.340**
			(0.119)
Equality of coeffs p-val		<0.01	0.03

N=2428; all specs. include full controls.

3.1.8 Magnitude of Moral Hazard vs. Liquidity Effect

MAGNITUDE OF MORAL HAZARD VS LIQUIDITY EFFECT

- Doubling UI benefit reduces hazard rate by approximately 41%.
- Severance pay estimated to reduce hazard by approximately 21%.
  - At mean spell length and mean job tenure, receipt of severance pay is equivalent to an 85% increase in UI benefit level
  - Cash grant equivalent to doubling UI benefit would reduce hazard by 21/0.85 = 25%

$$\Rightarrow B\frac{\partial s_0}{\partial A} / \frac{\partial s_0}{\partial b} = \frac{25}{41} = 0.6$$

- Roughly 60% of UI-duration link due to liquidity effect
  - → Durations rise largely because job losers have more cash-on-hand; not purely “gaming the system” because of distorted wage

CALIBRATION: WELFARE IMPLICATIONS

- Plug this estimate into formula for dW/db, assuming that agent is unemployed for 5% of his life as in Shimer-Werning (2007):

$$\Rightarrow \frac{dW}{db}(b = 0.5w) = 0.04$$

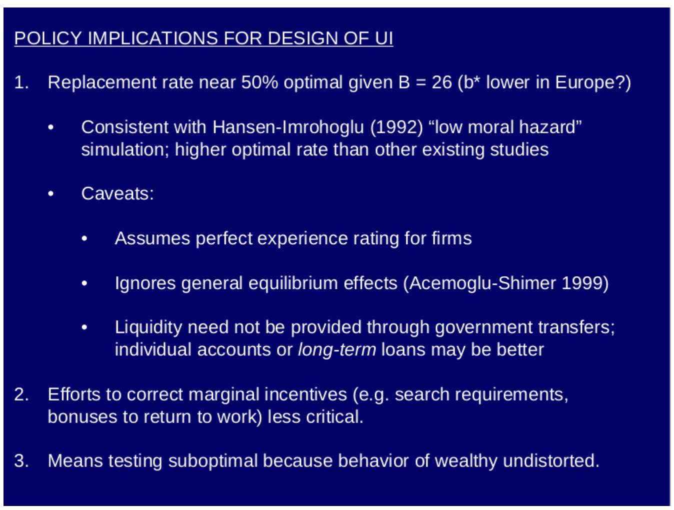
- Welfare gain from raising weekly benefit level by $1 from current level in U.S. (50% wage replacement) is equivalent to a 4 cent weekly wage increase for all workers, or $2.00 per year.
- Aggregating over population of 135 million workers, total gain from a 10% increase in UI benefit level is $5.9 bil (0.05 percent of GDP)
- → Small but positive welfare gain from raising benefit level in U.S.

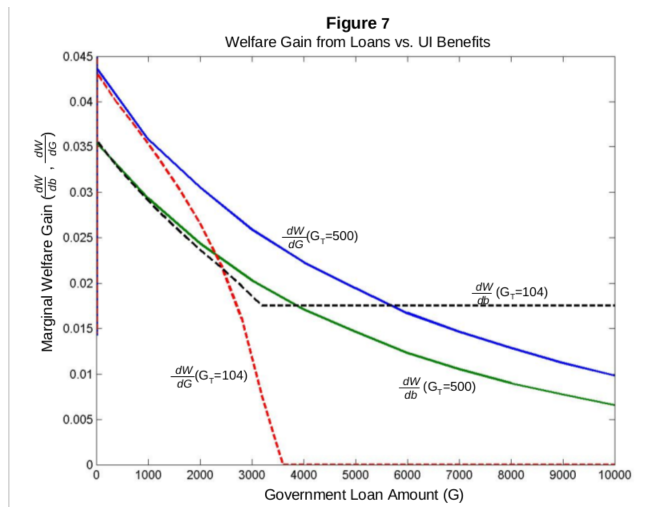
3.1.9 Policy Implications for Design of UI Benefits

A natural alternative instrument to resolve credit market failures is the *provision of loans* or *UI savings accounts* (***(Feldstein and Altman (1998)***, ***Shimer and Werning (2006)***). He considers the following:

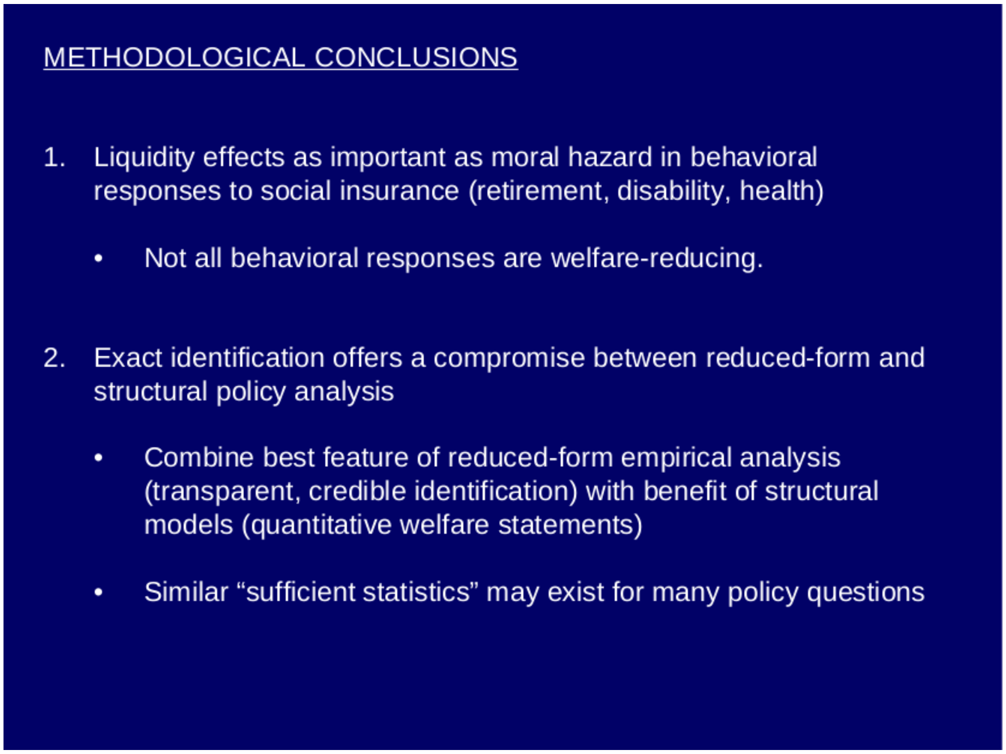
Suppose the government provides a loan of \$$G$ upon job loss that must be repaid within G_T weeks. With this loan, the agent's budget constraint is $A_t \geq -(L+G)$ for $t \leq G_T$ and $A_t \geq -L$ for $t > G_T$. Let us compare the welfare gain from increasing the government loan by \$$B$ ($\frac{dW}{dG} = B\frac{dJ_0}{dG}/\frac{dJ_0}{dw}$) with the welfare gain from raising the UI benefit by \$1 for B periods ($\frac{dW}{db} = \frac{dJ_0}{dG}/\frac{dJ_0}{dw}$). Assume $b = 0.5w$ and all other parameters as in Figure 2. The solid curves in Figure 7 plot $\frac{dW}{dG}$ and $\frac{dW}{db}$ as a function of G when the government loan has to be repaid by death ($G_T = T = 500$). The dashed curves plot $\frac{dW}{dG}(G)$ and $\frac{dW}{db}(G)$ for a short-term loan ($G_T = 104$).

The simulations have three lessons. First, the welfare gains from providing long-term liquidity can be quite large. The welfare gain of initiating a long-term government loan when $b = 0.5w$ is $\frac{dW}{dG}(G = 0) = 0.044$. The marginal welfare gain of increasing b falls rapidly with G: when $G = 5000$, $\frac{dW}{db}$ is 40% of the value of $\frac{dW}{db}$ when $G = 0$. Substantial welfare gains can be achieved by correcting credit market failures while leaving insurance markets incomplete because unemployment shocks are small relative to permanent income.



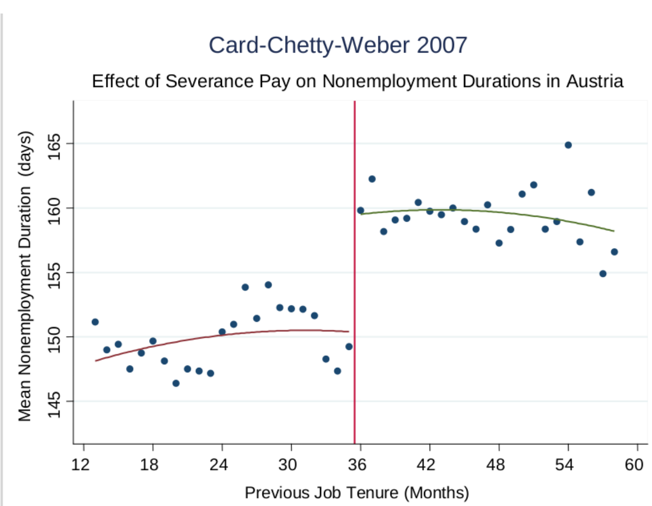


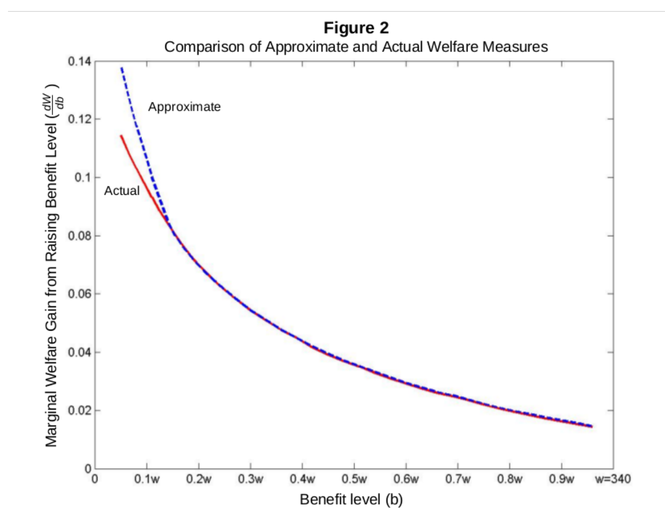
3.1.10 Conclusions



** An interesting fact is that the $\frac{\text{home price}}{\text{home rent}}$ ratio SIGNIFICANTLY INCREASED before the crisis. **

3.1.11 Followup Study: Card, Chetty, and Weber (2007)



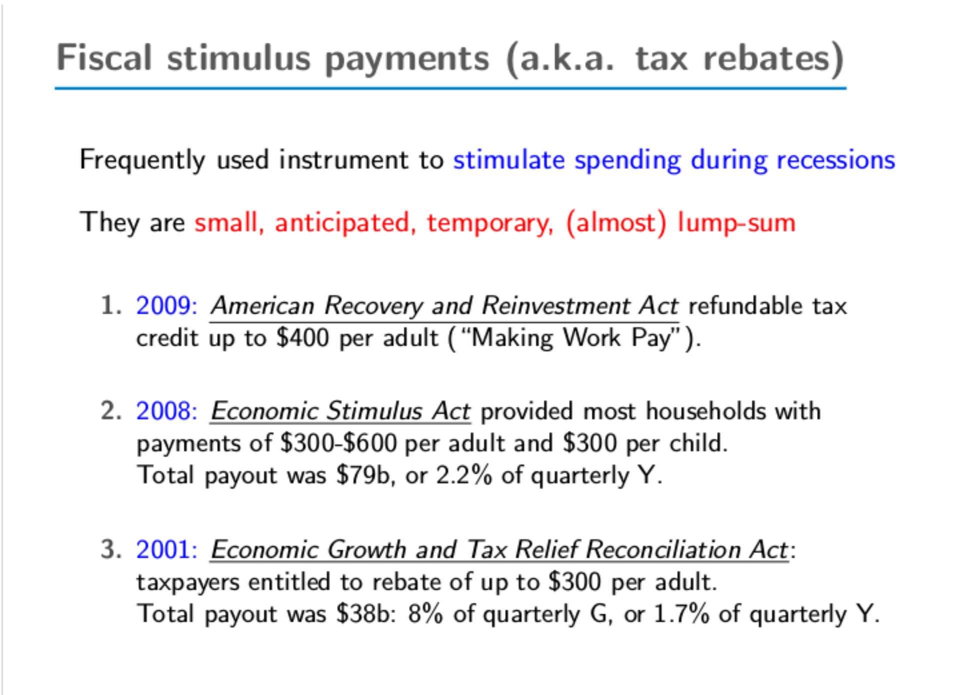


3.2 Kaplan and Violante (Econometrica, 2014): *A Model of the Consumption Response to Fiscal Stimulus Payments*

Abstract: A wide body of empirical evidence finds that around 25 percent of fiscal stimulus payments (e.g., tax rebates) are spent on nondurable household consumption in the quarter that they are received. To interpret this fact, we develop a structural economic model where households can hold two assets: a low-return liquid asset (e.g., cash, checking account) and a high-return illiquid asset that carries a transaction cost (e.g., housing, retirement account). The optimal life-cycle pattern of portfolio choice implies that many households in the model are "wealthy hand-to-mouth": they hold little or no liquid wealth despite owning sizeable quantities of illiquid assets. They therefore display large propensities to consume out of additional transitory income, and small propensities to consume out of news about future income. We document the existence of such households in data from the Survey of Consumer Finances. A version of the model parameterized to the 2001 tax rebate episode yields consumption responses to fiscal stimulus payments that are in line with the evidence, and an order of magnitude larger than in the standard "one-asset" framework. The model's nonlinearities with respect to the size of the rebate, its degree of phasing-out, and aggregate economic conditions have implications for policy design.

3.2.1 Introduction

FISCAL STIMULUS PAYMENTS or ***ECONOMIC STIMULUS PAYMENTS (ESPs)*** such as transfers to HHs in the form of *tax rebates*, are frequently used by govt's to alleviate the impact of recessions on HHs' welfare.

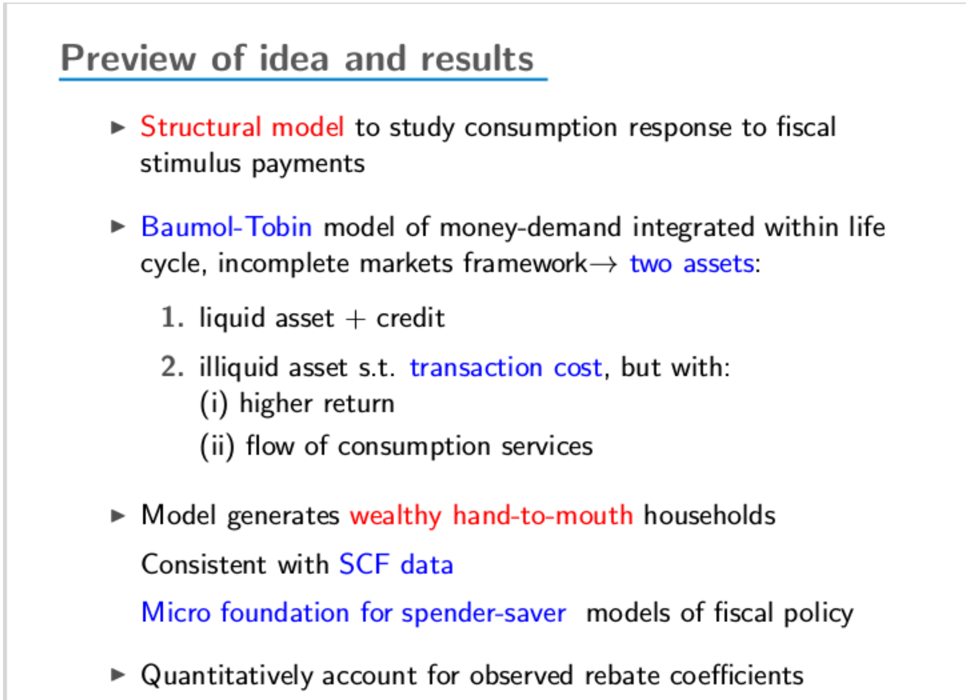


Fact: This collective evidence convincingly concludes that HHs spend ***approximately 25%*** of rebates on ***non-durable consumption*** in the quarter that they are received. This *strong consumption response* is measured relative to the *control group of HH*s (comparable, because of the randomization) that do not receive the rebate in that same quarter. In the paper, the authors call this magnitude the ***rebate coefficient***.

- Sharp ***violation*** of rational expectations, standard life-cycle model, buffer stock with one risk-free asset, which predicts...

  1. Response to *temporary shock* is small
  2. Response to *anticipated income change* is zero

- In this model, the only agents whose consumption would react significantly to receiving a rebate check are those who are *constrained*. However, under parameterizations where the model's distribution of net worth is in line with the data, the fraction of constrained HHs (usually around 10%) is TOO SMALL to generate a big enough response in the aggregate (as seen in the data). The authors overcome this challenge by proposing a new model, that uses data on *BOTH liquid and illiquid wealth* rather than just *net worth*



3.2.2 Summary and Interpretation of the Empirical Evidence on the 2001 Fiscal Stimulus Tax Rebates

3.2.2.1 General Information

The *tax rebate of 2001* was part of a broader tax reform, the ***Economic Growth and Tax Relief Reconciliation Act (EGTRRA)***, enacted in May 2001 by the US Congress. The reform included a reduction in the *federal personal income tax rate* for the ***lowest bracket*** (the first \$12,000 of earnings for a married couple filing jointly and the first \$6,000 for singles) from **15% to 10%**, effective retroactively to January 2001.

- Majority of the rebate checks were mailed between the *end-July 2001* and *end-September 2001*, in a sequence based on the last 2 digits of the social security number (SSN). This sequence featured in the news in *June 2001*
- The Treasury calculated that checks were sent out to ***92 million taxpayers***, with ≈ 80% of them paying the maximum amount (\$600, or 5% of \$12,000, for married couples), corresponding to a total outlay of \$38 Billion, or ≈0.4% of 2001 GDP.

From the point of view of economic theory, the 2001 tax rebate has ***three salient characteristics***

1. essentially a ***lump sum***, since almost every HH received ***\$300*** per adult;
2. ***anticipated***, at least for population which received the check later and that, presumably, had enough time to learn about the rebate
3. ***randomized timing*** of receipt of the rebate, since checks mailed out by last 2 digits of a SSN, which are uncorrelated with any individual characteristics.

3.2.2.2 Empirical Strategy

JPS (2006) added a special module of questions to the Consumer Expenditure Survey (CEX) that asks HHs about the ***timing*** and ***amount of their rebate check***. Among the various specifications estimated by ***JPS (2006)*** to assess the impact of the rebate on consumption expenditures, we will focus on their baseline regression:

$$\Delta c_{i,t} = \sum_s \beta_{0,s} \cdot month_s + \beta_1^{'} \mathbf{X}_{i,t-1} + \beta_2 Rebate_{i,t} + \varepsilon_{i,t}$$

- $\Delta c_{i,t}$= change in *non-durable expenditures* of HH i in quarter t
- $month_s$ = time dummy
- $\mathbf{X}_{i,t-1}$ = vector of demographics: *age, change in # of adults, change in # of children*
- $Rebate_{i,t}$ = dollar value of the rebate received by HH i in quarter t.

β_2 is the ***rebate coefficient***. Identification of β_2 comes from randomization in the ***timing*** of the receipt of rebate checks across HHs.

- The *rebate size* is potentially endogenous, so **JPS (2006)** estimated the regression equation by *2SLS* using, as an instrument, an indicator for whether the rebate was received: $\mathbf{1}_{\{\text{rebate was received}\}}$

3.2.2.3 Empirical Results

TABLE I

ESTIMATES OF THE 2001 REBATE COEFFICIENT ($\hat{\beta}_2$)[a]

	Nondurables
JPS 2006, 2SLS ($N = 13{,}066$)	0.375 (0.136)
Trim top & bottom 0.5%, 2SLS ($N = 12{,}935$)	0.237 (0.093)
Trim top & bottom 1.5%, 2SLS ($N = 12{,}679$)	0.219 (0.079)
MS 2011, IVQR ($N = 13{,}066$)	0.244 (0.057)

[a]Nondurables include food (at home and away), utilities, household operations, public transportation and gas, personal care, alcohol and tobacco, miscellaneous goods, apparel good and services, reading materials, and out-of-pocket health care expenditures. JPS 2006: Johnson, Parker, and Souleles (2006); MS 2011: Misra and Surico (2011). 2SLS: Two-Stage Least Squares; IVQR: Instrumental Variable Quantile Regression.

- In this table they also report the *2SLS estimate* that is obtained by dropping the ***top*** and ***bottom 0.5%*** and ***1.5%*** of the distribution of non-durable consumption growth from CEX. The rebate coefficient drops to a range of 22% to 24%, in line with ***Hamilton's (2008)*** results.
- $\widehat{\beta_2}$ ranges between 20% and 40% for non-durable consumption across all specifications.

More recent estimates put weight in 20% to 25% range. To facilitate the comparison between *model* and *data*, the authors find it useful to focus on one number, and they take ***25% as their preferred estimate***.

$\widehat{\beta_2}$ measures the consumption growth for the ***treatment group*** (the rebate recipients at date t) relative to consumption growth of the ***control group*** of non-recipients, with the common consumption growth component being subsumed by the *time dummies*.

- The ***control group*** is composed of those who are already aware of the policy but will receive the check at a later date, and those who have already received the payment in the past.
- The ***consumption response of the control group***, which ideally should be unaffected by the policy, is, generally, a mixture: ***MPC out of the news*** + ***lagged MPC out of the payment***

The authors simplify the analysis of **what β_2 measures** by splitting the population into 2 groups: early recipients (***group A***) who receive the check in 2001:Q2 and late recipients (***group B***) who receive it in 2001:Q3.

$$\beta_2 = \frac{\left(\Delta c^A_{Q2} - \Delta c^B_{Q2}\right) + \left(\Delta c^B_{Q3} - \Delta c^A_{Q3}\right)}{2}$$

- Δc^A_{Q2} = consumption growth of the *treatment group* in ***2011:Q2*** (group A who receive the check in 2011:Q2)
- Δc^B_{Q2} = consumption growth of the *control group* in ***2011:Q2*** (group B who receive the check in 2011:Q3)
- Δc^B_{Q3} = consumption growth of the *treatment group* in ***2011:Q3*** (group B who receive the check in 2011:Q3)
- Δc^A_{Q3} = consumption growth of the *control group* in ***2011:Q3*** (group A who receive the check in 2011:Q2)

The authors also consider three alternative information structures of HHs, which imply different interpretations for β_2

1. the ESP policy is announced in 2001:Q1, ***every consumer becomes aware of it at that date***, and hence ***NO consumer is surprised by the arrival of the check***.
2. the ESP policy enters agents' information sets ***only when the check is actually received***, and hence ***every consumer is surprised by the arrival of the check***.
3. an ***intermediate structure*** where the ESP policy enters all agents' information sets after the first batch of checks is sent out (2001:Q2), that is, ***group A is surprised***, but ***group B is not surprised***.

Cases 1. and 2. are handled by modifying their baseline regression:

$$\Delta c_{i,t} = \sum_s \beta_{0,s} \cdot month_s + \beta_1^{'} \mathbf{X}_{i,t-1} + \beta_2 Rebate_{i,t} + \beta_3 Rebate_{i,t-1} + \varepsilon_{i,t}$$

since the *lag of the rebate variable* absorbs the lagged consumption response resulting from both cases.

In spite of these difficulties in mapping directly β_2 to an MPC, the ***rebate coefficient is an informative statistic***: *only if the true MPC out of the check is sizable and the MPC out of the news is small, can the rebate coefficient be as large as is empirically estimated!*

3.2.3 The Life-Cycle Model with Liquid and Illiquid Assets

The advantage of the structural model is that it enables one to identify all the separate components of the baseline regression. As a result, it allows one to quantify the ***current and lagged MPCs*** out of an *income shock*, out of an *anticipated income change*, and out of the *news of a future change in income* — all magnitudes that are essential for policy analysis.

3.2.3.1 Model Description

Demographics: The stationary economy is populated by a continuum of HHs, indexed by i. Age is indexed by $j = 1, 2, ..., J$.

HHs retire at age J^w and retirement lasts for J^r periods.

Preferences: HHs have an Epstein–Zin–Weil objective function defined recursively by

$$V_{i,j} = \left[\left(c^{\phi}_{i,j} s^{1-\phi}_{i,j}\right)^{1-\sigma} + \beta \left\{E_j \left[V^{1-\gamma}_{i,j+1}\right]\right\}^{\frac{1-\sigma}{1-\gamma}}\right]^{\frac{1}{1-\sigma}}$$

- $c_{i,j} \geq 0$ = consumption of nondurables
- $s_{i,j} \geq 0$ = service flow from housing for HH i at age j.

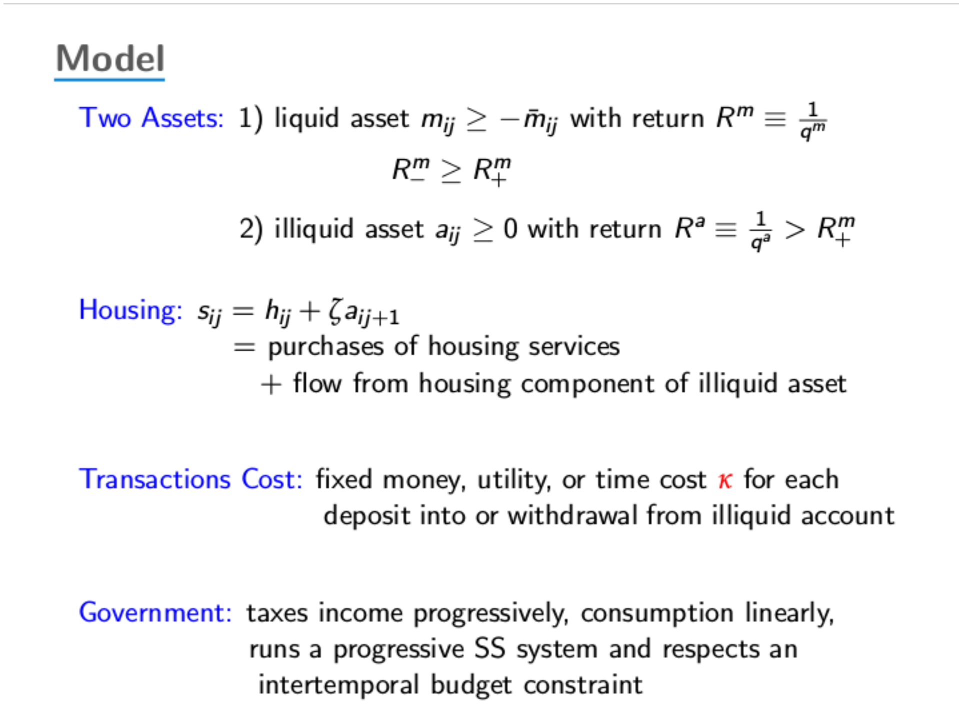
- β = discount factor
- ϕ = measures the weight of nondurables relative to housing services in period-utility
- γ = risk aversion
- $\frac{1}{\sigma}$ = elasticity of intertemporal substitution

Idiosyncratic Earnings: In any period during the working years, *HH labor earnings (in logs)* are given by

$$log\left(y_{i,j}\right) = \chi_j + \alpha_i + z_{i,j}$$

- χ_j = deterministic age profile common across all HHs
- α_i = HH-specific fixed effect
- $z_{i,j}$ = stochastic idiosyncratic component that obeys the conditional c.d.f $\Gamma^z\left(z_{j+1}, z_j\right)$
- ***NO AGGREGATE UNCERTAINTY***

Assets and Government:



- KEY ASSUMPTION: No *secured debt* (*collateralized debt*)
- ***LIQUID*** *asset* denoted $m_{i,j}$
- ***ILLIQUID*** *asset* denoted $a_{i,j}$

HH Problem: We use a recursive formulation of the problem. Let $\mathbf{s}_j = (m_j, a_j, z_j)$ be vector of individual states at age j. The value function of a household at age j is $V_j(\mathbf{s}_j) = max\left\{V_j^N(\mathbf{s}_j), V_j^A(\mathbf{s}_j)\right\}$ where

- $V_j^N(\mathbf{s}_j)$ = value functions conditional on ***not adjusting***
- $V_j^A(\mathbf{s}_j)$ = value functions conditional on ***adjusting***

This decision takes place at the *beginning of the period*, after receiving the current endowment shock, but before consuming.

Model

$$
\begin{aligned}
V_j^N(a_j, m_j, z_j) \quad = \quad & \max_{c_j, h_j, m_{j+1}} \left\{ \left(c_j^{\phi} s_j^{1-\phi} \right)^{1-\sigma} + \beta \left(\mathbb{E}_j \left[V_{j+1}^{1-\gamma} \right] \right)^{\frac{1-\sigma}{1-\gamma}} \right\}^{\frac{1}{1-\sigma}} \\
& \text{subject to} \\
& c_j + h_j + q^m m_{j+1} \leq m_j + y_j(z_j) - \mathcal{T}(y_j, a_j, m_j, c_j) \\
& q^a a_{j+1} = a_j \\
& s_j = h_j + \zeta a_{j+1} \\
& m_{j+1} \geq -\bar{m}_j \\
V_j^A(a_j, m_j, z_j) \quad = \quad & \max_{c_j, h_j, a_{j+1}, m_{j+1}} \left\{ \left(c_j^{\phi} s_j^{1-\phi} \right)^{1-\sigma} + \beta \left(\mathbb{E}_j \left[V_{j+1}^{1-\gamma} \right] \right)^{\frac{1-\sigma}{1-\gamma}} \right\}^{\frac{1}{1-\sigma}} \\
& \text{subject to} \\
& c_j + h_j + q^a a_{j+1} + q^m m_{j+1} \leq a_j + m_j - \kappa + y_j(z_j) - \mathcal{T}(\cdot) \\
& s_j = h_j + \zeta a_{j+1} \\
& a_{j+1} \geq 0, m_{j+1} \geq -\bar{m}_j
\end{aligned}
$$

- Gross financial return of ***LIQUID*** *asset*: $\frac{1}{q^m}$
- Gross financial return of ***ILLIQUID*** *asset*: $\frac{1}{q^a}$

Balanced Budget: The government always respects its intertemporal budget constraint

$$
G + \sum_{j=J^w+1}^{J} \int p\left(y_{J^w}\right) d\mu_j + \left(\frac{1}{q^s} - 1 \right) B =
$$

$$
\tau^c \sum_{j=1}^{J} \int c_j d\mu_j + \sum_{j=1}^{J} \int \mathcal{T}\left(y_j, a_j m_j\right) d\mu_j
$$

- μ_j = distribution of HHs of age j over the individual state vector $\mathbf{s}_j$

3.2.3.2 Behavior in the model: "wealthy hand-to-mouth" HHs

For ease of exposition, they first focus on a *stylized version of the model* with time-separable preferences ($\gamma = \sigma$), without service flow from illiquid assets ($\varphi = 1, \zeta = 0$), with logarithmic period-utility, deterministic labor income ($z_{i,j} = 0$), and no taxes ($\mathcal{T}(\cdot) = \tau^c = 0$)

Moreover, they assume that $\overline{q}^m < q^q < q^m$. The second inequality states that the *illiquid asset has a HIGHER return than the return on the liquid asset (when saving)* and the first one ensures that HHs do not borrow to deposit into the illiquid account.

$$
\overline{q}^m < q^q < q^m \implies R_+^m < R^a < R_-^m
$$

Two Euler equations: Consumption and portfolio decisions are characterized by a ***"short-run" Euler equation (EE-SR)*** that corresponds to (dis)saving in the liquid asset, and a ***"long-run" Euler equation (EE-LR)*** that corresponds to (dis)saving in the illiquid asset.

"short-run" Euler equation (EE-SR)

$$u^{'}(c_j) = \frac{\beta}{q^m(m_{j+1})} u^{'}(c_{j+1})$$

This is the Euler equation that applies when the working HH *DOESN'T adjust*

- The ***slope of her consumption path*** is governed by $\frac{\beta}{q^m(m_{j+1})}$.
  - For plausible parameterizations, when HH is in *debt* i.e. negative balance of liquid assets ($m_{j+1} < 0$), this ratio is **ABOVE 1**: the consumption path ↑, as the HH saves her way out of expensive borrowing. In other words, $\frac{\beta}{q^m(m_{j+1})} > 1 \implies u^{'}(c_j) > u^{'}(c_{j+1}) \implies c_j < c_{j+1} \implies$ consumption is INCREASING.
    - The *implied parameterization* here is $\beta > q^m \equiv \frac{1}{R_+^m}$
  - For plausible parameterizations, when the HH is *saving* i.e. positive balance of liquid assets ($m_{j+1} > 0$), this ratio is **BELOW 1**: consumption path ↓ because of impatience and the low real return on cash. In other words, $\frac{\beta}{q^m(m_{j+1})} < 1 \implies u^{'}(c_j) < u^{'}(c_{j+1}) \implies c_j > c_{j+1} \implies$ consumption is DECLINING.
    - The *implied parameterization* here is $\beta < \overline{q}^m \equiv \frac{1}{R_-^m}$
- There are two kinks in the budget constraints where equation *(EE-SR)* does not hold: **(1)** the debt limit $m_{j+1} = \underline{m}_{j+1}(y_j)$ and **(2)** $m_{j+1} = 0$ because of the wedge between the *return on liquid saving* and the *interest on unsecured credit* ($\overline{q}^m < q^m$).
- HHs on the kinks are ***HtM*** $\implies$ ***they consume all their income*** ($c_j = y_j$)

"long-run" Euler equation (EE-LR)

$$u^{'}(c_j) = \left(\frac{\beta}{q^a}\right)^N u^{'}(c_{j+N})$$

This is the Euler equation that dictates consumption dynamics across two such adjustment dates N periods apart.

- Given the fixed cost of adjusting, HHs accumulate liquid funds and choose *infrequent dates* at which to add some or all of their liquid holdings to the illiquid asset.
- $\frac{\beta}{q^a} > \frac{\beta}{q^m} \implies$ consumption grows MORE (or falls LESS) *across* adjustment dates than *between* adjustments.
- When the HH taps into its ILLIQUID asset and pays the fixed cost, ***consumption jumps***.

***** Extremely important thing to remember: the presence of <u>fixed costs</u> creates jumps in the consumption profile, fixed cost ↑ ⟹ jumps in consumption ↑ and less frequent adjustments *****

**** Even with <u>*no uncertainty*</u>, the presence of a ILLIQUID asset ↑precautionary savings motive ****

3.2.3.3 "Poor hand-to-mouth" Behavior

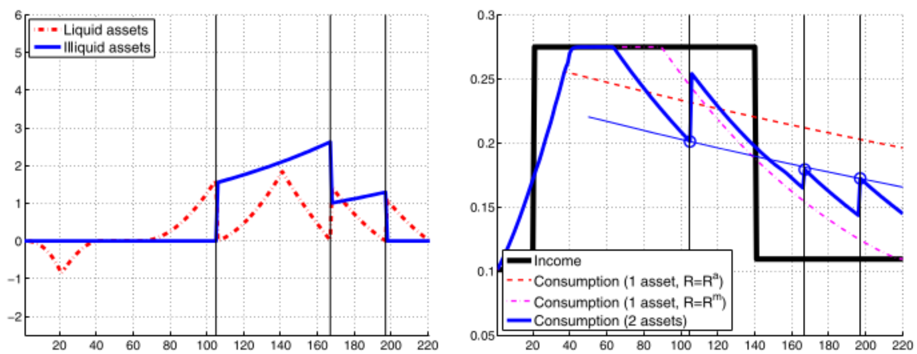
This figure shows *consumption* and *wealth dynamics* in an example where an agent starts her working life with *zero wealth*, receives an INCREASING endowment while working (i.e. $j \leq J^w$), and a *constant endowment* when retired. To make this example as stark as possible, they impose a *very large* κ

Panel (a): INCREASING earnings profile $\implies$ the agent in this example chooses ***first*** to borrow in order to smooth consumption, ***and then*** starts saving for retirement. She adjusts her illiquid account at only 3 points in time: **(1)** one deposit while working, **(2)** after repaying her debt, and **(3)** two withdrawals in retirement.

- ***Value*** of the *illiquid asset account* grows at rate $\frac{1}{q^a}$

Panel (b): Associated *earnings* and *consumption paths*. In the same panel, they plot the paths for consumption arising in the two versions of the corresponding one-asset model: one with the *short-run interest rate* $\frac{1}{q^m(m_{j+1})}$, and one with the *long-run interest rate* $\frac{1}{q^a}$.

- Sawed pattern for consumption arising in the two-asset model is a combination of the ***short-run*** and ***long-run*** behavior:
  - ***between*** adjustment dates: the *consumption path is parallel to the path* in the *one-asset model with the low return*;
  - ***across*** adjustment dates: the *slope is parallel to consumption* in the *one-asset model with the high return.*
- After repayments of her debts, this agent is *poor HtM* $\Longrightarrow$ *keeps zero net worth and consumes all her income for a phase of her life, before starting to save.*



(a) Life-cycle asset accumulation (b) Life-cycle income and consumption path

FIGURE 1.—Example of life-cycle of a poor hand-to-mouth agent in the model.

3.2.3.4 "Wealthy hand-to-mouth" Behavior

This figure shows how the model can feature HHs with *positive net worth* who consume their income every period: the *wealthy HtM*. The parameterization is the same as in the figure above, except for a *higher return on the illiquid asset*. The HH retires at age $J^w = 140$ in the figure above.

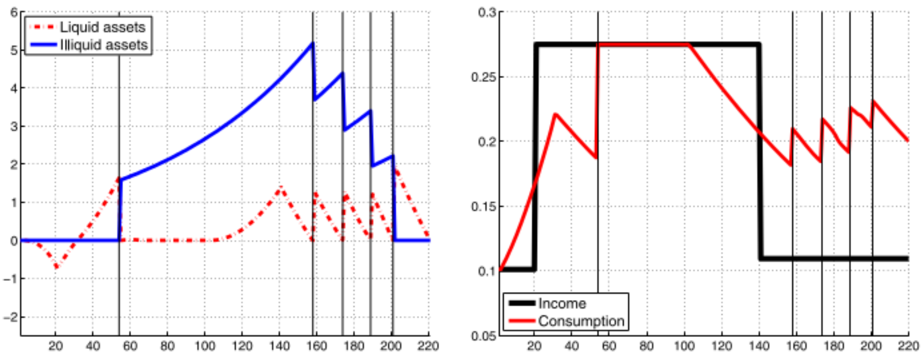
Panel (a): This *higher return on the illiquid asset* leads to ***stronger overall wealth accumulation***, but rather than INCREASING the number of deposits during its working life, the HH changes the ***timing*** of its single deposit to take advantage of this higher return.

- the deposit into the illiquid account is now made EARLIER IN LIFE in order to take advantage of the *high return for a longer period* $\Longrightarrow$ HH optimally chooses to hold *zero liquid assets* in the middle of the working life, after her deposit, while the illiquid asset holdings are positive and are growing in value.

Panel (b): Associated *earnings* and *consumption paths*. This is a HH that, upon receiving the rebate, will *consume a large part* of it and, upon the news of the rebate, will *not increase her expenditures*. We can see that HHS choose to consume all of their earnings and deviate from the optimal consumption path imposed by the ***"short-run" Euler equation (EE-SR),*** even for long periods of time

- Intuition: HHs are better off taking this welfare loss because avoiding it entails either **(i)** paying the transaction cost more often to withdraw cash in order to consume more than income; **(ii)** holding larger balances of liquid wealth and hence foregoing the high return on the illiquid asset (and, therefore, the associated higher level of long-run consumption); or **(iii)** using expensive unsecured credit to finance expenditures.

- Agent features ***endogenous HtM*** behavior
- Small welfare gain of smoothing vs κ and $R^a - R^m$ ***Cochrane (1989)***



(a) Life-cycle asset accumulation (b) Life-cycle income and consumption path

FIGURE 2.—Example of life-cycle of a wealthy hand-to-mouth agent in the model.

- *LIQUID* assets are cheaper source of funds than *ILLIQUID* assets ($\frac{1}{q^a} > \frac{1}{q^m}$)

3.2.4 Liquid and Illiquid wealth in *SCF 2001*

3.2.4.1 Summary Statistics

The authors include some *descriptive statistics* about HH portfolios in the ***Survey of Consumer Finances (SCF)***.

Households' Portfolio Data: Their data source is the 2001 wave of the SCF, a triennial cross-sectional survey of the *assets* and *debts* of US HHs. For comparability with the CEX sample in ***JPS (2006)***, they exclude the *top 5% of HHs by net worth*. Average (median) labor income for the working-age population is \$52,745 (\$41,000), a number close to the one reported by ***JPS (2006, Table 1)***

Baseline measures of ***illiquid assets*** and ***liquid assets***:

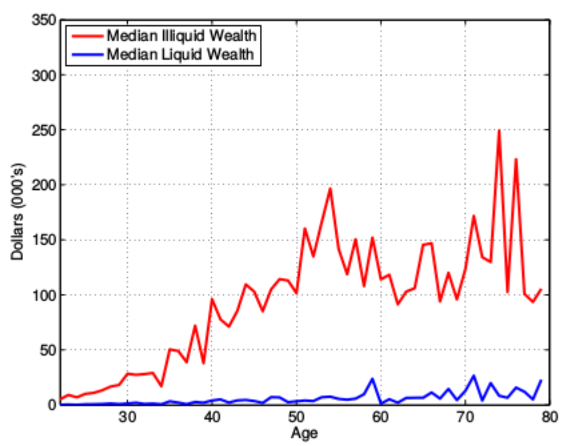
Liquid and illiquid wealth in SCF 2001

- Sample: all households 22+, except top 5% of distribution of net worth, to make SCF and CEX samples comparable
- Liquid assets: checking, savings, money market, directly held mutual funds, stocks and bonds and call accounts plus cash holdings ($2,800)
- Unsecured debt: revolving debt on credit card balances ($0)
- Illiquid assets: net worth minus net liquid assets ($54,600)
  - housing net of mortgages and other secured debt ($31,000)
  - retirement accounts ($950)

As expected, the ***bulk of HH wealth is held in illiquid assets***, notably housing and retirement accounts:

- ***Median*** of the *liquid* and *illiquid* asset distributions are **$2,629** and **$54,600**, respectively.
- Moreover, over their working life, ***HHs save disproportionately through illiquid wealth and keep holdings of liquid wealth fairly stable***: median illiquid assets grow by around $100,000 from age 30 to retirement, whereas median liquid wealth increases by less than $5,000.

Liquid and illiquid wealth over the lifecycle



- Median liquid wealth: $2,600. Median illiquid wealth: $54,600

Liquid and illiquid wealth in SCF 2001

	50th pct	Mean	Fraction Positive	After-Tax Real Return
Earnings + benefits (22-59)	41,000	52,745	–	–
Net worth	62,441	150,411	0.95	1.8
Net liquid wealth	2,630	31,001	0.77	-1.5
Cash, checking, saving, MM	2,816	12,456	0.87	-2.0
MF, stocks, bonds, T-Bills	0	19,935	0.28	1.9
Revolving credit card debt	0	1,617	0.20	–
Net illiquid wealth	54,600	119,409	0.93	2.3
Housing net of mortgage debt	31,000	72,592	0.68	2.0
Retirement accounts	950	34,455	0.53	3.8×1.35
Life insurance	0	7,740	0.27	0.4
Certificates of deposit	0	3,807	0.14	1.2
Saving bonds	0	815	0.17	0.4

3.2.4.2 Measurement of Hand-to-Mouth (HtM) Households.

In the model, they define a HH to be HtM if it chooses to be at ***one of the kinks of her budget constraint***, *either zero liquid wealth (i.e.* $m_j = 0$*) or the credit limit (i.e.* $m_j = -\underline{m}_j$*)* . Such a HH will have a ***high MPC out of an extra dollar of windfall income***.

To measure ***HtM HHs at the zero kink for liquid wealth***, they start from the observation that, since these HHs do not borrow and do not save through liquid assets, they do not carry any liquid wealth *across pay-periods*.

- ISSUE: SCF reports *average balance*, which are are *positive for all HHs (HtM and not-HtM)* because *labor income is paid as liquid assets* and because of a mismatch in the timing of consumption and earnings within a pay-period.

A strict criterion to identify *HtM agents liquid wealth* in the data is to count those HHs in the SCF whose *average balance of liquid wealth* is equal to or less than *half their earnings per pay-period* ($\frac{y}{2}$). (The "half" presumes resources being consumed at a constant rate). Symmetrically, *HtM agents at the credit limit* as those SCF HHs with *negative holdings of liquid wealth* that are lower than *half their pay-period earnings minus their self-reported total credit limit*.

- ***HtM in liquid wealth (LW)***: HHs with $LW^+ \leq \frac{y}{2}$
  - In terms of the model's notation, we have $a_j \geq 0$ and $0 \leq m_j \leq \frac{y_j}{2}$
    - **poor HtM**: $a_j = 0$ and $0 \leq m_j \leq \frac{y_j}{2}$
    - **wealthy HtM**: $a_j > 0$ and $0 \leq m_j \leq \frac{y_j}{2}$
- ***HtM in credit limit using LW***: HHs with $LW^- \leq \frac{y}{2} -$ credit limit
  - In terms of the model's notation, we have $a_j \geq 0$ and $m_j \leq 0$ and $m_j \leq \frac{y_j}{2} - \underline{m}_j$
    - **poor HtM**: $a_j = 0$ and $m_j \leq 0$ and $m_j \leq \frac{y_j}{2} - \underline{m}_j$
    - **wealthy HtM**: $a_j > 0$ and $m_j \leq 0$ and $m_j \leq \frac{y_j}{2} - \underline{m}_j$
- Also for comparisons...

– ***HtM in net worth (NW):*** HHs with $NW^{+} \leq \frac{y}{2}$
– ***HtM in credit limit using NW***: HHs with $NW^{-} \leq \frac{y}{2}$ – credit limit

** This sample split based on *income* and *liquid wealth* is bound to contain both ***type I*** and ***type II*** classification error (see, e.g., ***Jappelli (1990)***). Nevertheless, their estimate is likely to be a *lower bound*: All *non-HtM HHs* would always hold average liquid balances above half their earnings, and some *HtM HHs* at the zero kink may fall in this latter group as well **

The examples in Section **3.2.4** show that there are ***two types of HtM agents.***

1. *poor HtM agents* without any illiquid assets

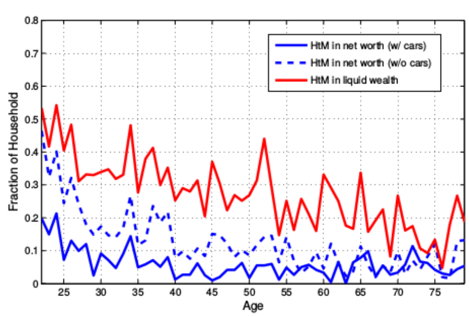
2. *wealthy HtM agents* who have positive balances of illiquid wealth.

In the SCF, they identify ***wealthy HtM agents as those HHs who satisfy the HtM requirements listed above and, at the same time, hold illiquid assets***.

Their estimates imply that ***17.5% to 35% of HHs are HtM in the US***. *Among these, 40% to 80% are wealthy HtM*, depending mainly on the pay frequency and on whether one expands the notion of illiquid wealth by including vehicles.

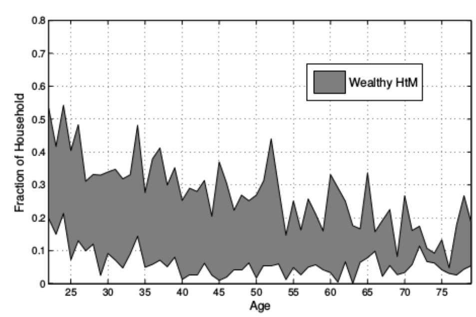
- This group of wealthy HtM HHs, which represents a sizable fraction of the population (between 7% and 26%), is *only visible through the lens of the two-asset model.* From the distorted point of view of the standard one-asset model, these are *HHs with positive net worth*, and are hence unconstrained.
- It is useful to compare these estimates with those that one would obtain when HtM agents are measured in terms of net worth: ***4% to 14% of U.S. HHs are HtM in terms of net worth***, depending largely on whether vehicles are considered part of wealth
- *The figures below are from the working paper version, which contain outdated estimates relative to the published version of the paper.*

Hand-to-mouth households



► Hand to Mouth: 30% in liquid wealth, 5% – 13% in net worth

Hand-to-mouth households



► Wealthy Hand to Mouth: 17% – 25%

HtM estimator is a LOWER BOUND: Because of the *lower bound nature of our estimator*, in the model *they target a total fraction of HtM HHs on the high end of the range, around $\frac{1}{3}$ of the population*. This target is also consistent with 3 additional pieces of survey evidence:

1. SCF asks HHs whether "***in the past year their spending exceeded their income, but did not spend on a new house, a new vehicle, or on any investment***." Almost **36%** of HHs fall into this category.

2. ***Lusardi, Schneider, and Tufano (2011)*** documented that $\approx \frac{1}{3}$ of US HHs would "*certainly be unable to cope with a financial emergency that required them to come up with \$2,000 in the next month.*" The authors also reported that, among those giving that answer, a high proportion of individuals are at middle class levels of income.

3. ***Broda and Parker (2012)*** documented, from the AC Nielsen Homescan database, that ***40% of HHs report*** that they do not have "*at least two months of income available in cash, bank accounts, or easily accessible funds.*"

3.2.5 Calibration of the Two-Asset Model

3.2.5.1 Calibration

The authors calibrate their model and its various parameters as follows:

Calibration

- Assets Returns:
  Illiquid asset After-tax real return $r^a = 2.3\%$
  Liquid asset After-tax real return $r^m_+ = -1.5\%$
- Housing Services ζ: Match imputed rent of owner-occupied housing net of maintenance, mortgage interest, and property tax $\Rightarrow$ 4.0% (annualized)
- Discount Factor β: Match median illiquid wealth of \$54,600 $\Rightarrow$ 0.953 (annualized)
- Borrowing rate r^m_-: Match fraction of households with revolving cc debt of 20% $\Rightarrow$ 6% (annualized)
- Transactions Cost κ: Match fraction of hand-to-mouth households of 1/3 $\Rightarrow$ \$1,000

Calibration of asset returns

1. Construct average returns by asset class from 1960-2009:
   - Cash and checking accounts: zero nominal return
   - Money market and savings accounts: 3 month treasury bills
   - Stocks: CRSP value-weighted portfolio incl dividends
   - Bonds: 3 month treasury bills
   - Housing: Flow of Funds & Piazzesi-Schneider (2007)
   - Retirement accounts: Return ×1.35 (employer contribution)
   - Certificates of deposit: Federal Reserve Board database
2. All returns are risk adjusted subtracting *var*(*return*)
3. Use observed portfolios in SCF to construct household-specific returns on liquid and illiquid wealth $\rightarrow$ cross-sectional mean

Calibration of consumption flow from housing

$$\zeta = r^h - m^h - n^h - (1 - \tau^{ded})(\tau^{prop} + i^{mort})$$

- r^h: imputed rents for owner-occupied housing (NIPA) (8.6%)
- m^h: maintenance and repair expenditures (1.0%)
- n^h: home-owner insurance expenditures (0.35%)
- τ^{prop}: property taxes (1.0%)
- i^{mort}: mortgage interests times L/V ratio (2.9%)
- τ^{ded}: average marginal tax rate (23.8%)

3.2.5.2 Features of the Model

This figure displays some features of the model as a function of κ. For each value of $\kappa > 0$, they re-calibrate β to match ***median holdings of illiquid wealth***.

Panel (a): % of HHs adjusting — accessing the illiquid account to withdraw or deposit — DECREASE with the transaction cost κ

- At $\kappa = \$1000$, 4.5% of workers and 21% of retirees adjust each quarter.

Panel (b): Holdings of liquid wealth (i.e. m_j) INCREASE with the transaction cost κ

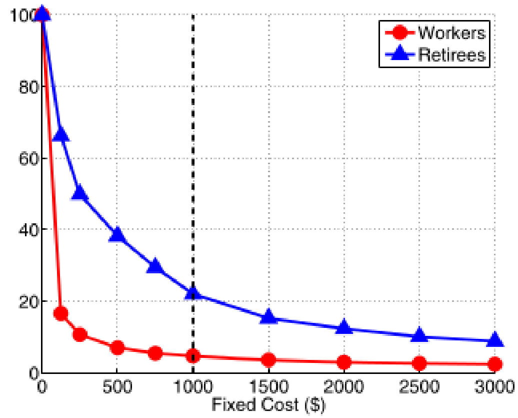
- $\kappa \uparrow \Longrightarrow$ HHs deposit into or withdraw from the illiquid account less often and carry larger balances of liquid assets.
- However, even for LARGE κ, *median liquid wealth remains small.*
- Liquid balances are more sensitive to κ at the *upper end of the distribution* since, in that range, κ have more of an impact on the optimal frequency of adjustment.

Panel (c): plots the % of HtM consumers in the model and divides them into those who also have *zero illiquid wealth* — ***poor HtM*** — and those with *positive illiquid wealth* — ***wealth HtM***. The size of both groups is INCREASING in the transaction costκ

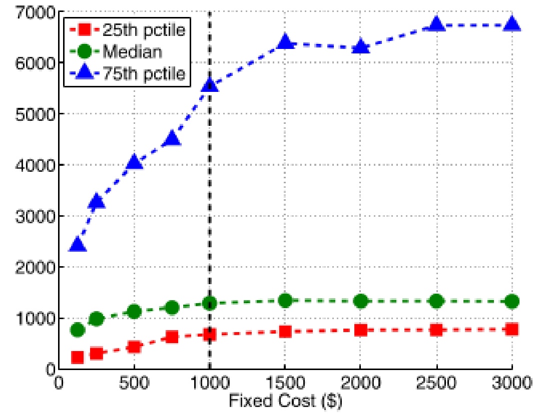
- At $\kappa = \$1000$, share of ***poor HtM*** $=\approx \frac{1}{5}$ and share of ***wealthy HtM*** $\approx \frac{4}{5}$

Panel (d): % of ***borrowers*** in the model DECREASES with the transaction cost κ

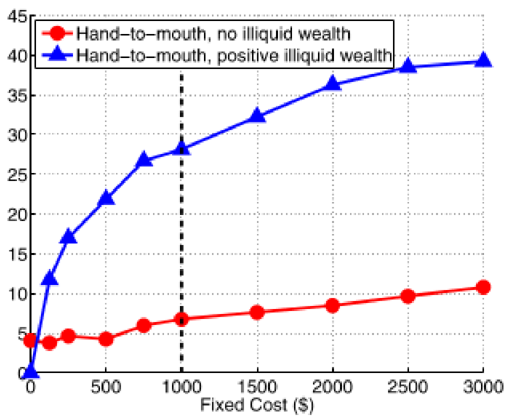
- This result is the mirror image of *panel (b)*: as $\kappa \uparrow \Longrightarrow$, HHs hold larger liquid balances and respond to negative shocks by *dis-saving rather than by taking up debt.*



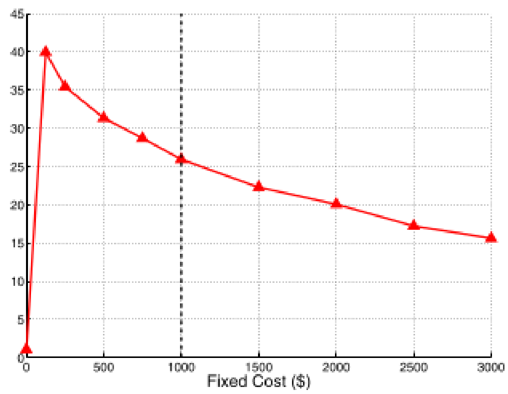
(a) Percentage of households adjusting



(b) Distribution of liquid wealth ($)



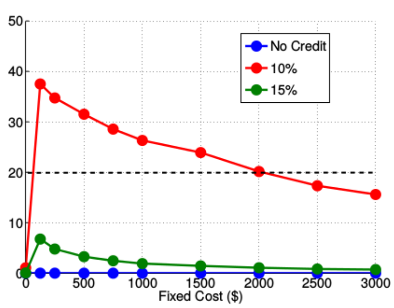
(c) Percentage of HtM households



(d) Percentage of borrowers

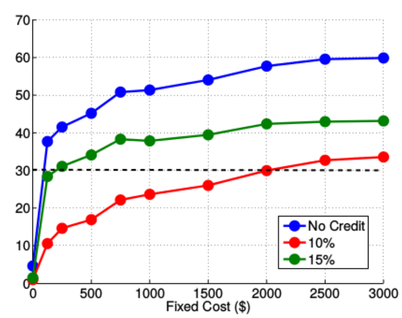
** A more detailed version of Panel (d) (see left panel) and a different version of Panel (c) (see right panel) **

Borrowers in the model



- Model matches the data for $r^m_{-} = 10\%$ & $\kappa = \$2,000$

Hand to mouth in the model



- Model matches the data for $\kappa = \$2,000$

3.2.6 The 2001 Tax Rebate Experiment

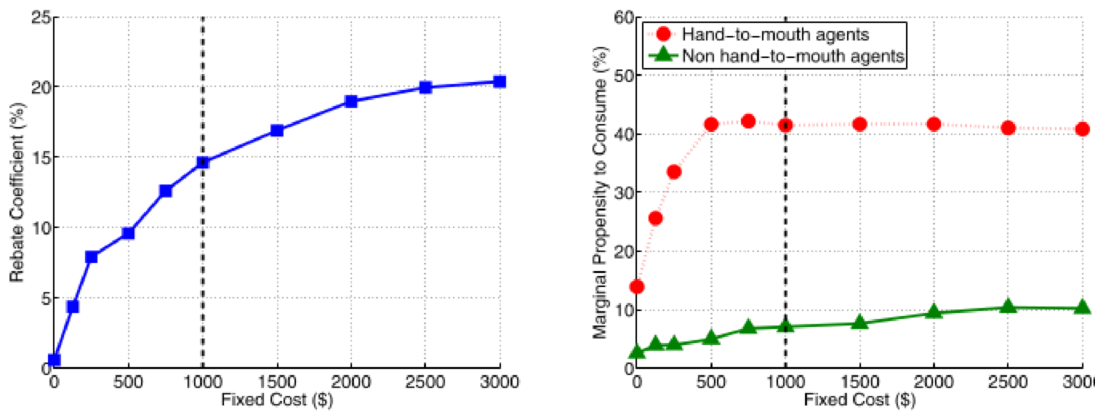
3.2.6.1 No Aggregate Economic Conditions

The authors also reproduce the reproduce the ***2001 tax rebate episode*** within their economic model.

Experiment Design: The economy is in its ***steady state in 2001:Q1***. The rebate checks are randomly sent out to $\frac{1}{2}$ the eligible population in ***2001:Q2 (group A)***, and to the other $\frac{1}{2}$ in ***2001:Q3 (group B)***. The size of the rebate is set to **$500** based on ***JPS (2006)***, who reported that the average rebate check was $480 per HH.

- They assume that the news/check reaches HHs before making their consumption/saving and adjustment decisions for that quarter.
- The government finances the rebate program by INCREASING debt, and after 10 years it permanently INCREASES the payroll tax to gradually repay the accumulated debt (plus interest).

The following *information structure* is assumed: an ***intermediate structure*** where the policy enters all agents' information sets after the first batch of checks is sent out (2001:Q2), that is, group A is surprised, but group B is not. The figure below shows the ***rebate coefficient*** and ***MPC***, by transaction cost κ.

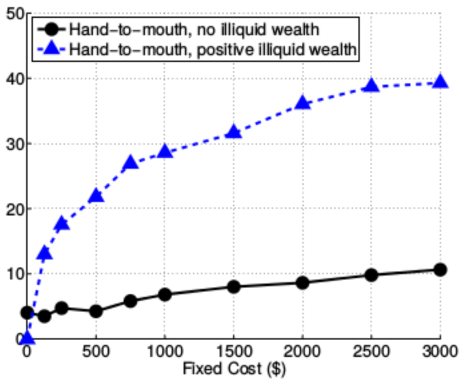


(a) Rebate coefficient (b) Average marginal prop. to consume

FIGURE 5.—Rebate coefficient and marginal propensity to consume, by transaction cost.

Panel (a): **Rebate Coefficient INCREASES with** κ

- The rebate coefficient computed through *baseline regression* run on simulated panel data, exactly as in ***JPS (2006)***
- The rebate coefficient $\uparrow$ steadily from 0.6% at $\kappa = 0$ (the one-asset model) to 20% at $\kappa = \$3000$. For $\kappa = \$1000$, the calibrated value of the transaction cost, the model generates a rebate coefficient of 15% or nearly $\frac{2}{3}$ of the empirical estimate.
- In a more detailed version of Panel (a), we can also see that rebate coefficient $\uparrow$ as the % of HtM HHs $\uparrow$



***Panel (b)*: MPC**

- Displays the powerful amplification mechanism intrinsic in the two-asset model: the rebate coefficient is 14% larger than its one-asset model counterpart ($\kappa = 0$)
- This amplification works through both an *extensive* and an *intensive* margin: **(1)** two-asset model features a much larger fraction of HtM consumers, many of whom hold sizable quantities of illiquid assets and **(2)** even among HtM agents, the wealthy HtM have larger MPCs out of tax rebates than the poor HtM (44% versus 34%) since they have higher wealth (tied in the illiquid asset) and, therefore, higher desired target consumption:

$$MPC_{\textbf{wealthy HtM}} > MPC_{\textbf{poor HtM}}$$

- If we look at the MPC across HHs in much closer detail, we can see that *most of the action is coming from the HtM HHs* and the *Average MPC* $\simeq$ *Rebate coefficient.*

3.2.6.2 Heterogeneity in rebate coefficients

The stark dichotomy in the MPC of HtM and non HtM agents $\Longrightarrow$ model features a *large amount of heterogeneity in consumption responses* to fiscal stimulus payments across HHs.

Panel (a) of the figure below plots the ***distribution of rebate coefficients in the model***:

- almost $\frac{1}{2}$ of HHs in the model have consumption responses close to zero, 15% spend more than $\frac{1}{2}$ the rebate in the quarter they receive it, and the remaining $\frac{1}{3}$ are in between.

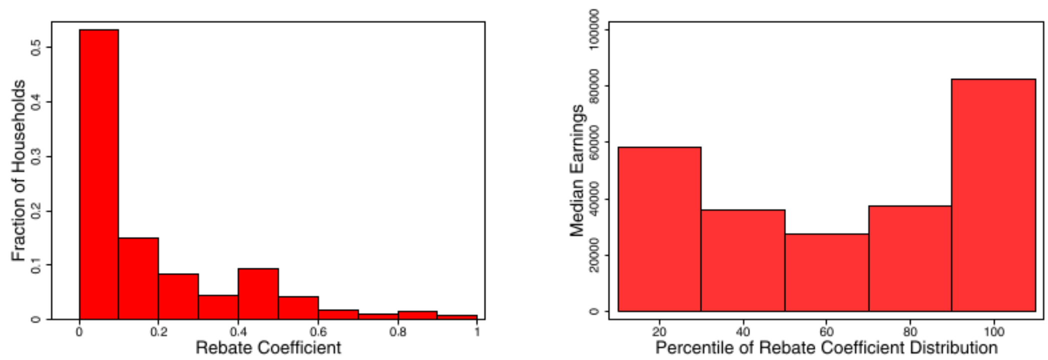
Misra and Surico (2013) applied quantile regression techniques to the ***JPS (2006)*** data to estimate the *empirical cross-sectional distribution* of consumption responses to the 2001 rebate. Their results line up remarkably well with the model predictions.

Misra and Surico (2013, Figure 5) also documented that high income HHs are disproportionately concentrated in the two tails of the distribution of consumption responses, a finding that rationalizes two former results in the literature.

JPS (2006) reported that, when splitting the population into *three income groups*, differences in rebate coefficient across groups are not statistically significant.

Panel (b) of the figure below shows that their model can replicate the ***bimodality of the income distribution by size of the rebate coefficient***.

- Intuition: The reason why there are *high earnings HHs* at both ends of the distribution in the model is that some of them are ***unconstrained*** (those at the bottom end) and some are *wealthy HtM* (those at the top end).



(a) Distribution of rebate coefficients in the population

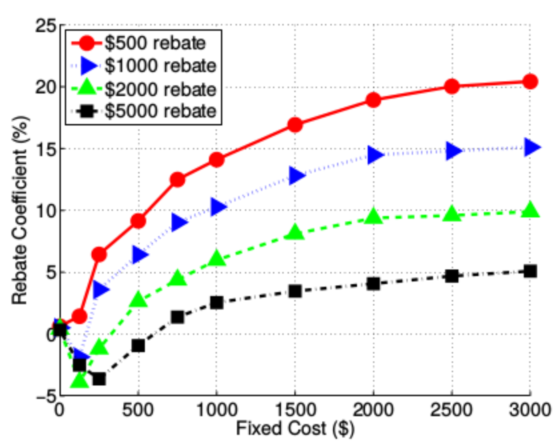
(b) Median earnings by quintile of rebate coefficient distribution

FIGURE 7.—Heterogeneity in rebate coefficients in the model ($\kappa = \$1{,}000$).

3.2.6.3 Size Asymmetry

The figure below shows that in their baseline economy, the *rebate coefficient* DECREASES with the size of the rebate. With a $\kappa = \$1000$ transaction cost, the rebate coefficient $\downarrow$ by over a factor of 2 (from 15% to 6%) as the size of the stimulus payment $\uparrow$ from \$500 to \$2,000.

Same households who have large MPC out of 2001 tax rebate do not respond to (larger) distributions from Alaskan Permanent Fund



- Larger rebate $\Rightarrow$ more adjustment $\Rightarrow$ lower consumption response

- A large enough rebate *loosens the liquidity constraint*, and even ***constrained HHs find it optimal to save a portion of their payment***.
- Moreover, for rebates that are *sufficiently large relative to the transaction cost*, many working HHs will choose to pay the transaction cost and make a deposit upon receipt of the rebate. But adjusting HHs are unconstrained, so they save a large portion of the rebate, as in the one-asset model.

- Estimated rebate coefficients (but not the MPC) ***may become negative*** when the stimulus payment is large relative to the transaction cost. In this case, many working HHs choose to make a *deposit into the illiquid account upon receipt of the payment.* As a result, these HHs consume even less than the control group during that period.

Their *mechanism's size asymmetry* feature is consistent with two well-known empirical findings. ***Hsieh (2003)*** showed that the same CEX consumers who "overreact" to small income tax refunds respond very weakly to much larger payments (around $2,000 per HH) received from the Alaskan Permanent Fund. ***Browning and Collado (2001)*** documented similar evidence from Spanish survey data: workers who receive anticipated double-payment bonuses (hence, again, large amounts) in the months of June and December do not alter their consumption growth significantly in those months

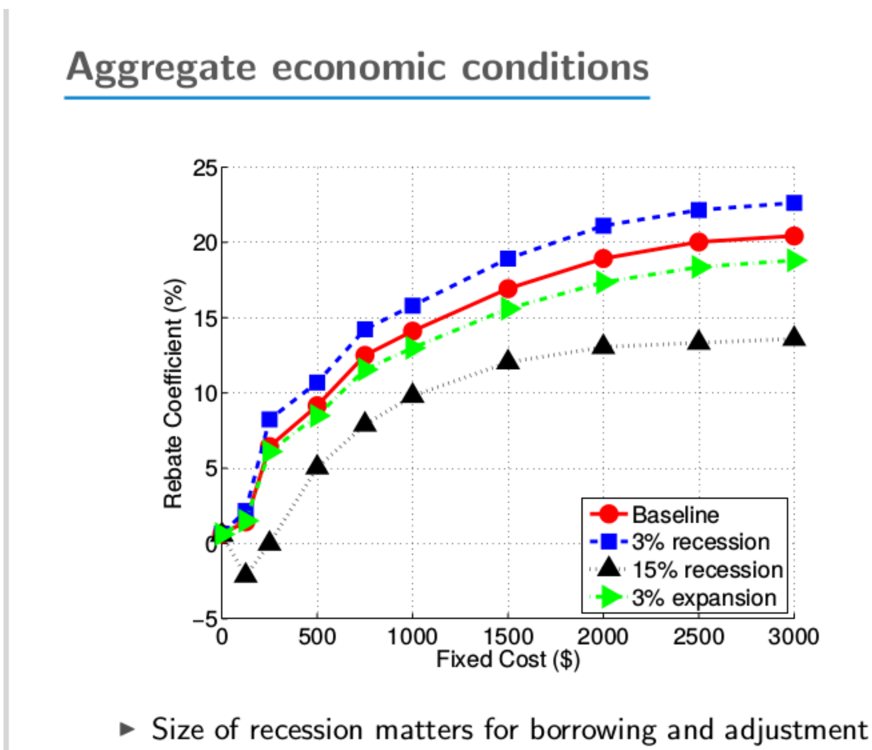
3.2.6.4 Aggregate Economic Conditions

They also incorporate two features of ***2001's macroeconomic environment*** into the analysis:

1. ***Bush tax cuts (EGTRRA) reform***: Unexpected tax reform announced in 2001:Q2 (with rebate), takes effect gradually from 2002:Q1

2. ***Mild 2001-02 recession***: Unexpected 1.5% decline in earnings, over 3 quarters, followed by 8 quarter recovery.

The figures below summarize their results:



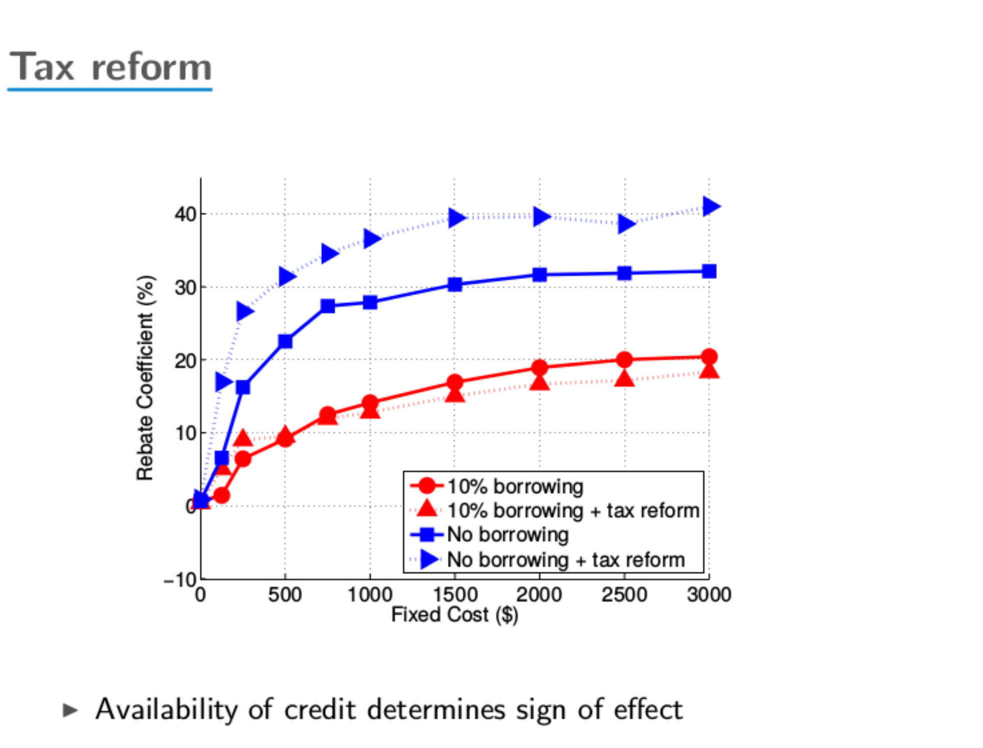
$$Rebate_{\textbf{mild recession}} > Rebate_{\textbf{mild expansion}} > Rebate_{\textbf{severe recession}}$$

State Dependence: The figure above shows that the consumption response to the rebate is *highly dependent* on the aggregate economic conditions.

- e.g. when the rebate is distributed during a ***mild expansion*** (of the same size of the mild recession of 2001, with the sign reversed, and of the same duration), the consumption response is more muted in the model. Since most episodes of fiscal stimulus payments occur in recessions, it is difficult, empirically, to isolate the role of aggregate economic conditions on the size of the consumption response.
- The above figure shows that the ***occurrence of a mild recession***, such as the ***2001 episode***, INCREASES the number of HtM HHs in the economy and adds nearly 2 percentage points to the rebate coefficient.

The size and expected duration of an income drop caused by a recession affects this trade-off. A ***sufficiently sharp recession*** leads many wealthy HtM HHs to pay the transaction cost and withdraw from their illiquid account in order to avoid an abrupt dip in consumption. Similarly, the poor HtM at the zero liquid wealth kink start using credit heavily to sustain their consumption. As a result, many HHs who were HtM before the recession become effectively unconstrained at the time of the rebate, and *their consumption response to the transfer can be quite low*.

- Intuition: Expectations of a REALLY BAD recession induce the ***wealthy HtM*** to tap into their illiquid assets in order to INCREASE their liquid funds as a caution against a potentially really bad dip income. The ***poor HtM*** use credit to borrow and also INCREASE their liquid funds (for the same obvious reason). Having done so, both HtM HHs have enough liquid funds that an ESP won't do much to help them, given their *optimal forward-looking behavior*.



The figure above shows the consumption responses to the tax rebate when the baseline economy is *augmented with the tax reform*. The fall in future tax liabilities leads to a rise in the desired level of lifetime consumption which, in turn, triggers ***two offsetting forces***:

1. HHs who are already *borrowing sizable amounts* may reach their credit limit, which tends to INCREASE the number of HtM HHs in the economy.
2. HtM HHs at the *zero kink may start borrowing* and, once off the kink, they have low MPCs out of the rebate.

For SMALL κ, when there are already lots of HHs borrowing the *first channel dominates*, and the rebate coefficient is slightly higher than in the baseline. However, for LARGE κ the *second channel appears to dominate.*

- $\kappa = \$1000$, one year after the tax reform the % of HHs using credit is twice the initial one.

$$\text{LOW } \kappa : \text{ Channel 1} > \text{Channel 2}$$
$$\text{HIGH } \kappa : \text{ Channel 2} > \text{Channel 1}$$

3.2.7 Conclusion

Conclusions

- Baumol-Tobin model of money demand integrated into a lifecycle incomplete markets framework
- Generates wealthy hand-to-mouth consumers

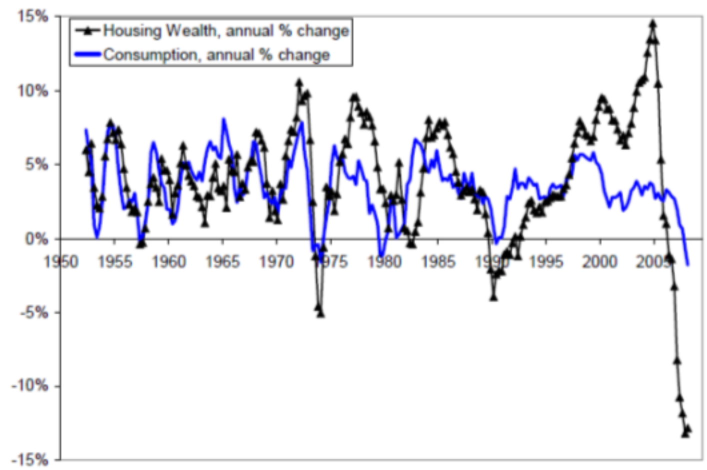
  Microfoundation for Campbell-Mankiw spender-saver model
- Model capable of responses to fiscal stimulus payments that are: (i) large; (ii) heterogeneous; and (iii) size-asymmetric
- Model displays strong non-linearities in the aggregate

Lecture 4

Household Finance and The Great Recession

Motivation:

Housing wealth very correlated with consumption



4.1 Case, Quigley and Shiller (Cowles, 2011): *Wealth Effects Revisited 1975–2009*

Table 4
Consumption Models in First Differences:
Quarterly Observations on States, 1978-2009*

Dependent variable: Change in Consumption per capita	Ordinary Least Squares			Instrumental Variables**		
	I	II	III	IV	V	VI
Income	0.128	0.127	0.074	1.351	1.296	0.984
	(14.61)	(14.51)	(9.71)	(5.52)	(5.62)	(5.53)
Stock Market Wealth	0.015	0.015	0.005	-0.090	-0.092	-0.072
	(7.17)	(6.93)	(2.80)	(2.53)	(2.67)	(3.41)
Housing Market Wealth	0.090	0.090	0.038	0.198	0.239	-0.009
	(12.99)	(12.90)	(6.13)	(3.81)	(4.71)	(0.19)
State Specific Time Trends	No	Yes	No	No	Yes	No
Year/Quarter Fixed Effects	No	No	Yes	No	No	Yes
Regression R^2	0.0754	0.0795	0.35	-	-	-
t-Ratio	10.101	10.080	5.023	4.679	5.178	1.179
p-value for H_0	0.000	0.000	0.000	0.000	0.000	0.238
p-value for H_1	1.000	1.000	1.000	1.000	1.000	0.881

Note: H_0 is a test of the hypothesis that the coefficient on housing market wealth is equal to that of stock market wealth.
H_1 is a test of the hypothesis that the coefficient on housing market wealth exceeds that of stock market wealth.
* See also note to Table 2.
** Using Lags 2 to 4 of Income, Stock market and Housing market variables as instruments for Income, Stock market and Housing market wealth.

We can see that $MPC_{\text{housing market wealth}} > MPC_{\text{stock market wealth}}$ (Table above). Several reasons are:

1. housing market assets are *collateralized*, while equities are not *collaterialized*
2. housing market assets have *more PERSISTENT* dynamics relative to equities.

Table 8: Housing Wealth Increases vs Decreases
Consumption Models in First Differences and Error Correction Models:
Quarterly Observations on States, 1978-2009*

Dependent variable: Change in Consumption per capita	Models in First Differences I	II	III	Error Correction Models IV	V	VI
Change in Income	0.126 (14.42)	0.125 (14.34)	0.074 (9.68)	0.139 (16.21)	0.149 (17.36)	0.083 (10.84)
Change in Stock Market Wealth	0.015 (6.95)	0.014 (6.53)	0.005 (2.78)	0.015 (7.31)	0.014 (6.86)	0.006 (3.06)
Dummy for Housing Wealth Decreases * Change in Housing Market Wealth	0.154 (13.42)	0.170 (13.95)	0.051 (4.74)	0.138 (12.07)	0.153 (12.68)	0.056 (5.31)
Dummy for Housing Wealth Increases * Change in Housing Market Wealth	0.024 (2.08)	0.011 (0.87)	0.026 (2.56)	0.030 (2.65)	0.024 (2.04)	0.033 (3.27)
Lagged Change in Consumption	-	-	-	0.109 (8.99)	0.115 (9.46)	-0.089 (7.20)
Lagged Ratio of Consumption to Income	-	-	-	-0.036 (11.06)	-0.063 (14.98)	-0.032 (8.96)
State Specific Time Trends	No	Yes	No	No	Yes	No
Year/Quarter Fixed Effects	No	No	Yes	No	No	Yes
R^2	0.0825	0.0888	0.3502	0.1120	0.1300	0.3626

We can also see (Table above) that HHs are *MUCH MORE sensitive* to ↓house prices than ↑ in house prices.

4.2 Mian and Sufi (AER, 2011): *House Prices, Home Equity-Based Borrowing, and the U.S. Household Leverage Crisis*

Abstract: Borrowing against the increase in home equity by existing homeowners was responsible for a significant fraction of the rise in US household leverage from 2002 to 2006 and the increase in defaults from 2006 to 2008. Instrumental variables estimation shows that homeowners extracted 25 cents for every dollar increase in home equity. Home equity-based borrowing was stronger for younger households and households with low credit scores. The evidence suggests that borrowed funds were used for real outlays. Home equity-based borrowing added $1.25 trillion in household debt from 2002 to 2008, and accounts for at least 39 percent of new defaults from 2006 to 2008.

Motivation: The dramatic absolute and relative rise in U.S. household leverage from 2002 to 2007 is unprecedented compared to the last 25 years. In comparison, the contemporaneous increase in corporate debt was modest.

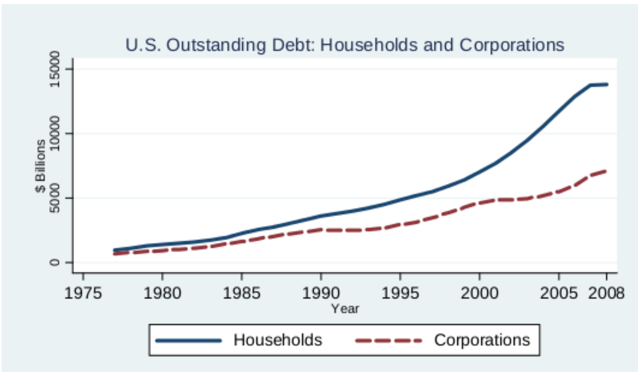
One reason for the rapid expansion in household leverage during this period is that mortgage credit became more easily available to new home buyers as documented in ***Mian and Sufi (2009).*** The authors' central goal in this study is to *estimate* how homeowner borrowing responded to the ↑ in house prices and to identify which homeowners respond most aggressively. They examine this ***home equity-based borrowing channel*** using a data set consisting of anonymous individual credit files of a national consumer credit bureau agency.

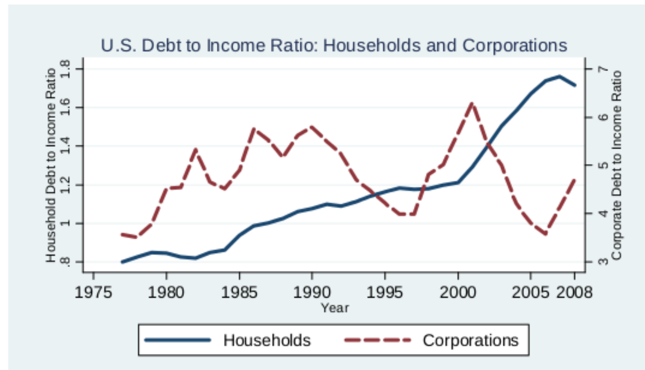
Data: They follow a random sample of over 74,000 U.S. homeowners (who owned their homes as of 1997) at an annual frequency from the end of 1997 until the end of 2008. The Equifax data doesn't contain an *explicit measure of homeownership*. Instead, they measure homeownership by splitting the sample into three groups of individuals based on 1997 credit report information:

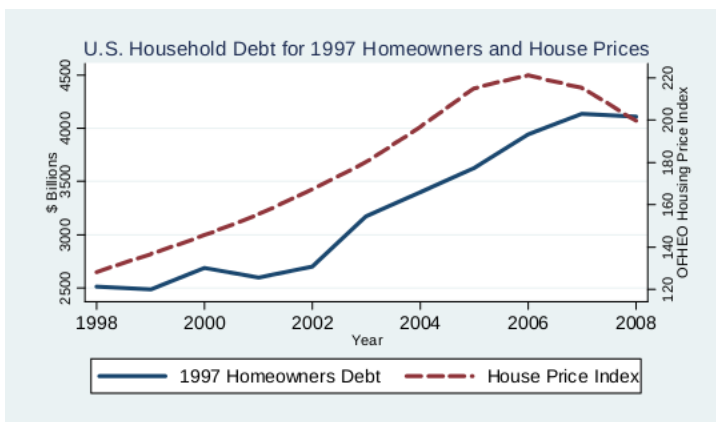
1. The ***first group*** (34%) contains individuals that *have outstanding* mortgage or home equity debt.

2. The ***second group*** (8%) contains individuals that *don't currently have outstanding mortgage or home equity debt*, but their credit report indicates that they have had a mortgage or home equity account in the past.
3. The ***third group*** (58%) contains individuals that *don't have either a current or previous mortgage account*.

They define as "***1997 homeowners***" individuals in *groups 1 and 2*







- The third figure above focuses on the ***intensive margin*** (existing homeowners in 1997) — not the *extensive margin* (new homeowners in 1997). As house prices ↑, existing homeowners increase their debt through *home-equity extraction borrowing* (via ***cash-out refinancing***)

Definition. Cash Out Refinancing — refinancing your existing mortgage for more than you currently owe, then pocket the difference.

- Here's an example: *Let's say you still owe \$80,000 on a \$150,000 house, and you want a lower interest rate. You also want \$20,000 cash, maybe to spend on your child's first semester at Princeton. You can refinance the mortgage for \$100,000. Ideally, you get a better rate on the \$80,000 that you owe on the house and you get a check for \$20,000 to spend as you wish.*

Empirical Strategy: The aggregate trend is suggestive of a link but changes in *house prices* and *homeowner borrowing* may be jointly determined by an omitted variable such as a ***shock to expected income growth*** (***Attanasio and Weber (1994)***, ***Muellbauer and Murphy (1997)***). As a result, proper identification of the effect of house prices on borrowing requires an exogenous source of variation in house price growth.

They use 2 different instruments for house price growth: **(1)** ***across-MSA variation*** and **(2)** ***within-MSA variation*** where ***MSA*** denotes Metropolitan Statistical Area.

1. The ***across-MSA variation*** specification uses *housing supply elasticity* at the MSA level as an **instrument for house prices**:

    - *elastic housing supply* MSAs should experience slight ↑ in house prices in response to large shifts in the demand for housing because housing supply can be expanded relatively easily.
    - *inelastic housing supply* MSAs should experience large ↑ in house prices in response to the same housing demand shock (***Glaeser, Gyourko, and Saiz (2008)***).

Baseline Results: In the table below, they present *IV estimates* of the effect of an INCREASE in home equity on home borrowing in $ units. The ***first stage*** estimate (highly significant) in column 1 implies that a one standard deviation ↓ in housing supply elasticity leads to a $32 thousand ↑ in home equity. The ***second stage*** estimates in columns 2 through 5 suggest that 1997 homeowners borrow 25 cents on every dollar of additional home equity value. As columns 3 to 5 show, the estimate is *insensitive* to both individual and zip code level control variables.

TABLE 3—THE EFFECT OF HOUSE PRICES ON HOUSEHOLD BORROWING FOR 1997 HOMEOWNERS, DOLLAR-FOR-DOLLAR CHANGES

Left-hand-side variable	Change in home value 2002–2006 (thousands US dollars)	Change in total debt 2002–2006 (thousands US dollars)			
	(1)	(2)	(3)	(4)	(5)
Housing supply elasticity	−50.736***				
	(11.179)				
Instrumented change in home value, 2002–2006		0.245***	0.271***	0.253***	0.246***
		(0.050)	(0.056)	(0.056)	(0.065)
Median home value, 2002	0.459***	0.020	−0.014	−0.010	−0.076
	(0.103)	(0.039)	(0.044)	(0.037)	(0.079)
(Credit score, 1997)/100			−8.176***		
			(1.260)		
Ln(household income, 2008)			26.960***		
			(3.858)		
Debt to income ratio, 1997			4.537***		
			(1.150)		
Age, 1997			−1.847***		
			(0.216)		
Male dummy variable			7.287*	6.978*	6.253
			(4.234)	(3.996)	(4.259)
Additional control variables				Individual dummy variables	Individual dummy, census, income variables
Observations	13,328	13,328	13,199	13,199	12,497
R^2	0.6	0.03	0.07	0.1	0.12

- Intuition for IV: If *housing supply is inelastic* in a given MSA region, all the effect will be on *prices*, not *quantities.*

Does the Home Equity-Based Borrowing Channel Vary By Consumer Type? The authors explore the *cross-sectional heterogeneity* of the effect, which provides important insights into the underlying model of consumer behavior that is most consistent with the *home equity-based borrowing channel*.

They examine how the propensity to borrow against INCREASED home equity *varies* by the homeowner's ***base year credit score*** and ***credit card utilization rate***.

- The literature on consumer credit often interprets ***low credit scores*** and ***high credit card utilization rates*** as indicators for liquidity constrained HHs (see ***Gross and Souleles (2002)***).

The table below presents estimates of the following ***1st stage*** and ***2nd stage*** specifications:

$$\begin{aligned} HousePriceGrowth0206_{i,2m} =& \delta \cdot X_{i,2m} + \rho \cdot Inelasticity_{m,1997} \\ &+ \omega \cdot Inelasticity_{m,1997} \times InteractionTerm_{i,2m} + \varepsilon_{i,2m} \end{aligned}$$

$$\begin{aligned} LeverageGrowth0206_{i,2m} =& \theta \cdot X_{i,2m} + \beta \cdot \widehat{HousePriceGrowth}0206_{i,2m} \\ &+ \tau \cdot \widehat{HousePriceGrowth}0206_{i,2m} \times InteractionTerm_{i,2m} + u_{i,2m} \end{aligned}$$

TABLE 4—CROSS-SECTIONAL HETEROGENEITY IN EFFECT OF HOUSE PRICES ON HOUSEHOLD BORROWING FOR 1997 HOMEOWNERS

Left-hand-side variable	Total debt growth 2002–2006					
Interaction variable	(Credit score, 1997)/100 (1)	CC utilization, 1997 (2)	Debt to income, 1997 (3)	Ln(household income, 2008) (4)	Age, 1997 (5)	Male (6)
Instrumented house price growth, 2002–2006	2.282***	0.361***	0.356**	0.789*	1.416***	0.684***
	(0.497)	(0.108)	(0.177)	(0.400)	(0.362)	(0.142)
Instrumented house price growth, 2002–2006 *interaction term (listed at top of column)	−0.213***	0.825***	0.130	−0.032	−0.017**	0.016
	(0.059)	(0.241)	(0.099)	(0.085)	(0.007)	(0.128)
(Credit score, 1997)/100	0.054*	−0.044**	−0.036**	0.002	0.004	−0.055**
	(0.032)	(0.018)	(0.018)	(0.031)	(0.030)	(0.024)
Credit cart utilization, 1997	−0.096*	−0.479***	−0.043	0.048	0.135**	−0.097*
	(0.056)	(0.106)	(0.055)	(0.054)	(0.051)	(0.057)
Ln(household income, 2008)	0.146***	0.147***	0.162***	0.202***	0.148***	0.148***
	(0.019)	(0.019)	(0.020)	(0.042)	(0.018)	(0.021)
Debt-to-income ratio, 1997	−0.032***	−0.032***	−0.104**	−0.044***	−0.041***	−0.037***
	(0.006)	(0.006)	(0.046)	(0.007)	(0.005)	(0.007)
Age, 1997	−0.012***	−0.012***	−0.014***	−0.015***	−0.008***	−0.012***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)
Male dummy variable	0.031	0.031	0.017	0.003	−0.002	0.006
	(0.026)	(0.026)	(0.022)	(0.025)	(0.029)	(0.054)
Observations	13,198	13,198	13,198	12,598	12,889	11,690
R^2	0.02	0.02	0.01	0.04	0.07	0.01

- In column 1, the estimated coefficient on the *interaction term* $\frac{\text{Credit Score, 1997}}{100}$ is ***-0.213*** and statistically significant, which implies that the *effect* of house price growth on home equity-based borrowing from 2002 to 2006 is LOWER for individuals with a higher credit score in 1997.

- The estimate of ***0.825*** on the *interaction term* **CC utilization rate** in column 2 is statistically significant, which implies that individuals with a high credit card utilization rate have a LARGER borrowing response to house price growth.

- The coefficient estimate on the age *interaction term* **Age, 1997** in column 5 is ***-0.017*** and statistically significant at the 5%. The evidence suggests that the borrowing of older consumers is less responsive to house price growth than young consumers, which is inconsistent with life-cycle models of consumer financial behavior.

**** We can see clear heterogeneity in the home equity withdrawals ****

4.3 Mian, Rao, and Sufi (QJE, 2013): *Household Balance Sheets, Consumption, and the Economic Slump*

Abstract: We investigate the consumption consequences of the 2006 to 2009 housing collapse using the highly unequal geographic distribution of wealth losses across the United States. We estimate a large elasticity of consumption with respect to housing net worth of 0.6 to 0.8, which soundly rejects the hypothesis of full consumption risk-sharing. The average marginal propensity to consume (MPC) out of housing wealth is 5 to 7 cents with substantial heterogeneity across zip codes. Zip codes with poorer and more levered households have a significantly higher MPC out of housing wealth. In line with the MPC result, zip codes experiencing larger wealth losses, particularly those with poorer and more levered households, experience a larger reduction in credit limits, refinancing likelihood, and credit scores. Our findings highlight the role of debt and the geographic distribution of wealth shocks in explaining the large and unequal decline in consumption from 2006 to 2009.

Motivation: The authors address the following questions: *How does consumption respond to large negative shocks to household wealth*? *Do households with different levels of wealth have different marginal propensities to consume out of a dollar lost*?

This paper's key contribution is providing detailed empirical evidence on the *distribution of wealth shocks* across the US population at the onset of the Great Recession and on the *consumption consequences of these wealth shocks*.

They find evidence supportive of *heterogeneity in the MPC* by ***HH income*** and ***HH leverage***. Their *estimated MPC* includes three channels through which the Δhousing wealth might impact household spending.

1. The ***first channel*** is the direct "***wealth effect***."
2. The ***second channel*** is the indirect effect due to the *feedback effect from the non-tradable employment sector*. Given the decline in spending is so dramatic in hard hit areas, *non-tradable employmen*t is disproportionately affected (see ***Mian and Sufi (2014)*** for evidence).
3. The ***third channel*** is through a *collateral constraint. Housing net worth* serves as collateral for access to credit; a decline in *housing net worth* can force households to cut back spending due to *credit constraints*

Data: They construct a new data set that enables them to observe ΔHH consumption and Δwealth at the county and zip code levels. Since *micro-level consumption data* is hard to obtain, the authors use two new sources of consumption data based on *actual HH expenditure*, as opposed to survey responses (which are noisy):

1. **Source #1 of consumption data**: ***(zip code-level) auto sales data*** from R.L. Polk from 1998 to 2012. These data are collected from new automobile registrations and provide information on the total number of new automobiles purchased in a given zip code and year.
   - Intuition: $CORR\,(\Delta\text{auto sales}, \Delta\text{durable goods consumption})$ is HIGH.
2. **Source #2 of consumption data**: ***(county-level) consumer purchases (via credit) from MasterCard Advisors from 2005 to 2009.*** These data provide us with total consumer purchases in a county that use either a credit card or debit card for which MasterCard is the processor. The data are based on a 5% random sample of the universe of all transactions from merchants in a county. They group the MasterCard purchases into three categories: **(1)** *durable goods* (furniture, appliances, home centers), **(2)** *groceries*, and **(3)** *other non-durable goods* (all remaining categories).

Empirical Strategy: Their estimation strategy exploits *cross-sectional variation* in *housing wealth shock*s across the US. An important factor driving cross-sectional variation is differences in ***housing supply elasticity*** across counties. Earlier work such as ***Mian and Sufi (2009, 2010, and 2011)*** used *housing supply elastici*ty as an instrument for *house price growth* from 2002 to 2006. A reversal of the same cross-sectional pattern generates substantial variation in the cross-sectional decline in housing wealth from 2006 to 2009. They therefore use *housing supply elasticity* as an instrument for a city's exposure to the housing boom-bust cycle.

Theory: How should HH consumption respond to wealth shocks? The benchmark representative agent model assumes that HHs can PERFECTLY *insure* each other against consumption risk. Hence consumption growth for household i is completely insensitive to the idiosyncratic changes in wealth (recall the first few lectures on "complete markets" by Demian Pouzo in Econ 202B)

The representative-agent consumption risk insurance assumption (which assumes ***complete markets***) implies an *elasticity of consumption with respect to wealth* β, of zero:

$$\Delta log\left(C_t^i\right) = \alpha_t + \beta \cdot \Delta log\left(X_t^i\right) + \varepsilon_t^i$$

- $\Delta log\left(C_t^i\right)$= log difference in consumption of HH i (growth rate of consumption of HH i)
- $\Delta log\left(X_t^i\right)$= log difference in wealth of HH i (growth rate of wealth of HH i)

Constantinides and Duffie (1996), ***Telmer (1993)*** and ***Heaton and Lucas (1992, 1996)*** point out that above relationship can also be obtained under LESS restrictive assumptions of *incomplete markets* and *limited borrowing capacity*.

The authors estimation of the above equation ***easily rejects*** the consumption risk-sharing hypothesis. The figure below graphically illustrates the test by plotting the *growth in spending in a given county* against the *housing net worth shock from 2006 to 2009*.

FIGURE 3

Elasticity of Spending with Respect to Housing Net Worth Shock

The scatter-plot relates total spending growth in a county from 2006 to 2009 to the housing net worth shock over the same time period. The housing net worth shock reflects the growth in total net worth per household due to the growth in housing net worth. The scatter-plot and regression line are weighted by the number of households in the county.

- The plotted line represents the *fitted values* of the linear regression of consumption growth on the housing net worth shock, which corresponds to the specification reported in column 1 of the table below

TABLE III
Net Worth Shock and Consumption Growth, 2006 to 2009

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Total spending growth, 2006 to 2009 (%)					
				IV	State FE	Excluding AZ, CA, FL, NV
Housing net worth shock, 2006-2009	0.634**	0.613**	0.590**	0.774**	0.457**	0.869**
	(0.125)	(0.122)	(0.130)	(0.239)	(0.101)	(0.148)
Financial net worth shock, 2006-2009		-0.595				
		(1.032)				
Construction employment share, 2006			-0.448**	-0.287	-0.171	-0.288
			(0.150)	(0.216)	(0.127)	(0.160)
Tradable employment share, 2006			0.051	0.011	0.042	-0.027
			(0.067)	(0.092)	(0.066)	(0.065)
Other employment share, 2006			-0.025	-0.045	-0.057	-0.058
			(0.038)	(0.050)	(0.037)	(0.039)
Non-tradable employment share, 2006			0.193	0.095	0.228	0.106
			(0.157)	(0.167)	(0.137)	(0.158)
Ln(income per household, 2006)			-0.002	0.024	-0.006	0.028
			(0.033)	(0.047)	(0.046)	(0.045)
Ln(net worth per household, 2006)			-0.028	-0.035	-0.023	-0.034
			(0.018)	(0.023)	(0.020)	(0.025)
Constant	-0.034*	-0.092	0.167*	0.147	0.120	0.132
	(0.015)	(0.099)	(0.077)	(0.092)	(0.090)	(0.087)
N	944	944	944	540	944	833
R^2	0.298	0.301	0.355	0.319	0.547	0.230

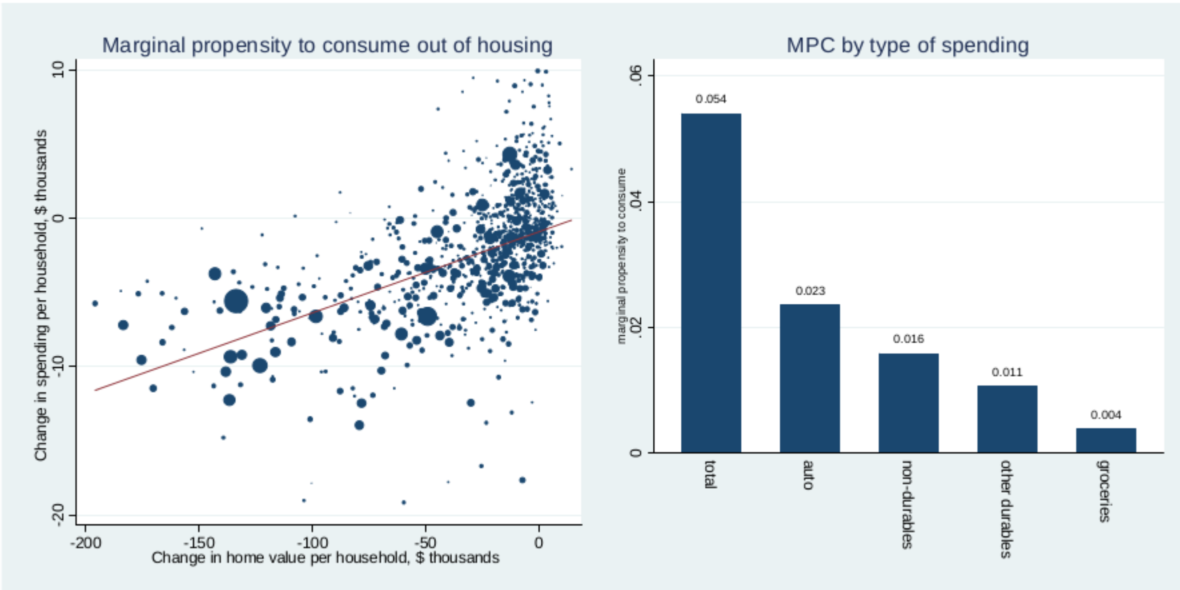
- The ***consumption risk-sharing hypothesis is REJECTED***. The elasticity of consumption with respect to the housing net worth shock is 0.63 and coefficient is precisely estimated. In fact the housing net worth shock variable explains 30% of the overall variation in spending growth across counties.

Baseline Results: Given the failure of the *full risk-sharing hypothesis*, they test for concavity of the consumption function as implied by consumer theory under uncertainty and limited insurance. Doing so requires estimating the ***average MPC*** and then ***testing for heterogeneity in MPC***. The average MPC can be estimated by regressing the dollar change in total spending per capita on the dollar change in housing net worth. The left panel of the figure below plots the county-level change in spending per HH from 2006 to 2009 on the county-level change in home value per HH over the same period.

In the right panel of the figure below, they split out the MPC by the ***four categories of measurable spending***: *autos*, *non-durables*, *other durables*, and *groceries*. Each bar in the panel represents the coefficient on the change in home value from a regression identical to the one reported in column 1 of the table above.

FIGURE 4
The Average Marginal Propensity to Consume

The left-panel scatter-plot relates the change in total spending per household in a county from 2006 to 2009 to the change in home values over the same time period. The scatter-plot and regression line are weighted by the number of households in the county. The gradient of the red line represents the average marginal propensity to consume. The right panel plots the marginal propensity to consume for various spending categories.



- All of the *estimated MPCs* are statistically distinct from zero at the 1% level. The *higher MPC for durables* is consistent with a larger elasticity of demand for these products with respect to income or wealth.
- As the right panel shows, the *MPC* is the *largest* for **autos** (i.e. $\frac{0.023}{0.054}$) and the *smallest* for **groceries** (i.e. $\frac{0.004}{0.054}$)

Heterogeneity in MPCs: The most important question of this study is to test whether the *estimated MPC* differs by ***HH wealth*** and ***HH leverage***. The authors address this by estimating this equation (also used to test for concavity of consumption function)

$$\begin{aligned} \Delta C_t^i =& \alpha_t + \beta_1 \cdot \Delta NW_t^i + \beta_2 \cdot NW_{t-1}^i + \beta_3 \cdot \Delta NW_t^i \cdot NW_{t-1}^i + \varepsilon_t^i \\ NW =& \textbf{ net worth} = (\text{mkt value of } Stocks) + (\text{mkt value of } Bonds) \\ &+ (\text{mkt value of } Housing) - (\text{mkt value of } Debt) \end{aligned}$$

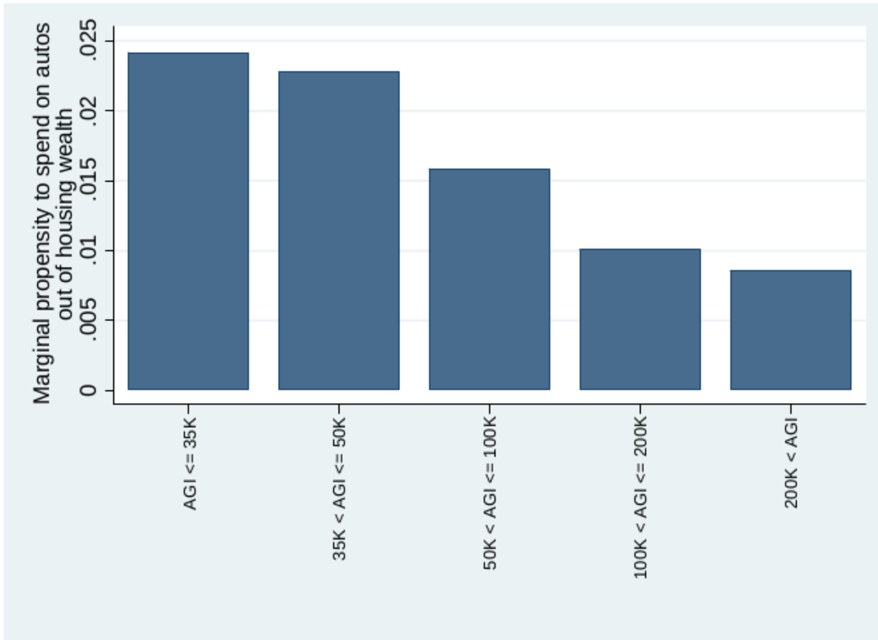
that interacts the *estimated MPC coefficient* with the *level of initial wealth*. They use two variables for net worth: *net worth per HH in 2006* and *income per HH in 2006* (both in millions of $ to make coefficients easily readable).

The magnitude of the difference in the MPC between rich and poor HHs can be understood more clearly through the figure below. The figure is based on separately estimating the *MPC for various income categories*. They find that the MPC for HHs in zip codes with an average adjusted gross income (AGI) less than \$35 thousand is $\approx 3x$ as large as that for HHs in zip codes with an average AGI greater than \$200 thousand.

FIGURE 5

Marginal Propensity to Consume out of Housing across 2006 Income Distribution

The figure plots the estimated marginal propensity to spend on autos based on 2006 per household income in a zip code. AGI is adjusted gross income. The MPC is estimated using zip code level data and regressing the change in spending on automobile purchases between 2006 and 2009 on the change in home values over the same period. Each regression is run separately for zip codes in a given income category and the resulting MPC coefficient is plotted below.



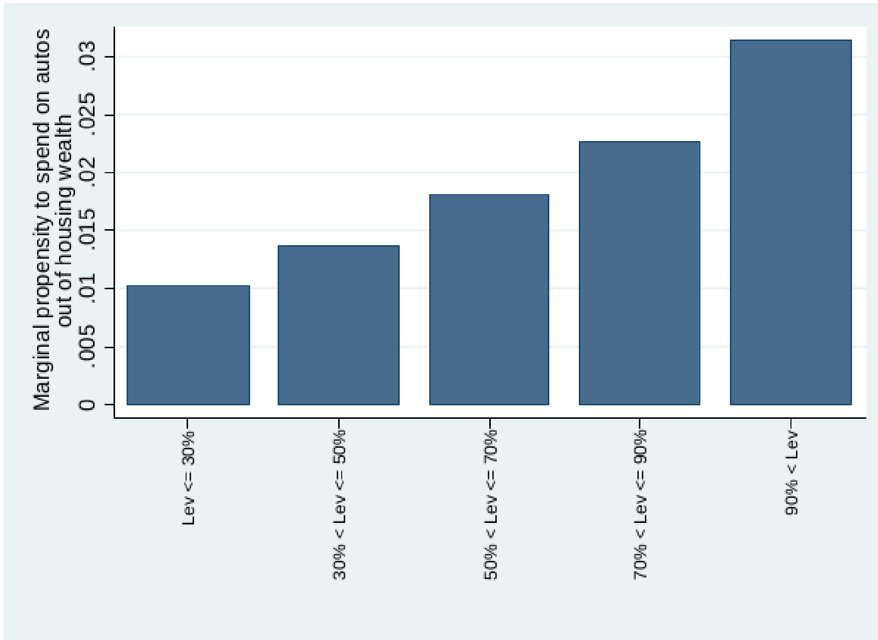
A second rationale for heterogeneity in MPC comes from models that emphasize the importance of *credit constraints*. If credit constraints matter, then HHs with limited borrowing capacity may respond more aggressively to changes in housing value than unconstrained HHs. The magnitude of the heterogeneity in MPC by leverage is also seen in the figure below. It estimates the MPC separately for various HH leverage categories.

Zip codes with a housing leverage ratio below 30% cut spending on autos by \$0.01 for every dollar decline in home value. However, the same effect is 3x as large for zip codes with a housing leverage ratio of 90% or higher. *The fact that levered zip codes cut back more on spending for the same dollar decline in home value is the essence of* ***Fisher's (1933)*** *"debt deflation" argument.*

FIGURE 6

Marginal Propensity to Consume out of Housing across Housing Leverage Ratio Distribution

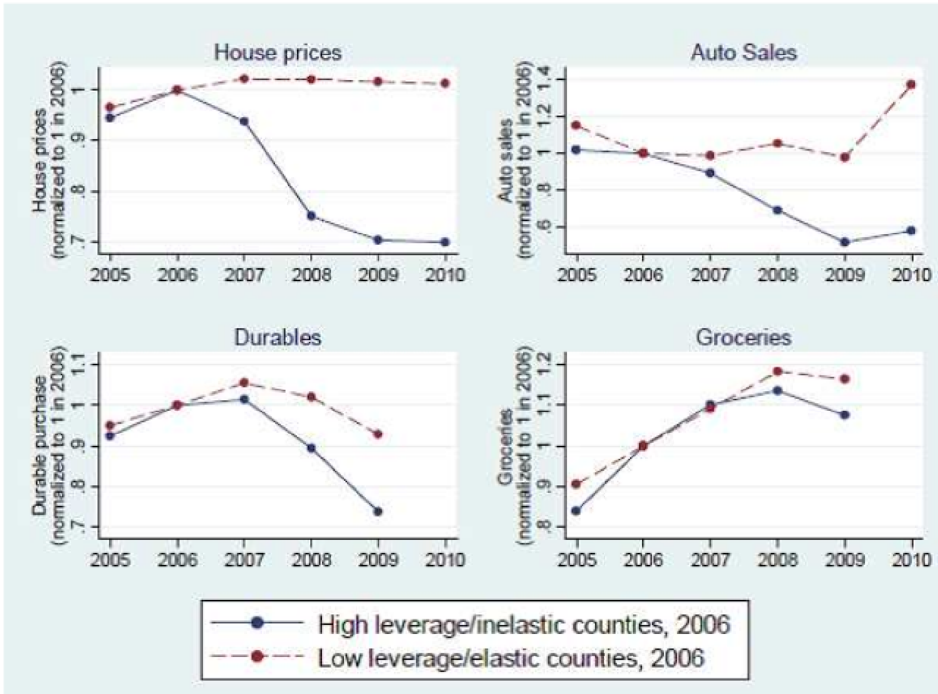
The figure plots the estimated marginal propensity to spend on autos based on the 2006 housing leverage ratio of a zip code. The housing leverage ratio is defined to be total mortgage and home equity debt scaled by the total value of owner-occupied homes in a zip code. The MPC is estimated using zip code level data and regressing the change in spending on automobile purchases between 2006 and 2009 on the change in home values over the same period. Each regression is run separately for zip codes in a given housing leverage ratio category and the resulting MPC coefficient is plotted below.



- The authors find that *home values* ↓ $\Longrightarrow$ TIGHTER *credit constraints*. A lower home value leads to reduced home equity and credit card limits, a DECLINE in refinancing volume, and an INCREASE in the fraction of subprime borrowers in the zip code.

High Unemployment and Aggregate Demand Channel: ***Mian and Sufi (2014)*** show that *non-tradable employment* catering to the local economy ↓ by MORE in counties that experience a MORE *negative housing net worth shock*; the same is not true for *tradable employment*. The initial reduction in local demand due to the decline in wealth is amplified due to the feedback effect on local non-tradable employment. The authors' estimate of the effect of *net worth shock* on *consumption* includes both the ***initial direct effect*** and the ***subsequent feedback effect***.

What explains the high unemployment?



- Decomposing regions into *LOW leverage* (i.e. low $\frac{\text{debt}}{\text{income}}$ ratio) regions and *HIGH leverage* (i.e. high $\frac{\text{debt}}{\text{income}}$ ratio) regions, we can see that *HIGH leverage* regions experience GREATER declines in house prices than *LOW leverage* regions.
- We can see the ***differences in types of consumption*** in *LOW leverage regions* and *HIGH leverage regions* in the figure above.

4.4 Mian and Sufi (Econometrica, 2014): *What Explains the 2007-2009 Drop in Employment?*

Abstract: We show that deterioration in household balance sheets, what we refer to as the housing net worth channel, played a significant role in the sharp decline in U.S. employment between 2007 and 2009. Using geographical variation across U.S. counties, we show that counties with a larger decline in housing net worth experience a larger decline in non-tradable employment. This result is not driven by industry-specific supply-side shocks, exposure to the construction sector, policy- induced business uncertainty, or contemporaneous credit supply tightening. We find little evidence of labor market adjustment in response to the housing net worth shock. There is no expansion in the tradable sector in affected counties, and the correlation between the housing net worth decline and job losses in the tradable sector is zero. There is no evidence of wage adjustment, or of net labor emigration out of affected counties either.

Motivation: The authors address the following question: *Why did the employment level drop so drastically between 2007 and 2009?* They approach this question with a particular focus on the *housing net worth channel*. The *housing net worth channel* refers to a decline in employment because of a sharp reduction in the housing net worth of consumers. A DECLINE in *housing net worth* could reduce employment by *suppressing consumer demand* either through a ***direct wealth effect*** or through ***tighter borrowing constraints*** driven by the fall in collateral value.

This paper's key contribution is the finding that job losses in the *non-tradable sector* between 2007 are 2009 are significantly HIGHER in *counties with a large decline in housing net wort*h. A one standard deviation change in housing net worth ↓ is associated with a 3.1% ↓ in non-tradable employment, or 51% of the standard deviation of change in non-tradable employment.

Using the ***Saiz (2011)*** *housing supply elasticity* as an instrument for housing net worth decline, they show that the impact of housing net worth shock on non-tradable employment is not driven by exposure to construction-related sectors. Specifically, the *endogeneity* could be that Δhousing wealth are due to *non-housing net worth shocks* such as ***supply side industry-specific shocks*** that impact both employment and housing net worth, credit supply tightening, or policy-induced business uncertainty

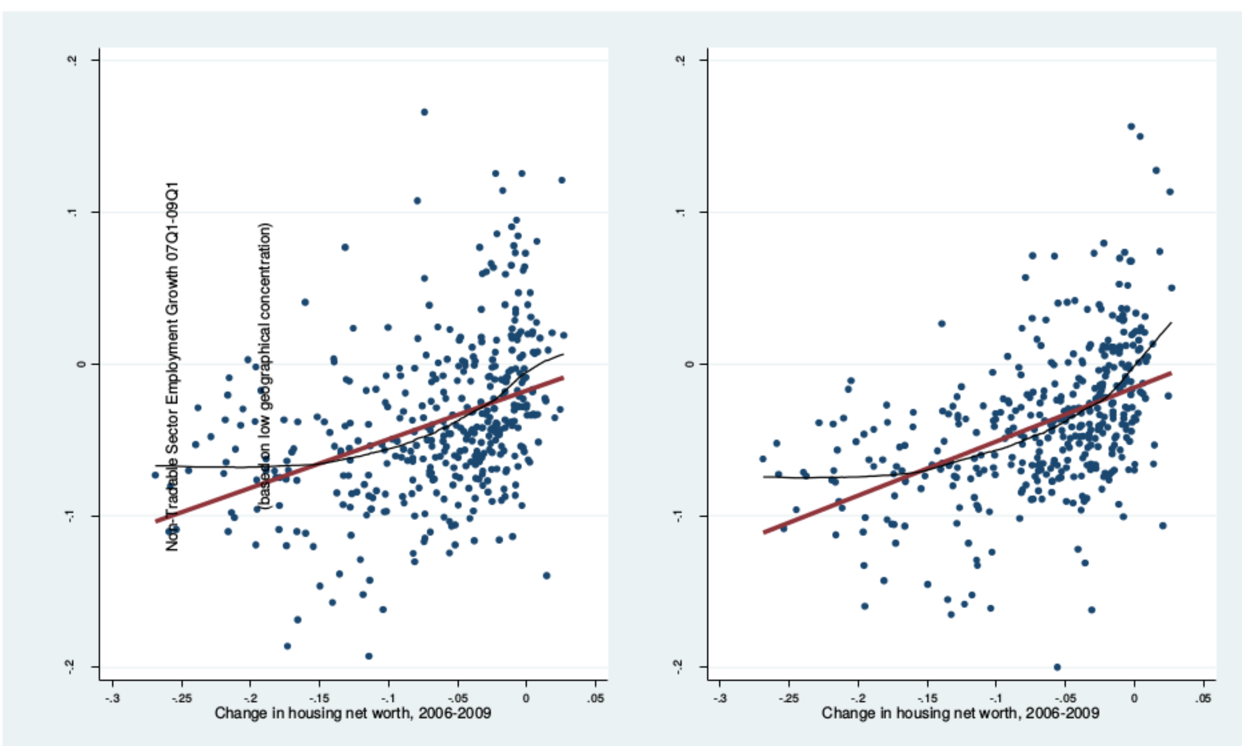
Data: They build a county-level data set that includes employment data by 4-digit industry in a county, HH balance sheet information including total debt and housing value, wages and other demographic and income information. One of their key right hand side variables is the ΔHH net worth between the end of 2006 and 2009.

Empirical Strategy: The authors isolate the impact of change in net worth on employment in the *non-tradable sector*. The non-tradable sector relies primarily on spending in its geographical proximity by definition. Therefore by restricting attention to employment in the non-tradable sector, we can test if housing net worth shocks translate into employment loss. Their identification scheme is given by the equation

$$\Delta log\left(E_i^{NT}\right) = \alpha + \eta \cdot \Delta NHW_i + \epsilon_i$$

- E_i^{NT}= non-tradable employment (excluding construction) in county i between 2007 and 2009
- ΔNHW_i = *housing net worth shock* defined as $\frac{\Delta log\left(p_{06-09}^{H,i}\right) \cdot H_{2006}^i}{NW_{2006}^i}$ and η is the elasticity of interest.

The figure below plots $\Delta log\left(E_i^{NT}\right)$ against ΔNHW_i for two definitions of non-tradable employment. The left panel is based on *restaurants and retail stores*, while the right panel is based on *geographical concentration of each 4-digit industry*. There is a ***strong positive correlation*** between the two variables.



Non-Tradable Sector Results: Since the authors are interested in addressing the *housing net worth hypothesis,* the key parameter of interest is the *elasticity of employment with respect to housing net worth shock*. They address the following question: *How much does employment decline for each percentage decline in housing net worth*?

Columns 1 and 2 of the table below regress the Δ*non-tradable employment* (using the two definitions of non-tradable employment) on Δ*housing net worth*. The correlation is strong and significant at the 1% level. The point estimates are ***0.190*** and ***0.199***, respectively.

Columns 3 and 4 in the same table below present the IV estimate using *housing supply elasticity* as an instrument for *housing net worth* shock. The *estimated coefficient increases* in the IV estimate (***0.190*** $\rightarrow$ ***0.305*** and ***0.199*** $\rightarrow$***0.277***). ***The IV estimates suggest that variation in housing net worth decline generated by differences in land topology – as opposed to economic fundamentals – lead to changes in employment in the non-tradable sector!***

Columns 5 and 6 control for *cross-county differences* in industry exposure by including the share of a county's employment in 2006 that is in each of the 23 two-digit industries. In Columns 7 and 8, they repeat the same IV estimate using these controls. They do this to show their results are NOT driven by such ***supply-side concerns***. There is a slight decline in the coefficient estimates in Columns 5 and 6, which could result from measurement error. This is consistent with the *increase* in IV estimate in Columns 7 and 8. The robustness check corroborates their results.

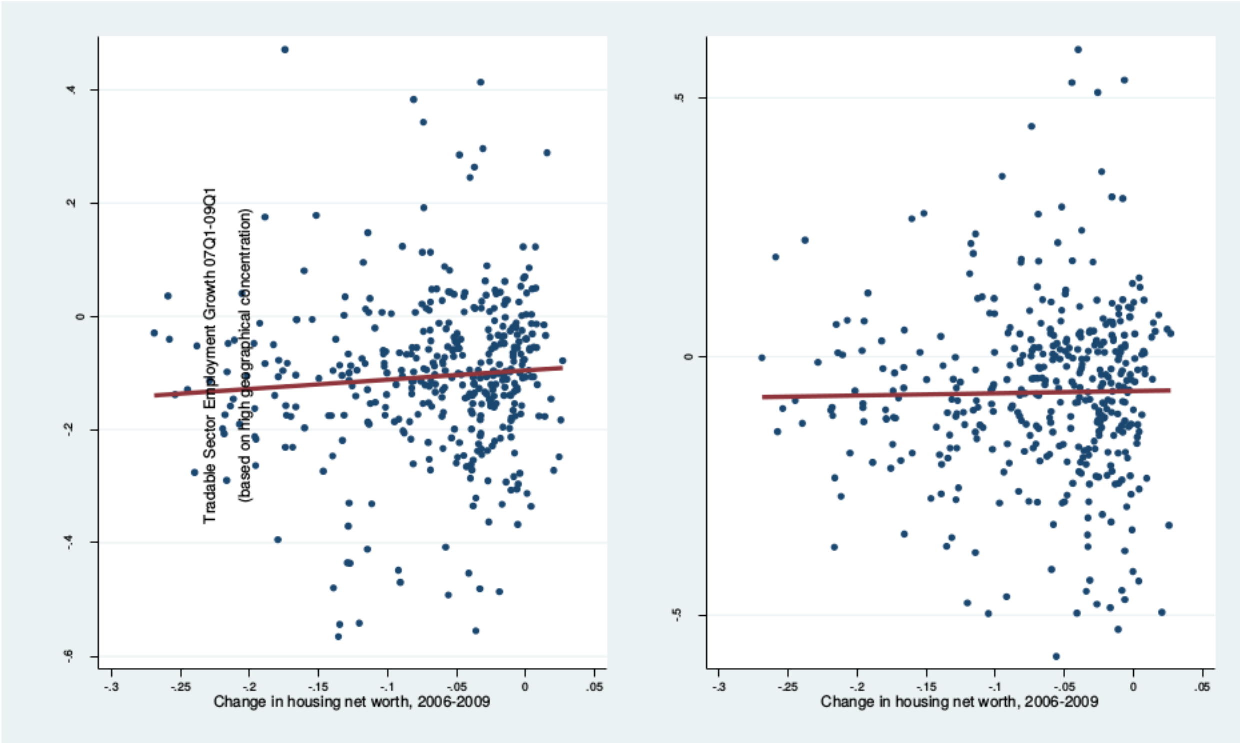
Table 4
Non-Tradable Employment Growth And The Housing Net Worth Shock

This table presents coefficients from regressions relating non-tradable employment growth in a county from 2007 to 2009 to the change in housing net worth between 2006 and 2009. Non-tradable employment is defined at the 4-digit industry level and then aggregated up separately for each county. We use two different definitions of non-tradable industries, one based on restaurant and retail sector, and another based on an industry's geographical concentration. All regressions are weighted using the total number of households in a county as weights. The instrumental variables specifications use the housing supply elasticity as an instrument for the change in housing net worth in the first stage. Standard errors are adjusted for spatial correlation across counties, with the correlation proportional to the inverse of the distance between any two counties.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Employment growth, non-tradable industries, 2007-2009							
Non-tradable definition used:	Restaurant & Retail	Geographical Concentration	Restaurant & Retail	Geographical Concentration	Restaurant & Retail	Geographical Concentration	Restaurant & Retail	Geographical Concentration
Change in Housing Net Worth, 2006-2009	0.190**	0.199**	0.305**	0.227*	0.174**	0.166**	0.374**	0.208*
	(0.042)	(0.049)	(0.101)	(0.106)	(0.043)	(0.046)	(0.132)	(0.086)
Constant	-0.022**	-0.021**	-0.010	-0.017	0.176	0.070	0.445	1.233**
	(0.007)	(0.007)	(0.010)	(0.010)	(0.443)	(0.286)	(0.536)	(0.438)
Specification	OLS	OLS	IV	IV	OLS	OLS	IV	IV
2-digit 2006 employment share controls included?#					YES	YES	YES	YES
N	944	944	540	540	944	944	540	540
R^2	0.096	0.156	0.057	0.166	0.175	0.236	0.158	0.275

**,* Coefficient statistically different than zero at the 1% and 5% confidence level, respectively.
The 23 two-digit industries are: Agriculture, Mining, Utilities, Construction, Manufacturing (3 2-digit industries),Wholesale Trade, Retail trade (2 2-digit industries), Transportation (2 2-digit industries), Information, Finance, Real Estate, Professional Services, Management, Administrative Services, Education, Health Care, Entertainment, Accommodation and Food Services, Other Services.

Tradable Sector Results: The figure below plots Δtradable employment in a county between 2007 and 2009 against the Δhousing net worth from 2006 to 2009. The left panel uses the *first definition* of tradable employment based on industries that are traded internationally, while the *right panel* uses the second definition of tradable employment based on geographical concentration of industries. There is ***NO evidence of a gain in tradable employment in counties experiencing larger decline in housing net worth***.



The table below shows the regression results using *tradable sector employment*, instead of *non-tradable sector employment.* Columns 1 and 2 of this table regress the two definitions ofΔlog(tradable employment) on Δhousing net worth. The estimated coefficients are ≈ 0 and precisely estimated.

Columns 3 and 4 add the share of employment in each of 23 two-digit industries separately to control for differences in industry exposure across counties. The coefficient on housing net worth change is materially unchanged.

Column 5 uses the entire distribution of industries based on industry concentration instead of grouping firms into *non-tradable* and *tradable* categories. The regression is thus run at the county-industry level, with each county-industry observation weighed by the total employment in that cell in 2007.

Column 6 adds *4-digit industry fixed effects* (294 industries) and column 7 further adds *county fixed effects* (944 counties). The industry fixed effects force comparison to be made within the same 4-digit industry across counties. Such fixed effects thus control for aggregate shifts at the industry level during the 2007-2009 period. Despite including these fixed effects, the key result remains unchanged: ***the effect of change in housing net worth is much stronger for non-tradable industries that are geographically least concentrated across the US***.

Table 7

Tradable Employment Growth And The Housing Net Worth Shock

This table presents coefficients from regressions relating tradable employment growth in a county from 2007 to 2009 to the change in housing net worth between 2006 and 2009. Tradable employment is defined at the 4-digit industry level and then aggregated up separately for each county. We use two different definitions of tradable industries, one based on US import/export, and another based on an industry's geographical concentration. There are 23 2-digit industry employment share variables as controls in columns 3 and 4. There are 294 4-digit industry fixed effects in columns 6 and 7, and 944 county fixed effects in column 7. All regressions are weighted using the total number of households in a county as weights. The instrumental variables specifications use the housing supply elasticity as an instrument for the change in housing net worth in the first stage. Standard errors are adjusted for spatial correlation across counties, with the correlation proportional to the inverse of the distance between any two counties.

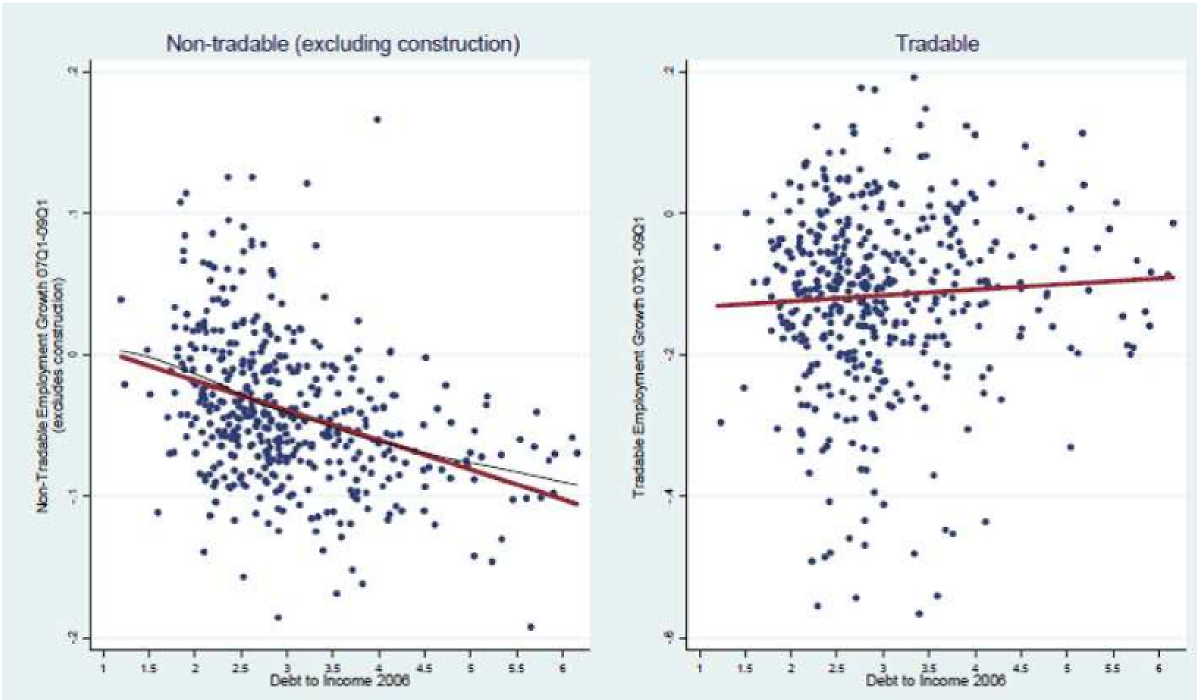
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Employment growth, tradable industries, 2007-2009				Employment growth, 2007-2009 (county-4digitIndustry level)		
Tradable definition used:	Global Trade	Geographical Concentration	Global Trade	Geographical Concentration			
Change in Housing Net Worth, 2006-2009	0.018	-0.085	0.064	-0.063	0.221**	0.157***	-
	(0.099)	(0.063)	(0.098)	(0.074)	(0.062)	(0.065)	
Industry Geographical Herfindahl Index					-3.864**	-	-
					(0.600)		
ΔHNW * (Geographical Herfindahl)					-13.592**	-11.22**	-11.24**
					(3.089)	(2.22)	(2.19)
Constant	-0.114**	-0.091**	-0.286	0.542	-0.067**	-	-
	(0.012)	(0.012)	(0.950)	(1.144)	(0.011)		
2-digit 2006 employment share controls?			Yes	Yes			
4-digit Industry Fixed Effects						Yes	Yes
County Fixed Effects							Yes
N	944	944	944	944	180,756	180,756	180,756
R^2	0.000	0.002	0.079	0.064	0.006	0.134	0.17

**,* Coefficient statistically different than zero at the 1% and 5% confidence level, respectively

Extrapolating to Other Sectors? ***Stumpner (2014)*** shows that the *trade channel* acts as a powerful mechanism to transmit the impact of housing net worth shocks throughout the US. Moreover, he uses trade-weighted HH balance sheet shocks to estimate the *elasticity of tradable employment with respect to housing net worth* denoted as $\eta_{\bar{l}}$

Figures from Older Working Paper Version:

Nice identification



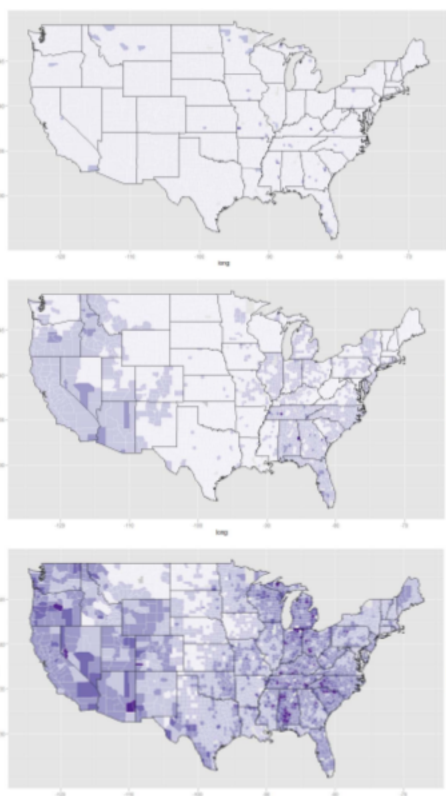
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Employment growth, non-tradable industries, 2007-2009				Employment growth, food retail only, 2007-2009	Employment growth, tradable industries, 2007-2009	
Debt to income, 2006	-0.021** (0.002)	-0.023** (0.003)	-0.031** (0.007)	-0.023** (0.002)	-0.017** (0.002)	0.007 (0.006)	-0.001 (0.007)
Construction share, 2007				0.135** (0.047)			0.029 (0.119)
Non-tradable share, 2007				-0.070 (0.046)			0.147 (0.118)
Tradable share, 2007				-0.035 (0.026)			-0.318** (0.069)
Constant	0.026** (0.006)	0.033** (0.009)	0.054** (0.019)	0.034* (0.016)	0.031** (0.006)	-0.137** (0.016)	-0.111** (0.038)
Specification	WLS	OLS	IV	WLS	WLS	WLS	WLS
Sample	Full	> 50K	elasticity available	Full	Full	Full	Full
N	3,132	450	877	3,132	3,132	3,053	3,053
R^2	0.078	0.081	0.087	0.085	0.047	0.001	0.018

4.5 Stumpner (JMP, 2014): *Trade and the Geographic Spread of the Great Recession*

Abstract: I use the large spatial variation in consumer demand shocks at the onset of the Great Recession to study the mechanisms behind the ensuing geographic spread of the crisis. While the initial increase in unemployment was concentrated in areas with housing busts, subsequently unemployment slowly spread across space. By 2009, it was above pre-crisis levels in almost all U.S. counties. I show that trade was an important driver of this geographic spread of the crisis. To identify the trade channel empirically, I make use of heterogeneity in the direction of trade flows across industries in the same state: Industries that sold relatively more to states with housing boom-bust cycles grew by more before the crisis and declined faster from 2007-09. These results cannot be explained by a collapse in credit supply. I then link the reduced form empirical evidence to a formal model of contagion through trade. In a quantitative exercise, the model delivers a cross-sectional effect of similar magnitude as the one found empirically and reveals that the trade channel can explain roughly half of the overall spread.

Motivation: The author looks at the "geographic spread" of the financial crisis (see figure below). He addresses the following quesiton: *How did local shocks diffuse through the economy, causing business cycle co-movement across US states?*

Figure 1: Yearly change in unemployment rate across US counties, 2006-07, 2007-08, and 2008-09



This paper provides evidence that *trade* has contributed to the geographic spread of the Great Recession, i.e. the shift of the recession away from states with housing boom-bust cycles. Empirically, he identifies the *trade channel* by comparing economic outcomes of industries with different shipment patterns that are located in the same state.

The figure below gives a unique view of the *expenditure imbalances across states* at the beginning of the crisis. It shows the ***state-level trade deficit*** (calculated from the CFS) against ***state-level HH leverage***: The higher expenditure of high-leverage-states are mirrored in their sizable trade deficits against other states.

Figure 5: State-level trade deficit vs. state-level HH leverage

Notes: This figure shows the relationship between the state -level (normalized) trade deficit, calculated as total expenditure minus total sales, divided by the average of total expenditure and total sales: $TradeDeficit_i = \frac{\sum_n X_{in} - \sum_n X_{ni}}{0.5 \cdot (\sum_n X_{in} + \sum_n X_{ni})}$

- states that accumulated MORE *HH debt* also incurred MORE trade deficits.
- Why? A big fraction of consumption in a given region i is financed by production in another region j. A decline in consumption of a good produced in region j affects region j through its production and employment - ***propagation mechanism***

Main Empirical Results: The author defines a ***trade demand shock*** at the state i, industry k level as follows:

$$TDS_i^k = \sum_{n=1}^{N} \frac{X_{n,i}^k}{Y_i^k} Lev_n$$

- TDS_i^k is the weighted sum of destination-state pre-crisis HH leverage, where the weights are given by ***outgoing trade shares***. He aggregates county-level leverage ratios to the state-level using the number of HHs in a county as weights. The fraction of total shipments in industry k from state i to destination n, $\frac{X_{n,i}^k}{Y_i^k}$, is observed from shipments data detailed in the paper. (**e.g.** if *all production* was exported to destination n, then $\frac{X_{n,i}^k}{Y_i^k} = 1$)
- Lev_n is a "proxy" for the *demand* of destination n to industry k in state i.

TDS_i^k tells us how much industry k in state i is exposed to the $\Delta demand$ of each destination n.

Empirical Strategy: He considers the following specification:

$$dlog\left(Y_i^k\right) = \beta_0 + \beta_1 TDS_i^k + \gamma_i + \alpha^k + \epsilon_i^k$$

- Y_i^k = employment, earnings, or the average wage
- γ_i = state fixed-effect, whose addition in the estimation makes use of differences in trading patterns across industries within a state.
- α^k = industry fixed-effect, which controls for shocks that hit all producers in a specific industry.

The table below shows a *negative* and *large* effect of the ***trade demand shock*** on ***state-industry level employment*** and ***earnings***. The point estimate reveals that a one standard deviation ↑ in the ***trade demand shock*** causes a ↓ in ***employment growth*** by approximately 3%. Given a standard deviation of employment growth of 16 percentage points, this corresponds to almost 20% of a standard deviation. The fall in employment accounts for most of the earnings adjustment (70%-80%), while the remainder is accounted for by the average wage.

Demand Shocks and Tradables

Table 3: The Effect of the Trade Demand Shock on Industry Growth

	(1)	(2)	(3)	(4)	(5)	(6)
	Employment 2007-09		Earnings 2007-09		Av. Wage 2007-09	
TDS	-0.090***	-0.095***	-0.115***	-0.135***	-0.025	-0.040***
	(0.027)	(0.017)	(0.032)	(0.023)	(0.021)	(0.014)
Observations	1,519	1,519	1,519	1,519	1,519	1,519
R-squared	0.402	0.568	0.428	0.548	0.232	0.280
Industry FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Specification	OLS	WLS	OLS	WLS	OLS	WLS

$$TDS_i^k = \sum_{n=1}^{N} \frac{X_{ni}^k}{Y_i^k} Lev_n$$

TDS is the weighted sum of destination-state pre-crisis household leverage. (weights=outgoing trade shares)

- ***Trade demand shock is a predictor of a decline in unemployment.***

4.5 Mondragon (JMP, 2015): *Household Credit and Employment in the Great Recession*

Abstract: How much did the contraction in the supply of credit to households contribute to the decline in employment during the Great Recession? To answer this question I provide new estimates of: (1) the elasticity of employment with respect to household credit; and (2) the size of the supply shock to household credit. I exploit a county's exposure to the collapse of a large and previously healthy lender as a natural experiment. This gives an estimated elasticity of employment with respect to household credit of 0.3, caused by declines in both housing and non-housing demand. To estimate the size of the credit supply shock I use non-parametric methods to identify lender-specific supply-side shocks, which I then aggregate into a simple measure of credit supply shocks to counties. Combining this measure with estimates of the elasticity of employment with respect to the measure, I calculate that shocks to household credit were responsible for at least a 3.6% decline in employment from 2007 to 2010.

Motivation: ***Mian and Sufi (2014)*** focused on how Δhousing net worth ↓ $\Longrightarrow$ Δconsumption ↓ $\Longrightarrow$ Δlocal non-tradable employment ↓. Mondragon looks at how the Δconsumption ↓ is not directly due to just the DECLINE in housing net worth BUT ↓ in *access to financial services of HHs*. Much of the theoretical modeling of the Great Recession argues that the primary shock was a ***decline in credit supply to HHs***, which then caused a collapse in demand and employment. Mondragon's paper addresses two things: **(1)** how strongly employment responded to supply-driven declines in HH credit; and **(2)** the size of the supply-side shock to HH credit.

1. First, he estimates the *elasticity of employment with respect to declines in HH credit caused by credit supply shocks*. He relies on *exogenous variation* in credit supply across counties due to the collapse of Wachovia, a large and healthy lender before the crisis. He finds that contractions in HH credit supply caused declines in both housing and non-housing demand. This resulted in significant declines in employment, with losses concentrated in construction and non-tradables.

2. Second, he estimates the **size** of the *credit supply shock* by non-parametrically identifying lender-specific supply shocks to HH credit using data on lender-county credit flows. His measured shock to a county is then the weighted sum of the lender shocks to an area. With this *credit supply shock* and the *elasticity of employment with respect to this measure*, it is straightforward to calculate the direct contribution of the HH credit channel to total employment losses.

He finds that *shocks to HH credit* caused at least a *3.6% decline in employment*, which is about 60% of the observed decline within the estimation sample.

Data: He uses *US counties* as the primary unit of observation.

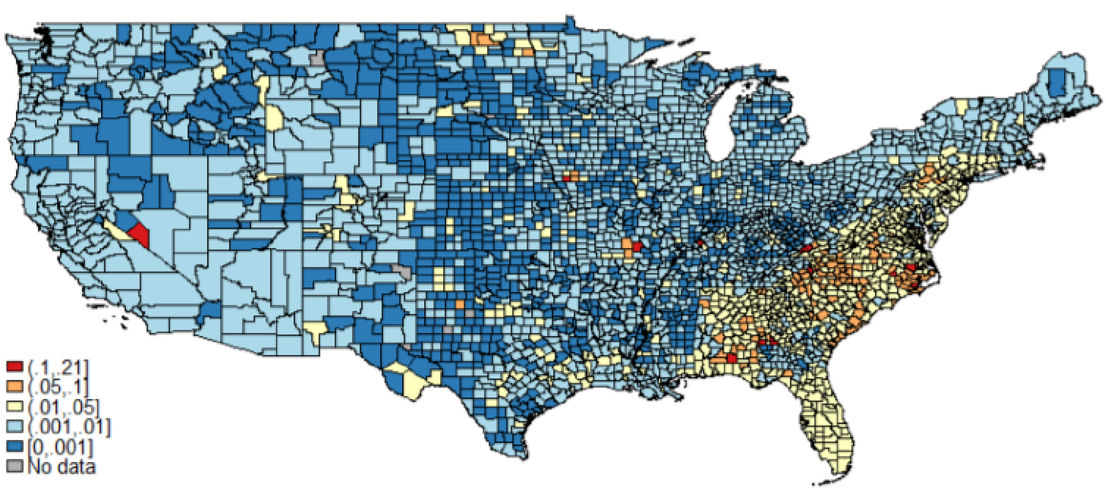
The data he uses to measure ***HH credit*** is from the Home Mortgage Disclosure Act (HMDA). He relies on the ***flow of non-refinance mortgages*** as his measure of HH credit. He also relies on data from the Community Reinvestment Act (CRA) to measure and control for firm credit.

He measures ***employment*** with the County Business Patterns (CBP) dataset, which contains annual observations on employment and payrolls by 4-digit NAICS identifier and size constructed from various administrative data from the universe of firms in the Census Bureau's Business Register. He uses the Zillow Home Value Index for single-family residences to measure ***house prices*** as well as Zillow's measure of sales volume.

To measure ***non-housing expenditures*** he uses the Nielsen Retail Scanner database. Additional data on ***debt stocks at the county level*** come from the county aggregates of the Federal Reserve Bank of New York-Equifax Consumer Credit Panel (CCP).

Wachovia: In 2007, Wachovia held about 6.6% of all *bank deposits* and over $260 billion dollars of consumer loans, about 87% of which were secured by real estate. Wachovia was a national lender with wholesale operations in every state. But due to its consistent pattern of expansion into neighboring markets, the bank tended to have a significantly larger market share in the East and South (average of 2% and median of 1.5%, see figure below)

Figure 3: Distribution of Average of Wachovia Share of Home Mortgage Lending in 2005-2006



Note: This figure plots Wachovia's average market share of originated and purchased loans over 2005-2006 in the home mortgage market as measured in the HMDA data. It shows that Wachovia had a national presence, but that its market share tended to be fairly small everywhere but the East and South.

Empirical Strategy: He relies on the *cross-section of counties* to estimate parameters of interest and perform the aggregation. The central requirement for this approach to be informative is that the *credit supply shock* to a county is a function ONLY of the c*ounty-specific set of lenders*. Thus, if ***lender A*** contracts credit by MORE than ***lender B***, then counties dependent on ***lender A*** will suffer a larger credit contraction than counties dependent on ***lender B***. The size of this effect on outcomes of interest depends on the presence of frictions that limit the elasticity of substitution across lenders.

This exclusion restriction is satisfied by using exposure to Wachovia as a natural experiment. Exposure to Wachovia is largely uncorrelated with any pre-crisis trends in house prices, employment, and household credit. To summarize, exposure to Wachovia appears to be a *shock to HH credit supply that was orthogonal to other local factors*. Using a county's exposure to Wachovia as an instrument for household credit supply gives the employment elasticity of 0.3 reported above.

Mondragon wants to examine the intensive margin of credit for loans that were originated by Wachovia using the loan-level data in HMDA. He first bins an application as a *high*-, *middle*-, and *low-income application* depending on whether or not it fell into the top, middle, or bottom third of the income distribution of applications in the county. Within each income bin, he regresses the ***log of the loan-to-income (LTI) ratio on originated loan*** i ***in county*** c on a full set of county-fixed effects, a dummy for whether or not the loan was submitted to Wachovia (excluding GWF), and controls using OLS

$$log\,(LTI_{i,t}) = \alpha_{c,t} + \beta_t \cdot Wachovia_i + \gamma_t \cdot X_{i,t} + e_{i,t}$$

- He restricts the sample to *home purchase loans* as here the LTI will primarily reflect down-payment requirements and lending standards. In contrast, LTIs on refinance originations are difficult to interpret due to the inability to distinguish between "cash-out" and "rate-and-term" refinance loans.

Results: The figure below (left panel) plots the estimated coefficients and shows that Wachovia originations to *low*-and *middle-income applicants* are significantly less leveraged in 2008 and 2009. Wachovia's loans to *low-income* applicants had LTIs almost 80% lower than originations at non-Wachovia lenders, and almost 60% for *middle-income* applicants. Interestingly, LTIs for high-income originations at Wachovia actually increased by a little less than 20%, suggesting Wachovia was actively substituting to borrowers likely to be better credit risks. Much of the changes in LTI are explained by *Wachovia excluding low-income borrowers from credit*.

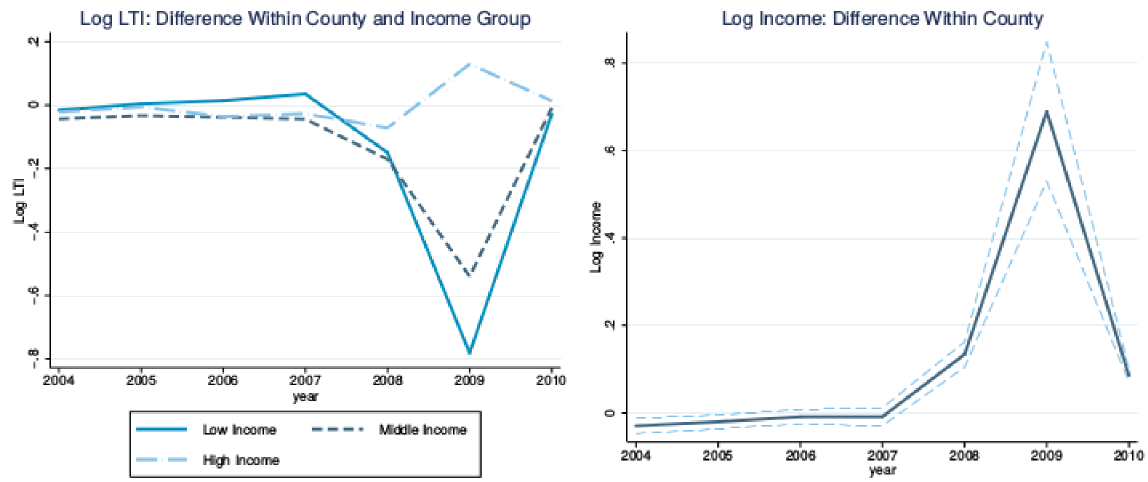
- Intuition: Wachovia's lending sources DECREASED significantly during the crisis. As a result, it chose to lend mostly to the "best" borrowers.

The right panel of the figure plots the coefficients from putting log income on the left-hand side

$$log\,(Income_{i,t}) = \alpha_{c,t} + \beta_t \cdot Wachovia_i + \gamma_t \cdot X_{i,t} + e_{i,t}$$

(here with county-clustered 95% confidence intervals) and combining all income groups. Beginning in 2008, home purchase loans originated by Wachovia have an income over 10% higher than originations at the average non-Wachovia lender.

Figure 6: Wachovia and Log LTI and Log Income on Originated Home Purchase Loans:



- Intuition: Wachovia lent mostly to higher-income earning HHs → ***flight-to-quality***.

Effect of Exposure to Wachovia on Household Credit: The table below gives the results from regressing *HH credit growth from 2007 to 2010* on *exposure to Wachovia*. The standard first stage diagnostics in column one are very good with a large F-statistic and R-squared. The estimate suggests a one percentage point increase in exposure to Wachovia decreases home mortgages by about 2.5% from 2007-2010.

Table 5: Effect of Exposure to Wachovia on Household Credit Growth 2007-2010 (First Stage)

	(1) OLS β /p/(CI)	(2) OLS β /p/(CI)	(3) Quantile β /p/(CI)	(4) OLS β /p/(CI)	(5) OLS β /p/(CI)	(6) OLS β /p/(CI)	(7) WLS β /p/(CI)
Wachovia Exposure	-2.532	-2.465	-2.570	-2.409	-1.430	-2.689	-2.157
	0.000	0.000	0.000	0.000	0.342	0.000	0.182
	(-3.247, -1.816)	(-3.107, -1.824)	(-3.577, -1.562)	(-3.268, -1.551)	(-5.044, 2.183)	(-3.539, -1.838)	(-5.596, 1.282)
Mortgage Leverage 2006		-0.064	-0.076	-0.063	-0.021	-0.061	-0.025
		0.478	0.738	0.540	0.840	0.214	0.826
		(-0.225, 0.097)	(-0.303, 0.151)	(-0.219, 0.093)	(-0.106, 0.064)	(-0.146, 0.024)	(-0.144, 0.094)
Construction Share 2005		-0.238	-0.242	-0.165	-0.136	-0.321	-0.086
		0.898	0.720	0.934	0.446	0.326	0.754
		(-1.015, 0.538)	(-1.083, 0.599)	(-0.807, 0.477)	(-0.429, 0.157)	(-0.847, 0.206)	(-0.375, 0.204)
HUD Share 2005		-0.815	-0.800	-0.834	-0.721	-0.830	-0.624
		0.000	0.002	0.000	0.002	0.000	0.006
		(-1.208, -0.423)	(-1.190, -0.410)	(-1.293, -0.376)	(-1.109, -0.333)	(-1.339, -0.321)	(-0.969, -0.280)
FE	–	–	–	Region	State	–	State
N	478	478	478	478	478	478	478
Clusters	25	25		25	25	25	25
R2	0.120	0.313	0.313	0.317	0.536	0.281	0.608
Robust F-stat	28.187	48.197		34.335	11.144	16.187	14.632

Note: This table reports point estimates, p-values, and 95% confidence intervals for household credit growth at the county level (measured as non-refinance mortgage growth) regressed on exposure to Wachovia: $\bar{L}_i = \alpha + \beta \text{Wachovia Exposure}_i + \theta X_i + \epsilon_i$. I measure exposure with Wachovia's market share in 2005-2006 of non-refinance mortgages within the county. Exposure to Wachovia had a large and robust effect on household credit growth across counties. The fairly high R-squared suggests Wachovia is a reasonably strong instrument. The baseline estimate in column one shows that increasing exposure to Wachovia by one percentage point leads to a decrease in household credit of 2.4% over three years. This estimate is robust to controls, quantile regression to check for outliers (column three), region fixed effects (column four), and, to a lesser extent, state fixed effects (column five), although to a lesser extent. The sample is restricted to all counties in the South and East with CCP controls and at least 50,000 residents. Pair bootstrap-t used to construct symmetric p-values and 95% confidence intervals clustered at the state level.

- Mondragon also controls for ***HUD shares in 2005***, which is the *share of lending regulated by the Department of Housing and Urban Development (HUD)*. He uses this variable as a proxy for *subprime lending* since much of the subprime market was driven by mortgage brokers regulated by HUD (see ***Engel and McCoy (2011)***).

Effect of Exposure to Wachovia on Expenditures: The decline in HH credit from Wachovia could have affected *HH demand* in several ways. First, declines in home equity lines of credit (HELOCs) or cash-out refinancing loans will directly reduce household liquidity and expenditures (see ***Hurst and Stafford (2004)*** and ***Cooper (2013)***). Second, as HHs are denied mortgages they are less likely to purchase a home. In addition, any consumption (often durables and home services) complementary to a home purchase will be foregone, although this is potentially countered by any substitution away from housing.

The table below shows that exposure to Wachovia affected retail expenditures, measured with the Nielsen Retail Scanner data. *These expenditures declined by about .9% in response to a one percentage point increase in Wachovia exposure* with the effect very robust to controls, state fixed effects, and weighting by population.

Table 6: Effect of Wachovia Exposure on Retail Expenditures 2007-2010

	(1) OLS β /p/(CI)	(2) OLS β /p/(CI)	(3) WLS β /p/(CI)	(4) WLS β /p/(CI)
Wachovia Exposure	-0.853	-0.902	-0.948	-1.167
	0.000	0.024	0.000	0.000
	(-1.268, -0.438)	(-1.677, -0.127)	(-1.309, -0.587)	(-1.523, -0.810)
Mortgage Leverage 2006	-0.083	-0.062	-0.043	-0.032
	0.018	0.014	0.000	0.254
	(-0.144, -0.021)	(-0.110, -0.014)	(-0.066, -0.021)	(-0.083, 0.019)
FE	–	State	–	State
N	471	471	471	471
Clusters	25	25	25	25
R2	0.090	0.229	0.076	0.209
F-stat	15.283	5.608	17.470	17.030

Note: This table reports regression point estimates, p-values, and 95% confidence intervals of retail expenditure growth at the county level regressed on exposure to Wachovia: $\widehat{\text{Retail Sales}}_i = \alpha + \beta \text{Wachovia Exposure}_i + \theta X_i + \epsilon_i$. I measure exposure with Wachovia's market share in 2005-2006 of non-refinance mortgages within the county. Counties exposed to Wachovia experienced larger declines in retail sales growth and this result is robust to state fixed effects and controlling for mortgage leverage. Retail expenditures growth is measured using total retail sales as reported in the Nielsen Retail Scanner data. The sample is restricted to all counties in the South and East with CCP controls and at least 50,000 residents. Pair bootstrap-t used to construct symmetric p-values and 95% confidence intervals clustered at the state level. WLS estimates are weighted using county population in 2006.

Effect of Exposure to Wachovia on Employment: The decline in *retail expenditures* might cause a decline in *local non-tradable employment* if employment is at all demand determined. The table below shows the effect of *exposure to Wachovia* on *non-tradable employment and payrolls*.

Columns 1 and 2 show that losses in local non-tradables are higher, about 0.7% decline, in counties exposed to Wachovia, both within and across states. Columns 3 and 4 show that payrolls also decline as a result with a similar but slightly larger effect.

One important possibility to rule out is that the employment losses are purely local, and that neighboring counties might experience growth in employment as workers and business activity leaves the distressed county. To check for this he aggregates the data to the ***commuting zone (CZ) level*** in columns 5 and 6 and finds strikingly similar estimates to those in columns 1 and 2. This suggests that *much of the losses are in fact absorbed by the counties* experiencing the shock.

Table 9: Effect of Wachovia Exposure on Non-tradable Employment and Payrolls 2007-2010

	(1) Employment β /p/(CI)	(2) Employment β /p/(CI)	(3) Payroll β /p/(CI)	(4) Payroll β /p/(CI)	(5) CZ Employment β /p/(CI)	(6) CZ Employment β /p/(CI)
Wachovia Exposure	-0.874	-0.662	-0.933	-0.850	-0.706	-0.615
	0.000	0.180	0.006	0.006	0.002	0.028
	(-1.308, -0.439)	(-1.608, 0.285)	(-1.586, -0.281)	(-1.391, -0.308)	(-1.123, -0.289)	(-1.130, -0.101)
Mortgage Leverage 2006	-0.033	0.018	-0.048	-0.046	-0.036	0.011
	0.004	0.404	0.016	0.328	0.010	0.690
	(-0.053, -0.012)	(-0.021, 0.057)	(-0.086, -0.010)	(-0.141, 0.049)	(-0.060, -0.011)	(-0.018, 0.039)
FE	–	State	–	State	–	State
N	478	478	478	478	289	289
Clusters	25	25	25	25	24	24
R2	0.095	0.314	0.049	0.129	0.166	0.481
Robust F-stat	5.311	3.156	7.413	7.996	7.459	4.610

Note: This table reports regression point estimates, p-values, and 95% confidence intervals of non-tradable employment growth at the county level regressed on exposure to Wachovia: $\widehat{\mathrm{E}}_i = \alpha + \beta \text{Wachovia Exposure}_i + \theta X_i + \epsilon_i$. I measure exposure with Wachovia's market share in 2005-2006 of non-refinance mortgages within the county. Non-tradable employment follows the definition in Mian and Sufi [2014] and is primarily retail and food services. Counties exposed to Wachovia experience larger declines in non-tradable employment and payrolls. The results are very robust to the inclusion of state fixed effects and controlling for mortgage leverage. The sample is restricted to all counties in the South and East with CCP controls and at least 50,000 residents. Pair bootstrap-t used to construct symmetric p-values and 95% confidence intervals clustered at the state level. All regressions are weighted using county population in 2006.

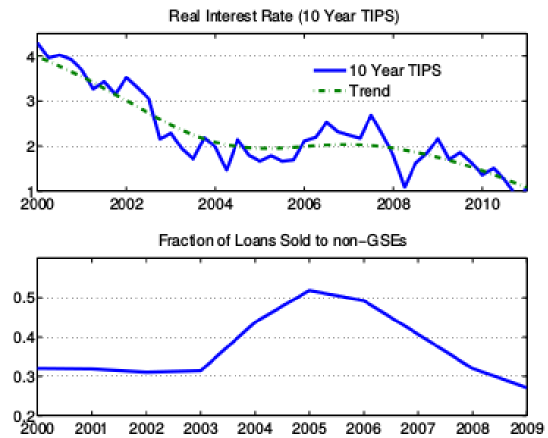
4.6 Kermani (JMP, 2013): *Cheap Credit, Collateral and the Boom-Bust Cycle*

Abstract: This paper proposes a model of booms and busts in housing and non-housing consumption driven by the interplay between relatively low interest rates and an expansion of credit, triggered by further decline in interest rates and relaxing collateral requirements. When credit becomes available, households would like to borrow in order to frontload consumption, and this increases demand for housing and non-housing consumption. If the increase in the demand for housing translates into an increase in prices, then credit is fueled further, this time endogenously, both because of the wealth effect (the existing housing stock is now more valuable) and because housing can be used as collateral. Because a lifetime budget constraint still applies, even in the absence of a financial crisis, the initial expansion in housing and non-housing consumption will be followed by a period of contraction, with declining consumption and house prices. My mechanism clarifies that boom-bust dynamics will be accentuated in regions with inelastic supply of housing and muted in elastic regions. In line with qualitative predictions of my model, I provide evidence that differences in regions' elasticity of housing and initial relaxation of collateral constraints can explain most of the 2000-2006 boom and the subsequent bust in house prices and consumption across US counties. Quantitative evaluation of the model shows that reversal in the initial relaxation of collateral constraints is important in explaining the sharp decline of house prices and consumption. However, the model shows that most of the decline would have happened even without a reversal in the initial expansion of credit, albeit over a longer period of time.

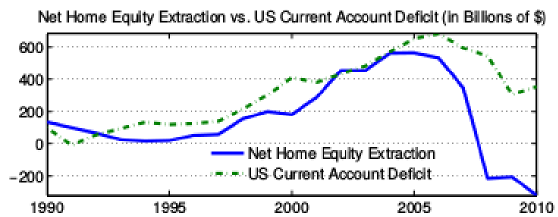
4.6.1 Motivation

The usual explanation of the Great Recession: ***"Negative" shocks*** in 2007/08 (financial crisis / house prices $\downarrow$ / uncertainty) $\Longrightarrow$ households deleveraging $\Longrightarrow$ decline in consumption and economic activity.

During the period of 2000 to 2006, there was a DECLINE in real interest rates followed by an INCREASE of securitization and an easing of collateral requirements (see figure below). The US flow of funds during this period shows that in just 7 years the stock of HH mortgage liabilities more than doubled, increasing by 5.7 trillion dollars (see figure below). During this period the total value of cash-outs and the US current account deficit followed each other very closely.



(a) Decline in Interest Rates and the Rise of Securitization



(b) Home Equity Extraction and Current Account

Figure 1: Expansion of Credit During 2000 to 2006

Notes: In Figure 1a,10-Year TIPS contains quarterly yields on treasury-inflation-protected securities (TIPS). Data are obtained from J. Huston McCulloch, http://www.econ.ohio-state.edu/jhm/ts/ts.html. HP filter with $\lambda = 400$ is used for the calculation of the interest rate trend. Fraction of Loans sold to non-GSEs are fraction of purchase loans that mortgage originators sold to an institution other than government sponsored organizations like Fannie Mae and Freddie Mac. In Figure 1b, Net Home Equity Extraction is defined as the change in the total mortgage liabilities of household minus the net investment of households in residential housing. Data are obtained from US Flow of Funds.

Between 2006 and mid-2008, there was a decline in house prices and in car sales but an increase in mortgage liabilities. Regions with high debt growth continued to accumulate debt faster than other regions although they experienced a larger decline in house prices and in consumption

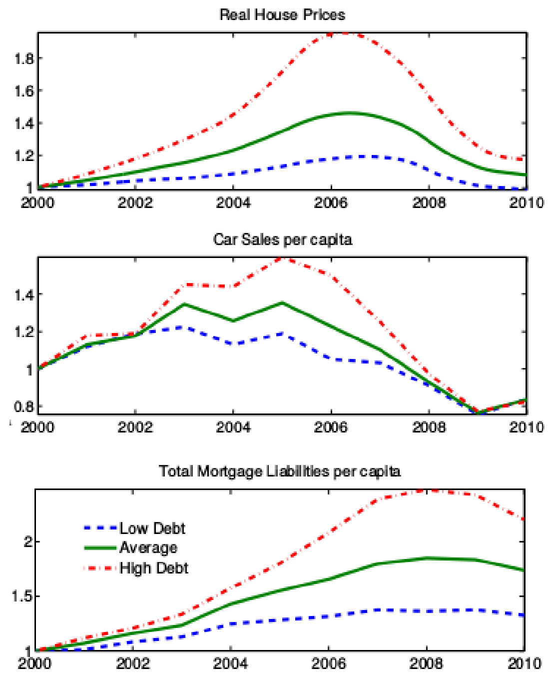


Figure 2: High Debt Growth versus Low Debt Growth Regions Dynamics

- The DECLINE in consumption (car sales per capita) in *bust years* is just a correction of the debt-fueled SURGE in consumption in *boom years.*

- Before 2006, ≈ 5%-6% of consumption was debt-fueled, which was unsustainable. Contrary to the "deleveraging" theories, there was no deleveraging before 2008 (after the financial crisis began). Almost all the DECLINE in consumption happened by 2008 and the decline was not necessarily due to deleveraging but the reduction in debt-financed consumption.

Kermani proposes that ***"Positive" shocks*** in early 2000s (permanent ↓ in real interest rates / permanent relaxation of borrowing constraints) can explain both the *boom period* of 2000-2006 and the *bust period* of 2007-2010.

- Positive shock $\Longrightarrow$ credit to HHs $\uparrow \overset{\text{short term}}{\Longrightarrow}$ consumption demand ↑, demand for housing that is financed with debt accumulation $\uparrow \overset{\text{medium term}}{\Longrightarrow}$ unused borrowing capacity↓ $\Longrightarrow$ consumption ↓, house prices ↓: ***bust is a direct consequence of initial boom***

- ***Mian and Sufi (2013)***: housing wealth↓ $\Longrightarrow$ consumption ↓ **VS.** ***Kermani (2013)***: over-consumption (debt-finance consumption during boom years)↑ $\Longrightarrow$ consumption ↓

  - *Elasticity of Housing Supply* is IV for both ***housing wealth*** and ***over-consumption*** — *confounding factor*!

Theoretical Results

In an (open) economy where *credit is relatively cheap* and *housing is the main collateral of households*,

- a permanent decline in the real interest rate causes:
  - boom-bust cycle in consumption and housing wealth in regions with inelastic supply of housing.
  - gradual increase in consumption and housing wealth in regions with elastic supply of housing.
- a permanent increase in the maximum loan-to-value ratio causes:
  - boom-bust cycle in consumption and housing wealth that is magnified in regions with more inelastic supply of housing.
- Both shocks result in accumulation of debt by households in all regions all throughout the transition.
- The level of the interest rate and the level of collateral requirements determine how large are the boom-bust cycles caused by the same interest rate shock or a loan-to-value shock.

Reduced-Form Results

(building on Mian and Sufi):

- Regions with more inelastic supply of housing and more increase in the fraction of privately securitized loans experienced a larger boom and bust in house prices and in consumption.
- A same increase in the fraction of privately securitized loans result in larger boom-bust cycles in regions with more inelastic supply of housing. (Amplification of the initial credit expansion)
- Almost all of the decline in consumption between 2006 and 2008 is just a reversal of part of the increase in consumption in 2000 to 2006 that was caused by expansion of credit to households.

4.6.2 The Model

Kermani develops a model of a ***continuous-time*** *small*, *open economy* with a *representative HH* whose borrowing is constrained by the collateralizable fraction of its housing wealth. He begins by characterizing the environment and solving for the HH's optimization problem, taking *house prices dynamics* as EXOGENOUS. Next, he solves for the equilibrium of elastic regions and inelastic regions by *endogenizing house prices*. Finally, he shocks the economy with surprise changes in interest rate and collateral requirements and characterizes the transition path of the economy.

Environment Characterization

- Small open economy. (1)
- Cheap credit (impatient households) : $r - \rho < 0$.
  - savings from China (global saving glut)
  - middle class versus top income earners (+incomplete markets)
- Housing the main collateral of households.
  - 85% of household debt is mortgage debt.
- Representative household for each region.
- No migration between regions.
- No adjustment cost in house construction. (no Mankiw-Weil)
- No rental market.

On the relevance of open economy assumption

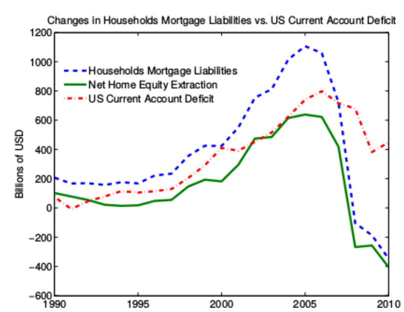


Figure : US Current Account versus Household Mortgage Liabilities.

- *open-economy assumption* is practical: location of *lenders* and *borrowers* is not restricted to one location in reality.
- *cheap credit (impatient HHs)* is essential for boom-bust mechanism to work.

4.6.2.1 Home Production

Houses in region i, ($h_{i,t}$): produced by a combination of land (l) and capital (k) according to a Leontief production function:

$$h_{i,t} = min\left\{l_{i,t}, \frac{k_{i,t}}{B}\right\}$$

- Housing production and land markets are competitive.

- Leontief production function + no adjustment cost for the capital used in a house + capital produced using numeraire $\Longrightarrow$

$$h_{i,t} = l_{i,t} = \frac{k_{i,t}}{B}$$
$$q_{i,t} = q_{i,t}^{L} + B$$

where the price of 1 unit of land $l_{i,t}$ in region i at time t is $q_{i,t}^{L}$ and the cost of 1 unit of capital B

4.6.2.2 Representative HHs problem and maximization

Region i's HH problem can be written as:

$$\underset{[c_{i,t},a_{i,t},h_{i,t}]_0^\infty}{Max} \left\{ \int_0^\infty e^{-\rho t} \left[log\left(c_{i,t}\right) + \eta \underbrace{log\left(h_{i,t}\right)}_{\text{housing consumption}} \right] dt \right\}$$

subject to

$$(\mu_{i,t}) \text{ budget constraint : } \dot{a_{i,t}} + q_{i,t}\dot{h_{i,t}} = w_i - c_{i,t} + r a_{i,t} - \delta_k B h_{i,t}$$
$$(\lambda_{i,t}) \text{ (borrowing) collateral constraint : } a_{i,t} \geq -\theta_i q_{i,t} h_{i,t}$$

- θ_i= maximum LTV ratio of HH i
- When a HH is buying a house, it receives the title for the land that is used in that house as well as the title for the house itself. Only the capital used in the house, and not the land, is subject to depreciation rate δ_k , which can be compensated for with household investment $i_{i,t}$ in the house. Therefore the capital used in the house evolves according to

$$\dot{k_{i,t}} = -\delta_k k_{i,t} + i_{i,t}$$

- Similar to ***Kiyotaki and Moore (1997)***, he assumes the only financial asset is the short term paper which has return r, and the minimum holding of financial assets by the representative household $(a_{i,t})$ is constrained by fraction $\theta_i((<1)$ of household housing wealth (see collateral constraint)
- It is assumed that the interest rate is lower than the HH's time preference rate $(r < \rho)$. This assumption can be rationalized by a ***global saving glut hypothesis*** (***Bernanke (2005)***) or by the presence of a small fraction of the population who are more patient than others as in ***Guvenen (2009)***.

Defining the total wealth of the representative household as $W_{i,t} \equiv q_t h_{i,t} + a_t$, and $\delta \equiv \delta_k B$, we can rewrite the representative HH problem as:

$$\underset{[c_{i,t},W_{i,t},h_{i,t}]_0^\infty}{Max} \left\{ \int_0^\infty e^{-\rho t} \left[log\left(c_{i,t}\right) + \eta log\left(h_{i,t}\right) \right] dt \right\}$$

subject to

$$(\mu_{i,t}) \text{ budget constraint : } \dot{W_{i,t}} = w_i - c_{i,t} + r\left(W_{i,t} - q_t h_{i,t}\right) - \delta h_{i,t} + \dot{q_{i,t}} h_{i,t}$$
$$(\lambda_{i,t}) \text{ (borrowing) collateral constraint : } W_{i,t} \geq \left(1-\theta_i\right) q_{i,t} h_{i,t}$$

Using an extension of the maximum principle for an optimal control problem with mixed constraints (see ***Seierstad and Sydsæter (1987)***), one can form the discounted Hamiltonian as:

$$\hat{\mathcal{H}} \equiv \left[log\left(c_{i,t}\right) + \eta log\left(h_{i,t}\right) \right] + \mu_{i,t} \left[w - c_{i,t} + r\left(W_{i,t} - q_t h_{i,t}\right) - \delta h_{i,t} + \dot{q_{i,t}} h_{i,t} \right]$$

and the associated Lagrangian:

$$\hat{\mathcal{L}} \equiv \hat{\mathcal{H}} + \lambda_{i,t} \left[W_{i,t} - \left(1-\theta_i\right) q_{i,t} h_{i,t} \right]$$

Inter-period allocation:

$$\frac{\dot{c_{i,t}}}{c_{i,t}} = (r-\rho) + \frac{\lambda_{i,t}}{\mu_{i,t}}$$

- $\mu_{i,t}$= is the *marginal benefit* of 1 more unit of consumption and, therefore $\frac{\lambda_{i,t}}{\mu_{i,t}}$= is the *relative marginal value* of 1 more unit of borrowing.
- Intuition: Without the borrowing constraint, this equation is the usual *Euler equation.*
- This equation shows that the GREATER the *relative marginal value of borrowing* $\Longrightarrow$ GREATER the *growth rate of consumption* $\Longrightarrow$ LOWER the ability of HH to transfer resources from the future to now. When the constraints bind, HHs can't smooth their consumption as much as they want and the *consumption profile is flatter*
- Loose Intuition: Combining ***both constraints***, we can think of a HH having access to a "credit card" and using it in a controlled manner to smooth consumption. Once the "credit limit" is maxed out (i.e. the *borrowing constraint binds*), the consumption of the HHs remains *constant.*

***Intra-period allocation*:**

$$\frac{c_{i,t}\eta}{h_{i,t}} = \underbrace{\left(rq_{i,t} + \delta - \dot{q_{i,t}}\right)}_{\text{user cost of housing in frictionless economy}} + \frac{\lambda_{i,t}}{\mu_{i,t}} \underbrace{\left(1-\theta_i\right) q_{i,t}}_{\text{required downpayment}}$$

- This is essentially a special form of *Cobb-Douglas demand.*
- In a frictionless economy *without the borrowing constraint*, consumption smoothing between non-housing goods and housing implies $c_t = \left(rq_{i,t} + \delta - \dot{q_{i,t}}\right) \frac{h_{i,t}}{\eta}$
- In an economy with the borrowing constraint binding, the representative HH can't afford the *down payment for buying a house* and the HH's demand for housing declines in comparison with the frictionless case. Intuition:
  - The HIGHER (LOWER) the required down payment for each unit of housing $(1-\theta_i)\, q_{i,t}$, the HIGHER (LOWER) the decline in the demand for housing, the MORE (LESS) consumption you have to sacrifice today to save MORE to have that down payment.
- When *borrowing constraint binds*, then 1 unit of capital is MORE valuable *now* than before. The MORE binding is the borrowing constraint ($\lambda_{i,t} \uparrow$), the HIGHER the user cost of housing, the LESS HHs consume houses.

and

$$\lambda_{i,t} \geq 0\,(= \text{ iff } a_{i,t} > -\theta_i q_{i,t} h_{i,t})$$

4.6.2.3 Steady-State (SS) Equilibrium Characterization

The final step is to add the *supply side* of the *housing marke*t and to find the equilibrium house prices for the given behavior of the representative HH.

Now in order to show the main insights of the model, he considers *two extreme cases* for the *housing supply* (which also serve as simplifications):

- ***Inelastic Supply***: The supply of land in this case is very limited, such that all the land in the region has been used and the *aggregate supply of housing is FIXED* and equal to the total supply of land in the region ($h_{i,t} = L_i, i \in \{InelasticRegions\}$).

- ***Elastic Supply***: In this case there is plenty of unused land and therefore the price of land, $q_L = 0$. Thus the *price of housing is FIXED* and equal to the cost of capital used for building the house ($q_{i,t} = B, i \in \{ElasticRegions\}$).

Equilibrium Characterization

Definition of Equilibrium

Equilibrium is a set of $\left[c_{it}, a_{it}, h_{it}, q_{it}, q_{it}^{L}\right]_{t=0}^{\infty}$ such that

- House Producers take $[q_{it}]_{t=0}^{\infty}$ and $\left[q_{it}^{L}\right]_{t=0}^{\infty}$ as given and maximize their profit. (and in equilibrium earn zero profit)
- Households take $[q_{it}]_{t=0}^{\infty}$ and a_{i0}, h_{i0} as given and maximize their lifetime utility according to (2) to (4).
- The market for housing and and the market for land clear.

Equilibrium Characterization Strategy

Lemma

For any finite value of a_{i0} and h_{i0}, there exists $t_1 \geq 0$ at which the borrowing constraint becomes binding and remains binding thereafter.

intuition: relatively low interest rates leads households to front load their consumption and use their borrowing capacity earlier rather than later.

Solve backward for the equilibrium:

- Steady state equilibrium
- Constrained regime transitional dynamics
- Unconstrained regime transitional dynamics

The *Lemma* above argues that independent of initial financial holdings of the representative HH in region i ($a_{i,0}$), there exists a time t_1 at which the HH borrowing constraint binds ($\lambda_{t_1} > 0$). Intuition for this lemma is that since $r - \rho < 0$, when the HH borrowing constraint does not bind, HH consumption has a *negative growth rate*. This means the HH wants to transfer as many of the resources as it can to TODAY which results in the *borrowing constraint eventually binding. For a proof of this lemma (Lemma A), see Appendix A in Kermani's paper.*

The next lemma claims that in an economy without changes in r and θ_i , whenever the *borrowing constraint BINDS*, it remains BINDING FOREVER.

Lemma: Suppose r and θ_i are fixed. If there exists a time t_1 such that $\lambda_{t_1} > 0$, then $\lambda_t > 0$ for all $t \geq t_1$.

PROOF: see Appendix B in Kermani's paper.

The intuition for this result is that in order for a ***constrained*** *borrowing constraint* to become ***unconstrained***, the representative HH should either reduce: **(1)** its consumption or **(2)** its housing stock or **(3)** the growth in house prices should *increase*. Because of the front-loading motivation, a decline in consumption or in housing stock are not desirable for a HH. The proof shows an *increase* in growth of house prices that leads to a transition from a ***constrained*** *borrowing constraint* to an ***unconstrained*** one can't be an equilibrium because it results in housing demand > housing supply.

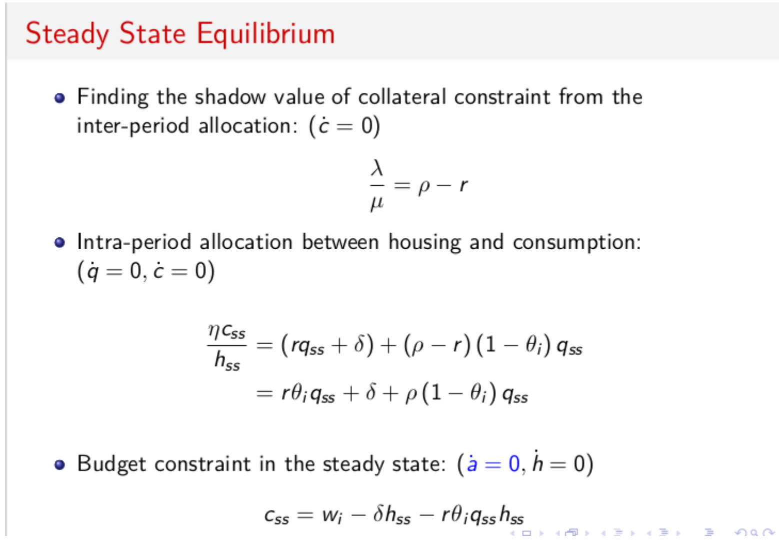
** The *two lemmas together* show that in the SS the *borrowing constraint is binding*. Moreover it shows that there is, at most, one point in time in which the *borrowing constraint* of the representative HH becomes binding. **

Equilibrium Characterization Strategy revisited: Therefore in order to solve for the entire equilibrium path, we must solve the ***problem backwards.*** First, we solve for the SS equilibrium. Second, we characterize the transition path while the *HH borrowing constraint is* ***binding***. Then we characterize the transition path when the *borrowing constraint* ***doesn't bind***. Finally, using the HH's initial financial assets and the fact that house prices are a continuous function of time, we find the point in time at which the *borrowing constraint becomes binding*.

Intuition: It is worth noting that if the *HH starts at a state* where the *borrowing constraint BINDS*, then in subsequent periods, the constraint *STILL BINDS*. Why? There is ***no uncertainty*** in this economy.

- If you start at a state where the *borrowing constraint BINDS* then it remains *BINDING* (as you transition to the SS).
- Likewise, if you start at a state where the *borrowing constraint DOESN'T BIND* then it will eventually *BIND* (as you transition to the SS).

***Steady State (SS) Equilibrium*:**



- $\dot{c} = 0 \implies$ *consumption* is constant.
- The *relative marginal value* of 1 more unit of borrowing is just $r - \rho < 0$
- $\frac{\eta c_{ss}}{h_{ss}}$ is the SS relation between how much the HH spends on *housing* relative to *(non-durable) consumption* in SS.
- The SS *budget constraint* tells us we don't accumulate any debt in SS.

***SS Equilibrium Characterization for Inelastic Regions*:** In regions with an *inelastic housing supply*, the *aggregate housing supply* is FIXED and therefore the budget constraint of the representative HH reduces to:

$$(\mu_{i,t}) \text{ budget constraint} : \dot{a_{i,t}} = w_i - c_{i,t} + ra_{i,t} - \delta L_i$$

When the borrowing constraint is binding, we end up with the following:

Inter-period allocation:

$$\frac{\dot{c_{i,t}}}{c_{i,t}} = (r - \rho) + \frac{(1 + \theta_i \eta) c_{i,t} - (w_i - (1 - \theta_i) \delta L_i)}{\theta_i (1 - \theta_i) L_i q_{i,t}}$$

Intra-period allocation:

$$\dot{q_{i,t}} = rq_{i,t} + \frac{\delta}{\theta_i} - \frac{w_i - c_{i,t}}{\theta_i L_i}$$

and

$$a_{i,t} = -\theta_i q_{i,t} L_i$$

setting $\dot{c_{i,t}} = \dot{q_{i,t}} = 0$ we get the steady state:

$$c_{ss}^{Inelastic} = \frac{[\theta_i r + (1 - \theta_i) \rho] w_i - \delta L_i (1 - \theta_i) \rho}{(1 + \eta) \theta_i r + (1 - \theta_i) \rho}$$

$$(q_{ss} h_{ss})^{Inelastic} = q_{ss}^{Inelastic} L_i = \frac{\eta w_i - (1 + \eta) \delta L_i}{(1 + \eta) \theta_i r + (1 - \theta_i) \rho}$$

***SS Equilibrium Characterization for Elastic Regions*:** The representative HH utility maximization when its *borrowing constraint is binding* ($\lambda_{i,t} > 0$), in addition to *house prices* being FIXED ($q_{i,t} = B$) results in

Inter-period allocation

$$(1-\theta_i) B \frac{\dot{c_{i,t}}}{c_{i,t}} = -\left[\theta_i r B + (1-\theta_i) \rho B + \delta\right] + \frac{\eta c_{i,t}}{h_{i,t}}$$

Intra-period allocation:

$$(1-\theta_i) B \dot{h_{i,t}} = w_i - c_{i,t} - (\theta_i r B + \delta) h_{i,t}$$

setting $\dot{c_{i,t}} = \dot{q_{i,t}} = 0$ we get the SS:

$$c_{ss}^{Elastic} = \frac{\left[\theta_i r + (1-\theta_i) \rho + \frac{\delta}{B}\right] w_i}{(1+\eta)\left(\theta_i r + \frac{\delta}{B}\right) + (1-\theta_i) \rho}$$

$$(q_{ss} h_{ss})^{Elastic} = B h_{ss}^{Elastic} = \frac{\eta w_i}{(1+\eta)\left(\theta_i r + \frac{\delta}{B}\right) + (1-\theta_i) \rho}$$

4.6.2.4 Transitional Equilibrium Dynamics

***Transitional Equilibrium Characterization for Inelastic Regions*:**

After characterizing the SS equilibrium, we can now characterize the transition path for the representative HH that begins with an initial condition (initial debt holding) that is different from the SS. The next lemma shows that in *inelastic regions*, whenever the *borrowing constraint is binding*, the economy is in SS.

Lemma: For any region i with an inelastic supply of housing, if $\lambda_{i,t} > 0$ then $q_{i,t} = q_{ss}^{Inelastic}$ and $c_{i,t} = c_{ss}^{Inelastic}$

PROOF: It can be shown that once the borrowing constraint becomes binding, it remains binding FOREVER and therefore the behavior of *house prices* and of *consumption* is fully characterized by equations:

$$\frac{\dot{c_{i,t}}}{c_{i,t}} = (r-\rho) + \frac{(1+\theta_i \eta) c_{i,t} - (w_i - (1-\theta_i) \delta L_i)}{\theta_i (1-\theta_i) L_i q_{i,t}}$$

$$\dot{q_{i,t}} = r q_{i,t} + \frac{\delta}{\theta_i} - \frac{w_i - c_{i,t}}{\theta_i L_i}$$

$$a_{i,t} = -\theta_i q_{i,t} L_i$$

Then from the $(q_{i,t}, c_{i,t})$ phase diagram in the figure below, we see that this system of equations ***doesn't have any stable path*** and the SS point given by $\dot{q}^{constrained} = 0, \dot{c}^{constrained} = 0$ is the ONLY stable point in this system of equations.

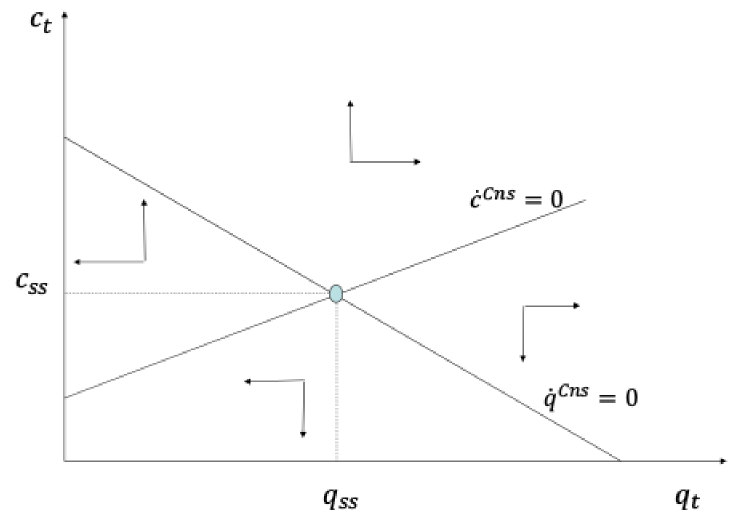
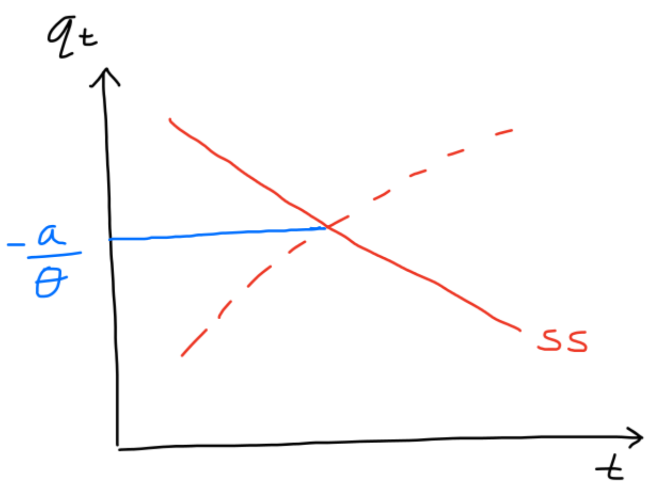
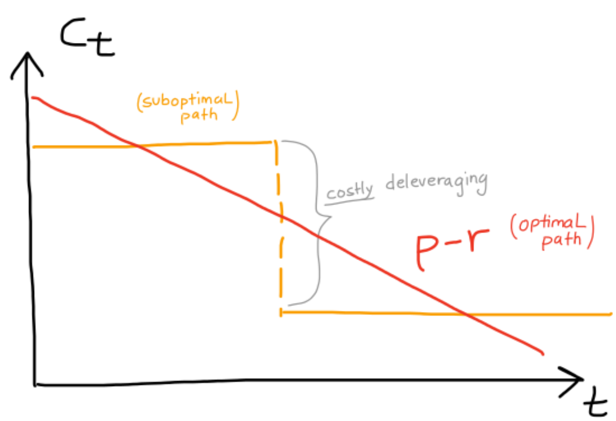


Figure 3: The phase diagram of (q_{it}, c_{it}) for an inelastic region when the borrowing constraint is binding. This graph is based on equations (16) and (17).

Starting from $a_{i,0} > -\theta_i q_{ss} L_i$, throughout the *transition*, the *borrowing constraint* does not bind and $\lambda_{i,t} = 0$ for $t < T_i$, where T_i is the time it takes the economy in region i to reach its SS.

- *Partial Equilibrium Intuition*: with *declining house prices*, a binding *collateral constraint* during the *transition* would result in a SHARP DECLINE in consumption and costly "deleveraging". This is not optimal, since HHs would incur consumption losses (see figure below). It is optimal for HHs to incur debt and use up their debt capacity in a controlled manner such that the *borrowing constraint EXACTLY BINDS* when they hit the SS.
- The amount of debt accumulation = *income* - *consumption*. In the transition, *consumption* > *income* $\implies$ HHs accumulate debt until the *borrowing constraint BINDS*.





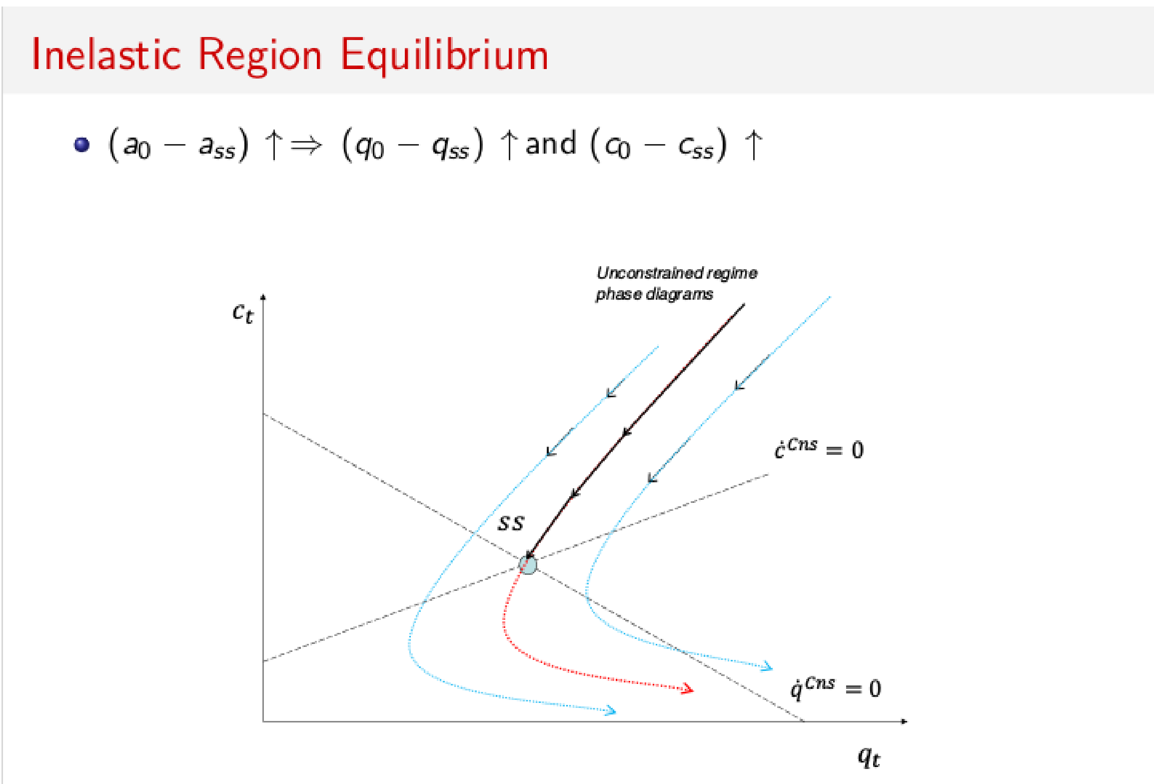
Therefore transition is characterized (for all $t \in [0, T]$) by:

$$\frac{\dot{c}_{i,t}}{c_{i,t}} = (r - \rho)$$

$$\frac{\eta c_{i,t}}{L_{i,t}} = r q_{i,t} + \delta - \dot{q}_{i,t}$$

$$\dot{a}_{i,t} = w_i - c_{i,t} + r a_{i,t} - \delta L_i$$

As the figure below illustrates, among the paths described by the *first two equations above*, there is only one saddle path that crosses the SS. In equilibrium the HH consumption and home prices move along this path until the *borrowing constraint becomes binding*. Moreover, initial point $(q_{i,0}, c_{i,0})$ should be such that exactly at the time the agent is reaching the SS point (q_{ss}, c_{ss}), the *borrowing constraint should become binding*.



** Proposition 2 characterizes the *equilibrium path for* ***inelastic region*** i, with initial level of debt holding $a_{i,0}$ **

Preposition 2: *In the inelastic region i, starting from an initial level of debt holding $a_{i0} > -\theta_i (q_{ss}h_{ss})^{Inelastic}$:*

- *The representative household borrowing constraint does not bind throughout the transition until the economy reaches its steady state characterized by (19), (20) and $a_{ss}^{Inelastic} = -\theta_i (q_{ss}h_{ss})^{Inelastic}$*
- *The economy in inelastic region i reaches its steady state in a finite time ($T_i < \infty$).*
- *The representative household non-housing consumption, house prices and representative household debt-holding during the transition (i.e. $t \in [0, T_i]$) are given by:*

$$
\begin{aligned}
c_{it} &= c_{ss}^{Inelastic} e^{(r-\rho)(t-T_i)} && (27)\\
q_{it} &= -\frac{\delta}{r} + \frac{\eta}{\rho L_i} c_{ss}^{Inelastic} e^{(r-\rho)(t-T_i)} + \left(q_{ss}^{Inelastic} + \frac{\delta}{r} - \frac{\eta}{\rho L_i} c_{ss}^{Inelastic} \right) e^{r(t-T_i)} && (28)\\
a_{it} &= a_{i0} e^{rt} + \left(\frac{w - \delta L_i}{r} \right) \left(e^{rt} - 1 \right) + \frac{c_{ss}^{Inelastic}}{\rho} e^{(r-\rho)(t-T_i)} \left(1 - e^{\rho t} \right) && (29)
\end{aligned}
$$

where T_i is the solution to:

$$
-\theta_i (q_{ss}H_{ss})^{Inelastic} = a_{i0} e^{rT_i} + \left(\frac{w - \delta L_i}{r} \right) \left(e^{rT_i} - 1 \right) + \frac{c_{ss}^{Inelastic}}{\rho} \left(1 - e^{\rho T_i} \right) \qquad (30)
$$

Proof: The fact that representative consumer borrowing constraint does not bind throughout the transition is because the only stable point of the constrained regime is the steady state (lemma 3). Equations (27) to (29) are solutions to the first-order differential equations that result from the household maximization problem, assuming the borrowing constraint is relaxed ((24)-(26)) plus imposing the following boundary conditions:

$$
\begin{aligned}
c_{iT} &= c_{ss}^{Inelastic}, \; q_{iT} = q_{ss}^{Inelastic}, \\
a_{i0} &: \; given
\end{aligned}
$$

Finally equation (30) arises from the fact that once the household reaches the steady state the borrowing constraint should become binding: $a_{iT} = -\theta_i (q_{ss}H_{ss})^{Inelastic}$.

***Transitional Equilibrium Characterization for Elastic Regions*:**

The main difference between ***elastic regions*** and ***inelastic regions*** is that house prices are *constant* in elastic regions. The following lemma characterizes the *transition path* of an *elastic region i* when the representative *HH borrowing constraint is binding*.

Lemma: In *elastic region i*, if $\lambda_{i,t} > 0$ then the solution to the HH maximization problem

$$\left(1-\theta_i\right) B \frac{\dot{c_{i,t}}}{c_{i,t}} = - \left[\theta_i r B + \left(1-\theta_i\right) \rho B + \delta\right] + \frac{\eta c_{i,t}}{h_{i,t}}$$

$$\left(1-\theta_i\right) B \dot{h_{i,t}} = w_i - c_{i,t} - \left(\theta_i r B + \delta\right) h_{i,t}$$

is a saddle path for $(h_{i,t}, c_{i,t})$ described by

$$c_{i,t} = f\left(h_{i,t}\right)$$

where $f(.)$is a strictly increasing function and $c_{ss}^{Elastic} = f\left(h_{ss}^{Elastic}\right)$.

PROOF: It can be shown that once the *borrowing constraint becomes binding*, it remains binding FOREVER and therefore the behavior of *house prices* and of *consumption* is fully characterized by equations:

$$\left(1-\theta_i\right) B \frac{\dot{c_{i,t}}}{c_{i,t}} = - \left[\theta_i r B + \left(1-\theta_i\right) \rho B + \delta\right] + \frac{\eta c_{i,t}}{h_{i,t}}$$

$$\left(1-\theta_i\right) B \dot{h_{i,t}} = w_i - c_{i,t} - \left(\theta_i r B + \delta\right) h_{i,t}$$

As the figure below (i.e. the $(q_{i,t}, c_{i,t})$ phase diagram) illustrates, among the paths described by the *2 equations above*, there is one saddle that passes through the SS.

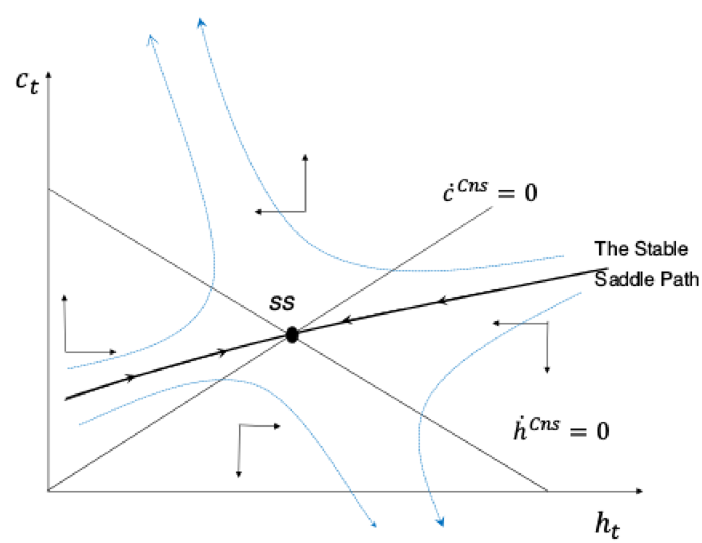


Figure 5: The phase diagram for (h_{it}, c_{it}) in elastic region when the borrowing constraint is binding. The saddle path is the solution to equations 31 and 32.

In *elastic region* i, when the *borrowing constraint DOESN'T BIND*, the HH maximization problem reduces to:

$$\frac{\dot{c_{i,t}}}{c_{i,t}} = (r-\rho)$$

$$c_{i,t} = \frac{rB+\delta}{\eta} h_{i,t}$$

$$\dot{a_{i,t}} = w_i - \frac{(1+\eta)\left(r+\frac{\delta}{B}\right)-\rho}{r+\frac{\delta}{B}} c_{i,t} + ra_{i,t}$$

From equation $c_{i,t} = \frac{r \cdot B+\delta}{\eta} h_{i,t}$ we can see that the point$(h_{t,h}, c_{t,h})$ is defined as a solution to this system of equations:

$$c_{t,h} = f\left(h_{t,h}\right)$$

$$c_{t,h} = \frac{rB+\delta}{\eta} h_{t,h}$$

is the only point at which the *borrowing constraint can go from being relaxed to being binding.*

If we define $a_{t,h} \equiv -\theta_i B h_{t,h}$ and $W_{i,0} \equiv a_{i,0} + Bh_{i,0}$ as the initial wealth of the representative HH in region i. Now we can characterize the full equilibrium path as follows:

Proposition 4:

- *If $W_{i0} \leq (1-\theta_i) Bh_{th}$, the household borrowing constraint is binding throughout the transition, and (h_{it}, c_{it}) is the solution to equations (31) and (32) with the initial conditions:*
$$h_{i0} = \frac{W_{i0}}{(1-\theta_i) B} \text{ , } c_{i0} = f(h_{i0})$$
and throughout the transition $c_{it} = f(h_{it})$.

- *If $W_{i0} > (1-\theta_i) Bh_{th}$, the household borrowing constraint does not bind initially and in finite time (T_i) the borrowing constraint becomes binding and remains binding. The equilibrium (h_{it}, c_{it}) is characterized by:*

  - *for $t \in [0, T_i]$ the borrowing constraint does not bind, and the equilibrium is the solution to equations (39) to (41) with boundary-condition equations $h_{iT} = h_{th}$, $c_{iT} = c_{th}$ and $a_{iT} = a_{th}$:*

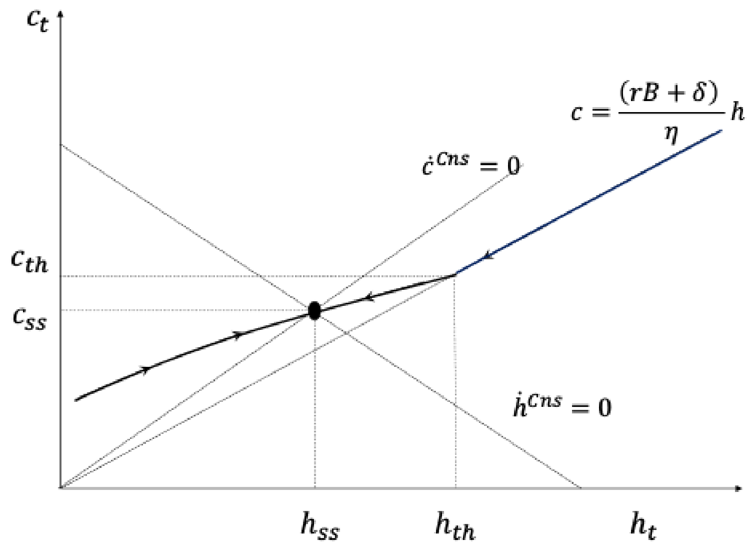
$$\begin{aligned}
c_{it} &= c_{th} e^{(r-\rho)(t-T_i)} \\
h_{it} &= h_{th} e^{(r-\rho)(t-T_i)} \\
a_{it} &= a_{th} e^{r(t-T_i)} + \frac{w}{r}\left(e^{r(t-T_i)} - 1\right) + \left(\frac{(1+\eta)\left(r+\frac{\delta}{B}\right) - \rho}{r+\frac{\delta}{B}}\right) \frac{c_{th}}{\rho} e^{(r-\rho)(t-T_i)} \left(1 - e^{\rho t}\right)
\end{aligned}$$

    And T_i is computed with the additional boundary condition that $W_{i0} (= a_{i0} + Bh_{i0})$ is given.

  - *for $t > T_i$, the borrowing constraint is binding and the equilibrium (h_{it}, c_{it}) is characterized by the solution to equations (31) and (32) with the boundary conditions $h_{iT} = h_{th}$, $c_{iT} = c_{th}$ and $a_{iT} = a_{th}$. and $c_{it} = f(H_{it})$*

The figure below shows the *equilibrium transition path in the elastic region*. If the HH initial wealth is high enough, the *HH borrowing constraint* is relaxed for awhile, and along the transition $c_{i,t} = \frac{(rB+\delta)H_{i,t}}{\eta}$. As the representative HH exhausts its borrowing capacity, its demand for housing and for consumption declines until it reaches the point $(h_{t,h}, c_{t,h})$. From that point forward the *borrowing constraint remains binding*, and it is moving on the saddle path characterized by $c_{i,t} = f(H_{t,h})$ until the HH reaches the steady state.

Elastic Region Equilibrium



4.6.2.5 Comparative Statics

So far Kermani assumed that the interest rate (r) and the maximum LTV ratio in each region (θ) don't change. He then studies the impact of ***unexpected permanent changes*** in r and θ for *elastic* and *inelastic regions*. He maintains the assumption that HHs in different regions assume r and θ are FIXED and, therefore, any change in r and θ is a surprise for them.

In lecture, he considers the impact of a ***permanent decline*** in r and a permanent increase in θ and shows ***endogenous boom-busts*** arise from these shocks by themselves.

The Impact of an Unexpected Permanent Decline in r

In both figures below, we can see that for $i \in \{Inelastic, Regions\}$ the equations

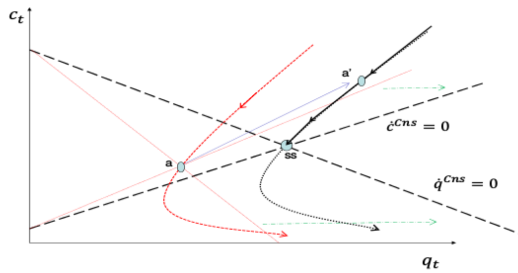
$$\frac{\partial\left(c_{ss}\right)^i}{\partial r} < 0$$
$$\frac{\partial\left(q_{ss}h_{ss}\right)^i}{\partial r} > 0$$

show that the real interest rate $r \downarrow \Longrightarrow$ housing wealth $\uparrow$, non-housing consumption $\uparrow$. LOWER interest rates DECREASE the *user cost of housing*. Since housing supply is FIXED, house prices should INCREASE enough so *housing demand = housing supply*. Taking *HH debt as given*, LOWER interest rates means LOWER interest payments for the HH, which leaves more resources for consumption. However, this effect is partly muted because in the SS HH debt is also increasing.

- Intuition: Since all HHs are borrowers, the effects of $r \downarrow$ should be obvious.

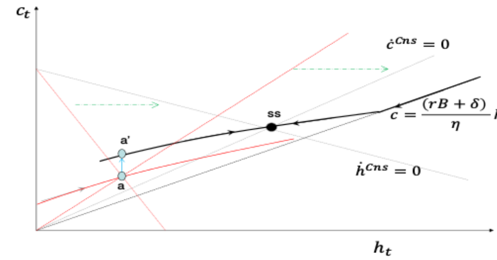
The Impact of a Surprise Decline in r (Inelastic)

$$\frac{\partial\left(c_{ss}\right)^{Inelastic}}{\partial r}<0,\ \frac{\partial\left(q_{ss}h_{ss}\right)^{Inelastic}}{\partial r}<0$$



The Impact of a Surprise Decline in r (Elastic)

$$\frac{\partial\left(c_{ss}\right)^{Elastic}}{\partial r}<0,\ \frac{\partial\left(q_{ss}h_{ss}\right)^{Elastic}}{\partial r}<0$$



The Impact of an Unexpected Permanent Increase in θ

The Impact of a Surprise Increase in θ

- Lower steady-state consumption:

$$\frac{\partial c_{ss}}{\partial \theta_i}<0$$

- Ambiguous impact on housing wealth:

$$\frac{\partial\left(q_{ss}h_{ss}\right)}{\partial \theta_i}\gtreqless 0 \ iff \ \left(\rho-r\right)-\eta r\gtreqless 0$$

  - Lower down-payment $\Rightarrow q_{ss}h_{ss}\uparrow\propto\rho-r$
  - Larger debt in the steady state $\Rightarrow c_{ss}\downarrow\rightarrow q_{ss}h_{ss}\downarrow\propto\eta r$

- More borrowing capacity:

$$\frac{\partial\left(\theta_i\left(q_{ss}h_{ss}\right)\right)}{\partial\theta_i}=\underbrace{q_{ss}h_{ss}}_{mechanical}+\theta_i\underbrace{\frac{\partial\left(q_{ss}h_{ss}\right)}{\partial\theta_i}}_{endogenouse}>0$$

  - The importance of low interest rates in amplification of LTV shocks.

- $\theta\uparrow\Longrightarrow$ HHs can borrow MORE against the value of their home.

In both figures below, we can see that for both $i\in\{Inelastic, Regions\}$ the equations show the following:

1. $\theta\uparrow$ (i.e. LOWER collateral requirement) $\Longrightarrow c_{ss}\downarrow$. The intuition for this result is that a HIGHER θ enables the representative HH to borrow MORE. But after the HH uses up this new borrowing capacity, it *can't borrow any more*, and the HH ends up with a higher amount of debt $\Longrightarrow$ higher interest payments $\Longrightarrow$ fewer resources remain for non-housing consumption: c_{ss} NOW is LESS than c_{ss}^{OLD}

2. The impact of $\theta \uparrow$on housing wealth is ambiguous but more interesting: $\theta \uparrow \implies$ down-payment required for each unit of housing $\downarrow \implies$ housing demand $\uparrow$. However, because of the consumption smoothing between *non-housing* and *housing consumption*, lower non-housing consumption in the SS $\implies$ housing demand $\downarrow$. Therefore the change in housing wealth depends on the relative importance of these two forces.

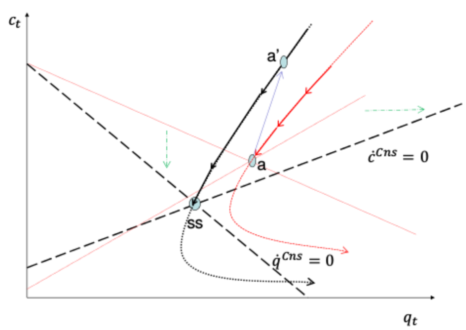
   - The HIGHER η is, the STRONGER the consumption-smoothing force and, therefore, the MORE NEGATIVE the change in housing wealth.
   - The HIGHER $\rho - r$ is, the MORE important is the lower down-payment in boosting the housing demand $\implies$ MORE positive is the change in the housing wealth.

3. Regardless if SS housing wealth $\uparrow$ or $\downarrow$, $\theta \uparrow \implies$ total borrowing capacity $\uparrow$ and total debt in SS $\theta\left(q_{ss}h_{ss}\right)^{Inelastic} \uparrow$. As noted above, from the chain rule, we get:

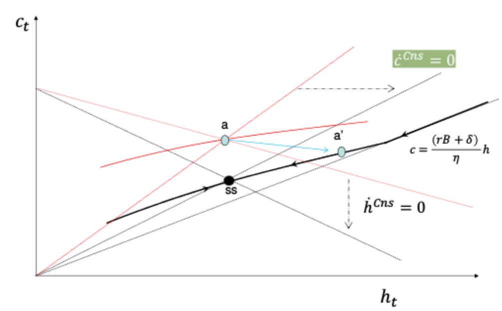
$$\frac{\partial\left(\theta_i\left(q_{ss}h_{ss}\right)\right)}{\partial\theta_i} = \underbrace{q_{ss}h_{ss}}_{\text{mechanical}} + \theta_i \underbrace{\frac{\partial\left(q_{ss}h_{ss}\right)}{\partial\theta_i}}_{\text{endogenous}} > 0$$

- The endogenous component completely depends on *interest rates*.

The Impact of a Surprise Increase in θ (Inelastic)



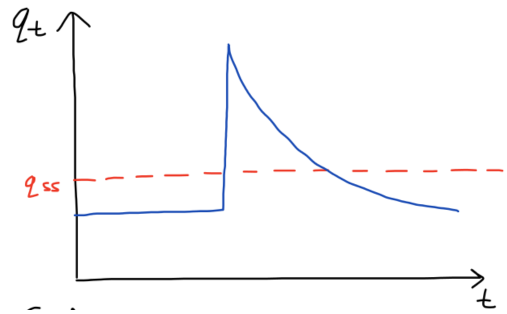
The Impact of a Surprise Increase in θ (Elastic)

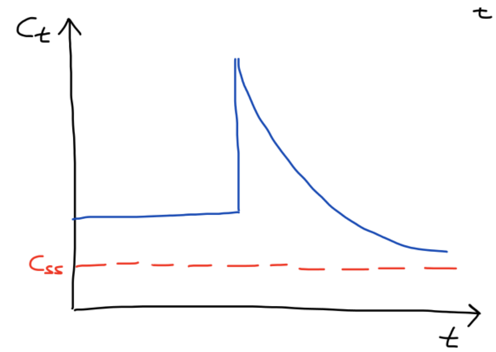


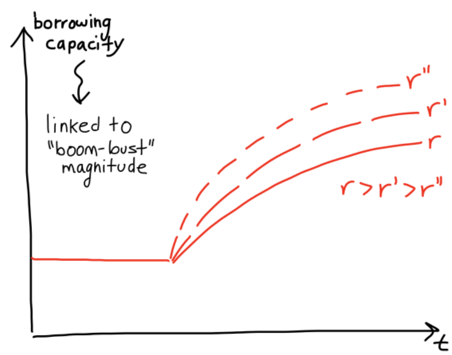
** The ***magnitude of the boom-bust cycle*** depends on the ***change in the borrowing capacity of HHs. The change in the borrowing capacity of HHs*** can be due *to* ***changes in financial liberalization - the scale and scope of financial activities****, is a function of the interest rate in this economy* **

IRFs: The following graphs show the impulse response of home prices q_t, consumption c_t, and the borrowing capacity $\theta q_t h_t$ to an unexpected permanent shock in θ.

- $c_t \uparrow$ on impact and then declines to the new but LOWER c_{ss} (relative to c_{ss}^{OLD})
- $q_t \uparrow$on impact and then decline to a new q_{ss}, which can be BELOW or ABOVE q_{ss}^{OLD}: *Whether q in the new SS $\uparrow$ or $\downarrow$ depends on r.*
- $\theta q_t h_t \uparrow$ on impact, with the magnitude in the change depending on the given r. For $r < r'$, we have $\theta q_t h_t\Big|_{r'} < \theta q_t h_t\Big|_{r'}$ (borrowing capacity under r is GREATER than that under r'







Model implications: If the financial liberalization of the pre-Great Recession period had taken place under an environment of tight monetary policy (interest rates of 5% or 6%), the boom-bust cycle would have been MUCH SMALLER than what occured pre- and post- Great Recession periods (when interest rates where 2% or so before the Great Recession).

Intuition: Financial liberalization + low interest rates $\implies$ BAD.

4.6.2.6 Empirics

In order to test implications of the model for the impacts of a DECLINE in interest rates (r) and an INCREASE in the maximum θ, he exploits the fact that there is a great deal of heterogeneity in the elasticity of the housing supply in different regions of the US.

In the reduced-form analysis of the next section, each county in US with a population of over 150,000 in 2000 comprises a *single observation*. The main reason for choosing the county as the level of aggregation (instead of MSA) is that Census contains many detailed information about the characteristics of counties. Aggregating at the state level not only reduces the number of observations considerably, but also reduces the variation of elasticity and changes in securitization rate by more than one half.

The ***postal ZIP code level*** is also not a good option since much regional information is not available at the ZIP code level or its accuracy is questionable. Moreover, there are other important factors that affect the housing market at the ZIP code level such as gentrification that are not included in my model.

As the figure below shows shows, a motivating fact in the data is that regions that experienced a *greater boom* in *home prices and in consumptio*n during the interval of 2000 to 2006 suffered from a more severe bust during the period of 2006 to 2009.

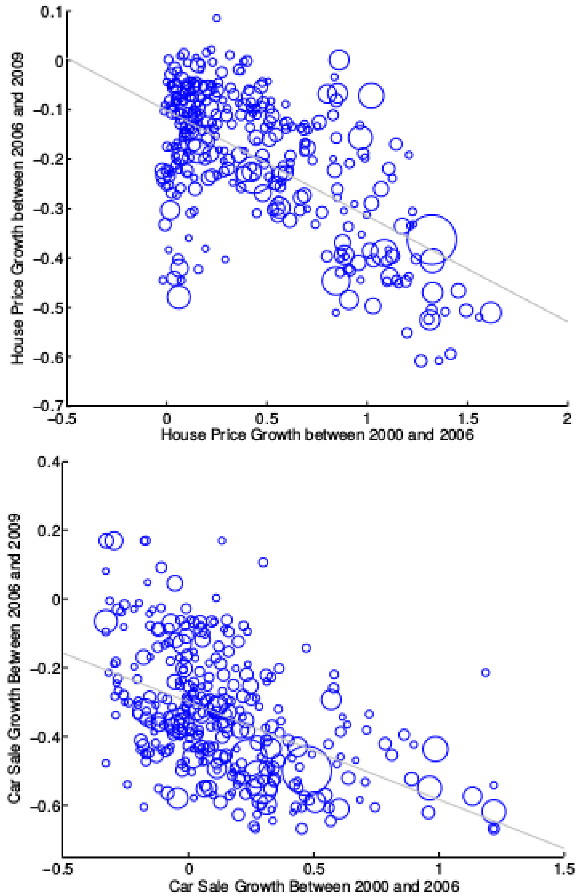


Figure 11: The Boom-Bust in House Prices and Consumption

The main prediction of the model in the previous section is that this boom-bust pattern in consumption and house prices should occur in regions with a less elastic supply of housing and in regions that experienced a greater easing of collateral constraints.

Data:

Data Sources

- Federal Reserve Bank of New York Consumer Credit Panel (FRBNY CCP)
  - Total mortgage
  - Constructing a measure of car sale
  - Fraction of households in different FICO buckets
- Zillow House Prices (Robustness check with CoreLogic HPI)
- ABS Net
  - Fraction of loans within conforming loan limits that were privately securitized
- Local elasticity of housing supply from Saiz(2010)
- Structure share in house value from Davis and Palumba (2007)
- Census and IRS

Empirical Strategy: Kermani addresses the relation between *inelasticity of housing supply* and *changes in the fraction of loans sold to non-GSEs* and *house prices*, *consumption* and *debt accumulation* in a ***reduced-form regression framework***

He first divides the sample into the ***boom period from 2000 to 2006***, and the ***bust period from 2006 to mid-2008.*** He estimates the following regression

$$\begin{aligned}\Delta log\left(Y_{i,t}\right) =& \alpha + \beta_1 Inelasticity_i + \beta_2 \Delta SecuritizaitonRate_i \\ &+ \beta_3 Inelastictiy_i \times \Delta SecuritizaitonRate_i + X_{i,t}\Gamma + \epsilon_i\end{aligned}$$

- $Y_{i,t}$= house prices / car sales in county i at time t / total mortgage liabilities.
- $Inelasticity_i$ = is based on ***Saiz (2010)*** measure of *elasticity of housing supply.*
- $\Delta SecuritizaitonRate_i$ = is the change in the fraction of loans sold to non-GSEs in county i from 2003 to 2006. This variable is a "proxy" for *changes in* θ
- $X_{i,t}$ = baseline controls, which include: the growth in average income of county residents during the associated period and its interaction with inelasticity, population growth, and the change in fraction of homes purchased by investors.

In order to compute the aggregate implications of Δinterest rates and Δsecuritization rate on the growth rate of variable Y, he does the following:

1. Use estimates of β_1, β_2, and β_3 from estimation of the regression equation.
2. Compute within-sample difference $\Delta \widehat{log\left(Y_{i,t}\right)} - \Delta \widehat{log\left(Y_{l,t}\right)}$ for each county i, where l is the average predicted value for counties in the LOWEST 10% of *inelasticity measure* and the LOWEST 10% of the Δsecuritization rate.
3. Take average of these differences weighted by the population of the county in 2000.

Results: The table below shows the results for the *Boom Period of 2000 to 2006.*

Boom Period (2000-2006)

	House Prices Growth		Car Sales Growth		Liabilities Growth	
	(1)	(2)	(3)	(4)	(5)	(6)
Inelasticity	0.11***	0.13***	0.02	0.03	0.06***	0.03*
	(0.02)	(0.03)	(0.01)	(0.03)	(0.01)	(0.02)
Change in Securitization Fraction 03_06	1.52***	1.38***	0.68***	0.79*	0.76***	1.21***
	(0.16)	(0.38)	(0.16)	(0.48)	(0.10)	(0.22)
Inelasticity X Change in Securitization Fraction 03_06	0.47***	0.76***	0.33***	1.08***	0.50***	0.63***
	(0.15)	(0.28)	(0.12)	(0.38)	(0.10)	(0.20)
Implied Aggregate Impact	0.4		0.13		0.2	
Percentage of Total	73		74		30	
Controls	Y	Y	Y	Y	Y	Y
Method	WLS	IV	WLS	IV	WLS	IV
Observations	429	425	735	425	742	425
R-squared	0.65	0.65	0.28	0.33	0.51	0.53

- $\Delta SecuritizaitonRate_i \uparrow \implies$ House price growth $\uparrow$
- $Inelasticity \uparrow \implies$ House price growth $\uparrow$

The table below shows the results for the *Bust Period of 2006 to 2008.*

Bust Period (2006-2008)

	House Prices Growth		Car Sales Growth between		Total Mortgage Liabilities Growth	
	(1)	(2)	(3)	(4)	(5)	(6)
Credit Induced House Price Growth	-0.55***					
Credit Induced Car Sales Growth			-1.37***			
Credit Induced Mortgage Growth					0.015	
Inelasticity		-0.03***		-0.04***		0.00
		(0.01)		(0.01)		(0.00)
Change in Securitization Fraction 03_06		-1.02***		-0.82***		-0.04
		(0.09)		(0.18)		(0.04)
Inelasticity X Change in Securitization Fraction 03_06		-0.21**		-0.44***		0.00
		(0.09)		(0.11)		(0.03)
Implied Aggregate Impact		-0.19		-0.18		0
Percentage of Total		151		78		0
Controls	N	Y	N	Y	N	Y
Observations	458	457	736	735	743	742
R-squared	0.51	0.69	0.17	0.19	0	0.37

- *Credit Induced Car Sales Growth* is fraction of consumption financed by debt. When you regress $CarSalesGrowth_{2006-2008}$ on *Credit Induced Car Sales Growth,* the coefficient estimate is **-1.37** (significant at 1% level): The DECLINE in $CarSalesGrowth_{2006-2008}$ is due to the reversal in the *credit-induced Car Sales Growth from the boom period* + some more.

4.6.2.7 Structural Estimation

One problem with the basic model is that assuming a ***FIXED housing supply in inelastic regions*** results an overestimation of the impact of a decline in interest rates (r) and in collateral requirements (θ) on house prices q_t and on consumption c_t.

The other problem with a ***FIXED housing supply*** is that during the boom period there was a rapid rise in activity in the construction sector even in the most inelastic regions (see ***Charles, Hurst, and Notowidigdo (2012)***).

In order to tackle this problem, Kermani extends the model by replacing the Leontief production function for the housing sector with a CES function:

Structural Estimation

- I modify the housing production function to CES to capture the fact that even in the most inelastic regions there was a massive construction boom:

$$h_{it} = \left[\omega_i^{1/\sigma} k_{it}^{\frac{\sigma-1}{\sigma}} + (1-\omega_i)^{1/\sigma} l_{it}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{6}$$

where $0 \leq \sigma, \omega_i \leq 1$

- $$log\left(\frac{k_{it}}{q_{it}h_{it}}\right) = log\left(\omega_i\right) + (\sigma-1)\, log\left(q_{it}\right) \tag{7}$$

- Normalizing the price of the base year to one:

$$\tilde{\omega}_i = Share\ of\ capital\ in\ the\ base\ year$$

- $\sigma - 1$: slope of $log(Capital\ Share)$ vs. $log(q_{it})$

Additionally he assumes *house producers* maximize their instantaneous profit. This pins down the relation between *house prices* and *aggregate stock of housing in region i* :

$$H_{i,t} = \left(1-\omega_k^i\right)^{-\frac{1}{1-\sigma}} \left(\frac{q_{i,t}^{1-\sigma} - \omega_k^i}{q_{i,t}}\right)^{\frac{\sigma}{1-\sigma}} L_i$$

4.6.2.8 Calibration

In order to analyze the main insights of the model, Kermani calibrates the model for *three different types of regions*:

1. *Inelastic regions* that experienced HIGH Δsecuritization rates
2. *Inelastic regions* that experienced LOW Δsecuritization rates
3. *Elastic regions.*

Static Parameters Calibration

- $\rho = 0.06$
- $w_i = 1$, $q_{i0} = 1$ (Since the predictions are about the time series of the changes and not the levels)
- η, δ, L_i
  - functions of the share of mortgage cost and depreciation cost in household income (as well as σ, ω_k, ρ)

	σ	ω_i	L_i	η_i	δ_i
Inelastic	0.5	0.3	6.12	0.38	0.078
Elastic	0.5	0.8	14.29	0.28	0.044

Dynamic Parameters Calibration

Model without a financial crisis (i.e. no decline in θ)

- r_t: declines from 4.3% in 2000 to 2.2% in mid-2003 and remains constant thereafter.
- θ_{it} : is calibrated to match the time series of changes in mortgage liabilities from 2000 to 2006.

Model with a financial crisis:

- r_t : from 2008 to 2011, interest rate declines to 1%.
- θ_{it} : calibration is extended to match the change in mortgage liabilities from 2007 to 2011.

4.6.2.8 Counterfactual of Past Policies

After Kermani tests the performance of the model, he considers *two informative counterfactuals about past events*:

1. What would have happened to *house prices* and *consumption* if there was the SAME DECLINE in the real interest rate (r) but there was NO CHANGE in collateral requirements (θ)

    - The model predicts only 30% ↑ in *house prices of inelastic regions* if there was NO DECLINE in θ compared to more than 60% ↑ when decline in r was followed by decline in θ (red line - model)
    - The *growth in consumption* would have been 60% LESS if there was NO DECLINE in θ compared to the decline in r that was followed by decline in θ (red line - model)
    - Absent a ↓ in θ, the decline in *house prices* and *consumption* would have started by mid-2003.
    - If r ↓ then this change in r by itself doesn't generate a *boom-bust in elastic regions.*

2. What would have happened to *house prices* and *consumption* if there was the SAME DECLINE in collateral requirements (θ) but there was NO DECLINE in the real interest rate (r) during the period of 2000 to 2003.

    - If there was NO DECLINE in r, the impact of the SAME DECLINE in θ on *house prices* and *consumption* would be ***significantly milder***. Intuition: With r closer to ρ HHs have less incentives to front-load and distribute the new borrowing capacity more evenly over their life time. The other channel through which r influences the impact of a DECLINE in θ is through its impact on q_{ss}.

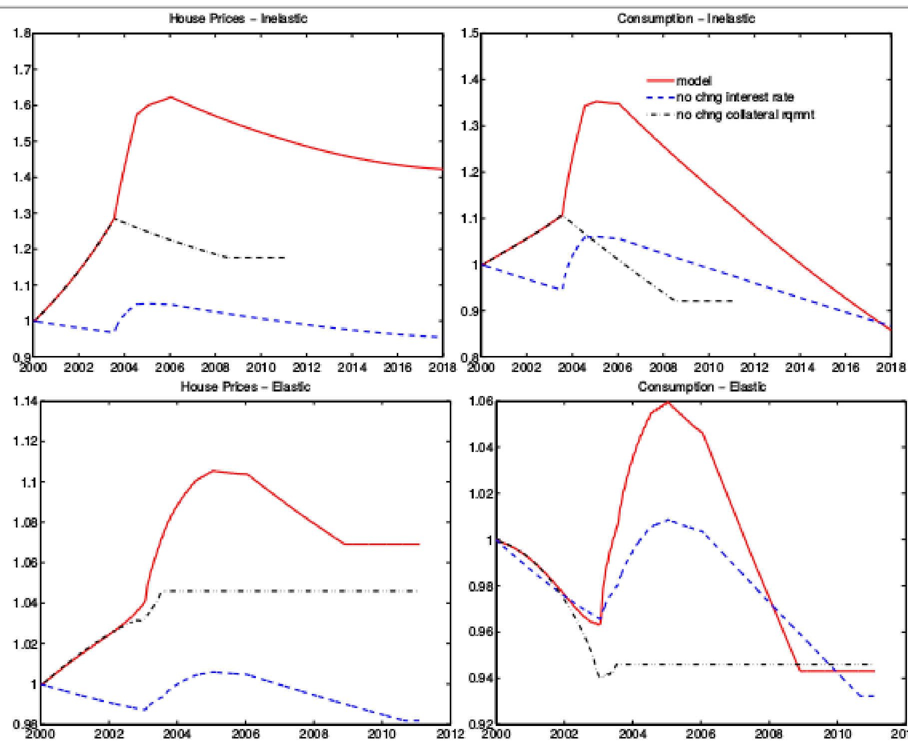


Figure 16: Counterfactual of Past Policies

Notes: This figure compares the predictions of the model without a financial crisis (baseline model) with two hypothetical scenarios; first, the interest rate remains at its level in 2000 but the decline in collateral requirements is the same as in the baseline model. Second, there is no decline in collateral requirements but decline in inters rates is the same is in the baseline model. Results are presented for inelastic regions that experienced high change in securitization rate and for elastic regions.

**** Main Lesson:** Impact of θ on *consumption* and *house prices* depends crucially on the level of r **

4.6.2.9 Conclusion

Conclusion

- We need to think about the period of the boom and the bust together.
    - A large fraction of decline in consumption is just a reversal in the unsustainable increase in consumption that was financed with the new borrowing capacity that became available for households.
- The same factors responsible for the boom are responsible for the bust. (Endogenous boom-bust cycles)
- In terms of employment this means by 2006 there was too much employment in the non-tradable sector.

Future work

- Revisiting macroprudential policies
- Distributional impacts of monetary policy and financial liberalization
- Interaction between inequality and financial crisis

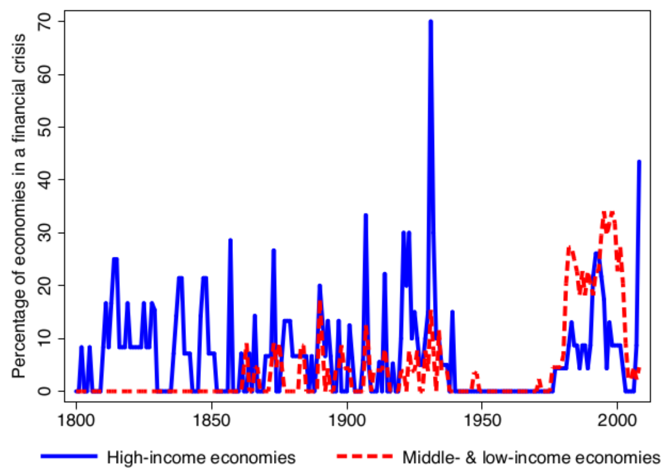
Lecture 5

Housing Wealth and the Great Recession

5.1 Taylor (WSSIE, 2014): *The Great Leveraging*

5.1.1 *Fact 1.* Crises, Almost forgotten - now they're back

A long standing problem for both *domestic* and *emerging* markets:

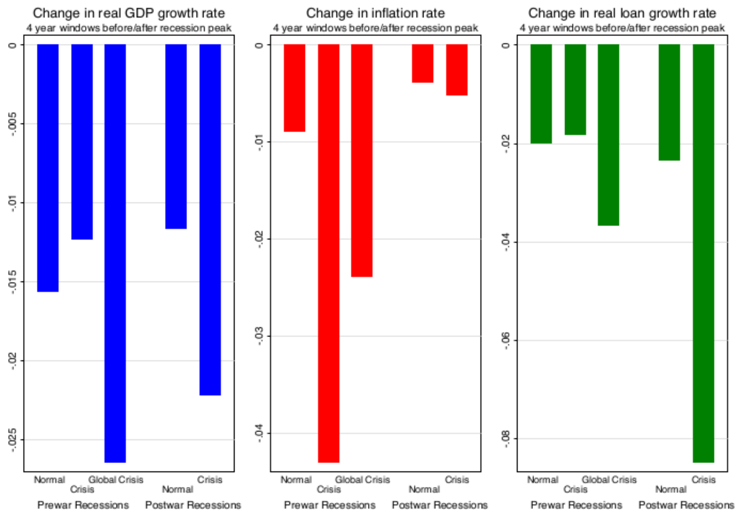


5.1.2 *Fact 2.* Consequences - forgot depressing/deflationary impacts

Taylor uses evidence-based macroeconomics, which involves data from 14 advanced countries over 140 years of history. He analyzes what goes on ***before***, ***during***, and ***after*** financial crises. Looking at **pre-WWII** vs. **post-WWII** recessions, it can be seen that they may be painful:

- Those with *financial crises* are more painful; those with *global financial crises* are worse still. Financial crises generate huge losses (in terms of GDP loss)

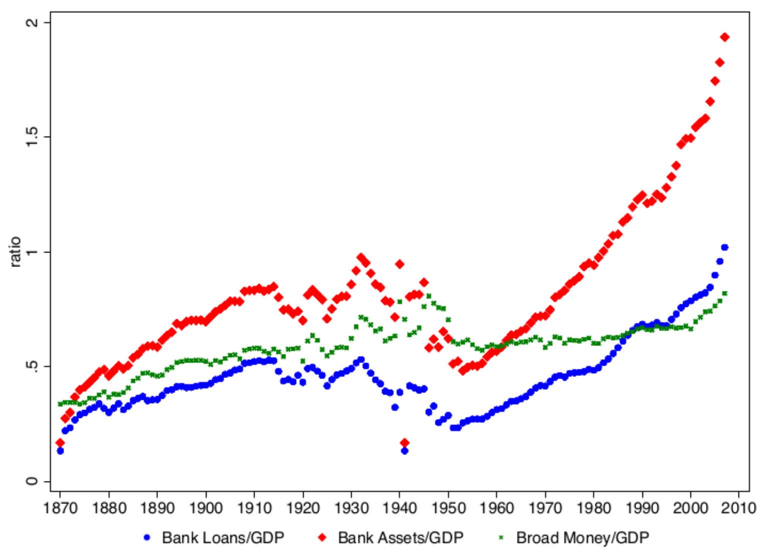
- Not much difference in Δ*real GDP growth rate* between both periods**.** Huge difference in Δinflation between both periods. ***Post-WWII*** recessions have been *less deflationary* in general, probably reflecting the escape from gold standard rules and *mentalité*, whereby more activist central banks could offset to some degree the raw deflationary forces at work.



5.1.3 *Fact 3A*. Extreme leverage: historically unprecedented

Then: Age of Money. **Now:** Age of Credit.

How? More leverage, wholesale funding. **Why?** Private actions (recovery from Great Depression and/or WWII) as well as Gov't policies (financial deregulation and financial liberalizations). In addition, *financial innovation* has helped securitize debt and increase lending capacities of financial institutions.

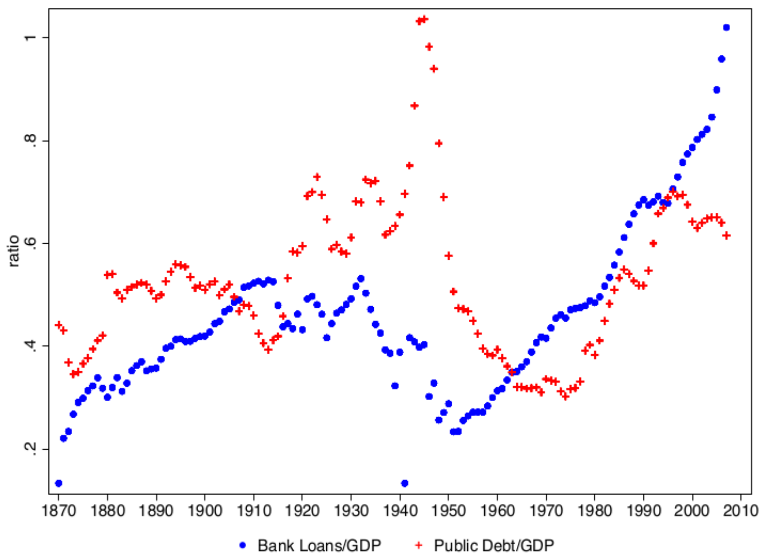


- Since WWII, the $\frac{\text{bank assets}}{\text{GDP}}$ ratio has surged in growth!

5.1.4 *Fact 3B*. banks versus sovereigns

This figure compares ***private credit*** to ***public credit.*** It can be seen that most financial crises are not really public debt crises (there is a post-2008 "blip"). Private credit is more excessive and has grown in size and has been trending up since 1990.

The reversal of the ratios $\frac{\text{private credit}}{\text{GDP}}$ and $\frac{\text{public credit}}{\text{GDP}}$ is striking after 1960 and may be due to "safe assets"



- *Private debt* is a "predictor" of financial crises. Taylor's main argument is that ***private credit booms cause financial crises***.

5.1.5 *Fact* 4. Global asymmetry - emerging markets buy insurance, domestic markets sell it

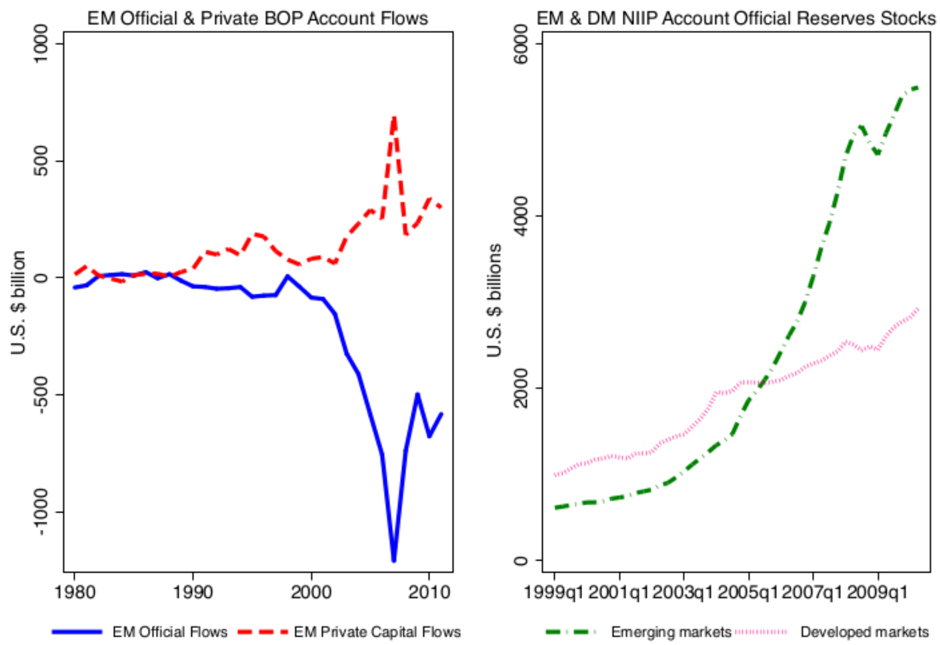
It can be seen that *post-1990s* emerging markets switch to safer, *countercyclical policies* and *larger buffers.* In the 1990s, emerging markets (EMs) joined developed markets (DMs) and integrated the global economy (globalization), but with very different economic fundamentals (asymmetry). The global financial system changed fundamentally for the following two linked reasons:

1. *Private capital* has been flowing $\underset{\text{EM}}{\overset{\text{DM}}{\downarrow}}$ all the time and in substantial quantities: *Private investors have moved capital from rich to poor countries all along, just as standard economic theory would predict*

2. *Official capital* has been flowing $\underset{\text{EM}}{\overset{\text{DM}}{\uparrow}}$, but at an even greater rate, sufficient on net to more than offset the private capital flows from $\underset{\text{EM}}{\overset{\text{DM}}{\downarrow}}$ (especially after the Asian crises of the late 1990s). These official flows are principally driven by what we might call the "***Great Reserve Accumulation***"

Definition. Official (financial) flows -

Taylor interprets the "***Great Reserve Accumulation***" s as a result of insurance motives in the EMs, particularly after the painful EM crises of the 1990s made clear to EM policymakers that the risk of currency crises, financial crises, and sovereign crises were extremely high for them. **No "Lucas paradox."**



5.1.6 *Fact* 5. Savings glut - short run panic vs. long run demography

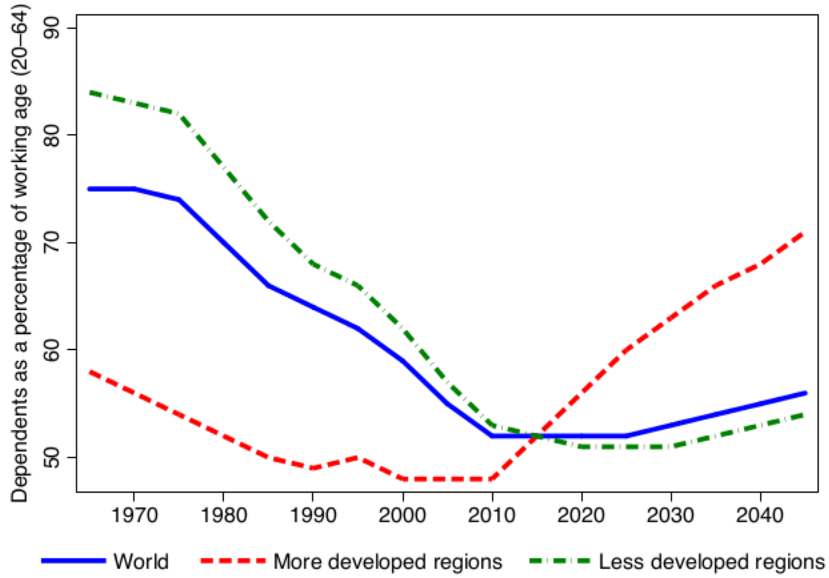
Data shows the *risk assets* are almost all on the *private side*, the *safe assets* on the *official side*. Taylor asks the following important questions: *Are we going to be in savings glut mode forever*? *Is cheap capital here to stay*? **Answers**:

1. One is simply to note that some of the demand for safe assets is probably *panic augmented*, even though the trend in real yields goes back over a decade, beyond the crisis.

2. There is reason to doubt that the stocks, and hence, flows, of EM reserve assets will expand *ad infinitum* at the same rate.

3. When we think about the deep determinants of real yields there are other more fundamental forces at work in the medium run, and the key one is demography. For decades first DMs and then EMs have experienced major demographic tailwinds.

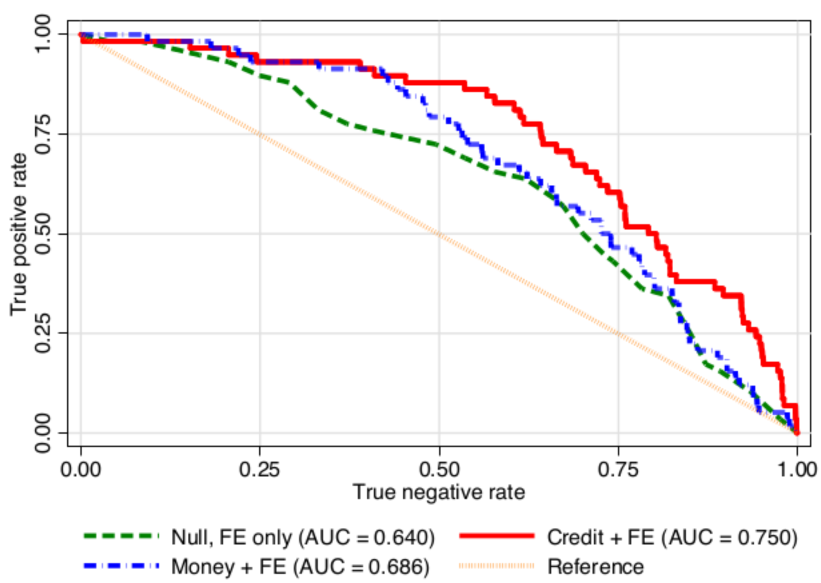
Looking forwards, these *short-term forces* are now starting to abate and will soon go into reverse as shown in the figure below.



5.1.7 *Lesson 1.* Past private credit growth does contain valuable predictive information about likelihood of a crisis

A formal approach can confirm that over the past course of history of *private credit growth* turns out to contain valuable predictive information about the likelihood of a financial crisis event ***(Schularick and Taylor 2012)***.

- They use lagged private credit growth T–$5, ..., T-1$ and forecast a *financial crisis* $\{0,1\}$ in year T.
- The finding is that *ex-ante* credit boom makes a financial crisis more likely: **(1)** *Beats* null (cointoss); **(2)** *Beats* narrow or broad money; **(3)** Robust to other controls including macro aggregates, interest rates, and stock prices.

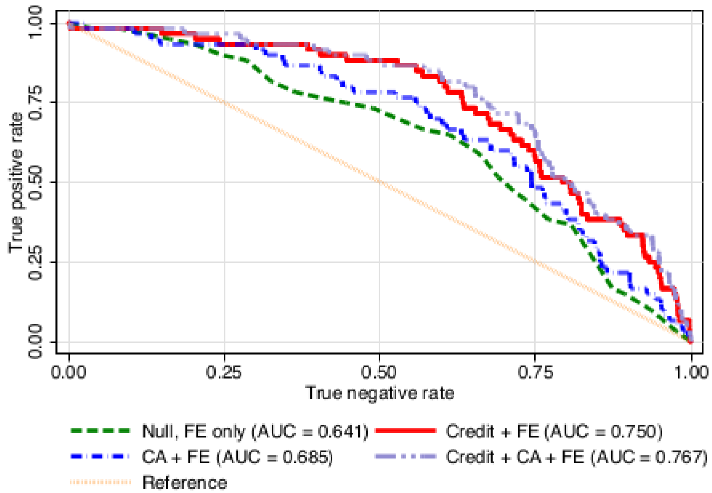


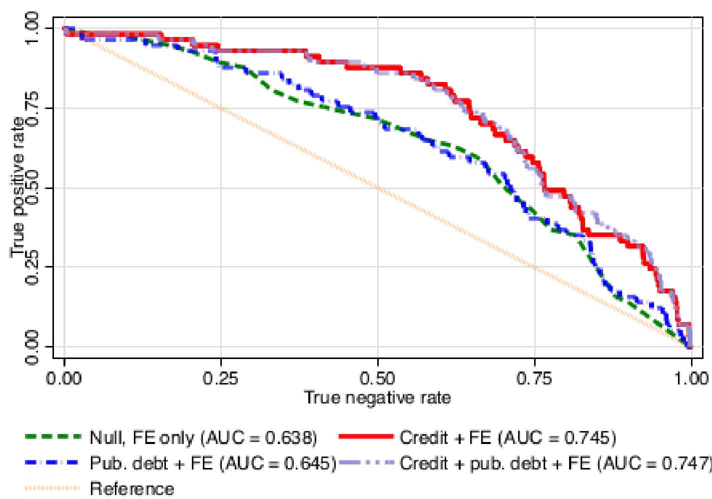
5.1.8 *Lesson* 2. External imbalances/public debts are a distraction

One can only check have if *current account deficits* (i.e. external imbalances) or rising *public debt levels* also contributed anything to the elevation of financial crisis probabilities. The question is do any of these other variables

add any information at all, either relative to the null or relative to the credit-based predictive model of ***(Schularick and Taylor 2012)***.

- Over 140 years there has been no systematic correlation of financial crises with either prior *current account deficits* or prior *growth in public debt levels*. **Private credit** has always been the only useful and reliable predictive factor.



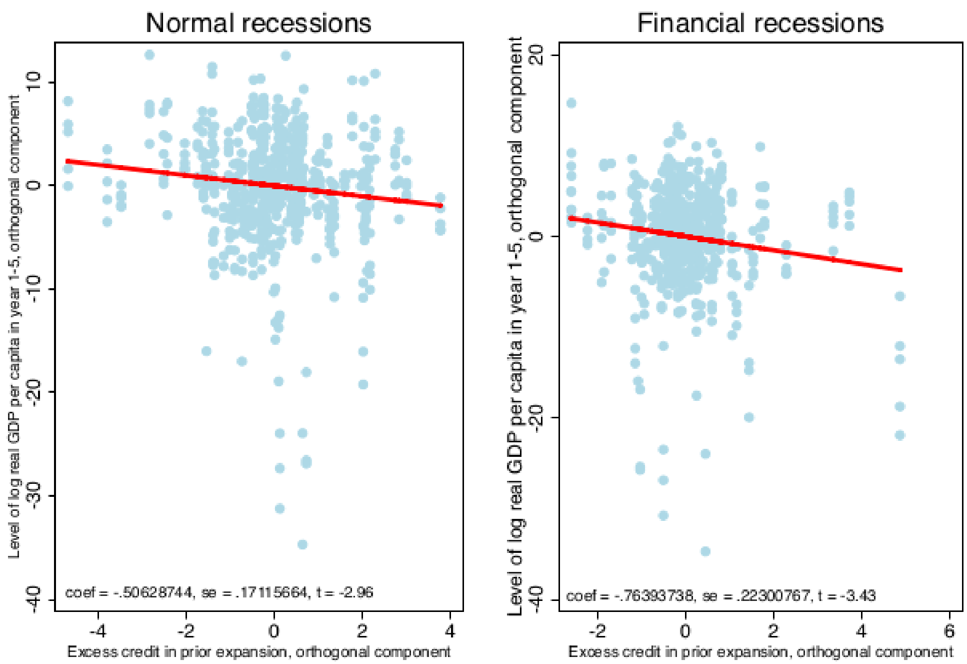


5.1.9 *Lesson* 3. After a private credit boom, expect a more painful recession, normal or financial-crisis

A *more general* (extending past just "financial crisis" recessions) and *worrying* correlation is evident. During any business cycle, whether ending in a *financial crisis recession* or just a *normal recession*, there is a very strong relationship between the ***growth of private credit (relative to GDP) on the upswing***, and the ***depth of the subsequent collapse in GDP on the downswing:***

$$CORR\left(\left(\frac{\text{private credit}}{\text{GDP}}\right)_{\text{growth}} \text{during BOOM}, \downarrow GDP \text{ during (subsequent) BUST}\right) \text{is HIGH}$$

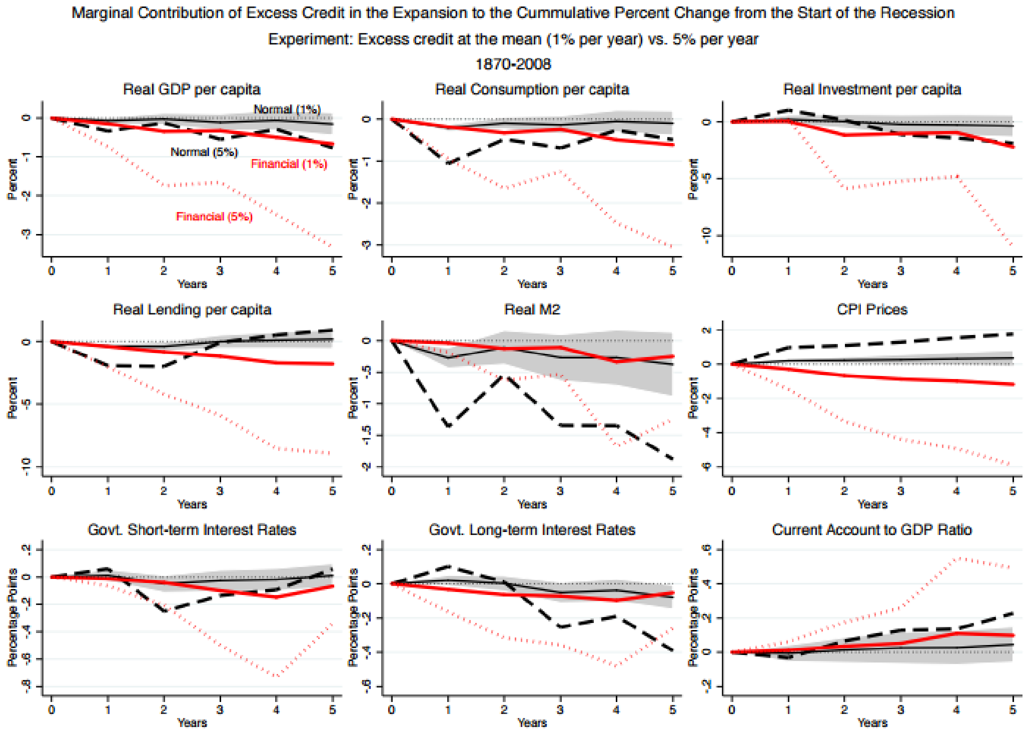
- Credit boom before v lost output afterwards
- Jordà, Schularick, Taylor 2012 "When credit bites back"
- Larger credit boom ex ante correlates with deeper recessions in each case
  - In addition to the larger credit boom making more painful financial crisis case more likely to occur



- The results challenge the view that credit is an *epiphenomenon*: something driven by real fundamentals, but not an interesting or important economic driver in its own right.
- Many economists were stating that the boom in 2006-2007 was normal. However, it is important to consider the fact that this period included *unsustainable* booms in private credit and consumption. Once this is to be corrected, the corrections will also be very large! The LARGER the *private credit boom* before a recession $\Longrightarrow$ the LARGER the build-up in consumption (if the surge is in HH debt) $\Longrightarrow$ the LARGER the "*correction*" will be in terms of output losses.

5.1.10 *Lesson* 4. In a financial crisis with large run-up in private sector credit, mark down growth/inflation more

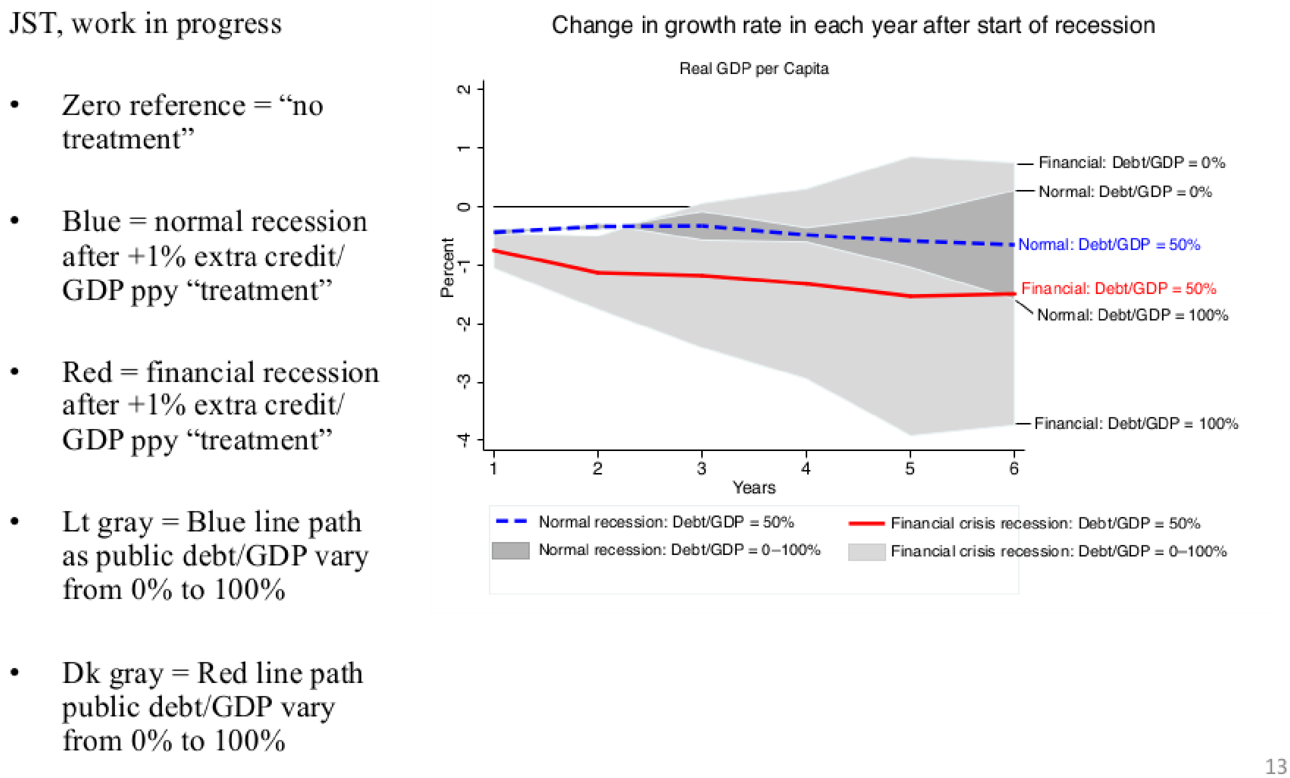
(Schularick and Taylor 2012) ask how are macroeconomic characteristics of the recession path related to expansion phase credit build up? This figure shows *cumulative impacts* from a 9-variable Jordá local-projection estimation cumulated over 5 years after a recession peak for their sample of 14 countries for 1870 to 2008.



- First, unsurprisingly, *excess private* credit generally makes matters worse, but especially so in a financial crisis, with lower ***output***, ***consumption***, ***investment***, ***lending***, ***M2 money***, ***CPI inflation***, and ***interest rate responses***, and a sharper move in the ***current account surplus***.
- Also noteworthy are the downward pressures on ***growth***, ***credit***, ***inflation***, and ***investment***, characteristics that are highly noteworthy in the context of the present weak recovery from the 2008 crisis

Main Lesson: The point is simply that from an empirical point of view, a *credit boom* and a *financial crisis* ***together*** appear to be a very potent mix that correlate with abnormally severe downward pressures on ***growth, inflation, credit*** and ***investment*** for long periods.

5.1.11 *Lesson* 5. In a financial crisis with large public debt, and large run-up in private sector credit mark down growth/inflation even more.



- If we look at *normal recessions* (blue dashed line, dark shaded fan), *excess private credit growth* in the prior expansion is correlated with *mild drag in the recession*, say 50– 75 bps in the central case, but the effect is small, and <u>does not vary all that much</u> when one *conditions* on $\frac{\text{public debt}}{\text{GDP}}$ levels (the dark fan is not that wide).
- Now looking at *financial crisis recessions* (red solid line, light shaded fan), *excess private credit growth* in the prior expansion is correlated with much larger drag, almost twice as large at 100–150 bps, and the <u>impact is very sensitive</u> when one conditions on $\frac{\text{public debt}}{\text{GDP}}$ levels (the light fan is very wide).

Main Lesson: Exposure to a credit boom can make recessions painful, but when combined with an adverse fiscal position at the onset of the crash, economies are perhaps even more vulnerable. Such empirical evidence would suggest that even if the stakes are lower in normal recessions, countries with more "***fiscal space***" are *better able to withstand a financial crisis*, perhaps by having room to offer stabilizing support to their economy (or at least dodge austerity).

5.1.12 Conclusion

Prevention of recessions, especially financial crisis recessions, is feasible before they occur through the *control of credit booms:* more banking supervision, *financial regulation.*

5.2 Kumhof, Rancière, and Winant (AER, 2015): *Inequality, Leverage and Crises*

Abstract: The paper studies how high household leverage and crises can be caused by changes in the income distribution. Empirically, the periods 1920–1929 and 1983–2008 both exhibited a large increase in the income share of high-income households, a large increase in debt leverage of low- and middle-income households, and an eventual financial and real crisis. The paper presents a theoretical model where higher leverage and crises are the endogenous result of a growing income share of high-income households. The model matches the profiles of the income distribution, the debt-to-income ratio and crisis risk for the three decades preceding the Great Recession.

5.2.1 Motivation

Empirical Motivation: Similarities in the US of pre-1929 and pre-2008 decades

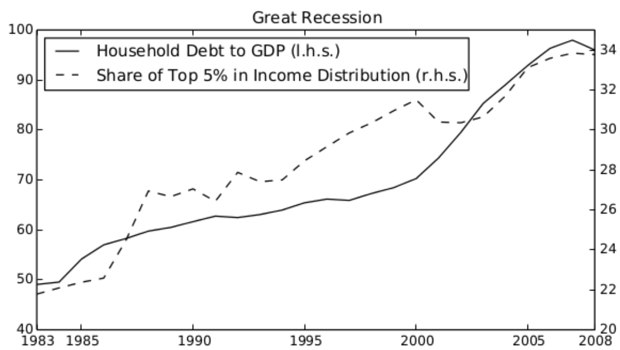
1. ***income inequality*** sharply ↑
2. ***debt leverage*** among low- and middle-income HHs sharply ↑
3. High ***debt leverage*** eventually triggered a large financial and real crash.

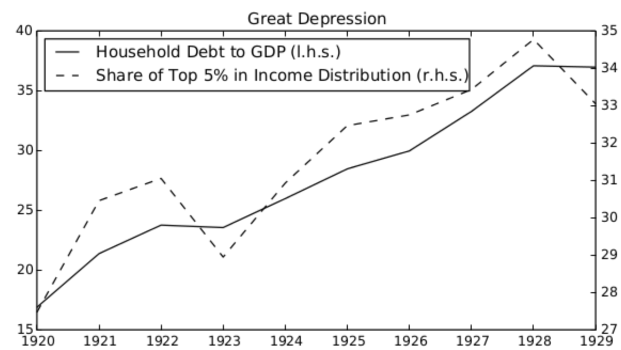
The authors provide a useful theoretical framework, including a new methodology for its calibration, that can be used to investigate the role of ***income inequality as an independent source of macroeconomic fluctuations***.

5.2.2 Literature Review

5.2.3 Stylized Facts (*Great Depression* vs. *Great Recession*)

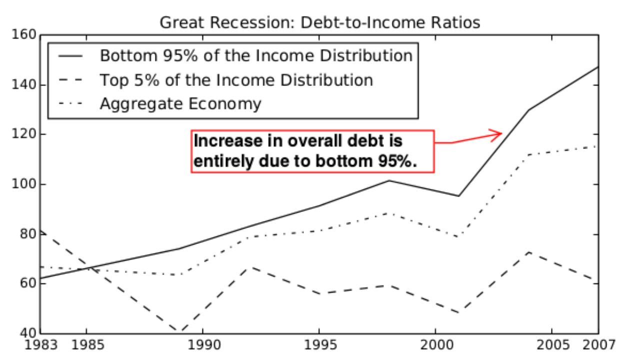
5.2.3.1 *Income Inequality* and *Aggregate HH Debt*

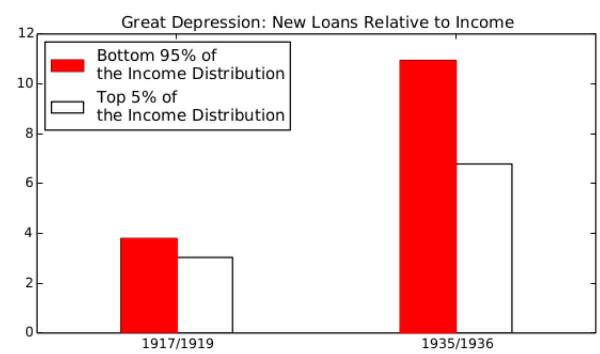




- Both variables ***moved up together*** *pre-1929* and *pre-2007* crisis periods.

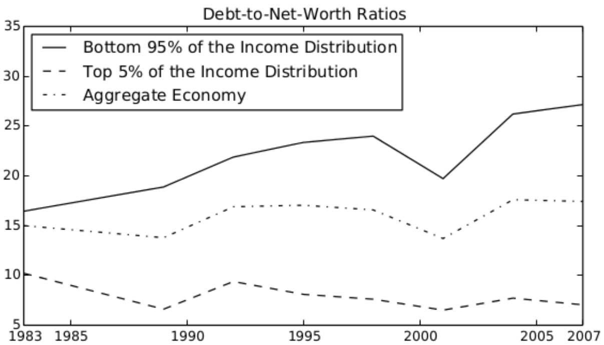
5.2.3.2 *Debt by Income Group*

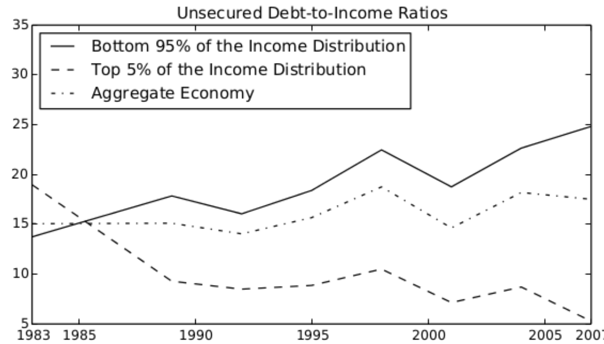




- *Lower* or *flat* for the rich (**top 5%**) and *sharply higher* for the remainder (**bottom 95%**). *Conjecture:* most of the build in aggregate debt is coming from bottom 95%

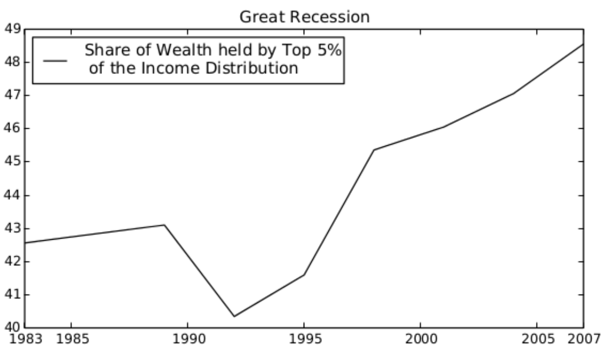
Alternative Debt Ratios

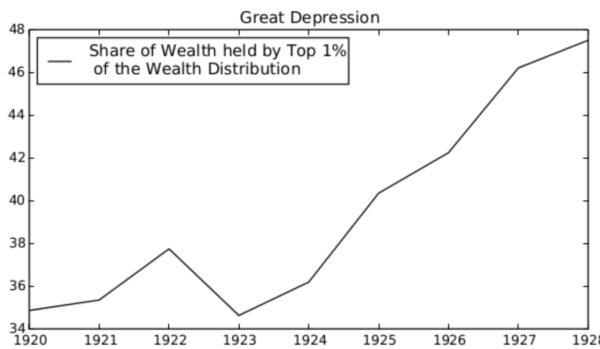




- *Alternative Debt Ratios* show the same pattern: Increasing only for ***Bottom 95%***.

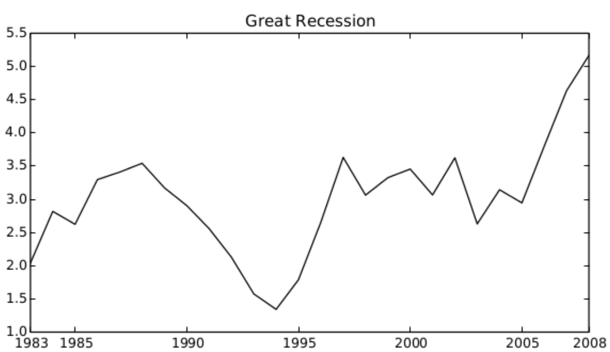
5.2.3.3 *Wealth by Income Group*

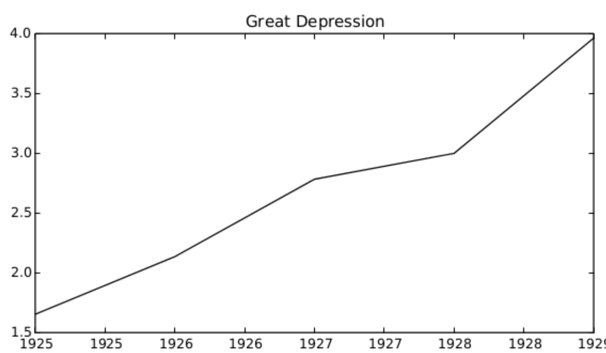




- *Wealth Inequality* INCREASED with *Income Inequality*

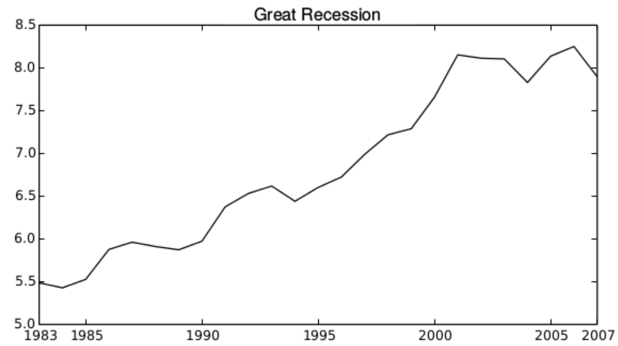
5.2.3.4 *Leverage and Crisis Probability*

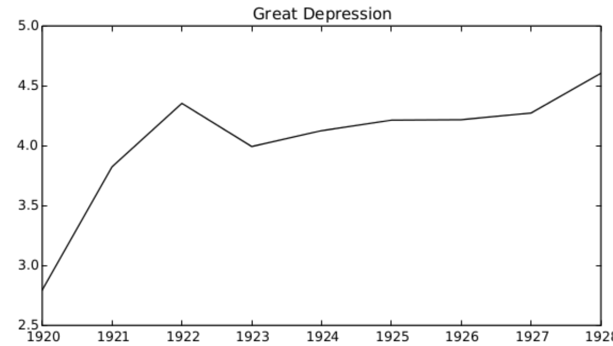




- ***Schularick and Taylor (2012)*** "Crisis Probabilities" INCREASED Dramatically: (i) from ***2% to 5%*** prior to the Great Recession. (ii) from ***1.5% to 4%*** prior to the Great Depression.

5.2.3.5 *Size of the Financial Sector*





- Both variables ***moved up together*** *pre-1929* and *pre-2007* crisis periods.

5.2.4 The Model - Overview

Economy consists of two *separate HH groups*, ***top earners*** (top 5% of incomes) and ***bottom earners*** (bottom 95% of incomes). Economy experiences *successive* and *permanent* drops in the income share of ***bottom earners***. There is *no production* in this economy.

The response of ***top earners***: **(1)** Higher *consumption* c; **(2)** Higher *financial wealth accumulation* (through savings) = loans to ***bottom earners***

- Intuition: Wealth in utility $\implies$ positive *marginal propensity to save* (MPS). This is in line with ***Carroll (2000)***

The response of ***bottom earners***: **(1)** Lower consumption c; **(2)** Much higher borrowing from ***top earners*** = higher risk of financial crisis.

- Intuition: Rational default decision $\implies$ growing benefits of default

Financial Crisis: Debt default (10%) + output contraction.

Main Idea: Inequality$\uparrow \implies$ ***top earners*** savings and lending to ***bottom earners*** $\uparrow \implies$ interest rate in economy $\uparrow \implies$ aggregate debt $\uparrow$ since $\frac{\text{total debt}}{\text{GDP}}\uparrow$; the *bottom earners* may take on too much debt to the point that default is optimal (incentive to default $\uparrow$)

The *timing of the crisis* is unpredictable: the *bottom earners* have following costs: (time-varying *utility cost of defaulting*) + (fixed cost from *output loss*) so the default is unpredictable.

5.2.5 The Model - Details

5.2.5.1 Households (HHs)

Two groups of infinitely-lived HHs: ***top earners***, with population share χ ; ***bottom earners***, with population share $1-\chi$

Total aggregate output y_t is given by an AR(1) stochastic process

$$y_t = (1-\rho_y)\,\overline{y} + \rho_y y_{t-1} + \varepsilon_{y,t}$$

where bar above a variable denotes its steady-state (SS) value. The share of output received by ***top earners*** z_t is also an AR(1) stochastic process, and is given by

$$z_t = (1-\rho_z)\,\overline{z} + \rho_z z_{t-1} + \varepsilon_{z,t}$$

- $z_t \uparrow \implies$ income inequality $\uparrow$
- $\varepsilon_{y,t} \sim WN\,(\sigma_y)$ and $\varepsilon_{z,t} \sim WN\,(\sigma_z)$

5.2.5.2 Top Earners (top 5% of HHs)

Top earners maximize their (lifetime) intertemporal utility function

$$U_t = E_t \left[\sum_{k=0}^{\infty} (\beta_\tau)^k \left\{ \frac{\left(c_{t+k}^\tau\right)^{1-\frac{1}{\sigma}}}{1-\frac{1}{\sigma}} + \underbrace{\varphi \cdot \frac{\left(1 + \overbrace{b_{t+k} \cdot \left(\frac{1-\chi}{\chi}\right)}^{\text{total debt per capita (in terms of \textbf{top earners} ONLY)}}\right)^{1-\frac{1}{\eta}}}{1-\frac{1}{\eta}}}_{\textbf{Carrol (2000)} \text{ component}} \right\} \right]$$

- c_t^τ= ***top earners***' per capita consumption
- $b_t \cdot \left(\frac{1-\chi}{\chi}\right)$ = ***top earners'*** per capita tradable financial wealth, which takes the form of loans to ***bottom earners***
- β_τ= ***top earners***' subjective discount factor; σ and η parameterize the curvature of the utility function with respect to *consumption* and *wealth.* These preferences nest the standard case of constant relative risk aversion (CRRA) consumption preferences for $\varphi = 0$.

When ***top earners*** lend to ***bottom earners***, they offer p_t units of consumption today.

- CASE I (***bottom earners*** default): ***top earners*** receive $(1-h)$ units of consumption tomorrow, where $h \in [0,1]$ is the haircut parameter, the proportion of loans defaulted on in a crisis. Bottom earners default only rarely, because doing so entails large output and utility losses.
- CASE II (***bottom earners*** don't default): ***top earners*** receive 1 unit of consumption tomorrow.

Consumption of each *top earner* is given by the budget constraint:

$$c_t^\tau = \underbrace{y_t z_t \frac{1}{\chi}}_{\text{share of aggregate output allocated to \textbf{top earners} (per capita)}} + \left(\overbrace{l_t - b_t p_t}^{\text{\$ received from period } t-1 \text{ lending - \$ received from period } t \text{ lending}} \right) \cdot \frac{1-\chi}{\chi}$$

- b_t = amount of debt per *bottom earner* ***issued*** in period t (at price p_t, to be repaid in period $t+1$)
- l_t = amount of debt per *bottom earner* ***repaid*** in period t
- The decision to default is given by $\delta_t \in \{0,1\}$, where $\delta_t = \begin{cases} 0 & \text{if no default} \\ 1 & \text{default} \end{cases} \implies l_t = b_{t-1}(1-h\delta_t) = \begin{cases} b_{t-1} & \text{if } \delta_t = 0 \\ b_{t-1} \cdot (1-h) & \text{if } \delta_t = 1 \end{cases}$

The *top earners* maximize their intertemporal utility function SUBJECT TO (budget constraint) $c_t^\tau = y_t z_t \frac{1}{\chi} + (l_t - b_t p_t) \cdot \frac{1-\chi}{\chi}$ **and** $l_t = b_{t-1}(1-h\delta_t)$

Their *pricing equation* for 1 unit of consumption TOMORROW (i.e. price of LENDING) is:

$$p_t = \beta_\tau E_t \left[\left(\frac{c_{t+1}^\tau}{c_t^\tau} \right)^{-\frac{1}{\sigma}} (1 - h\delta_{t+1}) \right] + \varphi \frac{\left(1 + b_t \frac{1-\chi}{\chi}\right)^{-\frac{1}{\eta}}}{(c_t^\tau)^{-\frac{1}{\sigma}}}$$

- Intuition: $\varphi \uparrow \implies p_t \uparrow$
- Intuition: $c_t^\tau \uparrow$ (LARGER the consumption of **top earners**) $\implies p_t \downarrow$

5.2.5.3 Bottom Earners (bottom 95% of HHs)

Bottom earners maximize their (lifetime) intertemporal utility function

$$V_t = E_t \left[\sum_{k=0}^{\infty} (\beta_b)^k \left\{ \frac{\left(c_{t+k}^\tau\right)^{1-\frac{1}{\sigma}}}{1 - \frac{1}{\sigma}} \right\} \right]$$

where we can clearly see that ONLY ***top earners*** derive utility from wealth.

- c_t^b= ***bottom earners***' per capita consumption
- β_b= ***bottom earners***' subjective discount factor; parameter σ takes the same value, as for ***top earners*** (where $\beta_b > \beta_\tau$)

Consumption of each *bottom earner* is given by the budget constraint:

$$c_t^b = \underbrace{y_t (1 - z_t)(1 - u_t) \frac{1}{1-\chi}}_{\text{share of aggregate output allocated to } \textbf{bottom earners} \text{ (per capita)}} + \overbrace{(b_t p_t - l_t)}^{\text{consumption financed by borrowing}}$$

- u_t = fraction of *bottom earners'* endowment that is absorbed by a penalty for current or past defaults.
- $y_t \cdot (1 - z_t) u_t$ = **output loss** to the economy
- u_t is given by $u_t = \rho_u u_{t-1} + \gamma_u \delta_t$ where the ***impact effect of a default*** is given by γ_u , while the ***decay rate*** (in absence of further defaults) is ρ_u

The *bottom earners* maximize their intertemporal utility function SUBJECT TO (budget constraint) $c_t^b = y_t (1 - z_t)(1 - u_t) \frac{1-\chi}{\chi} + (b_t p_t - 1)$ **and** $u_t = \rho_u u_{t-1} + \gamma_u \delta_t$

Their pricing equation for 1 unit of consumption TOMORROW (i.e. price of borrowing) is:

$$p_t = \beta_b E_t \left[\left(\frac{c_{t+1}^b}{c_t^b} \right)^{-\frac{1}{\sigma}} (1 - h\delta_{t+1}) \right]$$

5.2.5.4 Endogenous Default

At the beginning of period t , ***bottom earners*** choose whether to default on their past debt b_{t-1} . This, together with the haircut parameter h , defines the amount l_t that ***bottom earners*** repay during period t , according to equation. Their lifetime consumption utility V_t is a function of the state of the economy $s_t = (l_t, y_t, z_t, u_t)$and is recursively defined by

$$V(s_t) = \frac{\left(c_t^b\right)^{1-\frac{1}{\sigma}}}{1 - \frac{1}{\sigma}} + \underbrace{E_t [V(s_{t+1})]}_{\text{continuation value}}$$

where the decision to default δ_t is a rational choice made at the beginning of the period, given the pre-default **state variables**

$$\hat{s}_t = (b_{t-1}, y_t, z_t, u_{t-1})$$

by comparing the lifetime consumption utility values of ***defaulting*** $V_t^D = V(\hat{s}_t, \delta_t = 1)$ and ***not defaulting*** $V_t^N = V(\hat{s}_t, \delta_t = 0)$.

Bottom earners default when $V_t^D - V_t^N > \xi_t$where ξ_t is some *i.i.d* additive utility cost of default, following ***Pouzo and Presno (2012).*** *The decision to default* is given by:

$$\begin{aligned}\delta_t =& \underset{\delta_t \in \{0,1\}}{\text{argmax}} \left\{V_t^D - \xi_t, V_t^N\right\} \\ V_t^D =& V\left(b_{t-1} \cdot (1-h_t), y_t, z_t, \rho_u u_{t-1} + \gamma_u\right) \\ V_t^N =& V\left(b_{t-1}, y_t, z_t, \rho_u u_{t-1}\right)\end{aligned}$$

The distribution of δ_t is a function of the distribution of ξ_t. Specifically, $Prob\left(\delta_t = 1 \middle| \hat{s}_t\right) = CDF\left(V_t^D - V_t^N\right) = \begin{cases} \frac{\psi}{1+exp\left\{-\theta \cdot \left(V_t^D - V_t^N\right)\right\}} & \text{if } \left(V_t^D - V_t^N\right) < \infty \\ 1 & \text{if } \left(V_t^D - V_t^N\right) = \infty \end{cases}$ where we can see that the CDF of $\xi_t = \left(V_t^D - V_t^N\right)$ takes on a *modified Logistic form* and where $\psi < 1$.

- ψ = parameter that helps to determine the mean level of crisis probability over the sample.
- θ = parameter that determines the curvature of crisis probability with respect to the difference $\left(V_t^D - V_t^N\right)$

Intuition: Over the economically relevant range, ***default occurs with positive probability*** but ***never with certainty***. HHs expectations about the *likelihood of a crisis* ↑ when the difference $\left(V_t^D - V_t^N\right)$ ↑ but HHs can't expect the *timing of a crisis.* In addition, we can think of the shock ξ_t as some coordination mechanism that induces the *bottom earners* to default.

5.2.5.5 Equilibrium

In equilibrium, ***top earners*** and ***bottom earners*** maximize their respective lifetime utilities, the market for borrowing and lending clears, and the market clearing condition for goods holds:

$$y_t - \underbrace{y_t (1-z_t) u_t}_{\text{total output loss from BOTTOM defaulting}} = \chi c_t^{\tau} + (1-\chi) c_t^b$$

5.2.5.6 ISSUES with the model

1. The authors assume the *bottom earners* are homogeneous (representative *bottom earner* agent) — default is a "collective action" that occurs contemporaneously.
2. In the event of default, only the *bottom earners* face an output loss. This is inconsistent with what happens in reality: the *very top income* earners also experience output loss.

5.2.6 The Model - Results

The model combines two key mechanisms:

1. ***Mechanism 1: Debt Accumulation***
   - the *accumulation of debt by* ***bottom earners*** following a permanent INCREASE in income inequality
2. ***Mechanism 2: Rational Default***
   - a rational default decision, with default probabilities ↑ in the level of debt

5.2.6.1 Calibration

Parameters estimated using data from the period *1983-2009* at annual frequency.

TABLE 1—CALIBRATION OF THE BASELINE MODEL EXCEPT DEFAULT

	Source/target	Implied values
Panel A. Directly calibrated parameters		
Steady-state output level	Normalization	$\overline{y} = 1$
Population share of top earners	5 percent	$\chi = 0.05$
Steady-state real interest rate	Literature	$\beta_b = 1.04^{-1}$
Ies in consumption	Literature	$\sigma = 0.5$
Panel B. Indirectly calibrated parameters		
Top earners' weight on wealth in utility	MPS of top earners	$\varphi = 0.05$
Top earners' wealth elasticity	MPS of top earners	$\eta = 1.09$
Steady-state top 5 percent income share $\overline{\tau}$	Data: 21.8 percent in 1983	$\overline{z} = 0.1807$
Steady-state debt-to-income ratio $\overline{\lambda}$	Data: 62.3 percent in 1983	$\beta_\tau = 0.912$
Panel C. Exogenous stochastic processes		
Output	Estimated	$\rho_y = 0.669$
		$\sigma_y = 0.012$
Output shares	Estimated	$\rho_z = 1$
		$\sigma_z = 0.008$

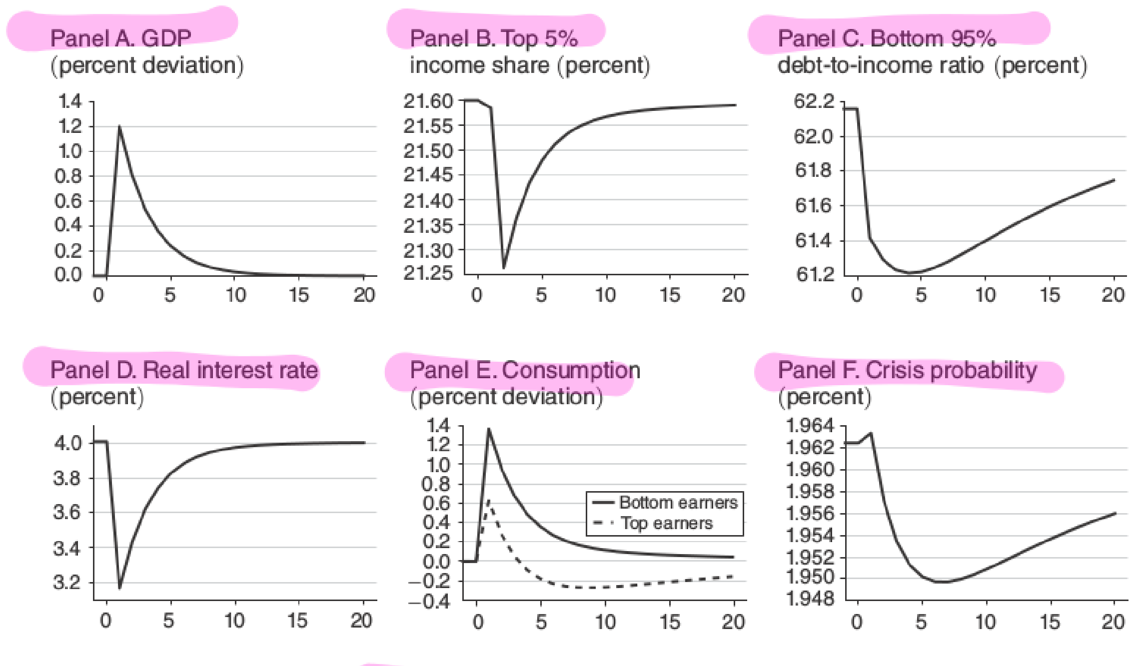
TABLE 2—CALIBRATION OF THE MODEL'S DEFAULT PARAMETERS

	Source/target	Implied values
Default parameters		
Haircut (percent of loans defaulted)	Data (cf. Section IE)	$h = 0.1$
Output penalty	Output costs of 2008 crisis	$\gamma_u = 0.04$
	Size and depth	$\rho_u = 0.65$
Random utility cost of default	Schularick and Taylor (2012)	$\psi = 0.15$
	Default probabilities (1983–2008)	$\theta = 18$

- It is important to note that in the calibration, the exogenous stochastic process for z_t is a RANDOM WALK $\Longrightarrow$ shocks to z_t are ***PERMANENT***

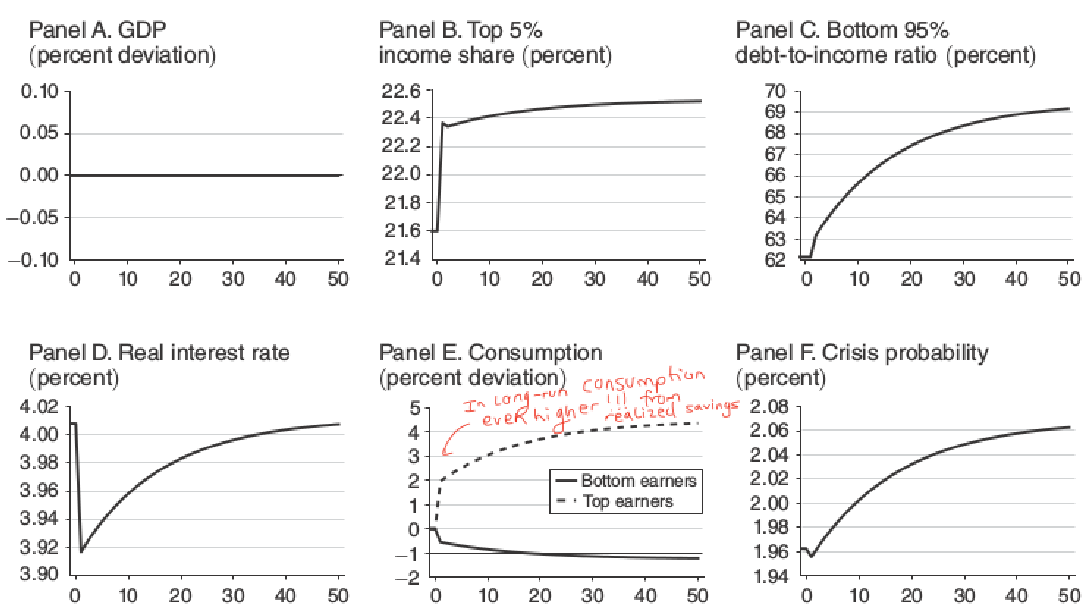
5.2.6.2 Impulse Responses

This figure shows a one σ positive shock to aggregate output y_t. This shock allows both ***top earners*** and ***bottom earners*** to INCREASE their consumption:



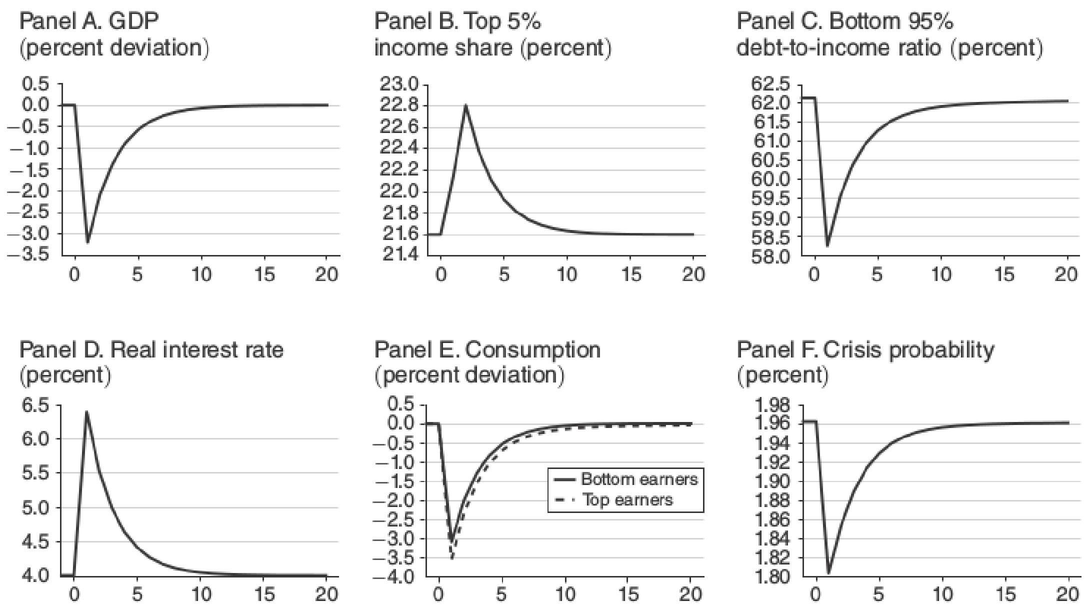
- equilibrium *loan* interest rate ↓ by around 85 basis points on impact, with a subsequent ↑ back to its long-run value that mirrors the gradual ↓ in output (*bottom earners* want to borrow as output ↓, so *top earners* demand a higher loan interest rate).
- equilibrium *loan* interest rate ↓ represents an additional income again for *bottom earners* relative to *top earners* so we have τ_t ↓ also as $(1 - \tau_t)$ ↑.

This figure shows a one σ positive ***permanent*** shock to the output share z_t. The top 5% income share τ_t immediately ↑ by 0.8%, accompanied by a downward jump of 0.5% in *bottom earners*' consumption and an upward jump of 1.9% in *top earners*' consumption:



- The long-run ↑ in *top earners'* consumption is even larger, because they initially limit their additional consumption in order to accumulate additional financial wealth.
- The real interest rate ↓ on impact by 9 basis points, due to the ***increase in credit supply*** from *top earners* that initially limits the drop in consumption of *bottom earners.*
- This *income distribution* shock is ***small*** compared to what occurred over the period 1983–2008.

This figure shows the impulse response for a *crisis shock*:



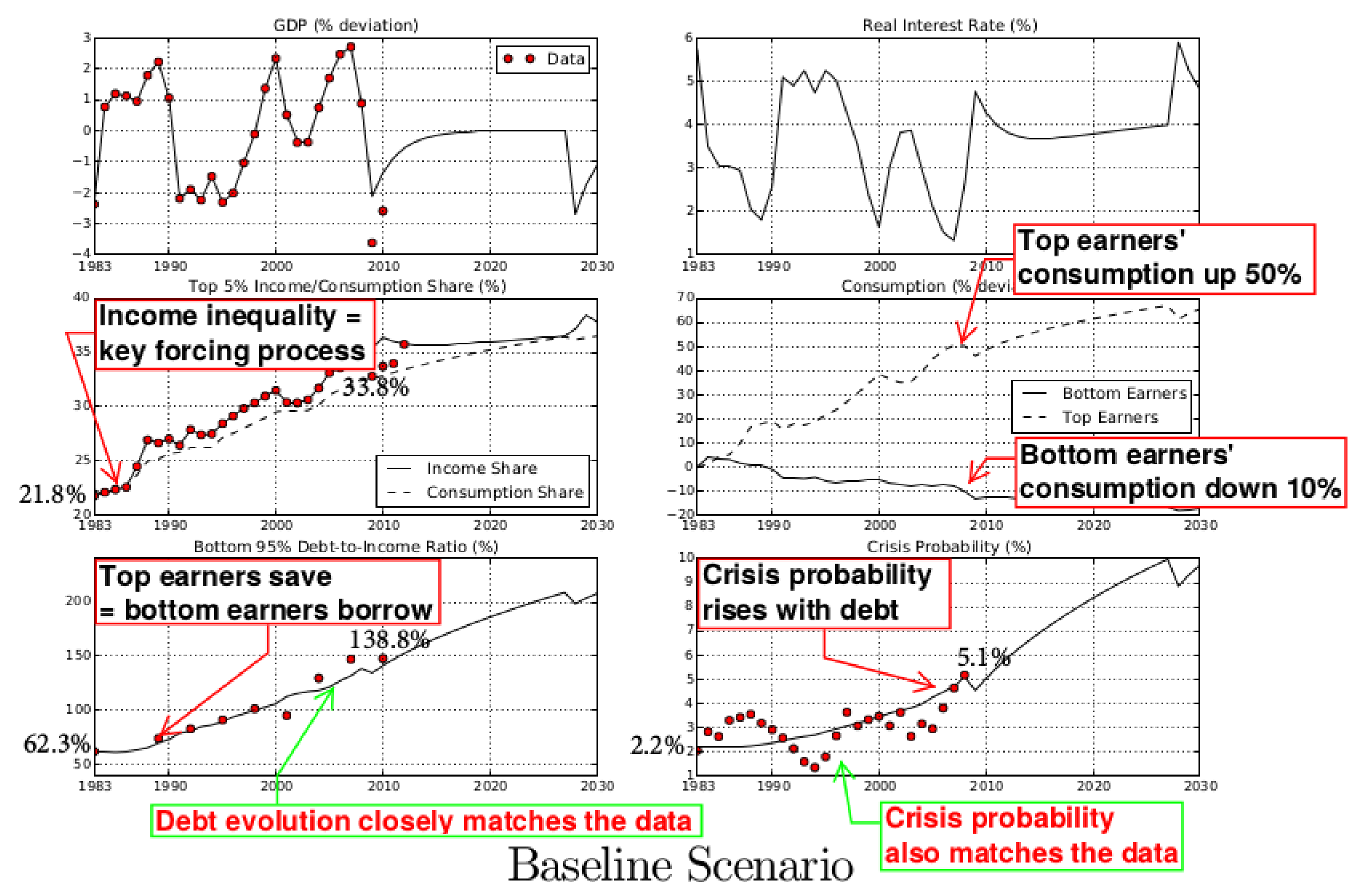
- *Bottom earners* default on 10% of their loans, but they also experience a 4% income loss due to the output costs of default, which are suffered exclusively by this group of agents.
- As a result, *bottom earners* $\frac{\text{debt}}{\text{income}}$ ratio only drops by around 3.9%
- The impact effect on the real economy is a 3.2% loss in GDP, followed by a V-shaped recovery.

5.2.6.3 Baseline Simulation

The figure below shows the central simulation of the paper. The variables shown are the same, and are shown in the same units, as in the impulse responses above.

- The horizontal axis represents time, with the simulation starting in 1983 and ending in 2030.
- The circular markers represent ***actual US data***, while the lines represent ***model simulations***.
- The data for GDP and for the top 5% income share are used as forcing processes that pin down the realizations of the shocks $\varepsilon_{y,t}$ and $\varepsilon_{z,t}$ between 1983 and 2008. Post-2008 data for GDP and the top 5% income share are shown but are not used as forcing processes.
- They assume that a crisis shock hits in 2009. The crisis event in 2009 is characterized by output losses that are somewhat lower than observed during the Great Recession. Starting in 2009, the model is *simulated* assuming a *random sequence of utility cost shocks*, but no further nonzero realizations of output or output share shocks.
- MPS of *top earners* = 0.397.

The key forcing variable is the ↑ in the top 5% income share from **21.8%** in 1983 to **33.8%** in 2008. Under the *random sequence of utility cost shocks* used in our simulation, the model generates one subsequent crisis in 2028.



Empirical Performance of the Model: The crucial implication of the MPS-based calibration is that the 1983–2007 evolution of the $\frac{\text{debt}}{\text{income}}$ ratio of *bottom earners* can be used to evaluate the quantitative performance of the model.

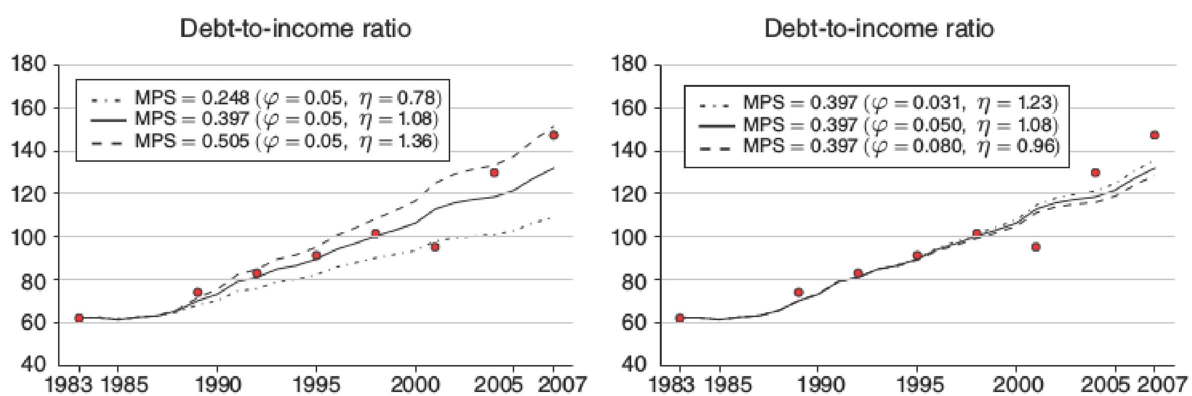


FIGURE 12. SENSITIVITY ANALYSIS

The left subplot of the above figure illustrates that this performance depends on the calibrated value of the MPS. For this figure, they calibrate the model based on the baseline $\boldsymbol{MPS = 0.397}$, the upper bound $\boldsymbol{MPS = 0.505}$, and the lower bound $\boldsymbol{MPS = 0.248}$.

- Their baseline simulation is reproduced as the solid line, the data as circular markers, and lower and upper bound MPS as dash-dotted and dotted lines. Differences in MPS are calibrated by holding φ at its baseline value of 0.05 and varying η , with a higher η (higher MPS) implying that *top earners* allocate a larger share of their additional income to financial wealth accumulation. The interest rate adjusts to ensure that this higher credit supply is taken up by *bottom earners*, who end up with a higher $\frac{\text{debt}}{\text{income}}$ ratio.
- Baseline tracks the data very well, except for around 25%-30% of debt growth in the 2000s: *Explanation for the 2000s*: Global saving glut, which is left since this is a closed-economy.

The right subplot of the above figure shows that, once a MPS has been chosen (in this case the baseline $\boldsymbol{MPS = 0.397}$), differences in the combinations of φ and η that give rise to that MPS have only a very small effect on the model's predictions: **What matters is therefore primarily the MPS itself**!

Overall, baseline model explains ≈100% of the increase in the $\frac{\text{debt}}{\text{income}}$ ratio of *bottom earners* over the first 15 years of the period of interest (1983–1998), and ≈ 70% over the last 9 years (1998–2007).

Conclusion: Income inequality = fundamental driver of the 2008 crisis.

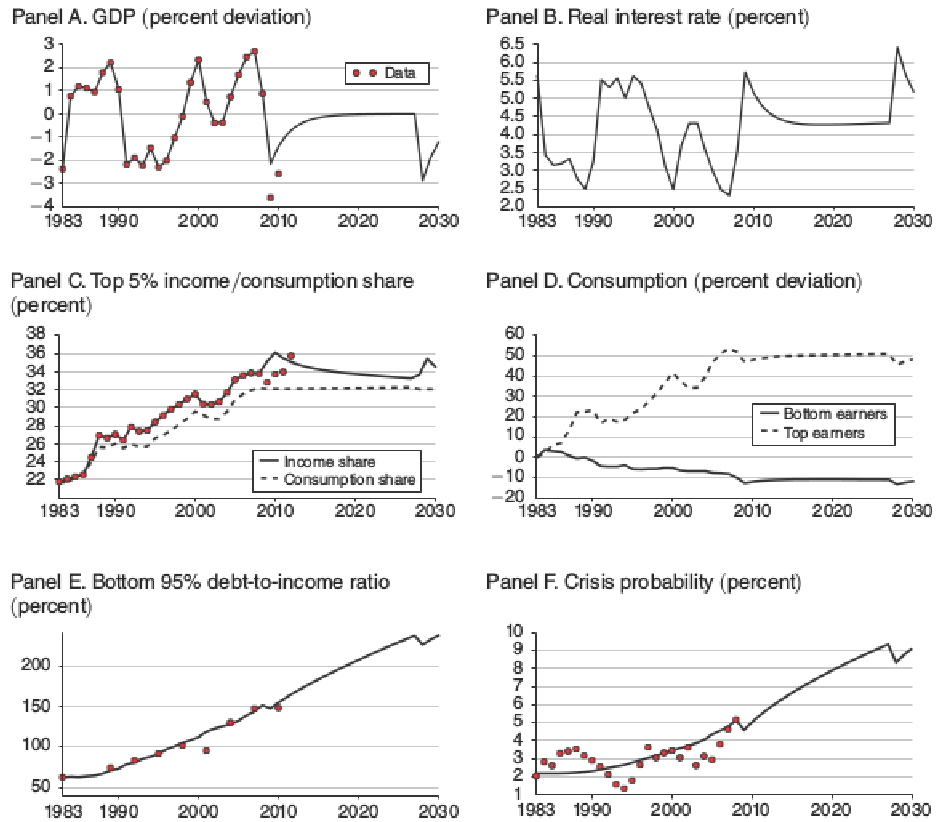
5.2.6.4 Alternative Scenario: Pure Consumption Smoothing and Shock Persistence.

In the baseline scenario, *bottom earners*' debt ↑ due to INCREASED credit supply from *top earners*. The reason is that *shocks to the income distribution* are **permanent**, so that neither *bottom earners* nor *top earners* have an incentive to smooth consumption, while top earners have a strong incentive to accumulate wealth.

It is nevertheless interesting to ask what quantitative role ***pure consumption smoothing***, in the complete absence of a wealth accumulation motive, could play if shocks to the income distribution were perceived to be *more temporary*.

- *top earners* would have no motive to accumulate wealth for its own sake, while both *bottom* and *top earners* would have a stronger incentive to borrow and lend to smooth consumption.
- In this scenario: there is an increased role for ***credit demand*** relative to ***credit supply***.

Wealth does not enter the utility function of *top earners* ($\varphi = 0$), both income groups are equally "patient" $\left(\beta_b = \beta_\tau = \frac{1}{1.04}\right)$, and shocks to the inequality process are *highly persistent* but only ***temporary***. The initial values of all endogenous variables are identical to the baseline case. The results are shown in the figure below, under the assumption $\rho_z = 0.98$.



- For a *less persistent* z_t, the ***consumption smoothing motive*** is much stronger since *bottom earners* continually expect their income to revert to a much higher level over a fairly short period.

- The cumulative effect of this perception, which would represent large and one-sided forecast errors over the 1983–2008 period, would be a *much larger build-up of debt*!

5.2.6.5 Alternative Scenario: Kumhof, Rancière, and Winant (2013)

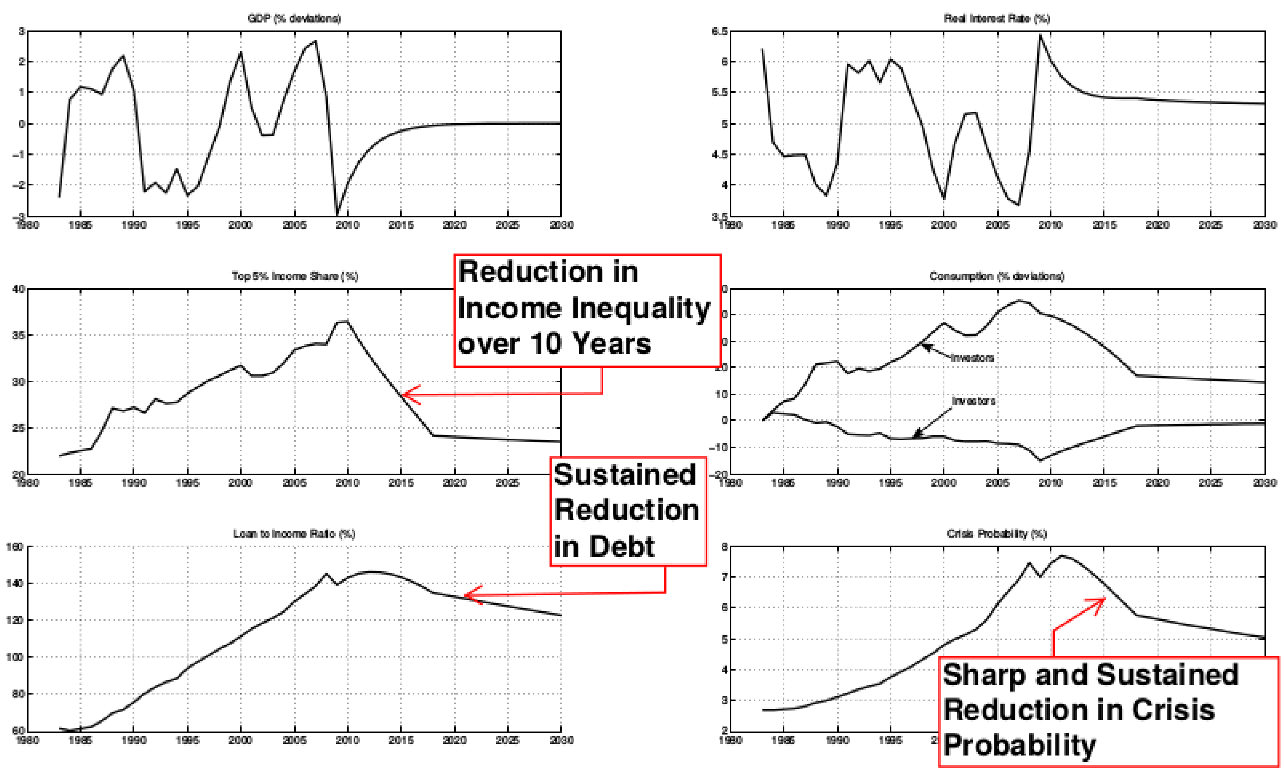
They look at the consequences of a *reversal* of the post-1983 ***increase in income inequality*** over a period of 10 years. They find that this would lead to a sustained reduction in *leverage* that would *significantly REDUCE* the probability of further crises.

7 Alternative Scenario: Gradual Reduction in Income Inequality Reduces Crisis Probability

- **Roosevelt 1936-1944:**
  - Top 5% income share reversed the 1920s increase.
  - Household debt reversed the 1920s increase.
  - This started well before the war.

- **Scenario:** Bottom earner output share returns to 1983 value over 10 years.

- **Debt Level Reductions:**
  - Crisis Alone: Only very short-lived effects.
  - Reduced Income Inequality: Sustained and large effects.
  - Bottom earners now have the means to pay down their debt over time.
  - This also reduces crisis probability in a major way.



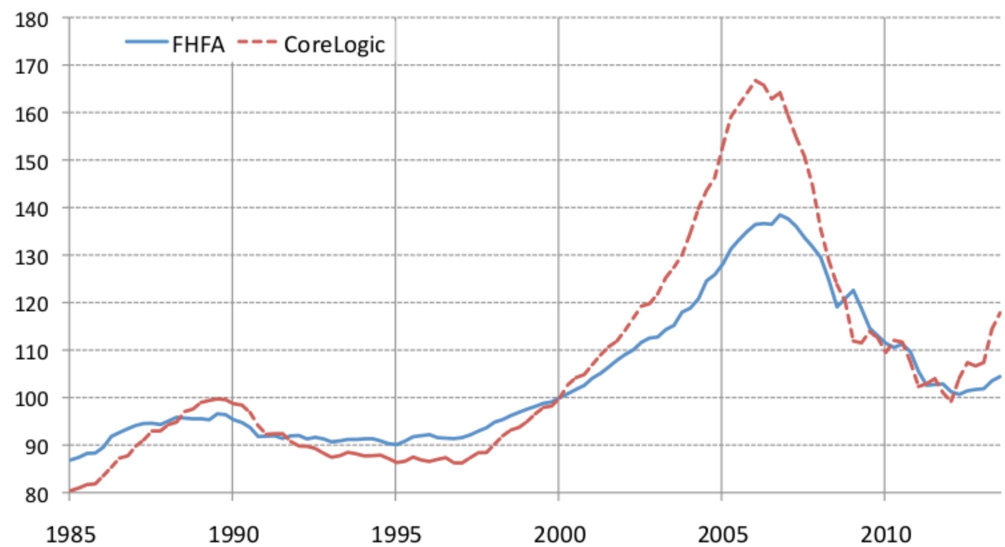
5.3 Justiniano, Primiceri, and Tambalotti (FRBNY Working Paper, 2014): *Credit Supply and the Housing Boom*

Abstract: An increase in credit supply driven by looser *lending constraints* in the mortgage market can explain four empirical features of the housing boom before the Great Recession: the unprecedented rise in home prices, the surge in household debt, the stability of debt relative to house values, and the fall in mortgage rates. These facts are more difficult to reconcile with the popular view that attributes the housing boom only to looser *borrowing constraints* associated with lower collateral requirements, because they shift the demand for credit. In fact, a slackening of collateral constraints at the peak of the lending cycle triggers a fall in home prices in our framework, providing a novel perspective on the possible origins of the bust

5.3.1 Motivation

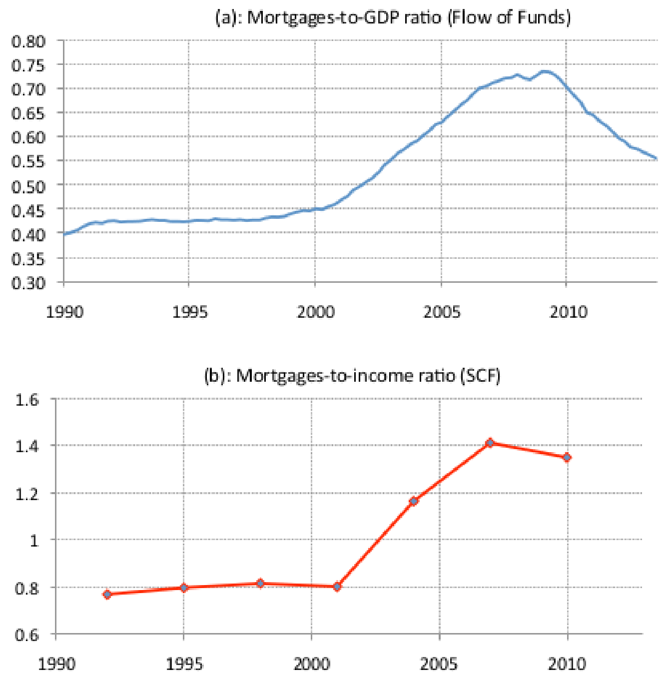
Four facts characterize the behavior of housing and mortgage markets in the period leading up to the collapse in house prices and the ensuing financial turmoil of 2007.

1. ***House prices rose dramatically and then declined***. Between 2000 and 2006 real home prices increased roughly between 40 and 70 percent, depending on measurement, as shown in the figure below. This unprecedented boom was followed by an equally spectacular bust after 2006.

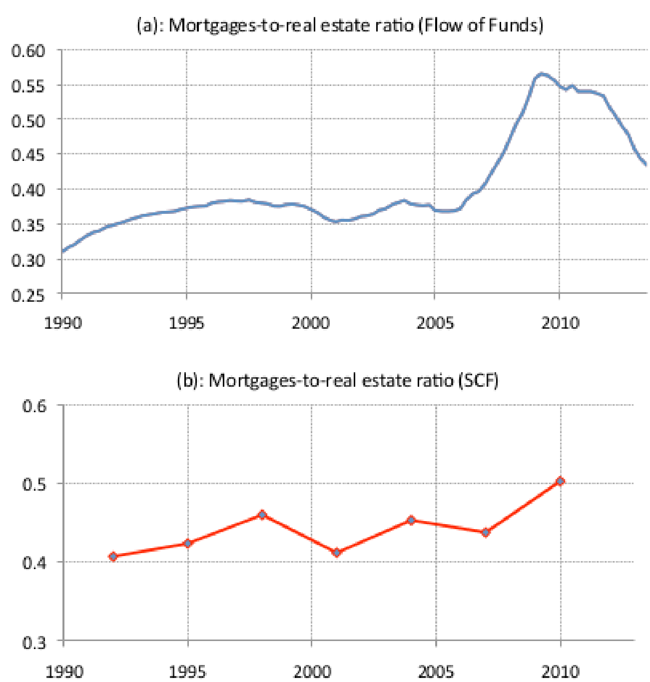


- *Unprecedented boom — bust cycle in house prices*

2. ***Massive HH mortgage debt accumulation, and then deleveraging***. This is illustrated in the figure below for both the *aggregate HH sector* and for *financially constrained HHs* in the Survey of Consumer Finances (SCF) — the group that is most informative for the parametrization of their model.



3. ***Mortgage debt and house prices increased in parallel***. As a result, the ***Leverage (i.e.*** $\frac{debt}{collateral}$ ***ratio) remained roughly unchanged*** into 2006. This often under-appreciated fact is documented in the figure below, which also shows that this *aggregate measure of HH leverage* spiked only when home values collapsed before the recession.



4. ***Real mortgage rates declined***. The figure below plots the 30-year conventional mortgage rate minus various measures of inflation expectations from the Survey of Professional Forecasters. It shows that *real*

*mortgage rate*s fluctuated around 5% during the 1990s, but fell by 2 to 3 percentage points as the housing boom unfolded.

The authors study these events in a *simple general equilibrium framework* that draws a particularly stark distinction between the ***supply*** and ***demand for credit***.

- **Demand side**: *collateral constraints* limits HHs' ability to borrow against the value of real estate, as in the large literature spawned by Kiyotaki and Moore (1997).
- **Supply side**: lending constraints — or, equivalently, a *leverage restriction on financial institutions*—impedes the flow of savings to the mortgage market.

It is harder to reproduce the same stylized facts as resulting only from a relaxation of *collateral requirement*s, which is how the literature based on Kiyotaki and Moore (1997) usually accounts for the recent credit cycle. In these models, *looser collateral requirement*s shift ***credit demand***, generating counterfactual implications for interest rates and aggregate LTV. The authors' paper shares with this literature the same *borrowing constraint*, but it complements it with a *limit to lending*. The interaction between these two constraints is their model's main novel mechanism, and the source of its interesting dynamics.

- **Question:** What is the fundamental driver behind these facts?
- **Answer:** An increase in credit supply brought about by looser lending constraints. Consistent with
  - decline in mortgage rates
  - large increase in house prices
  - constant debt-to-collateral ratio during the boom
- Looser collateral requirements not an important driving force of the boom. At odds with the behavior of
  - mortgage rates, house prices, household leverage
- Excessive loosening of collateral requirements can explain why house prices started to fall, even if liberalization was in full swing

- Importance of borrowing constraints in the boom-bust of the 2000s
  - Boom: Favilukis, Ludvigson, Van Nieuwerburgh (2013), Boz and Mendoza (2012), Garriga, Manuelli and Peralta-Alva (2012), Midrigan and Philippon (2011)
  - Bust: Guerrieri and Lorenzoni (2012), Eggertsson and Krugman (2012), Hall (2012)
  - We concentrate on barriers to lending and their interaction with collateral constraints
- Constraints on composition of balance sheet of intermediaries
  - Gertler and Kiyotaki (2010), Gerali et al. (2010), Adrian and Shin (2010), Adrian and Boyarchenko (2012 and 2013), Dewachter and Wouters (2012), He and Krishnamurty (2013), Brunnermeier and Sannikov (2014), etc…
  - We concentrate on the link between the availability of credit, household debt and home price in the 2000s
- Micro-econometric evidence
  - Mian and Sufi (2009, 2011), Ambrose and Thibodeau (2004), Favara and Imbs (2012), Di Maggio and Kermani (2014)

5.3.2 The Model

5.3.2.1 Overview

The model builds on: Kiyotaki and Moore (1997), Iacoviello (2005), Campbell and Hercowitz (2006)

There are two representative HHs: ***Patient HHs***, which lend (indexed by l); ***Impatient HHs***, which borrow (indexed by b)

No production (endowment economy): income is fully exogenous.

Fixed supply of houses (housing supply is *perfectly inelastic*)

5.3.2.2 Borrowers (Impatient HHs) and Lenders (Patient HHs)

The problem of the borrowers

$$\max E_0 \sum_{t=0}^{\infty} \beta_b^t \left[u(c_{b,t}) + v(h_{b,t}) \right]$$

$$c_{b,t} + p_t \left[h_{b,t+1} - (1-\delta) h_{b,t} \right] + R_{t-1} D_{b,t-1} \leq y_{b,t} + D_{b,t}$$

- Borrowing is limited by a collateral constraint

$$D_{b,t} \leq \theta \, p_t \, h_{b,t+1}$$

  - Associated multiplier: $\mu \geq 0$

The problem of the lenders ($\beta_l > \beta_b$)

$$\max E_0 \sum_{t=0}^{\infty} \beta_l^t \left[u(c_{l,t}) + v(h_{l,t}) \right]$$

$$c_{l,t} + p_t \left[h_{l,t+1} - (1-\delta) h_{l,t} \right] + R_{t-1} D_{l,t-1} \leq y_{l,t} + D_{l,t}$$

- Mortgage lending is limited by a lending constraint

$$-D_{l,t} \leq \bar{L}$$

- $c_{j,t}$= consumption of non-durable goods for $j \in \{l, b\}$
- $v_j(h_{j,t})$ = utility of the service flow derived from a stock of houses $h_{j,t}$ owned at the beginning of the period for $j \in \{l, b\}$
- p_t = price of houses in terms of the consumption good; δ = depreciation rate of the housing stock; $y_{j,t}$ = exogenous endowment of consumption goods and new houses for $j \in \{l, b\}$

- $D_{j,t}$= amount of one-period debt accumulated by the end of period t, and carried into period $t+1$, with gross interest rate R_t for $j \in \{l, b\}$. In equilibrium, $D_{b,t} > 0$ and $D_{l,t} < 0$ representing loans that the *patient HHs* extend to the *impatient HHs*.

Collateral Constraint*:** On the liability side of their balance sheet, the *collateral constraint* limits debt to a fraction θ of the value of the borrowers' housing stock, along the lines of ***Kiyotaki and Moore (1997). θ is the *maximum allowed LTV:* $\theta \uparrow \Longrightarrow$ *looser collateral requirements* (e.g. LOWER down payments, multiple mortgages on same property, and more generous home equity lines of credit)

***Lending Constraint*:**

$$-D_{l,t} \leq \overline{L}$$

- In reduced form, captures all factors hampering the free flow of funds from the savers to mortgage financing
- Implicit or explicit, regulatory and technological constraints on mortgage lending
- Example: Money-market funds, pension funds and insurance companies are restricted by regulations to holding only the safest securities
- Isomorphic to a leverage restriction or regulatory-capital requirement in economy with financial intermediaries

From a macroeconomic perspective:

- the ***lending limit*** $\Longleftrightarrow$ ***UPWARD sloping supply of funds*** in the mortgage market
- the ***borrowing limit*** $\Longleftrightarrow$ ***DOWNWARD sloping demand for credit*** in the mortgage market.

Without the lending limit, the supply of funds would be *perfectly elastic* at the lenders' discount rate, thus pinning down the long-run interest rate. In their framework, instead, the steady-state interest rate varies with the tightness of the borrowing and lending constraints. As a result, it falls permanently when the lending constraint is relaxed, as we saw in the data. The *positive slope of the credit supply schedule* is all that matters for this result.

Another property of their stylized economy is that the *lending constraint* also limits HHs' overall ability to save. This equivalence is an artifact of the assumption that mortgages are the only financial asset in the economy, which however is irrelevant for the results since if agents could save without restrictions using another asset, the equilibrium would be unaffected, as long as a limit remains on how much of these savings can be allocated to mortgage financing.

5.3.2.3 Equilibrium Simplifications

***Two additional simplifying assumptions*:** To characterize the equilibrium of the model, they make two convenient functional form assumptions:

1. First, they assume that the lenders' utility function implies a rigid demand for houses at the level $\overline{h}_l$. Thus, in this equilibrium, ***houses are priced by the borrowers***, who are leveraged and face a fiixed $h_{b,t} \equiv \overline{h} - \overline{h}_l$
    - This simple modeling device captures the idea that *houses are priced by the most leveraged individual*s, as in ***Geanakoplos (2010)***, amplifying the potential effects of borrowing constraints on house prices.

2. The second simplifying assumption is that *utility is linear in non-durable consumption.* As a result, the marginal rate of substitution between houses and non-durables does not depend on the latter. Furthermore, the *level and distribution of income* do not matter for the equilibrium in the housing and debt markets, which makes the determination of house prices simple and transparent

Two additional simplifying assumptions

Rigid demand for houses by the lenders	Linear utility in consumption

$$p_t = \frac{\beta_b}{1-\mu_t\theta}\left[mrs^{h,c} + (1-\delta)p_{t+1}\right]$$

- Implications
  - Borrowers are marginal buyers of houses
  - Variation in house prices only due to variation in discounting
- When collateral constraint binds ($\mu > 0$), $\theta\uparrow \rightarrow p\uparrow$

5.3.2.4 Characterization of the Equilibrium

The model of the previous section features two balance sheet constraints, both *limiting the equilibrium level of debt in the economy*.

The *collateral constraint* on the liability side of HHs' balance sheets limits the amount of borrowing to a fraction of the value of¯ their houses.

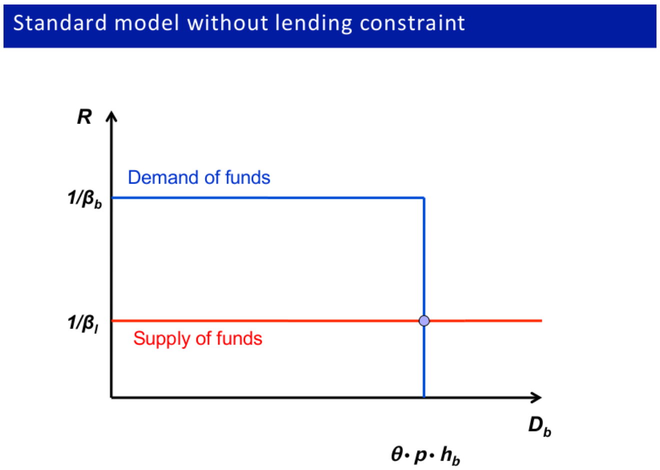
This is a standard tool used in the literature to introduce financial frictions. The *lending constraint*, instead, puts an upper bound on the ability of savers to extend mortgage credit. In this closed economy, where ***borrowing*** = ***lending*** in equilibrium, the lending limit also turns into a constraint on borrowing: $D_{b,t} \leq \bar{L}$.

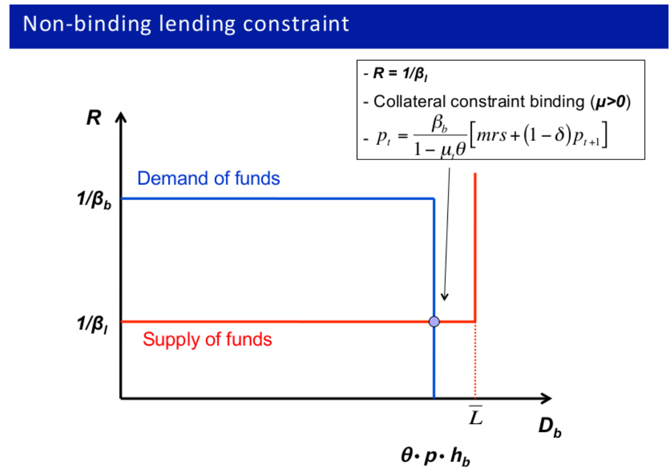
Interaction of borrowing and lending constraints

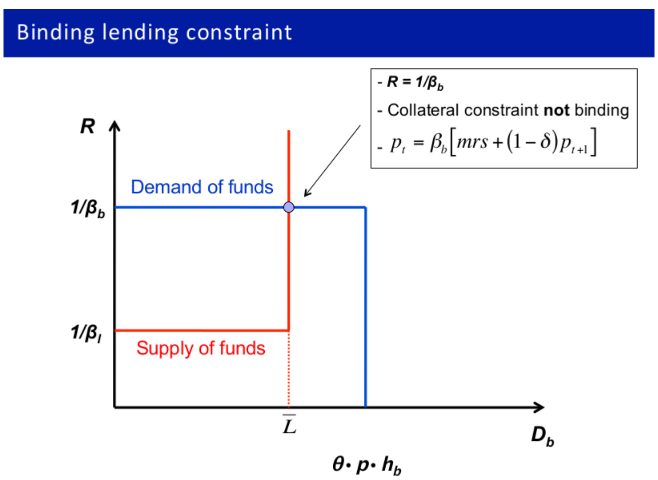
- Borrowing constraint: $\boxed{D_{b,t} \leq \theta\, p_t\, h_{b,t+1}}$
- Lending constraint: $-D_{l,t} \leq \bar{L} \rightarrow \boxed{D_{b,t} \leq \bar{L}}$

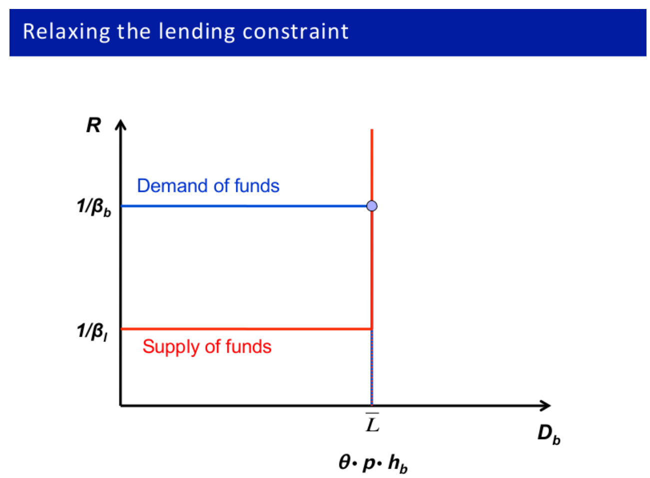
- Which constraint binds is
  - exogenous: $\bar{L}$ and θ
  - endogenous: $p_t = \frac{\beta_b}{1-\mu_t\theta}\left[mrs + (1-\delta)p_{t+1}\right]$

The figures below show what happens to the (steady-state) equilibrium interest rate R, debt D_b of the borrowers, and house price p









Which constraint, *borrowing* or *lending*, binds at any given point in time depends on: θ, $\overline{L}$ (exogenous) and house prices (endogenous).

5.3.2.5 Quantitative Analysis

Calibrate parameters to match ***1990-2000***

Micro data: Survey of Consumer Finances

Taking the model to the data: Challenges

① In the data, many HHs have both mortgages and assets

- Identify borrowers as agents with little liquid financial assets in SCF
- Kaplan and Violante (2012)

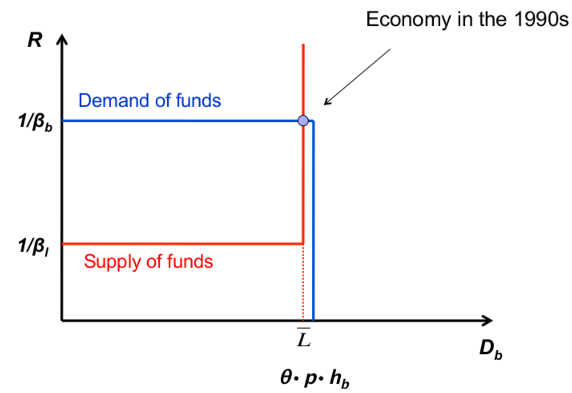
② Standard mortgage contracts specify accumulation of equity

- Replace simple collateral constraint with

$$D_{b,t} \leq \theta\, p_t\, d_t$$
$$d_t = (1-\rho)d_{t-1} + h_{b,t+1} - (1-\delta)h_{b,t}$$

- $\rho = \delta$ ➔ $D_{b,t} \leq \theta\, p_t\, h_{b,t+1}$
- $\rho > \delta$ ➔ HHs accumulate equity over time

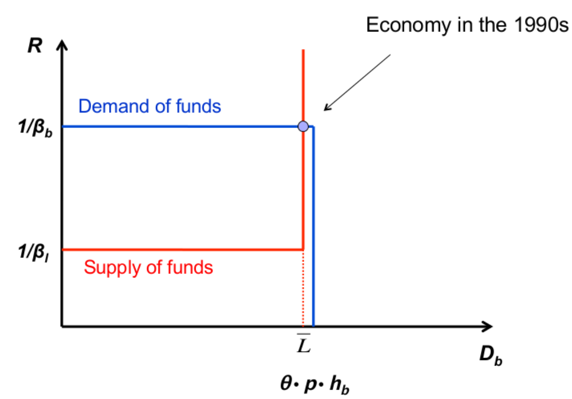
Calibration



Quarterly calibration

Parameter	Value	Source/Target
Discount factor borrower (β_b)	**0.9879**	5% real mortgage rate
Discount factor lender (β_l)	**0.9938**	• 2.5% decline in real mortgage rates • ~ Krusell and Smith (1998) • ~ Carroll et al. (2013)
Depreciation (δ)	**0.003**	Fixed Asset Tables
Maximum LTV (θ)	**0.80**	• Median LTV of new or recently refinanced mortgages of liquidity constrained HHs in the SCF • Evidence from Duca et al. (2012)
Amortization (ρ)	**0.0056**	• Collateral constraint close to binding • Mortgage-to-RE ratio of liquidity constrained HHs in the SCF (43%)

Calibration

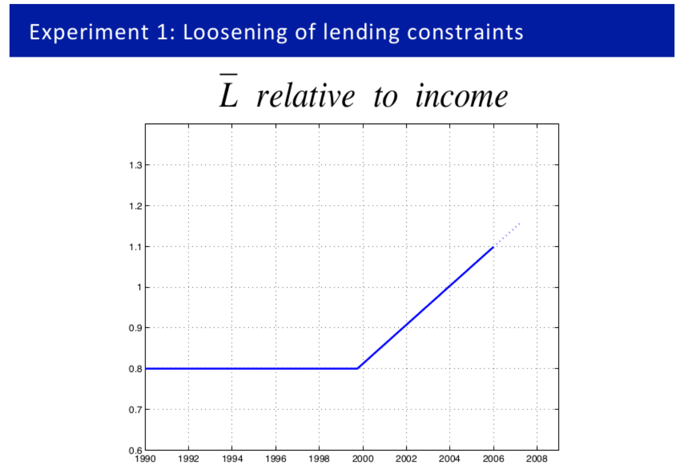


Experiment 1: ***Loosening of lending constraints***

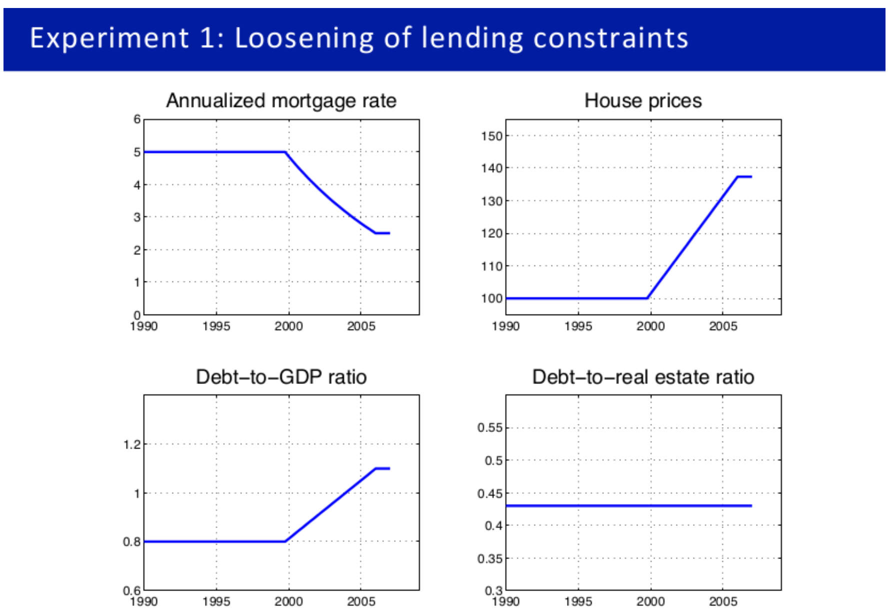
This relaxation captures in reduced form the many developments that made it easier for savings to flow towards the mortgage market, such as the large inflow of foreign funds, and the explosion of securitization and shadow banking. This so-called ***credit liberalization*** started well before the year 2000, but it accelerated significantly around the turn of the millennium.

Experiment 1: Loosening of lending constraints

- Starting in 2000, simulate the effects of a gradual relaxation of mortgage lending constraints
  - Securitization and tranching → pension and money market funds gain access to mortgage lending
  - Securitization and tranching → reduce banks' capital requirements for mortgage lending
  - SIVs allow banks to move assets off balance sheets
    - not counting them towards risk-weighted capital
    - Around 2003 regulators disregarded recommendations to apply to them the same risk-weighted capital requirements as other types of assets, thereby facilitating massive regulatory arbitrage (Acharya and Schnabel, 2009)
  - Foreign capital inflows from Emerging Asia + oil producing countries
    - mostly directed towards Government bonds and Agency MBSs
- Experiment timed to "complete" the transition in 2006



- The premise for this exercise is that at the end of the 1990s the U.S. economy was constrained by a ***limited supply of credit***. Starting in 2000, the *lending constraint* is gradually lifted, following the linear path depicted in the right panel of the figure above. Each movement in $\overline{L}$ is *unanticipated* by the agents and the experiment is timed so that the *lending constraint* doesn't bind in 2006 .
- The figure below plots the response of the key variables in the model to the loosening of $\overline{L}$ described above.



- credit supply ↑ $\Longrightarrow$ real mortgage rates ↓ by 2.5%. This decline reflects the gradual transition from a ***credit-supply-constrained economy***, where the interest rate equals $R = \frac{1}{\beta_b}$, to an economy that is ***credit-demand-constrained economy***, with a lower interest rate $R = \frac{1}{\beta_b}$ .This *permanent fall in mortgage rates* is a distinctive feature of our environment with *lending constraints* that can't be replicated in standard models with only a *borrowing limit*, since their steady state interest rate is always pinned down by the *discount factor of the lenders.*
- As interest rate ↓, borrowing and consuming more TODAY is more desirable, shadow value of relaxing the collateral constraint $\mu_t \uparrow \Longrightarrow$ value of houses p_t ↑to the borrowers.
- This substantial ↑ in house prices relaxes the collateral constraint in equilibrium, allowing HHs to borrow more against the higher value of their homes. In the model, mortgage debt rises by approximately 30 percentage

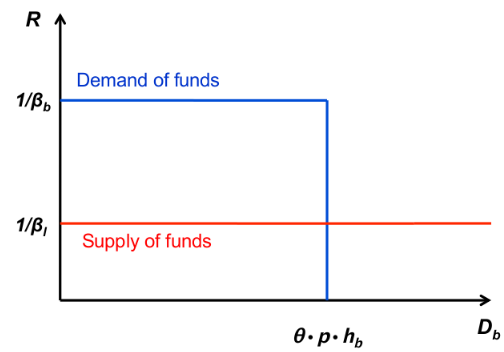
points of GDP. However, the ***debt-to-real estate ratio*** remains unchanged, since ***debt and home values increase in parallel***, as they did in the data previously shown.

Experiment 2: ***Loosening of collateral constraints***

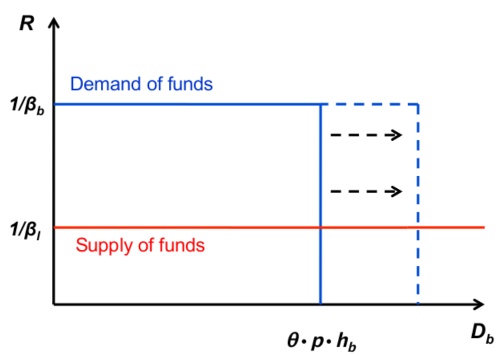
Experiment 2: Loosening of collateral requirements

- Standard model without lending constraints
- Simulate the effects of a gradual relaxation of collateral requirements

Standard model without lending constraint



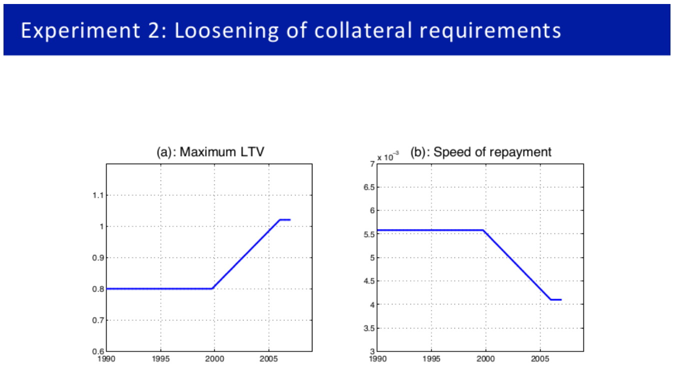
Standard model without lending constraint

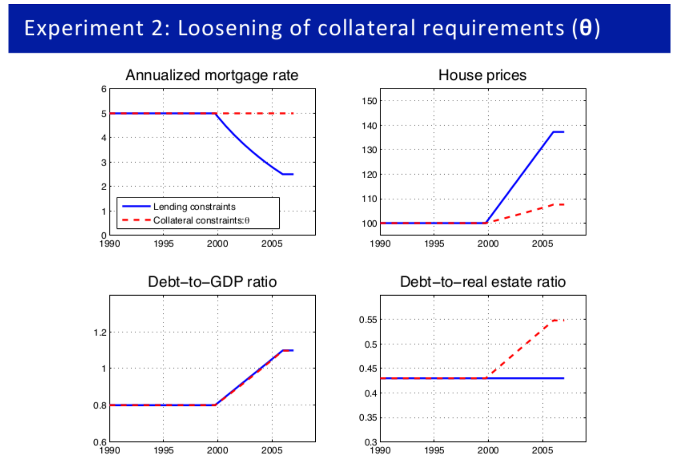


Experiment 2: Loosening of collateral requirements

- Standard model without lending constraints
- Simulate the effects of a gradual relaxation of collateral requirements
  - **θ** from 0.8 to 1.02, to match the increase in HH debt of experiment 1

- There is a gradual *increase* in the maximum LTV from $\theta = 0.8$ to $\theta = 1.02$ (seen in left panel of figure below). This change in θ is chosen to generate exactly the same *increase* in HH debt as in ***Experiment 2***, making the two simulations easily comparable.
- (right panel of figure below): interest rates do not change, since *lenders are unconstrained* and their discount factor pins down the interest rate.
- House prices p_t move little in response to the maximum LTV $\uparrow$, a finding that is common in the literature.
- with little movement in house prices p_t, the *increase* in HH debt is accompanied by $\uparrow$ in the $\frac{\text{debt}}{\text{real estate}}$ ratio. This ***increase is counterfactual,*** although its magnitude depends on the assumption that all borrowers take immediate advantage of lower down payments by taking on more debt. This assumption (standard in the literature), is quite extreme, since in reality many HHs simply pay down their mortgage as scheduled, without ever re-levering their collateral. **EXCEPTION**: *the boom period*, when refinancing activity was at historically high levels and an unusually large fraction of that activity was accompanied by equity withdrawal (so-called cash-out refinancings).



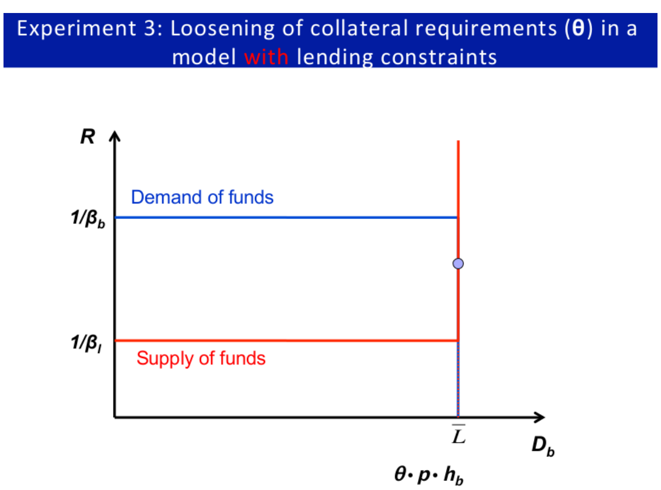


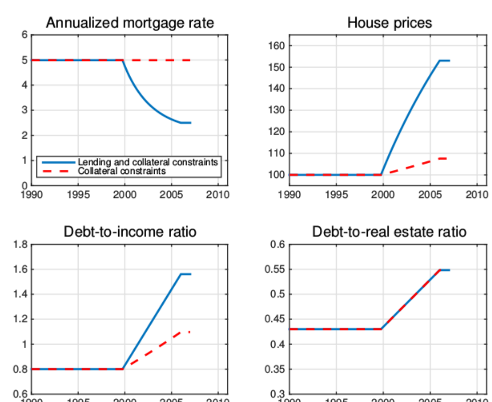
One of the lessons of this exercise is that the ***debt-to-real estate ratio*** is a particularly useful moment to discriminate among *theories of HH debt*. Explanations based on looser lending constraints fit this moment quite naturally over the boom.

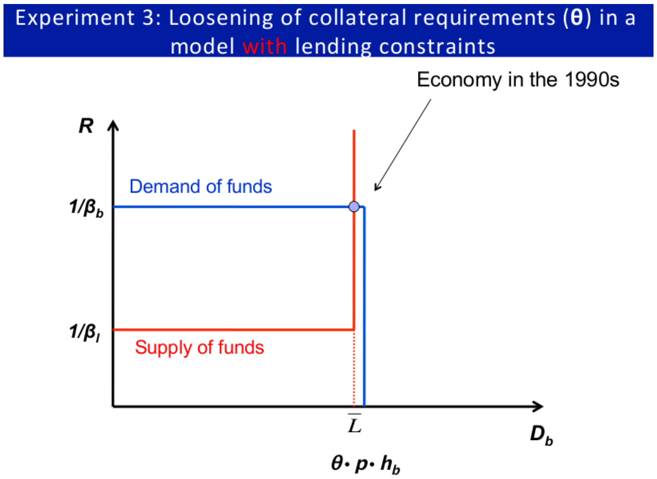
Results are very similar if the *same increase in HH debt* is driven by a reduction in the *speed of amortization* ρ, rather than by a rise in θ. This experiment delivers a looser borrowing constraint by increasing exogenously the stock of housing that can be pledged as collateral.

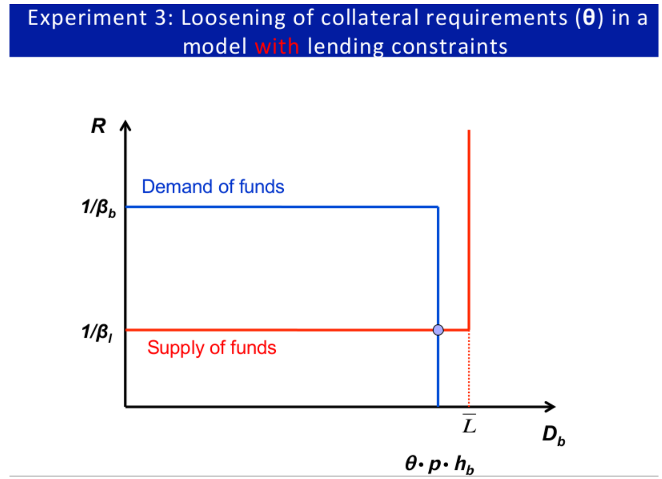
Experiment 3: ***Loosening of <u>collateral constraints</u> in a model with <u>lending constraints</u>***

The authors main claim is that their model can in fact accommodate an *increase* in required LTVs during the boom, as long as this *increase* in accompanied by a simultaneous expansion in credit supply. This experiment combines the same rise in θ considered previously with an increase in $\overline{L}$ that is large enough to produce a *decline* in mortgage rates of 2.5% by 2006.



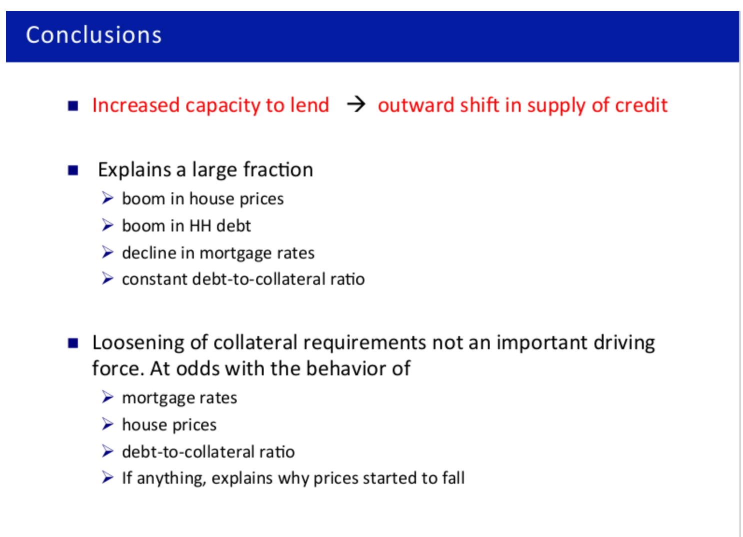






- House prices p_t and HH debt $\uparrow$ substantially, more than in the baseline experiment, bringing them even closer to the data.
- The $\frac{\text{debt}}{\text{real estate}}$ ratio $\uparrow$ counterfactually in this simulation, exactly as it does when they only loosen the *borrowing constraint*. This result suggests that the relaxation of collateral requirements in the data might have been of smaller magnitude.
- In summary, combining ***looser lending limits*** and ***looser borrowing limits*** enhances the model's ability to match the magnitude of the boom in HH debt and home prices, even if it comes at the cost of a counterfactual increase in aggregate HH leverage. ***However, this overall performance in matching the four stylized facts (that motivate their analysis) is mostly attributable to the <u>expansion in credit supply</u>***.

5.3.2.6 Conclusion



5.3 Bertrand and Morse (REStat, 2014): *Trickle-Down Consumption*

Abstract: Using state-level variation over time in the top deciles of the income distribution, we observe that nonrich households consume a larger share of their current income when exposed to higher top income and consumption levels. We argue that permanent income, wealth effects, and upward local price pressures cannot provide the sole explanation for this finding. Instead, we show that the budget shares which nonrich households allocate to more visible goods and services rise with top income levels, consistent with status-maintaining explanations for our primary finding. Non-rich households exposed to higher top income levels self-report more financial duress; moreover, higher top income levels in a state are correlated with more personal bankruptcy filings. Non-rich households might have saved up to 3 percent more annually by the mid-2000s had incomes at the top grown at the same rate as median income since the early 1980s.

Motivation: Income inequality and HH borrowing relationship. This paper is consistent with a popular explanation for the INCREASE in US HH debt in the years before the subprime mortgage crisis, which rests on the idea that HHs with stagnating incomes borrowed more to "***keep up with the Joneses***."

5.4 Coibion, Gorodnichenko, Kudlyak, and Mondragon (Working Paper, 2014): *Does Greater Inequality Lead to More Household Borrowing? New Evidence from Household Data*

Abstract: One suggested hypothesis for the dramatic rise in household borrowing that preceded the financial crisis is that low-income households increased their demand for credit to finance higher consumption expenditures in order to "keep up" with higher income households. Using household level data on debt accumulation during 2001-2012, we show that low-income households in high-inequality regions accumulated less debt relative to income than their counterparts in lower-inequality regions, which negates the hypothesis. We argue instead that these patterns are consistent with supply-side interpretations of debt accumulation patterns during the 2000s. We present a model in which banks use applicants' incomes, combined with local income inequality, to infer the underlying type of the applicant, so that banks ultimately channel more credit toward lower-income applicants in low-inequality regions than high-inequality regions. We confirm the predictions of the model using data on individual mortgage applications in high- and low-inequality regions over this time period.

Motivation: Income inequality and HH borrowing relationship. This paper is not consistent with a popular explanation for the INCREASE in US HH debt in the years before the subprime mortgage crisis, which rests on the idea that HHs with stagnating incomes borrowed more to "***keep up with the Joneses***.""

Lecture 6

Liquidity Constraints and the Role of Automatic Stabilizers

6.1 Krueger, Mitman, and Perri (Handbook of Macroeconomics, 2015): *Macroeconomics and Heterogeneity, including Inequality*

Introduction: Scope of the Chapter

- Broad Question: Is Microeconomic Heterogeneity Important for Macroeconomic Outcomes
- Narrower Version of this Question (and the one addressed in this chapter):
  - Is Household *income and wealth* heterogeneity important for *aggregate consumption expenditures, investment and output* response to an exogenous *Great Recession* shock?
  - How do social insurance policies impact *aggregate outcomes*?
  - And...how are consumption and welfare losses *distributed* across the population?
- Excluded Questions
  - *Firm* Heterogeneity and business cycles (see e.g. Khan and Thomas, 2008 or Bachmann, Caballero and Engel, 2013)
  - Interaction of inequality and *long run growth* (see e.g. Kuznets, 1952, Benabou, 2002 Piketty, 2014)
  - *Computation* of heterogeneous agent models (see e.g. JEDC Special Issue, 2010)

Why Does Inequality Matter for the Macroeconomy?

- Earnings fall in recessions (employment and wages fall)
- If low wealth households have higher MPC out of current earnings because of precautionary saving motives
- ...then the wealth distribution matters for aggregate C responses in recessions
- If, in addition, aggregate consumption matters for output (Endogenous TFP, Nominal Rigidities), then the wealth distribution matters for aggregate Y dynamics

6.1.1 Empirical Analysis

Plan: Data meets Theory

- *Empirical* analysis using PSID y, c, a data:
  - How did inequality look prior to Great Recession?
  - How did distribution change in during the recession?
  - How did different households respond to the recession?
- *Quantitative* analysis using versions of heterogeneous household business cycle model (Krusell and Smith, 1998):
  - Can the model match the cross-sectional facts?
  - How much does distribution matter for response of C, I, Y to Great Recession shock?
  - What are the aggregate consequences of falling expenditures when TFP is endogenous?
- *Policy* analysis: stylized unemployment insurance system:
  - How does it impact the wealth distribution?
  - How does it impact C for a *given* wealth distribution?
  - How is the distribution of welfare losses from a Great Recession shaped by policy?

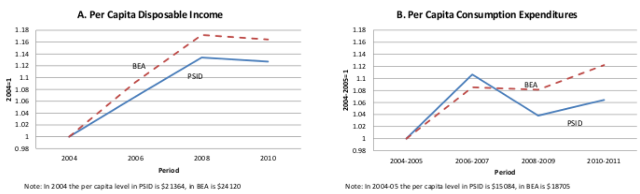
- PSID waves of 2004-2006-2008-2010
- Pluses
  - Panel dimension: can assess how a different households changed their actions (expenditures) during the Great Recession
  - Detailed information on earnings, income, wealth and consumption
  - Although sample not large ($\simeq 8000$), PSID yields similar results as other surveys (CPS, SCF) along comparable dimensions
- Minus
  - Coarse time series dimension (biannual surveys between 2004 and 2010)

Variables of Interest:

- Net Worth $= a =$ Value of all *assets* (including real estate) - *liabilities*
- Disposable Income $= y =$ Total money income net of taxes (computed using TAXSIM)

- Consumption Expenditures $= c =$ Expenditures on *durables*, *non-durables* and *services* (excluding health)

Aggregates in PSID



- Great Recesssion evident in PSID
- Consumption expenditure fall bigger in PSID

Heterogeneity (Inequality) in 2006: Marginal Distributions

	y	c	a	a (SCF 07)
Mean (2006\$)	62,549	43,980	291,616	497,747
%Share : $Q1$	4.3	5.7	-1.2	-0.3
$Q2$	9.7	10.7	0.7	0.9
$Q3$	15.1	15.6	4.1	4.2
$Q4$	22.9	22.5	13.3	11.8
$Q5$	48.0	45.5	83.1	83.4
$90-95$	10.8	10.4	14.0	11.1
$95-99$	13.1	11.4	23.2	25.6
Top 1%	7.8	8.0	30.2	34.1
Sample Size		6442		14725

- a: Bottom 40% holds basically no wealth
- y,c: less concentrated
- a distribution in PSID $\simeq$ SCF except at very top

Things to notice:

1. $a =$ *Net worth* is by far the ***most concentrated variable, especially at the top of the distribution***. The bottom 40% of HHs hold essentially no wealth at all, whereas the top quintile owns 83% of all wealth, and the top 10% holds around 70% of total wealth.

- Although the *marginal distributions* of y, c and a are interesting in their own right, the more relevant object for our purposes is the ***joint distribution*** of y, c, and a. To document the salient features of this *joint distribution* they divide the HHs in their 2006 PSID sample into ***net worth*** a ***quintiles***, and then for each *net worth quintile* they report, in the table below to the left, the share of the *relevant variable held by that quintile*.

Table 2: Earnings, Disposable Income and Expenditures by Net Worth in 2006

	% Share of:			% Expend. Rate	
Quintile(NetW)	Earn.	Disp Y	Expend.	Earn.	Disp Y
Q1	9.6	8.6	11.3	98.1	92.2
Q2	12.3	10.7	12.4	84.1	81.3
Q3	18.0	16.6	16.8	77.9	70.9
Q4	22.8	22.6	22.4	81.6	69.6
Q5	37.2	41.4	37.2	83.0	63.1
	Correlation with net worth				
	0.26	0.39	0.16		

Things to notice:

1. *Corr* (a, y) ***is POSITIVE and HIGH***: *HHs with higher net worth a tend to have higher earnings and higher disposable incomes y.*

2. **Top quintile (Q5)** have ***more disposable income*** y and ***consume less*** c (save MORE): *Consumption expenditures c are also positively correlated with net worth a, but less so than the two income variables . The reason is that, as can be seen in the last two columns of the table, as net worth a and/or disposable income y $\uparrow$, then consumption rate c $\uparrow$.*

- *ISSUE with tables: data does not account for* ***life-cycle components****.*

In the table below they report for HHs in *each of the five wealth quintiles of the net worth distribution*, the Δ in net worth, earnings, disposable income, consumption expenditures and consumption expenditure rates.

Pre v/s Post Recession dynamics in a,y,c/y across a

	Δ a		Δ y (%)		Δ c/y (pp)	
	04-06	06-10	04-06	06-10	04-06	06-10
$Q1$	27k($+\infty$)	12k($+\infty$)	14.3	12.3	-1.4	-8.8
$Q2$	40k(140%)	7k(35%)	13.8	9.1	-1.5	-4.2
$Q3$	40k(50%)	7k(9%)	9.4	3.9	6.3	-1.5
$Q4$	60k(28%)	8k(4%)	10.8	3.3	-1.3	-4.1
$Q5$	266k(21%)	-119k(-11%)	3.4	-2.3	1.4	-3.2

- Pre-Recession (04-06): uniform a,y growth, faster at the bottom (mean reversion)
- Post Recession (06-10):
  - Uniform slowdown in a,y growth, more marked at the top
  - Fall in expenditure rates, more marked at the bottom

Things to notice about **2004-2006:**

1. All groups of HHs experienced ***solid growth in net worth*** Δa between 2004-2006 (Column 1), mainly due to the *rapid growth in asset prices* (stock prices and especially real estate prices) during this period, with low wealth HHs (a_{Q1}) experiencing the strongest growth in wealth (but of course from very low levels).

2. Turning to disposable income (Column 3), we observe that HHs originally at the *bottom of the wealth distribution* (a_{Q1}) experience FASTER income growth than those in higher wealth quintiles. This is most likely due to ***mean reversion in income***: low wealth HHs are also low income HHs, and *on average* low income HHs experience faster income growth.

3. *Expenditure growth roughly tracked the growth of income variables* between 2004-2006 (Column 5), and as a result the **consumption rates** $\Delta\frac{c}{y}$ **of each group remained roughly constant**, perhaps with the exception of HHs initially in the middle quantile (a_{Q3}) who saw strong consumption expenditure growth, and thus their consumption rate displays a marked rise

Things to notice about **2006-2010:**

1. Growth in net worth a slowed down substantially for all quintiles, ***most significantly so at the top of the wealth distributio***n. In fact, on average net worth fell for HHs initially (that is, in 2006) in the top wealth quintile (a_{Q5}).

2. Income growth Δy also slowed down, although not uniformly across the wealth distribution. We see that the slowdown in income growth is very modest at the bottom of the wealth distribution (a_{Q1}), whereas the middle and top quintiles experience a more substantial slowdown.

3. In 2006 to 2010 ***all groups reduce their consumption rates*** $\Delta\frac{c}{y}$, but most pronouncedly at the *bottom end of the 2006 wealth distribution* (a_{Q1}). For this group the consumption rate fell by 8.8%, whereas the top quintile's (a_{Q5}) consumption rate declined only by 3.2%.

Empirical evidence showed: **(1)** Bottom 40% have no wealth but account for almost 25% of consumption. **(2)** Low wealth (a_{Q1}) HHs cut expenditure rates the most during Great Recession.

***Summary*:** The differences across groups delineated by wealth constitute *prima facie* evidence that the shape of the wealth distribution could matter for the aggregate consumption response to macroeconomic shocks such as the ones responsible for the Great Recession.

6.1.2 The Model and Calibration

Aggregate Technology

- Standard production function:

$$Y = Z^* K^\alpha N^{1-\alpha}$$

- Total factor productivity Z^* in turn is given by

$$Z^* = ZC^\omega$$

  - C is aggregate consumption
  - $\omega \geq 0$: aggregate demand externality.
  - Benchmark model $\omega = 0$
- Focus on $Z \in \{Z_l, Z_h\}$: recession and expansion.

$$\pi(Z'|Z) = \begin{pmatrix} \rho_l & 1-\rho_l \\ 1-\rho_h & \rho_h \end{pmatrix}.$$

- Capital depreciates at a constant rate $\delta = 0.025$ quarterly.
- Capital share: $\alpha = 36\%$

- The stationary distribution associated with this Markov chain satisfies

$$\Pi_l = \frac{1-\rho_h}{2-\rho_l-\rho_h}$$
$$\Pi_h = \frac{1-\rho_l}{2-\rho_l-\rho_h}$$

- With the normalization that $E[Z] = 1$ the aggregate productivity process is fully determined by the two persistence parameters ρ_l , ρ_h and the dispersion of aggregate productivity, as measured by $\frac{Z_l}{Z_h}$.

Household Preferences

- Measure 1 of households
- Period utility function $u(c) = \log(c)$
- Follow Carroll et al. (2014):
  - Households draw discount factor β at birth from $U[\bar{\beta} - \epsilon, \bar{\beta} + \epsilon]$
  - Choose $\bar{\beta}, \epsilon$ to match $K/Y = 10.26$, Wealth Gini=0.82
  - ($\bar{\beta} = 0.9835, \epsilon = 0.0104$)
- Working life is 40 years, constant quarterly death probability $\theta = 1 - 1/160$

- There is a measure one of potentially infinitely lived HHs, each of which faces a *constant probability of dying* equal to $1 - \theta \in [0, 1]$.
- ***Heterogeneity in the discount factor*** is what separates this model from *Krusell and Smith (1998)*; allows for better matching to the data.

Household Endowments

- Time endowment normalized to 1
- Idiosyncratic unemployment risk, $s \in S = \{u, e\}$
  - $\pi(s'|s, Z', Z)$
- Idiosyncratic labor productivity risk, $y \in Y$
  - Estimate AR(1) from PSID: quarterly process with $(\hat{\phi}, \hat{\sigma}_y^2) = (0.95, 0.04)$.
  - Discretized via Rouwenhorst method $\pi(y'|y, Z', Z)$
- $a \in A$ asset holdings
- No borrowing, perfect annuity markets
- Households born with 0 assets, and $y = \min Y$

Cross-sectional distribution: $\Phi(y, s, a, \beta)$

Aggregate state of economy summarized by: (Z, Φ)

Government Policy

- Balanced budget unemployment insurance system
  - Replacement rate $\rho = \frac{b(y,Z,\Phi)}{w(Z,\Phi)y}$ if $s = u$
  - Proportional labor income tax $\tau(Z, \Phi)$
  - Baseline $\rho = 0.5$

Fraction unemployed, $\Pi_Z(u)$, and thus tax rate τ only depends on the current aggregate state Z and replacement rate ρ:

$$\tau(Z, \Phi; \rho) = \left(\frac{\Pi_Z(u)\rho}{1 - \Pi_Z(u) + \Pi_Z(u)\rho}\right) = \left(\frac{1}{1 + \frac{1 - \Pi_Z(u)}{\Pi_Z(u)\rho}}\right) = \tau(Z; \rho)$$

- HHs can *save* (but not borrow) by accumulating (risky) physical capital and have access to perfect annuity markets. They denote by $a \in A$ the asset holdings of an individual HH and by A the set of all possible asset holdings.
- AR(1) specification for *idiosyncratic labor productivity* doesn't create enough heterogeneity: too much mean-reversion!

- UI benefits are *budget-balancing*. They give benefits b as a fraction of potential earnings wy of a HH, with $\rho = 0$ signifying the absence of public social insurance against unemployment risk.

Recursive Formulation

Let $x = (s, y, a, \beta)$

Recursive Formulation of HH Problem

$$
\begin{aligned}
v(x; Z, \Phi) &= \max_{c, a' \geq 0} u(c) + \theta\beta \mathbb{E}_{s', y', Z' | y, Z}[v(x'; Z', \Phi')] \\
&\quad \text{subj. to} \\
c + a' &= (1 - \tau(Z; \rho)) w(Z, \Phi) y [1 - (1 - \rho) 1_{s=u}] + \frac{(1 + r(Z, \Phi) - \delta) a}{\theta} \\
\Phi' &= H(Z, \Phi', Z') \\
x &= (y, s, a, \beta)
\end{aligned}
$$

Equilibrium concept: ▸ Recursive Competitive Equilibrium

Calibration of Aggregate Productivity Risk

The expected duration of a recession is:

$$EL_l = 1 \times 1 - \rho_l + 2 \times \rho_l (1 - \rho_l) + ... = \frac{1}{1 - \rho_l}$$

This suggests the following calibration strategy:

1. Choose ρ_l to match the average length of a severe recession EL_l. This is a measure of the persistence of recessions.
2. Given ρ_l choose ρ_h to match the fraction of time the economy is in a severe recession, Π_l.
3. Choose $\frac{Z_l}{Z_h}$ to match the decline in GDP per capita in *severe* recessions relative to normal times

What is a Severe Recession?

- We define a severe recession to start when $u \geq 9\%$ and to last as long as $u \geq 7\%$.
- From 1948 to 2014.III two severe recessions, 1980.II-1986.II and 2009.I-2013.III.
- Frequency of severe recessions: $\Pi_l = 16.48\%$, expected length of 22 quarters.
- Average unemployment rate $u(Z_l) = 8.39\%$, $u(Z_h) = 5.33\%$
- Implied transition matrix:

$$\pi = \begin{pmatrix} 0.9545 & 0.0455 \\ 0.0090 & 0.9910 \end{pmatrix}$$

- We target average output drop in severe recessions: $\frac{Y_l}{Y_h} = 0.9298$. This requires setting $\frac{Z_l}{Z_h} = 0.9614$.

Idiosyncratic Employment status Transitions

Transition matrices $\pi(s'|s, Z', Z)$ for employment status $s \in \{u, e\}$, are uniquely pinned down by the quarterly job finding rates (computed from CPS)

- Economy is and remains in a recession: $Z = Z_l.Z' = Z_l$

$$\begin{pmatrix} 0.34 & 0.66 \\ 0.06 & 0.94 \end{pmatrix}$$

- Economy is and remains in normal times: $Z = Z_h.Z' = Z_h$

$$\begin{pmatrix} 0.19 & 0.81 \\ 0.05 & 0.95 \end{pmatrix}$$

- Economy slips into recession: $Z = Z_h.Z' = Z_l$

$$\begin{pmatrix} 0.34 & 0.66 \\ 0.07 & 0.93 \end{pmatrix}$$

- Economy emerges from recession: $Z = Z_l.Z' = Z_h$

$$\begin{pmatrix} 0.22 & 0.78 \\ 0.04 & 0.96 \end{pmatrix}$$

6.1.3 Benchmark Results

Different versions of the model considered:

1. Krusell and Smith (1998) (single discount factor + income risk + low ρ),
2. 1. +Heterogenous β's + high $\rho + \theta > 0$ **[Benchmark]**
3. 2. + Demand externality ($\omega > 0$)

Inequality in the Benchmark Economy

New Worth	Data		Models	
% Share held by:	PSID, 06	SCF, 07	Bench	KS
$Q1$	-1.2	-0.3	0.3	7.2
$Q2$	0.7	0.9	0.5	12.0
$Q3$	4.1	4.2	3.0	16.8
$Q4$	13.3	11.8	11.6	23,6
$Q5$	83.1	83.4	84.9	40.3
90 – 95	14	11.1	15.9	10.1
95 – 99	23.2	25.6	28.9	10.4
$T1\%$	30.2	34.1	24.5	3.7

- Benchmark economy does a good job matching bottom and top of wealth distribution, misses very top
- Original KS economy does not produce enough inequality

Joint Distributions (2006): data v/s model

	% Share of:					
	y		c		% c/y	
a Quintile	Data	Model	Data	Model	Data	Model
$Q1$	8.6	7.5	11.3	7.5	92.2	100.1
$Q2$	10.7	13.6	12.4	13.5	81.3	98.9
$Q3$	16.6	19.1	16.8	18.6	70.9	97.1
$Q4$	22.6	24.6	22.4	23.8	69.6	96.4
$Q5$	41.4	35.2	37.2	36.7	63.1	104.3

- Model captures well that bottom 40% has almost no wealth but significant consumption share
- But understates income and overstates consumption rates of the rich

Pre v/s Post Recession dynamics in $a, y, c/y$ across a: Data v/s Model

	Δa(%)		Δy(%)		Δc/y(pp)	
	2004-06	2006-10	2004-06	2006-10	2004-06	2006-10
			DATA			
$Q1$	$+\infty$	$+\infty$	14	12	-1.4	-8.8
$Q3$	50	9	9	4	6.3	-1.5
$Q5$	21	-11	3	-2	1.4	-3.2
			MODEL			
$Q1$	471	309	43	30	-5.7	-6.1
$Q3$	22	10	3	-5	-2.5	0.5
$Q5$	3	1	-5	-15	4.8	14.3

- Model's issues:
  - Overall increase in c/y (as opposed to decline in the data), but captures differential change in c/y across a distrib.
  - Too much y growth for poor and too little for rich (too much mean reversion)

- Following Carroll (2014) and adding *wealth in the utility* of the very top wealthy 1% HHs could rationalize their HIGH savings rate.

6.1.4 The Impact of Social Insurance Policies

Question: How does presence of ***unemployment insurance (UI)*** affect the response of economy to aggregate shock? To answer this question they compare:

- Benchmark economy with $\rho = 0.5$ ***VS.*** Economy with same preference and technology parameters, but with smaller replacement rate $\rho = 0.1$

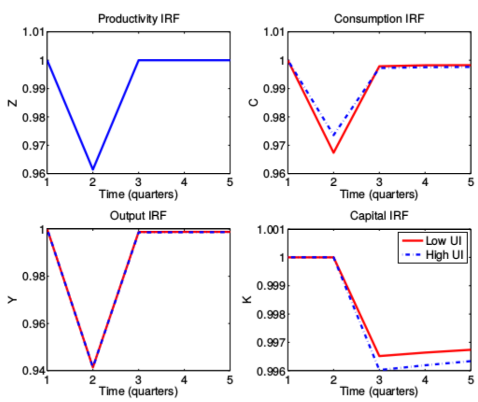
Important caveats:

1. UI does not impact individual incentives to seek jobs (will address in model with endogenous labor supply)
2. Abstract from impact of UI on firms' incentives to create jobs

- Hagedorn et al (2013), Hagedorn, Manovskii and Mitman (2015), and Mitman and Rabinovich (2014) suggest these effects might be large

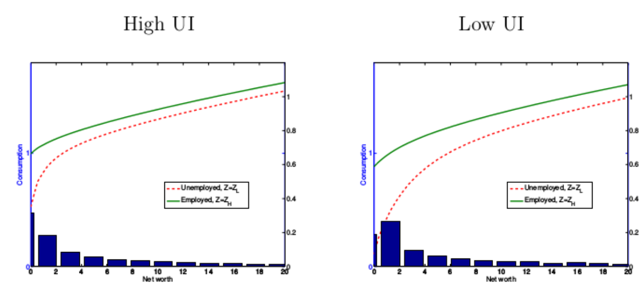
IRFs

IRF, 2 UI Economies: One Time Shock



Consumption drop: Low UI -3.26% vs Baseline -2.64%

Consumption Functions & Wealth Distribution

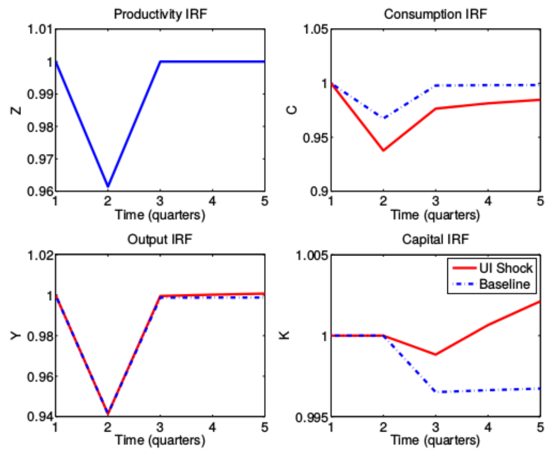


- Benchmark: 8% at zero NW, compared to 1% with low UI
- Impact of UI on aggregate consumption response muted because in its absence the wealth distribution shifts

- When UI is more generous (i.e. ***high UI***):
  - drop in consumption C across HHs is ***LESS*** when you go from *employed* $\rightarrow$*unemployed*
  - drop in capital K across HHs is ***MORE*** when you go from *employed* $\rightarrow$*unemployed*
- Looking at the right panel of the figure above, the authors want to highlight three observations:
  1. In the ***high UI*** economy, HHs with low wealth consume MUCH MORE than in the economy with ***small UI*** (green line is flatter and starts at 1 in *high UI* vs. below 1 in *low UI*)
  2. Second, and related, the decline in consumption for low wealth HHs from experiencing a recession with job loss is MUCH MORE severe in the ***low UI*** economy
  3. However, third, the size of the social insurance system, by affecting the extent to which HHs engage in precautionary saving, is a crucial determinant of the equilibrium wealth distribution. In the benchmark ***high UI*** economy (as in the data) a sizable mass of HHs has little or no wealth, whereas in the ***low UI*** economy this share of the population declines notably.
     - The difference in the consumption decline in a recession across the two economies can then be decomposed into: the differential consumption response of HHs, integrated with respect to the same cross-sectional wealth distribution (which is a counterfactual distribution for one of the two economies), and the effect on the consumption response stemming from a policy-induced difference in the wealth distribution coming into the recession. As it turns out, both effects (the change in the consumption functions and the change in the wealth distribution) are quantitatively large, but partially offset each other.

In order to *isolate the first effect* they now plot, in the figure below, the *recession impulse response* for the benchmark economy and the economy with ***low UI***, but starting at the *same pre-recession wealth distribution* as in the benchmark economy.

IRF, Fixed Distribution: One Time Shock



Consumption drop: Low UI -6.24% vs Baseline -2.64%

- They find that consumption ↓ MUCH MORE substantially in the economy with ***low UI*** (low ρ), by 6.24%, relative to 2.64% in the benchmark economy. ***This is of course exactly what the consumption functions in the previous figure predict***!

6.1.5 *Demand Externalities* Model Results

Their second version of the model focuses on the *demand side*, but retains the focus on real, as opposed to nominal, factors. They now consider a world in which $\omega > 0$ and thus TFP $Z^* = ZC^{\omega}$ endogenously responds to the level of aggregate demand. A decline in aggregate consumption triggered by a fall in Z ,an ensuing reduction of aggregate wages and HH incomes endogenously reduces TFP and thus output further.

A *social insurance program* that stabilizes consumption demand of those adversely affected by idiosyncratic shocks in a crisis might be desirable not just from a distributional and insurance perspective, but also from an aggregate point of view. In the model with consumption externalities, in addition to ***providing consumption insurance*** it ***increases productivity and accelerates the recovery.***

A Model with an Aggregate Consumption Externality

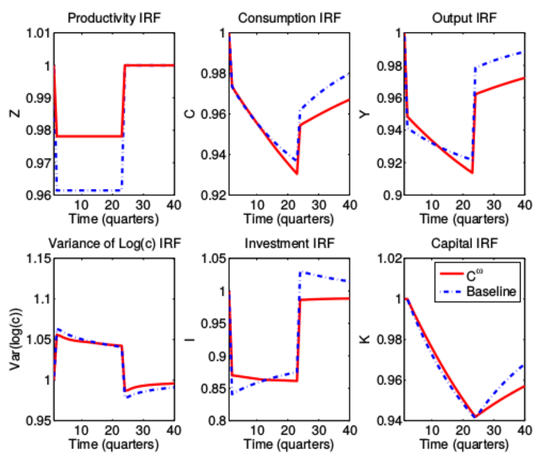
- Recall $Z^* = ZC^{\omega}$, now switch on $\omega > 0$
- Reduction in C feeds back into TFP
- "Demand management" may be called for even in absence of household heterogeneity
- Social insurance may be desirable from individual insurance *and* aggregate point of view
- Ours is a reduced form version of real aggregate demand externalities in spirit of e.g. Bai et al. (2012), Huo and Rios-Rull (2013) and Kaplan and Menzio (2014)
- Alternatively, could have introduced nominal rigidities that make output partially demand determined (see, e.g., Challe et al 2014, Gornemann et al 2013)

Thought Experiments

1. Re-calibrate Z, ω to match output volatility, simulate great recession
2. Simulate Great Recession with externality turned off. How much amplification?
3. Repeat the low-UI with fixed distribution thought experiment. Aggregate benefits of demand stabilization through UI?
4. Compare differential response of aggregates in baseline and externality economies to low-UI fixed distribution shock
5. Welfare losses of falling into a great recession

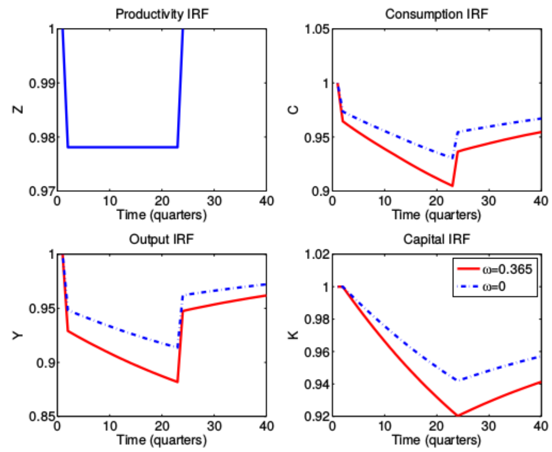
In the figure below they display the dynamics of a *typical great recession* (22 quarters of low TFP) in both the ***baseline economy*** and the ***demand externality economy*** (labeled C^{ω})

"Typical" Great Recession



- The upper right panel shows that, as determined in the calibration section, a *significantly smaller* exogenous shock is needed in the ***demand externality economy*** to generate a DECLINE in output (and thus consumption and investment) of a given size. The impulse response functions are qualitatively similar in both economies, but with important quantitative differences.
- Since aggregate consumption C declines during the course of a great recession and *aggregate consumption demand* impacts *productivity*, the ***decline in output is more pronounced*** and the *recovery slower* in the ***demand externality economy*** $\implies$ The *consumption externality* adds ***endogenous persistence*** to the model, over and above the one already present through endogenous capital accumulation.

In the figure below they display the *magnitude of this amplification* by comparing the impulse responses in two economies with the ***same exogenous TFP process*** (the one recalibrated for the ***demand externality model***), but with varying degrees of the externality ($\omega = 0$ and $\omega = 0.365$).

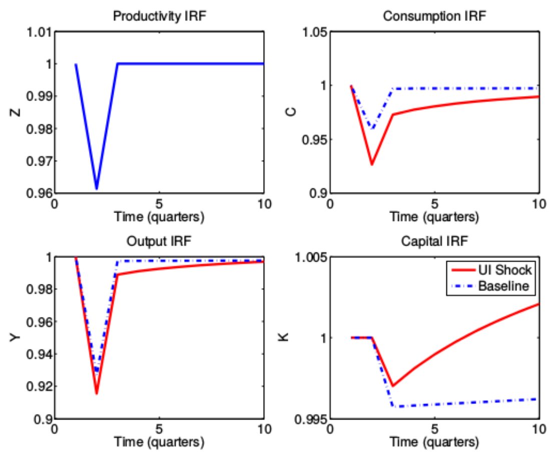


- In contrast to the previous figure, now the ***differences in the dynamics of the time series are purely driven by the presence of the demand externality*** ($\omega = 0 \to \omega > 0$)
- The amplification of the exogenous shock is economically important: the INITIAL FALL in output Y, consumption C and investment I is substantially GREATER (5.16%, 2.64% and 13.02% versus 4.23%, 1.98% and 11.23%, respectively).
- In addition, and consistent with the previous figure, these ***LARGER output and consumption losses are more persistent in the economy*** with negative feedback effects from aggregate demand on productivity and production $\Longrightarrow$ the losses last a LOT LONGER (***20 quarters*** vs. ***2 quarters***)!

On the Interaction of Social Insurance and Wealth Inequality with Demand Externalities: The presence of social insurance policies (UI benefits) had a strong impact (in the model with $\omega = 0$) on the aggregate consumption response to an adverse aggregate shock for a given wealth distribution, but also alters the long-run wealth distribution in the economy. With *output partially demand-determined*, now intuitively these *UI policies indirectly impact aggregate productivity and thus output.*

In a previous figure above it was documented that, holding the *wealth distribution fixed*, the ***size of the social UI system*** mattered greatly for the aggregate consumption (and thus investment) response to an aggregate productivity shock. The figure below repeats the same thought experiment (impulse response to a TFP shock in economies with $\rho = 50\%$ and $\rho = 10\%$ with same pre-recession wealth distribution), but now in the ***consumption demand externality model***.

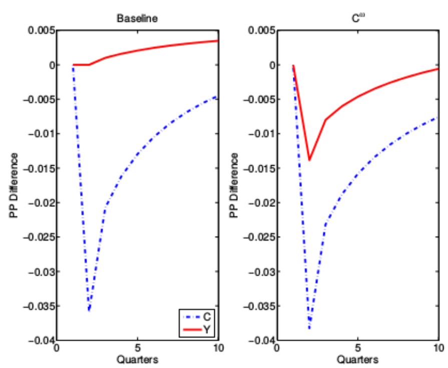
IRF, Fixed Distribution: One Time Shock



- The *key observations* are that now, in the consumption demand externality model the *size of the UI system* not only affects the *magnitude of the aggregate consumption decline on impact*, but also *aggregate output*, and the latter effect is quite persistent.

The figure below displays the difference in the impulse response functions for *output* Y and consumption C between economies with $\rho = 50\%$ and $\rho = 10\%$, both for the ***benchmark model*** and the ***demand externality model***.

Difference in C, Y IRF with High and Low UI in Two Economies: Fixed Wealth Distribution



- Persistent negative effect on output of low UI in demand externality economy

- Not only does ***the presence of sizable UI stabilize aggregate consumption more in the externality economy*** (the UI-induced reduction in the fall of C is 3.9% on impact and 0.8% after ten quarters of the initial shock in the externality economy, relative to 3.6% and 0.5% in the benchmark economy).
- In addition, whereas in the benchmark economy more generous UI has no impact on output in the short run (by construction) and a moderately negative impact in the medium run (since investment recovers more slowly in the presence of more generous UI), with ***partially demand-determined output UI stabilizes output significantly*** (close to 1.5% on impact, with the effect fading away only after 10 quarters, despite the fact that the shock itself only lasts for one quarter in this thought experiment.

6.1.6 Conclusion

In this chapter, the authors have used PSID data on earnings, income, consumption and wealth as well as different versions of a canonical business cycle model with HH earnings and wealth heterogeneity to study under which conditions the cross-sectional wealth distribution shapes the business cycle dynamics of aggregate output, consumption and investment in a quantitatively meaningful way. The authors have argued that the ***low end of the wealth distribution*** is crucial for the answer to this question and have studied mechanisms that helped to generate close to 40% of households without significantly positive net worth, including preference heterogeneity and publicly provided social UI programs.

In a model that does a good job in matching cross-sectional distributions, authors find ***wealth inequality*** has *significant effects* on ***aggregate consumption dynamics***.

With the ***demand externality*** (i.e. $\omega > 0$) channel, there is significant *amplification* of smaller productivity shocks on output y

Lastly, ***size of social insurance policies*** (low UI vs. high UI) can have LAREG impacts on output y as well as consumption c, more so in a model with $\omega > 0$

6.2 Di Maggio and Kermani (Working Paper, 2015): *The Importance of Unemployment Insurance as an Automatic Stabilizer*

DEF: Automatic Stabilizer: social programs/policy rules designed to ***offset*** fluctuations in a country's economic activity. These programs/policy rules act to "stabilize" business cycles and automatically get triggered without explicit government intervention

6.2.1 Motivation

There are several channels through which *automatic stabilizers* might attenuate business cycle fluctuations:

1. A more generous ***unemployment insurance*** (UI) may stabilize aggregate demand by reducing fluctuations in *disposable income* y
2. It can *redistribute* funds towards individuals with higher MPC than those who provide the funds.
3. However, by increasing firms' hiring costs, more generous UI may also discourage firms from creating new jobs (see Hagedorn et al. 2013).

This paper shows that UI might have a beneficial effect on the economy by *DECREASING its sensitivity to shocks* and by reducing the variability of aggregate income, employment and consumption. Authors provide empirical support for a *redistribution channel* as they observe that in counties with a *more generous UI*, consumption responds less to adverse shocks, because the unemployed individuals have higher disposable income. Furthermore, they also provide evidence suggesting that higher UI also increases the average wages of the employed individuals, for instance, due to an increase in aggregate demand and possibly by boosting their bargaining power.

Main Result: UI is a very effective automatic stabilizer – Not surprising given the fact that it delivers the money to people with the *highest MPC*.

6.2.2 Identification Strategy

Authors find a valid instrument for changes in the *local labor demand*. They follow the strategy proposed by ***Bartik (1991)*** and ***Blanchard and Katz (1992)*** to construct a *local demand index* by interacting cross-sectional differences in industrial composition with national changes in industry employment shares. The key identifying assumption: this proxy needs to be uncorrelated with unobserved shocks to local labor supply. Specifically, they are assuming that changes in industry shares at the national level are uncorrelated with city-level labor supply shocks and therefore can be used as a demand-induced variation in local employment.

Identification Strategy

- Our baseline specification is the following:

$$\Delta Y_{i,t} = \beta_1(\text{Bartik}_{i,t} \times UI_{i,2000}) + \beta_2 \text{Bartik}_{i,t} + \beta_3 \text{Bartik}_{i,t} \times X_i + \eta_i + \gamma_t + \varepsilon_{i,t}$$

- where $\Delta Y_{i,t}$ captures the main dependent variables in growth rate.
- β_1: captures how the sensitivity of ΔY is affected by the UI generosity (UI) measured in 2000.
- Control for a number of county-level characteristics as well as state level characteristics X_i, such as the fraction of subprime borrowers, the share of employees in each industrial sector, minimum wage and right-to-work legislations and their interactions with the Bartik shock.
- We also include county and year fixed effects, and to allow for a differential response of states to the Bartik shock, we also include state by year fixed effect.
- Standard errors clustered at the state level.

Summary statistics

	N	Mean	St. Dev
Max Weekly Benefit	3,072	298.0	64.20
Number of Weeks	3,072	26.18	0.820
Max Weekly Benefit / Average Income	3,072	0.491	0.141
Max Weekly Benefit / Median Income	3,069	0.371	0.110
(UI Expenditure / N. Unemployed)/Average Wage	3,025	0.230	0.107
Fraction of Subprime Borrowers	3,071	0.300	0.0893
Share of Employees in Construction Sector	3,021	0.0590	0.0190
Share of Employees in Manufacturing Sector	3,023	0.0842	0.0528
Share of Employees in Services Sector	3,072	0.642	0.101
Share of Employees in Government Sector	3,072	0.139	0.0596
Population	3,072	1052000	1881000
Panel B. Dynamic Variables			
Bartik Shock 2000	33,811	-0.00191	0.0198
Population Growth	33,805	0.00847	0.0153
Employment Growth	33,803	0.000565	0.0510
Employment in Non-Tradable Sector Growth	33,786	0.00814	0.0621
Employment in Tradable Sector Growth	33,163	-0.0221	0.194
Income Growth	33,805	0.0340	0.0468
Car Sales Growth	32,555	-0.0219	0.175
Average Wages Growth	33,805	0.0304	0.0222
Labor Force Growth	33,790	0.00693	0.0195

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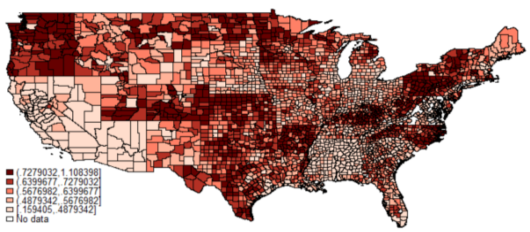
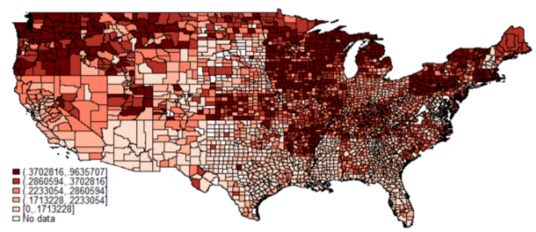
UI Generosity

Maximum Weekly Benefit / Average Weekly Wage
(as of 2000)



UI Generosity

UI Payment/ (Unemployed X Average Wage)



6.2.3 Main Results

Earnings Growth

	Full Sample	*Full Sample*	*Year <2008*	*Full Sample*	*Full Sample*
Bartik Shock × UI Generosity	-0.97***	-0.94***	-1.09***	-1.16***	-1.42***
	(0.20)	(0.19)	(0.35)	(0.20)	(0.36)
Bartik Shock	0.54***				
	(0.07)				
County Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Bartik Shock × Fraction of Subprime Borrowers		Yes	Yes	Yes	Yes
Industrial Characteristics × Bartik Shock				Yes	Yes
State × Year Fixed Effects					Yes
Observations	33,805	33,710	21,462	32,845	32,845
R-squared	0.02	0.02	0.02	0.03	0.02
Number of Counties	3,084	3,071	3,071	2,989	2,989

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Employment Growth

	Full Sample	*Full Sample*	*Year <2008*	*Full Sample*	*Full Sample*
Bartik Shock × UI Generosity	-0.95***	-0.96***	-1.46***	-0.96***	-0.89***
	(0.20)	(0.20)	(0.39)	(0.22)	(0.32)
Bartik Shock	0.76***				
	(0.08)				
County Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Bartik Shock × Fraction of Subprime Borrowers		Yes	Yes	Yes	Yes
Industrial Characteristics × Bartik Shock				Yes	Yes
State × Year Fixed Effects					Yes
Observations	33,803	33,708	21,456	32,843	32,843
R-squared	0.02	0.02	0.02	0.02	0.01
Number of Counties	3,084	3,071	3,071	2,989	2,989

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Employment Growth in Non-Tradable Sectors

	(1) *Employment in Non-Tradable Sector*	(2) *Employment in Non-Tradable Sector*	(3) *Employment in Tradable Sector*	(4) *Employment in Tradable Sector*
Bartik Shock × UI Generosity	-1.44***	-1.33***	-0.14	-0.00
	(0.17)	(0.21)	(0.42)	(0.45)
Bartik Shock	0.30***		1.18***	
	(0.08)		(0.18)	
County Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Bartik Shock × Fraction of Subprime Borrowers		Yes		Yes
Industrial Characteristics × Bartik Shock		Yes		Yes
Observations	33,784	32,843	33,153	32,379
R-squared	0.01	0.01	0.00	0.00
Number of Counties	3,081	2,989	3,051	2,969

Car Sales

	Full Sample	*Full Sample*	*Year <2008*	*Full Sample*	*Full Sample*
Bartik Shock × UI Generosity	-2.35***	-2.12***	-3.09***	-2.64***	-1.37***
	(0.45)	(0.40)	(0.94)	(0.63)	(0.48)
Bartik Shock	0.54***				
	(0.15)				
County Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Bartik Shock × Fraction of Subprime Borrowers		Yes	Yes	Yes	Yes
Industrial Characteristics × Bartik Shock				Yes	Yes
State × Year Fixed Effects					Yes
Observations	32,555	32,481	20,675	31,631	31,631
R-squared	0.00	0.01	0.00	0.01	0.00
Number of Counties	2,968	2,958	2,958	2,878	2,878

Average Wage

	Full Sample	*Full Sample*	*Year <2008*	*Full Sample*	*Full Sample*
Bartik Shock × UI Generosity	-0.62***	-0.60***	-0.77***	-0.51***	-0.91***
	(0.15)	(0.16)	(0.18)	(0.14)	(0.31)
Bartik Shock	0.18***				
	(0.06)				
County Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Bartik Shock × Fraction of Subprime Borrowers		Yes	Yes	Yes	Yes
Industrial Characteristics × Bartik Shock				Yes	Yes
State × Year Fixed Effects					Yes
Observations	32,927	32,839	20,649	31,994	31,994
R-squared	0.00	0.01	0.01	0.01	0.01
Number of Counties	3,067	3,055	3,055	2,973	2,973

Labor Force Growth

	Full Sample	*Full Sample*	*Year <2008*	*Full Sample*	*Full Sample*
Bartik Shock × UI Generosity	-0.35***	-0.37***	-0.44**	-0.33***	-0.52***
	(0.08)	(0.07)	(0.17)	(0.08)	(0.11)
Bartik Shock	0.16***				
	(0.05)				
County Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industrial Characteristics × Bartik Shock		Yes	Yes	Yes	Yes
Bartik Shock × Fraction of Subprime Borrowers				Yes	Yes
State × Year Fixed Effects					Yes
Observations	33,784	33,689	21,441	32,824	32,824
R-squared	0.01	0.01	0.02	0.02	0.02
Number of Counties	3,084	3,071	3,071	2,989	2,989

Controlling for Minimum Wage and Right-to-Work

	Earnings Growth	*Employment Growth*	*Car Sales*	*Average Wages*	*Labor Force Growth*
Bartik Shock × UI Generosity	-1.28***	-0.96***	-3.15***	-0.58***	-0.34**
	(0.36)	(0.33)	(0.60)	(0.15)	(0.15)
Bartik Shock × Rith-to-Work	0.32***	0.13	0.31	0.11	0.06
	(0.12)	(0.11)	(0.32)	(0.07)	(0.05)
Bartik Shock × Minimum Wage	0.16	0.76***	1.18*	-0.19	0.16
	(0.23)	(0.20)	(0.66)	(0.23)	(0.22)
County Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Bartik Shock × Fraction of Subprime Borrowers	Yes	Yes	Yes	Yes	Yes
Industrial Characteristics × Bartik Shock	Yes	Yes	Yes	Yes	Yes
Observations	32,845	32,843	31,631	31,994	32,828
R-squared	0.03	0.02	0.01	0.01	0.02
Number of Counties	2,989	2,989	2,878	2,973	2,989

Asymmetric Effects

	Earnings Growth	*Employment Growth*	*Car Sales*	*Average Wages*	*Labor Force Growth*	*Unemploymen t Growth*
Min Bartik Shock × UI Generosity	-1.53***	-1.31***	-3.64***	-0.99***	-0.38***	6.80***
	(0.19)	(0.19)	(0.53)	(0.11)	(0.13)	(0.90)
Median Bartik Shock × UI Generosity	-0.40	-0.29	-1.67**	-0.28	-0.26*	0.90
	(0.29)	(0.27)	(0.73)	(0.19)	(0.14)	(0.87)
Max Bartik Shock × UI Generosity	1.04	-0.87	0.63	-0.59	0.63**	4.72
	(0.64)	(0.74)	(1.61)	(0.82)	(0.30)	(3.58)
Min Bartik Shock	1.70***	1.27***	4.57***	0.75***	0.24***	-10.85***
	(0.04)	(0.04)	(0.21)	(0.03)	(0.02)	(0.28)
Median Bartik Shock	0.64***	0.79***	0.12	0.36***	-0.00	-5.06***
	(0.04)	(0.04)	(0.28)	(0.04)	(0.03)	(0.27)
Max Bartik Shock	1.22***	1.16***	-0.08	0.98***	0.51***	-4.09***
	(0.09)	(0.13)	(0.30)	(0.09)	(0.05)	(0.51)
Observations	33,805	33,803	32,555	32,927	33,790	33,790
R-squared	0.26	0.17	0.08	0.13	0.03	0.44

- *Min Bartik shock* is always NEGATIVE while *Max Bartik shock* is always POSITIVE.

- *Min Bartik Shock* × *UI Generosity* is where the action is happening: For an adverse (NEGATIVE) Bartik shock, once you have *more generous UI* then the consumption of those affected declines LESS.

6.2.4 Counties at the Border

Authors further control for potential *unobserved heterogeneity across counties* by focusing on the counties that border on another state. This figure depicts the heterogeneity in UI generosity for the sample of counties at the border, while this table reports the estimated results for this restricted sample.

Counties at the Border

Counties at the Border

	Earnings Growth	*Employment Growth*	*Employment in Non-Tradable Sector*	*Employment in Tradable Sector*	*Car Sales*	*Average Wages*	*Labor Force Growth*
Bartik Shock × UI Generosity	-0.88***	-0.92***	-1.20***	-0.55	-2.67***	-0.85***	-0.34**
	(0.26)	(0.33)	(0.35)	(0.65)	(0.69)	(0.27)	(0.14)
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industrial Characteristics × Bartik Shock	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bartik Shock × Fraction of Subprime Borrowers	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,015	14,007	14,007	13,813	13,553	13,518	14,009
R-squared	0.02	0.02	0.01	0.00	0.03	0.01	0.02
Number of Counties	1,275	1,275	1,275	1,266	1,233	1,262	1,275

- *Magnitude* of the effects very close to the ones provided in the previous sections using full sample of counties.

6.2.5 Jordá Local Projection

Coefficient on *Bartik Shock* × *UI Generosity*

Impulse Response

- Effect of interactive shock on *Income Growth* is **temporary**

6.2.6 Local Fiscal Multiplier Calculation

Authors estimate a local fiscal multiplier for UI expenditures. Fiscal multiplier μ for earnings obtained using the following regression specifications and equations.

Local Multiplier Calculation

- Let's define:

$$\text{EmploymentGrowth}_{i,t} = \beta_{12}\,(\text{Bartik}_{i,t} \times \text{UI}_{i,2000}) + \beta_2 \text{Bartik}_{i,t} + \beta_3 \text{Bartik}_{i,t} \times X_i + \eta_i + \gamma_t + \varepsilon_{i,t}$$

$$\text{EarningsGrowth}_{i,t} = \beta_{22}\,(\text{Bartik}_{i,t} \times \text{UI}_{i,2000}) + \beta'_2 \text{Bartik}_{i,t} + \beta'_3 \text{Bartik}_{i,t} \times X_i + \eta'_i + \gamma'_t + \varepsilon_{i,t}$$

- Local multiplier is:

$$\mu = \frac{\$\,increase\ of\ earnings}{\$\,increase\ of\ payments} = -\frac{\beta_{22}}{\beta_2} \times \frac{Total\ Earnings}{Total\ Wage\ Payments}$$

This result in a multiplier about 2.

Key Assumptions: **(1)** all unemployed workers apply for UI; **(2)** labor force participation does not change significantly, which makes the number of unemployed workers exactly equal to the negative change in the number of the employed ones.

6.3 Zidar (Working Paper, 2014)

** Kermani did not spend much time on this paper in lecture - see Owen Zidar's presentation slides **

Lecture 7

Household Balancesheets and Monetary Policy: Theory

7.1 Bernanke and Gertler (JEP, 1995): *Inside the Black Box: Credit Channel of Monetary Policy*

7.1.1 Motivation

Conventional Wisdom:

1. ***Interest rate channel****: Sticky price*s result in central bank having control over the (short-term) real interest rate $\implies$ monetary authorities change the *cost of capital* as well as *demand for consumption.*

Caveats with this view:

1. ***Empirical:*** *weak* cost-of-capital effect in estimated spending and investment equations. Usually *non-classical factors* are more important: sales, cash flows, lagged output.

2. ***Composition:*** monetary policy mainly impact *short-term interest rate* and not the *long-term interest rate*. This is in contrast with large impact of monetary policy on ***purchase of durables*** *(*which should be more sensitive to *long-term interest rate)*

7.1.2 Credit Channel *Theory*

The *direct effects* of monetary policy on interest rates are ***amplified*** by endogenous changes in the *external finance premium (EFP):* **credit channel** is an *amplification* mechanism working alongside the *interest rate channel*.

Definition. External finance premium (EFP) — wedge reflecting the difference in the cost of capital internally available to firms (i.e. retaining earnings) versus firms' cost of raising capital externally via equity and debt markets:

$$\text{EFP} = \text{cost of raising capital EXTERNALLY - cost of capital available INTERNALLY}$$

Contractionary monetary policy is thought to INCREASE the *size of the EFP*, and subsequently, through the credit channel, DECREASE credit availability in the economy.

Why does the central bank has any impact on EFP? The *size of the EFP* that results from these market frictions may be affected by monetary policy actions. The credit channel — or, equivalently, changes in the EFP — can occur through two conduits:

1. ***balance sheet channel:*** changes in *borrower's* and *lender'*s balance sheet and income statements $\implies$ *changes in income* can affect consumption behavior if $MPC_{borrower} > MPC_{lender}$

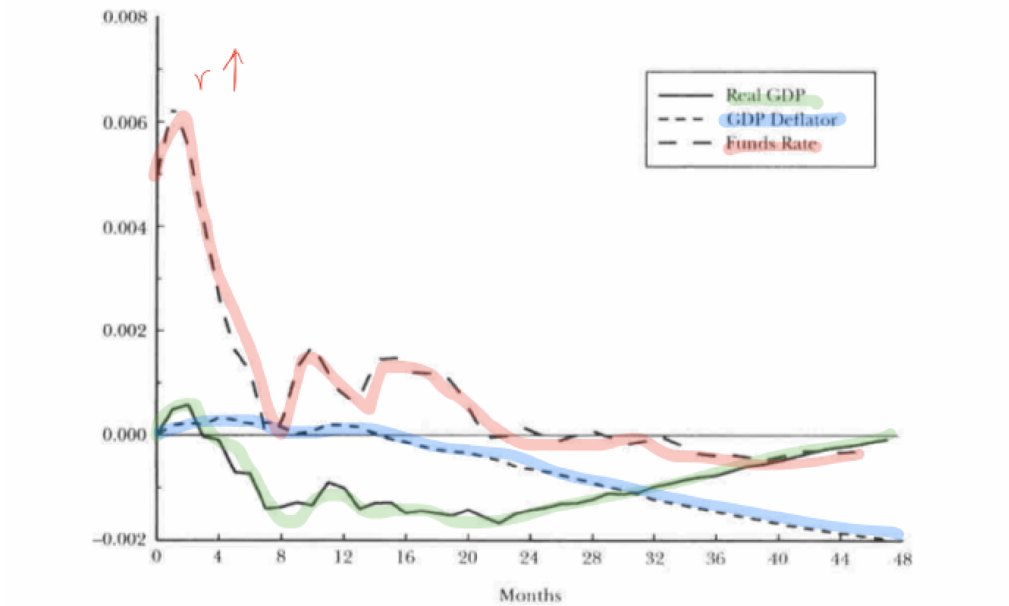
2. ***bank lending channel:*** changes to *supply of loans* disbursed by depository institutions: (mostly comes from finance literature)

7.1.3 Facts

7.1.3.1 *Fact 1*: Although an *unanticipated* tightening in monetary policy typically has only *transitory effects* on interest rates, a monetary tightening is followed by *sustained* declines in real GDP and the price level.

- Inflation does not respond *contemporaneously*; it responds over a long period of time.

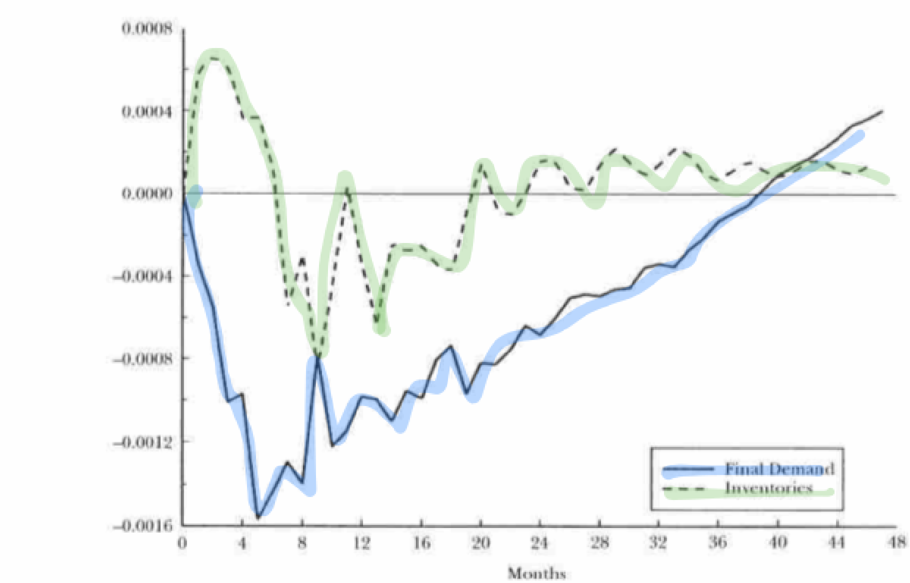
Figure 1
Responses of Output, Prices and Federal Funds Rate to a Monetary Policy Shock



7.1.3.2 ***Fact 2*****: Final demand absorbs the** ***initial impact of a monetary tightening*****, falling relatively quickly after a change in policy. Production (doesn't respond immediately) but follows final demand downward with a lag, implying that inventory stocks rise in the short run. Ultimately, however, inventories decline, and inventory disinvestment accounts for a large portion of the decline in GDP**

- GDP = *Final demand* + *inventory investment*
- Fall in *Inventories*, when it occurs, accounts for a substantial portion of the initial drop in GDP: consistent with Blinder and Maccini's (1994) evidence on the importance of ***inventory disinvestment in recessions.***
- Main effect is coming from DEMAND side; SUPPLY side then follows.

Figure 2
Responses of Final Demand and Inventories to a Monetary Policy Shock

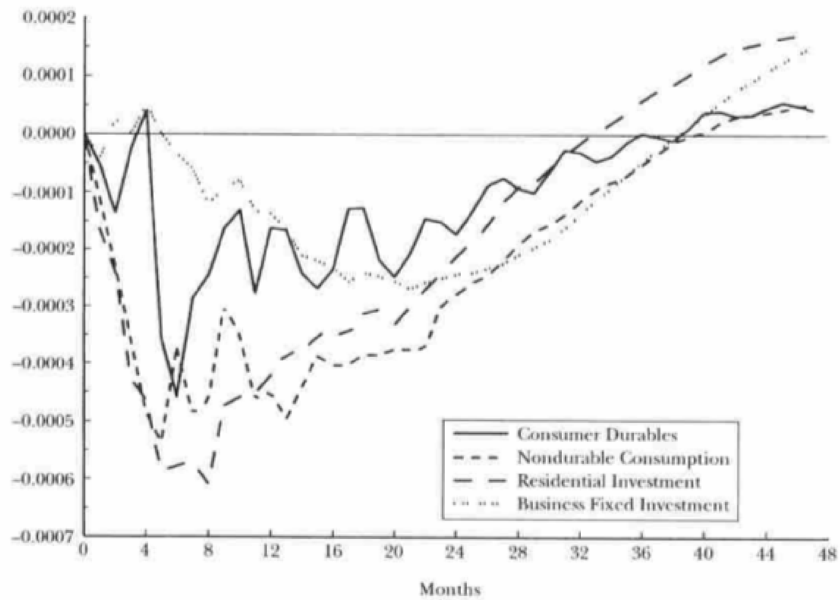


7.1.3.3 *Fact* 3: The earliest and sharpest declines in <u>Final Demand</u> occur in *residential investment* (long-term assets), with *spending on consumer goods* (including both durables and nondurables) close behind.

7.1.3.4 *Fact* 4: *Fixed business investment* eventually declines in response to a monetary tightening, but its fall lags behind those of housing and consumer durables and, indeed, behind much of the decline in production and interest rates.

Figure 3

Responses of Spending Components to a Monetary Policy Shock



Combining Fact 3 and Fact 4, on impact we have the following order in DECLINES (on **impact**) from the *most* to the *least*:

$$\text{Res Investment} > \text{Nondurables} \geq \text{Durables} > \text{Business Fixed Investment}$$

Another interesting result: *Equipment Investment* accounts for nearly all of the decline in *Fixed Investment*; *structures investment* by businesses appears to respond very little to a monetary policy shock.

7.1.4 Puzzles

The theory of a ***credit channel*** has been postulated as an explanation for a number of puzzling features of certain macroeconomic responses to monetary policy shocks, which the *interest rate channel* cannot fully explain

7.1.4.1 *Puzzle 1*: <u>Magnitude</u> of the policy effect

Authors and many other researchers have found that the real economy is *powerfully affected* by monetary policy innovations that induce relatively *small movements* in open-market interest rates.

7.1.4.2 *Puzzle* 2: <u>Timing</u> of the policy effect

Poor correspondence in *timing* between changes in the interest rates and movements in some components of spending observed in previous 3 figures helps explain why robust effects of interest rates on spending have been hard to pin down empirically.

7.1.4.3 *Puzzle* 3: Composition of the spending effects.

Monetary policy has its most direct effects on short-term rates, and it would seem that it should have its most significant impact on spending on assets with shorter lives. However, most rapid (and in % terms, by far the strongest) effect of monetary policy is on *residential investment* (typically *long-lived* asset, which are more sensitive to *long-term* real interest rate)

7.1.5 The Balance Sheet (Net Worth) Channel

Intuition: The ***balance sheet channel*** can be thought of as inducing changes in how FIRMS are constrained on the ***credit-DEMAND side***.

Assumption: borrowers' net worth affects the *EFP:* The *greater* is the borrower's net worth — defined operationally as the sum of her liquid assets and marketable collateral — the *lower* the EFP should be

$$EFP \propto \frac{1}{\text{borrower's Net Worth}}$$

Since the *quality of borrowers' financial positions* affect the terms of their credit, Δfinancial positions should result in Δ(investment and spending decisions). This idea is closely related to the ***financial accelerator***.

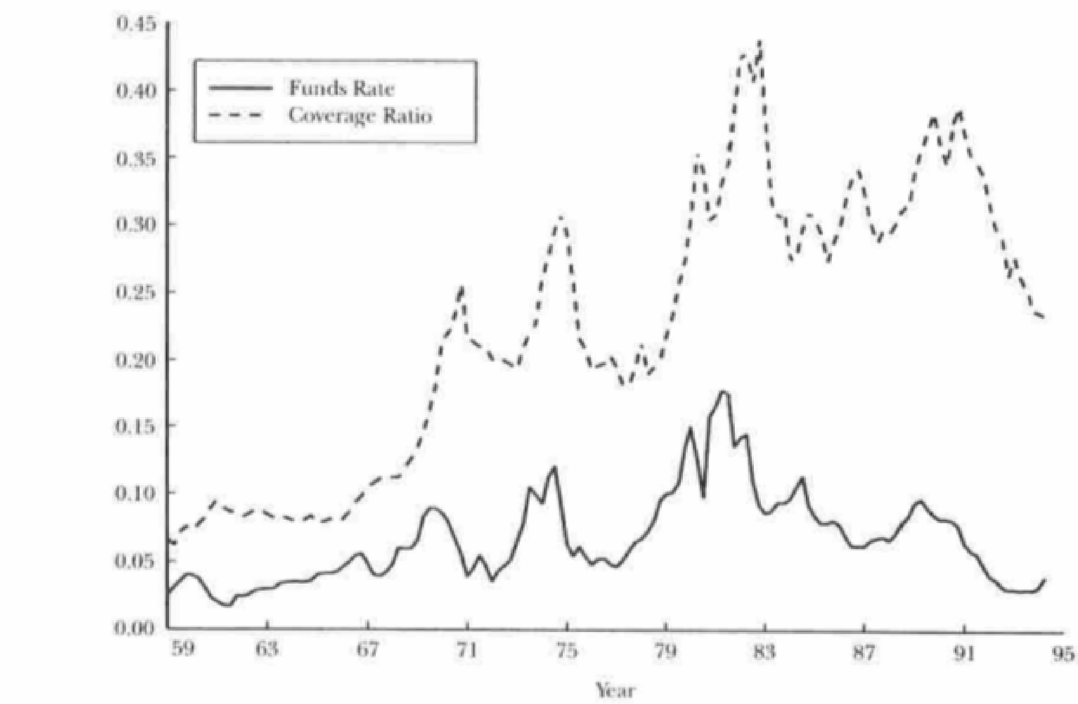
- A basic model of the ***financial accelerator*** suggests that a firm's spending on a variable input CAN'T EXCEED the *sum of gross cash flows* and *net discounted value of assets*. This relationship is expressed as a "***collateral-in-advance***" constraint.
- An INCREASE in interest rates (*contractionary* monetary policy) will ***tighten this constraint*** when it is binding; the firm's ability to purchase inputs will be reduced. This can occur in two ways:
  1. ***Direct impact:*** INCREASING interest rates directly INCREASE interest expenses (on outstanding debt or floating-rate debt), reducing net cash flows and weakening the borrower's financial position; INCREASING interest rates are also typically associated with DECLINING asset prices, which shrink the value of the borrower's collateral.
  2. ***Indirect impact:*** through demand-side shocks that reduce firms' net worth (similar to Kiyotaki-Moore *propagation* mechanism). Specifically, by DECREASING the consumer demand for a firm's products, which reduces the firm's revenue while its short-run fixed cost do not adjust (lowering the firm's gross cash flow). The resulting INCREASE in the "financing gap" (firms' needs - firms' sources of funds) DECREASES firms' net worth and creditworthiness over time.

A common and useful summary measure of a firm's financial condition is the "*coverage ratio*":

$$\text{coverage ratio} = \frac{\text{interest payments(by nonfinancial corps)}}{\text{interest payments (by nonfinancial corps)} + \text{profits (by nonfinancial corps)}}$$

If we interpret the *direction of causality* as ***fed funds rate*** $\implies$ ***coverage ratio***, which is most plausible, it seems that *increases* in the funds rate translate almost immediately into *increases* in the coverage ratio and hence, ultimately, into *weaker* balance sheet positions.

Figure 4
The Funds Rate and the Coverage Ratio



7.1.6 The Bank Lending Channel

Intuition: The ***bank lending channel*** can be thought of as inducing changes in how FINANCIAL INTERMEDIARIES (BANKS) are constrained on the ***credit-SUPPLY side***.

The *bank lending channel* is essentially the *balance sheet channel* as applied to the operations of lending institutions. Monetary policy actions may affect the *supply of loanable funds* available to banks (i.e. a bank's liabilities), and consequently the total amount of loans they can make (i.e. a bank's assets).

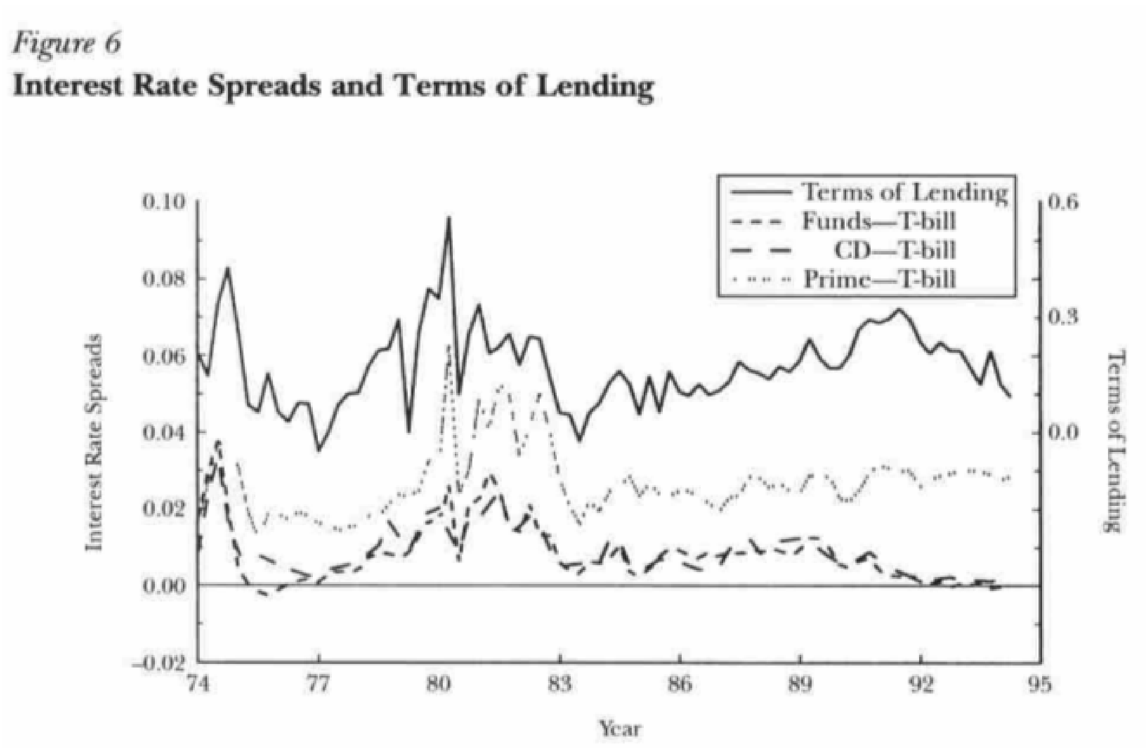
Beyond its impact on borrowers' balance sheets, monetary policy may also affect the *EFP* by shifting the ***supply of intermediated credit***, particularly loans by commercial banks. A DECREASE in the *supply of bank credit*, relative to other forms of credit, is likely to INCREASE the *EFP* and to reduce real activity.

Bernanke and Blinder's (1988) model of the *bank lending channel* suggested that open market sales by the Fed, which drain reserves and hence deposits from the banking system, would limit the supply of bank loans by reducing banks' access to loanable funds.

- **Assumption:** banks cannot easily replace lost (retail) deposits with other sources of funds, such as certificates of deposit (CDs) or new equity issues: works great pre-1980s, not so great after 1980s.
- Model is a *poorer description* of reality than it used to be, at least in the United States.

This channel — as proposed by ***Bernanke and Blinder's (1988)*** — is empirically WEAKER than the *balance sheet channel*. Because of *financial deregulation and innovation*, the importance of the traditional bank lending channel has most likely diminished over time. This is not to say that the bank lending channel is no longer relevant. On the contrary, the fact that banks can raise funds through liabilities that pay market interest rates exposes banks to an EFP as well. Forms of uninsured lending carry some credit risk relative to insured deposits. The cost of raising uninsured funds will reflect that risk, and will be more expensive for banks to purchase.

The behavior of *interest-rate spreads* and *terms of lending* shown in this figure offers some support for predictions of the *bank lending channel*.



- Behavior of *interest-rate spreads* and *terms of lending* are consistent with the *bank lending channel* as conceived by Bernanke and Blinder, it must be noted that they are also potentially consistent with the operation of a *balance sheet channel*
- ***Extremely difficult*** to carry out an empirical test that would conclusively separate the *bank lending channel* from the *balance sheet channel*.

7.1.7 Housing and Other Consumer Expenditures

Previous Analysis: Focused on the behavior of FIRMS, as has most of the literature on the *credit channel*. However, the credit market frictions that affect firms should also be relevant to the borrowing and spending decisions made by HHs, particularly spending on costly durable items such as automobiles and houses.

The *balance sheet channel* can also manifest itself via ***consumer spending on durables and housing***. These types of goods tend to be ***illiquid*** in nature. If consumers need to sell off these assets to cover debts they may have to sell at a steep discount and incur losses. Consumers who hold more ***liquid*** financial assets such as cash, stocks, or bonds can more easily cope with a negative shock to their income. Consumer balance sheets with large portions of financial assets may estimate their probability of becoming financially distressed as low and are more willing to spend on durable goods and housing.

- Monetary policy changes that DECREASE the valuation of financial assets on consumers' balance sheets can result in DECREASED spending on consumer durables and housing.

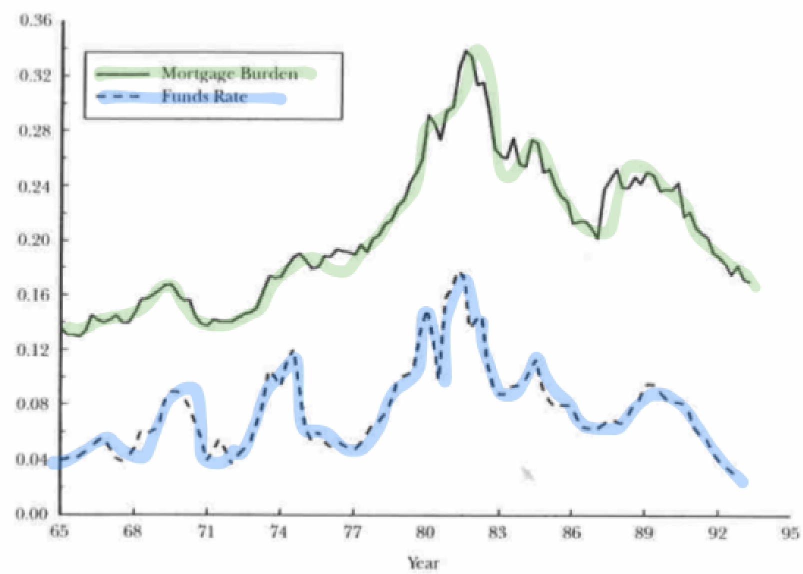
Boldin (1994) constructed a measure of the pressure that purchasing a home puts on the typical HH's balance sheet. His "*mortgage burden*" variable, which is (approximately) the ratio of mortgage payments to income for the *MEDIAN new home buyer* (i.e. extensive margin), can be considered analogous to the "coverage ratio" for firms.

$$\text{mortgage burden ratio}=\frac{\text{mortgage payments(by MEDIAN new home buyer)}}{\text{income (by MEDIAN new home buyer}}$$

- Boldin's mortgage burden variable has a close positive correlation with the federal funds rate, which we have used as a proxy for changes in monetary policy. The correlation arises both because nominal interest rates rise and household incomes fall following a tightening of monetary policy.

- The effects of monetary policy on such variables as the mortgage burden and mortgage terms help explain its strong impact on housing demand, despite the presumably weak link between monetary policy and long-term real interest rates.

Figure 7
The Mortgage Burden and the Funds Rate



7.2 Iacoviello (AER, 2005): *House Prices, Borrowing Constraints, and Monetary Policy in the Business Cycle*

7.2.1 Motivation

The paper wants to achieve ***two main goals***:

1. 1st *systematic evaluation* of the extent to which a general equilibrium model with *financial frictions* can explain the aggregate time-series evidence

2. To use such a model for *monetary policy analysis.*

7.2.2 The Model

Iacoviello's model is a variant of the ***BGG New Keynesian*** set-up (endogenous firms' balance sheet variations induce a "***financial accelerator***" by enhancing the *amplitude* of the business cycle), with two additional features:

1. *collateral constraints* à la Kiyotaki and Moore (1997) through *real estate values* for firms: ***housing collateral constraints***

2. ***nominal debt*** for a subset of HHs

Housing collateral constraints: *Practical reason:* empirically a large proportion of borrowing is secured by real estate. *Substantial reason*: the channel by which housing markets affect business fluctuations have not been understood yet.

Nominal debt: *Practical reason:* because in low inflation countries almost all debts are in nominal terms. *Substantial reason:* understand their implications for macroeconomic outcomes is a central task (nominal debt + sticky prices is important)

7.2.2.1 The Transmission Mechanism

Consider a *positive DEMAND shock*: consumer prices and asset prices $\uparrow$

- asset prices $\uparrow$ implies that also *debtors'* borrowing capacity $\uparrow$: debtor's expenditures and consumption $\uparrow$
- consumer prices $\uparrow$ implies that the *real value of their outstanding debt obligations* $\downarrow$, this effect will translate in an $\uparrow$ of their net worth.

If borrowers have a ***higher MPC*** than lenders $\implies$ net effect on *demand is positive*, it acts as a powerful *amplification mechanism.*

Consumer price inflation amplifies DEMAND shocks, but it dampens the shocks that induce a *negative correlation* between output and inflation (e.g. negative supply shocks are beneficial for borrowers' net worth when obligations are held in nominal terms). ***Novelty of the paper:*** the financial accelerator depends on where the shock comes from: the model features an ***accelerator of DEMAND shocks*** and a ***decelerator of SUPPLY shock***s.

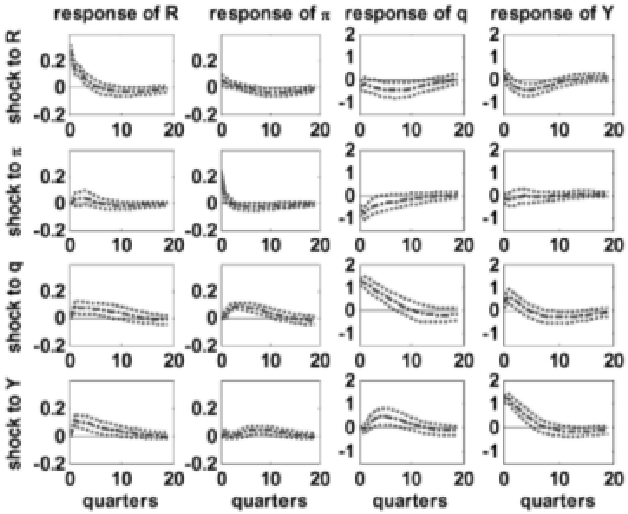
Thanks to this peculiar transmission mechanism the model is able to explain two important features of the data:

1. effects induced by *collateral constraints* on firms and HHs allow matching the *positive response* of spending to housing price shock.
2. thanks to the assumption of *nominal debt* the model is able to replicate the *hump-shaped dynamics of HH spending* to an inflation shock. The ***redistribution from lenders to borrowers*** doesn't kick in immediately but over time.

Model is able to explain these two key business facts and the interaction between asset prices and economic activity through estimation of the key *structural parameters* **minimizing the distance** between the IRFs generated by the model and those generated by a unrestricted VAR.

7.2.2.2 VAR results

IRFs from a VAR with *detrended real GDP* y, *Δlog(GDP deflator)* π, *detrended real house prices* q, and *Fed Funds rate* R from 1974:Q1 - 2003:Q2. Variables are expressed in **%** and in ***quarterly*** rates. Shocks are ***orthogonalized*** in the order R, π, q and Y .



- $-$ response of nominal prices, q and Y to tight money (first row)
- $-$ response of q and Y to a positive π disturbance (second row)
- $+$ comovement of q and Y to q shocks (third row)
- $+$ comovement of q and Y to Y shocks (fourth row)
- third and fourth rows highlight a two-way interaction between q and Y

- The ordering did not affect the results substantially so the VAR results.

7.2.3 The Basic Model

Essentially Kiyotaki and Moore (1997) + nominal debt. Discrete time, infinite horizon economy, populated by infinitely lived HHs and of measure one.

- ***entrepreneurs:*** produce a homogeneous good, hire HHs labor and combine it with collateralizable real estate.
- ***patient households*** (i.e. they have lower β than firms): consume, work and demand real estate and money

Both sectors may invest in housing, this assumption guarantees effects on economic activity from shifts in asset holdings. Real estate is fixed in the aggregate in order to guarantee a variable price of housing. Moreover there are:

- ***retailers:*** they are the source of nominal rigidity
- ***a central bank:*** adjust money supply and transfers to support an interest rate rule

7.2.3.1 Patient HHs

Maximize a lifetime utility function given by

$$U_{HH} = E_0 \left[\sum_{t=0}^{\infty} \beta^t \left(ln\left(c_t'\right) + j \cdot ln\left(h_t'\right) - \frac{\left(L_t'\right)^{\eta}}{\eta} + \chi \cdot ln\left(\frac{M_t'}{P_t}\right)\right)\right]$$

where c_t' is consumption, h_t' denotes the holdings of housing, L_t' are hours of work (HHs work for the entrepreneurs), and $\frac{M_t'}{P_t}$ are money balances divided by the price level. Denote with $q_t \equiv \frac{Q_t}{P_t}$ the real housing price, with $w_t' \equiv \frac{W_t'}{P_t}$ the real wage. Assume that HHs lend in real terms $-b_t'$ (or borrow $b_t' \equiv \frac{B_t'}{P_t}$) and receive back $\frac{-R_{t-1}B_{t-1}'}{P_t}$, where R_{t-1} is the nominal interest rate on loans between $t-1$ and t, so that obligations are set in money terms.

The flow of funds (i.e. budget constraint) is

$$c'_t + q_t\left(h'_t - h'_{t-1}\right) + \frac{R_{t-1}b'_{t-1}}{\pi_t} = b'_t + \underbrace{w'_t L'_t}_{\text{wage income}} + \underbrace{F_t}_{\text{gov't transfers}} + \underbrace{T'_t - \frac{\left(M'_t - M'_{t-1}\right)}{P_t}}_{\text{net transfers from central bank by printing money}}$$

- Solving this problem yields the following *FOCs*

$$\underbrace{\frac{1}{c'_t} = \beta E_t\left(\frac{R_t}{\pi_{t+1}c'_{t+1}}\right)}_{\textit{FOC for consumption}}$$

$$\underbrace{w'_t = \left(L'_t\right)^{\eta-1} c'_t}_{\textit{FOC for labor supply}}$$

$$\underbrace{\frac{q_t}{c'_t} = \frac{j}{h'_t} + \beta E_t\left(\frac{q_{t+1}}{c'_{t+1}}\right)}_{\textit{FOC for housing demand}}$$

- the *FOC* with respect to $\frac{M'_t}{P_t}$ yields a standard demand equation. Since the paper is focused on interest rate rules, money supply will always meet money demand at the desired equilibrium nominal interest rate.

7.2.3.2 Entrepreneurs

Use a Cobb-Douglas, CRS technology with factors of production: *real estate* h + *labor* L. ***Intermediate good*** Y_t is produced

$$Y_t = A \cdot \left(h_{t-1}\right)^v \left(L_t\right)^{1-v}$$

where A is technology. Following **BGG**, output cannot be transformed immediately into consumption. Retailers purchase Y_t at the wholesale price P_t^w and transform it into a composite ***final good***, whose price index is P_t. $X_t = \frac{P_t}{P_t^w}$ is the *markup* of ***final goods*** over ***intermediate goods***.

Kiyotaki and Moore (1997) ingredient: Limit on entrepreneurs' obligations $\Longrightarrow$ borrowing constraint (in real terms):

$$b_t \leq m \cdot E_t\left[\frac{q_{t+1} \cdot h_t \cdot \pi_{t+1}}{R_t}\right]$$

- If borrowers repudiate their debt obligations then lenders can re-posses borrowers'assets by paying a proportional transaction cost $(1-m) \cdot E_t\left[\frac{Q_{t+1}h_t}{R_t}\right]$ therefore the maximum amount B t that a
- **ISSUE:** Entrepreneurs' borrowing constraint depends on an *expectation,* but in reality the lender could receive *something substantially less* than this (perhaps the *worst* possible outcome). As a result, this constraint is strange. In practice, the borrowing constraint should depend on *current values.*

They also have lifetime utility with $\gamma < \beta$ (less patient than "patient" HHs)

$$U_e = E_0 \left[\sum_{t=0}^{\infty} \gamma^t \cdot ln\left(c_t\right) \right]$$

subject to technology constraint, borrowing constraint, and the flow of funds (budget constraint)

$$\frac{Y_t}{X_t} + b_t = c_t + q_t \cdot (h_t - h_{t-1}) + \underbrace{\frac{R_t b_{t-1}}{\pi_t}}_{\text{reflects assumption of nominal debt contracts}} + w_t' L_t$$

- Solving this problem yields the following *FOCs*

$$\underbrace{\frac{1}{c_t} = \gamma E_t \left(\frac{R_t}{\pi_{t+1} c_{t+1}} \right) + \lambda_t R_t}_{FOC\ for\ consumption}$$

$$\underbrace{w_t' = (1-\nu) \frac{Y_t}{X_t L_t}}_{FOC\ for\ labor\ demand}$$

$$\underbrace{\frac{q_t}{c_t} = \gamma \left[E_t \frac{1}{c_{t+1}'} \left(\nu \frac{Y_{t+1}}{X_{t+1} h_t} + q_{t+1} \right) + \lambda_t m \pi_{t+1} q_{t+1} \right]}_{FOC\ for\ housing\ demand}$$

- where λ_t defines the shadow value of the borrowing constraint at time t. It equals the increase in lifetime utility that would stem from borrowing R_t dollars, consuming or investing the proceeds and reducing the consumption by an appropriate amount the next period.

- Without uncertainty, the assumption $\gamma < \beta$ guarantees that entrepreneurs are constrained in and around the steady state. From the household consumption Euler equation in the steady state, with zero inflation we get $R = \frac{1}{\beta}$. Combining this result with the entrepreneur's steady state Euler equation yields: $\lambda = \frac{\beta - \gamma}{c} > 0 \Longrightarrow$ the borrowing constraint will hold with equality

$$b_t = m E_t \left(\frac{q_{t+1} h_t \pi_{t+1}}{R_t} \right).$$

7.2.3.3 Retailers

- The retailers' problem is borrowed by BGG.
- There are implicit costs of adjusting nominal prices and monopolistic competition for the retail sector.
- There is a continuum of retailers of mass 1, indexed by z. They buy intermediate goods Y_t from entrepreneurs at price P_t^w in a competitive market, differentiate the goods at no cost into $Y_t(z)$ and sell it at price $P_t(z)$. Final goods are

$$Y_t^f = \left(\int_0^1 Y_t(z)^{\frac{\varepsilon-1}{\varepsilon}} dz \right)^{\frac{\varepsilon}{\varepsilon-1}}$$

where $\varepsilon > 1$.

- The price level is a CES aggregator of retailers'prices:

$$P_t = \left(\int_0^1 P_t(z)^{\frac{\varepsilon-1}{\varepsilon}} dz \right)^{\frac{1}{1-\varepsilon}}$$

- Therefore, each retailer faces a demand curve of the following type

$$Y_t(z) = \left(\frac{P_t(z)}{P_t} \right)^{-\varepsilon} Y_t^f$$

- Each retailer chooses a sale price $P_t(z)$ taking P_t^w and the demand curve as given.

- The sale price can be changed in every period only with probability $1-\theta$. Denoting with $P_t^*(z)$ the "reset" price and with $Y_{t+k}^*(z) = \left(\frac{P_t^*(z)}{P_{t+k}}\right)^{-\varepsilon} Y_{t+k}$ the corresponding demand, the optimal $P_t^*(z)$ solves

$$\sum_{k=0}^{\infty} \theta^k E_t \left\{ \Lambda_{t,k} \left(\frac{P_t^*(z)}{P_{t+k}} - \frac{X}{X_{t+k}} \right) Y_{t+k}^*(z) \right\} = 0$$

- where $\Lambda_{t,k} = \beta^k \frac{c_t'}{c_{t+k}'}$ represents the household relevant discount factor and X_t is the markup, that in the steady state is $X = \frac{\varepsilon}{\varepsilon - 1}$
- P_t^* equates expected discounted marginal revenue to expected discounted marginal cost.
- Notice that profits $F_t = (1 - \frac{1}{X_t})Y_t$ are rebated to patient households.

- A fraction θ of retailers does not adjust prices, therefore the aggregate price level evolution is

$$P_t = \left[\theta P_{t-1}^{1-\varepsilon} + (1-\theta)(P_t^*)^{1-\varepsilon}\right]^{\frac{1}{1-\varepsilon}}$$

- Combining this relation with the one in the previous slide and linearizing yields a forward-looking Phillips curve

$$\hat{\pi}_t = \beta E_t \hat{\pi}_{t+1} - \kappa \hat{X}_t$$

- inflation depends positively on expected inflation and negatively on the markup of final over intermediate good.

7.2.3.4 Central bank policy and the interest rate rule

The central bank extends lump sum transfers of money to the real sector to implement a (BACKWARD-LOOKING) Taylor-type interest rate rule of the following form:

$$R_t = (R_{t-1})^{r_R} \left[\pi_{t-1}^{1+r\pi} \cdot \left(\frac{Y_{t-1}}{\overline{Y}}\right)^{r_Y} \overline{rr} \right]^{1-r_R} e_{R,t}$$

where $\overline{rr}$ and $\overline{Y}$ are the *steady state **real rate*** and ***output***, respectively. If $r_R > 0$ the interest rate rule allows for *interest rate inertia*. $e_{R,t}$ is a white noise shock process with zero mean and variance σ_e^2

7.2.3.5 Equilibrium

Absent shocks the model has a ***unique stationary equilibrium*** in which entrepreneurs hit the borrowing constraint and borrow up to the limit, they pay the interest payments on debt. The equilibrium is an allocation of

$$\{h_t, h_t', L_t, L_t', Y_t, c_t, c_t', b_t, b_t'\}_{t=0}^{\infty}$$

together with the sequence of values

$$\{w_t', R_t, P_t, P_t^*, X_t, \lambda_t, q_t\}_{t=0}^{\infty}$$

satisfying the FOCs, the constraints and the market clearing conditions for labor $L_t = L_t'$; real estate $h_t + h_t' = H$, goods $c_t + c_t' = Y_t$ and loans $b_t + b_t' = 0$, given $\{h_{t-1}, R_{t-1}, b_{t-1}, P_{t-1}\}$ and the sequence of monetary shocks $\{e_{R,t}\}$, together with the relevant transversality conditions.

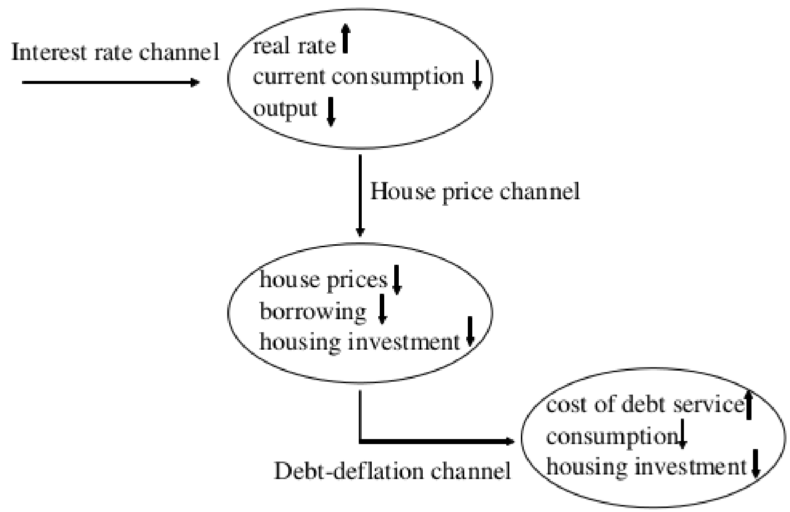
7.2.3.6 The transmission mechanism: indexation and collateral effects

The basic model highlights the links between three different transmission channels: consider *negative (contractionary) monetary shock* $\Longleftrightarrow$ *interest rate INCREASE*

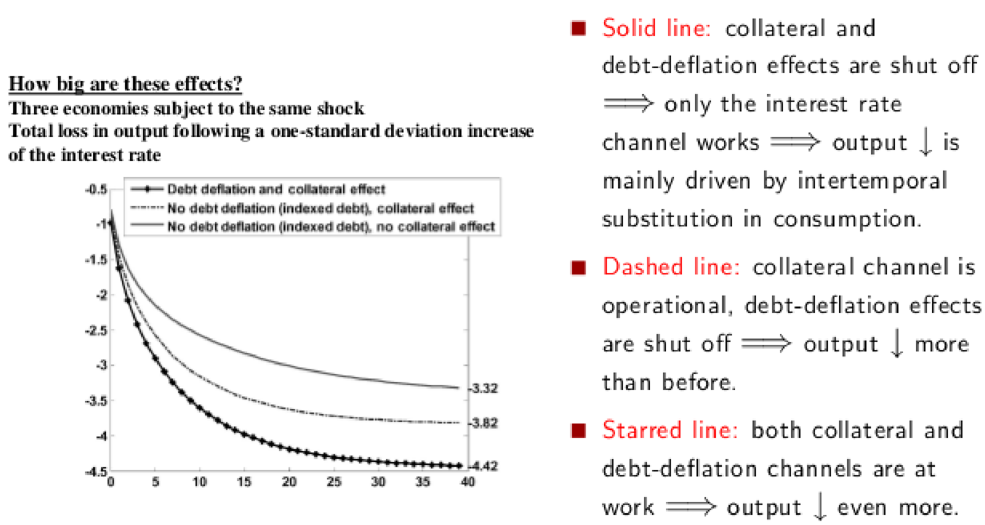
1. **Interest rate channel**:
   - because of the *sticky prices* assumption, monetary actions affect the *real interest rate*, which $\uparrow$
   - current consumption $\downarrow$ and hence AD (output)
2. **House price (collateral) channel** reinforces the effects above, in fact:
   - house (asset) prices $\downarrow$
   - borrowing capacity of entrepreneurs $\downarrow$ and hence their housing investment $\downarrow$
3. **Debt-deflation (redistribution) channel**

- obligations are not indexed, therefore deflation ↑ the cost of debt services
- further ↓ in entrepreneur's consumption and investment

A negative monetary shock



How big are these effects?



7.2.4 The Full Model

The Full Model is an ***extension of the Basic Model*** along 2 dimensions: **(1)** a *constrained*, *impatient* HH sector is added, **(2)** *variable capital investment* for the entrepreneurs is allowed.

Also, ***inflation***, ***technology*** and ***taste shocks*** are added.

- Full model *replicates* two key dynamic correlations that are present in the data:
  1. the ***collateral effect*** allows pinning down the *elasticity of consumption* to a *housing preference shock:* HHs that are borrowing constraint and value *current consumption* a great deal will be able to INCREASE their borrowing and consumption *more than proportionally* when housing prices ↑(positive effects on AD)
  2. the ***nominal debt effect*** allows matching the *delayed response* of output to an inflation shock

7.2.4.1 Entrepreneurs

They produce an intermediate good. Iacoviello assumes adjustment cost for both capital and housing.

Entrepreneurs

- They produce an intermediate good according to:

$$Y_t = A_t K_{t-1}^{\mu} h_{t-1}^{\nu} L_t^{'\alpha(1-\mu-\nu)} L_t^{''(1-\alpha)(1-\mu-\nu)}$$

- where A_t is random. L' and L'' are the patient and impatient household labor (α measures the relative size of each group) and K is capital created at the end of each period (it depreciates at rate δ).

- Iacoviello assumes adjustment cost for both capital and housing:

$$\xi_{K,t} = \frac{\psi}{2\delta}\left(\frac{I_t}{K_{t-1}} - \delta\right)^2 K_{t-1} \implies \text{capital installation cost}$$

$$\xi_{e,t} = \frac{\phi_e}{2}\left(\frac{h_t - h_{t-1}}{h_{t-1}}\right)^2 q_t h_{t-1} \implies \text{house stock changes cost}$$

with $I_t = K_t - (1-\delta) K_{t-1}$

- The flow of funds constraint is

$$\frac{Y_t}{X_t} + b_t = c_t + q_t (h_t - h_{t-1}) + \frac{R_t b_{t-1}}{\pi_t} + w_t' L_t' + w_t'' L_t'' + I_t + \xi_{e,t} + \xi_{K,t}$$

Solving this problem yields the following *FOCs*

$$\underbrace{\upsilon_t}_{\text{shadow price of capital}} = \underbrace{\frac{1}{c_t}\left[\frac{\psi}{\delta}\left(\frac{I_t}{K_{t-1}} - \delta\right)\frac{I_t}{K_{t-1}} - \frac{\psi}{2\delta}\left(\frac{I_t}{K_{t-1}} - \delta\right)^2\right]}_{\text{capital contribution to lower installation cost}} + \gamma E_t \underbrace{\left[\frac{\mu Y_{t+1}}{c_{t+1} X_{t+1} K_t} + \upsilon_{t+1}(1-\delta)\right]}_{\text{capital's marginal product next period plus shadow value of capital in the next period}}$$

where $\upsilon_t = \frac{1}{c_t}\left[1 + \psi\delta\left(\frac{I_t}{K_{t-1}} - \delta\right)\right]$

- Labor demand schedules are:

$$w_t' = \alpha(1-\mu-\nu)\frac{Y_t}{X_t L_t'}$$

$$w_t'' = (1-\alpha)(1-\mu-\nu)\frac{Y_t}{X_t L_t''}$$

7.2.4.2 Impatient HHs

They discount the future more heavily than patient ones.

Impatient households

- They discount the future more heavily than patient ones, they choose $c_t^{''}$, $h_t^{''}$, $L_t^{''}$ and $\frac{M_t^{''}}{P_t}$ to maximize

$$E_0 \sum_{t=0}^{\infty} \left(\beta^{''}\right)^t \left(\ln c_t^{''} + j_t \ln h_t^{''} - \frac{\left(L_t^{''}\right)^{\eta}}{\eta} + \chi \ln \frac{M_t^{''}}{P_t} \right)$$

where $\beta^{''} < \beta$. j_t allows for random disturbances to the marginal utility of housing, since it affects housing demand, it allows to assess the macro effects of an exogenous disturbance on house prices.

- Subject to the flow of funds constraint (in real terms)

$$c_t^{''} + q_t \left(h_t^{''} - h_{t-1}^{''}\right) + \frac{R_{t-1} b_{t-1}^{''}}{\pi_t} = b_t^{''} + w_t^{''} L_t^{''} + T_t^{''} - \frac{M_t^{''} - M_{t-1}^{''}}{P_t} - \xi_{h,t}$$

where $\xi_{h,t} = \frac{\phi_h}{2} \left(\frac{h_t^{''} - h_{t-1}^{''}}{h_{t-1}^{''}} \right)^2 q_t h_{t-1}^{''}$ is the housing adjustment cost.

- and the borrowing constraint (in real terms)

$$b_t^{''} \leq m^{''} E_t \left(\frac{q_{t+1} h_t^{''} \pi_{t+1}}{R_t} \right)$$

- Solving this problem yields the following *FOCs*

$$\underbrace{\frac{1}{c_t^{''}} = \beta^{''} E_t \left(\frac{R_t}{\pi_{t+1} c_{t+1}^{''}} \right) + \lambda_t^{''} R_t}_{FOC\ for\ consumption}$$

$$\underbrace{w_t^{''} = \left(L_t^{''}\right)^{\eta-1} c_t^{''}}_{FOC\ for\ labor\ supply}$$

$$\underbrace{\frac{q_t}{c_t^{''}} = \frac{\frac{j}{h_t^{''}} + E_t \left[\frac{\beta^{''} q_{t+1}}{c_{t+1}^{''}} \left(1 + \phi_h \frac{h_{t+1}^{''} - h_t^{''}}{h_t^{''}} \right) + \lambda_t^{''} m^{''} q_{t+1} \pi_{t+1} \right]}{1 + \phi_h \frac{h_t^{''} - h_{t-1}^{''}}{h_{t-1}^{''}}}}_{FOC\ for\ housing\ demand}$$

where $\lambda_t^{''}$ is the multiplier on the borrowing constraint.

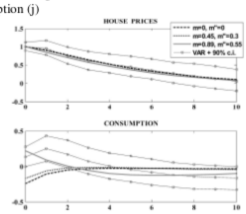
7.2.4.3 Collateral Effects and Effects on Consumption of a Housing Price Shock

Collateral effects

- Case et al (2001); Davis and Palumbo (2001) have found evidence for a positive long run elasticity of consumption to housing prices (between 0.06 and 0.08)
- This finding is hard to reconcile with the traditional life-cycle model.
- However, when borrowing constrained households are taken into account, if they value current consumption a great deal, than
- They will be able to increase their borrowing and consumption more than proportionally when housing prices $\uparrow$
- In this scenario an $\uparrow$ in housing prices might have positive effects on aggregate demand

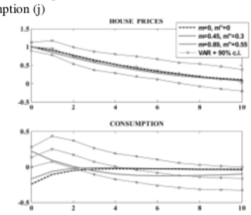
The figures illustrates an important point: the ***greater the importance of collateral effects*** (higher m and m''), the ***closer the simulated elasticity of consumption to a housing price shock***

Impulse response of consumption to a persistent housing price increase.
Shock to the marginal rate of substitution between housing and consumption (j)



- IRFs for several values of the loan-to-values m and m'' compared with the IRFs of the VAR
- The higher m and m'' $\Longrightarrow$ the greater the importance of collateral effects $\Longrightarrow$ the closer the simulated elasticity of consumption to a housing price shock

Impulse response of consumption to a persistent housing price increase.
Shock to the marginal rate of substitution between housing and consumption (j)



- Both in the model and in the VAR consumption falls below the baseline during the transition
- Without collateral effects (m, $m'' \longrightarrow 0$) predicts a negative response of consumption to housing prices (at odd with data)

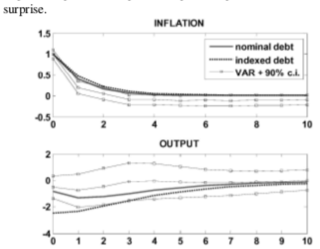
7.2.4.4 Debt Deflation and the Stabilizing Effects of an Inflation Shock

Nominal debt effects

- Consider a 1-percent, persistent inflation surprise
- Iacoviello contrasts the response of output with nominal debt to the model with indexed debt.

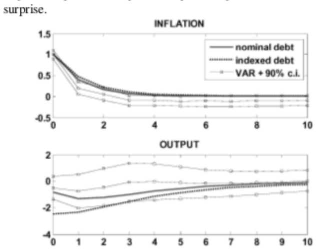
Interestingly, the ***negative correlation between inflation and output*** induced by an inflation shock acts as a ***built-in stabilizer*** for the economy. Debt deflation thus adds a new twist to the theories of financial accelerator mentioned in the introduction: while it *amplifies* ***demand-side*** *disturbances*, it can stabilize those that generate a trade-off between output and inflation.

Impulse response of output to a 1-percent, persistent inflation surprise.



- With nominal debt (solid line) the ↑ in prices reduces the desired supply of goods at a given price level ⟹ it transfers wealth from the lenders to the borrowers ⟹ Borrowers, ceteris paribus, have a higher propensity to consume
- Initially the two effects go in opposite directions ⟹ output ↓ of a small amount
- Later the first effect dominates and output drop is larger
- Output displays a hump-shaped pattern and a slow return to its initial steady state

Impulse response of output to a 1-percent, persistent inflation surprise.



- With indexed debt (dashed line) the drop in output is immediate and stronger in magnitude
- Beneficial effects of inflation are absent
- The assumption of nominal debt captures not only qualitatively but also quantitatively the hump-shaped and persistent response of output to inflation found in the VAR
- Debt-deflation amplifies demand-type disturbances and it can stabilize disturbances that generate a trade-off between output and inflation

7.2.5 Monetary Policy

There is a trade-off between ***output*** and ***inflation*** induced by shocks. The paper addresses 2 main questions:

Question 1: ***Should the monetary authority respond to asset prices***? Iacoviello's answer is **no**! In his model allowing the central bank to respond to asset prices *yields negligible gains* in terms of output and inflation stabilization. Here, asset prices matter in that they *transmit* and *amplify* a range of disturbances to the real sector. Despite this, ***if the central bank wants to minimize output and inflation fluctuations***, little is gained by responding to asset prices, even if their current movements are in the policymaker information set.

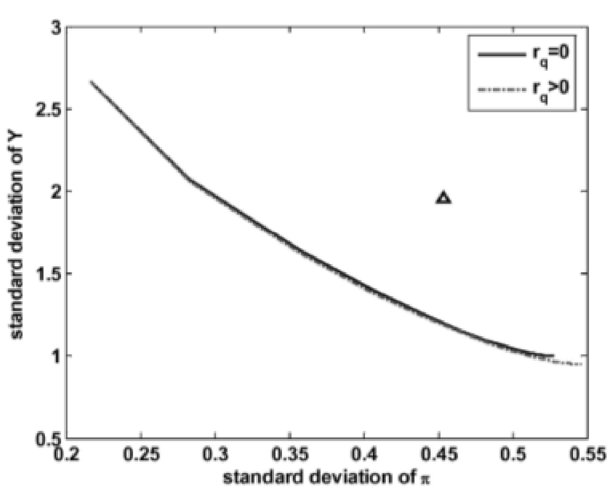
Monetary policy and housing prices

- Iacoviello computes the inflation-output volatility for different parameterization of the interest rate rule subject to a constraint to interest rate volatility
- He considers the following class of rules

$$\hat{R}_t = 0.73\hat{R}_{t-1} + 0.27\left[r_q\hat{q}_t + (1+r_\pi)\,\hat{\pi}_{t-1} + r_Y\,\hat{Y}_{t-1}\right]$$

- He computes two Taylor curves. One in which the central bank does not respond to housing prices ($r_q = 0$) and one in which he allows the central bank to respond to housing prices.
- Does responding to asset prices yield a significant gain in terms of output and inflation stabilization?

Policy Frontiers and Asset Prices Responses



- Keeping inflation standard deviation constant the decrease in the standard deviation of output is a rather small number, about 0.7 percent of its baseline value
- The role of asset prices in this model, therefore, consists in transmitting and amplifying a range of shocks to the real sector.
- But a central bank that wants to minimize output and inflation volatility has a really small gain by responding to asset prices.

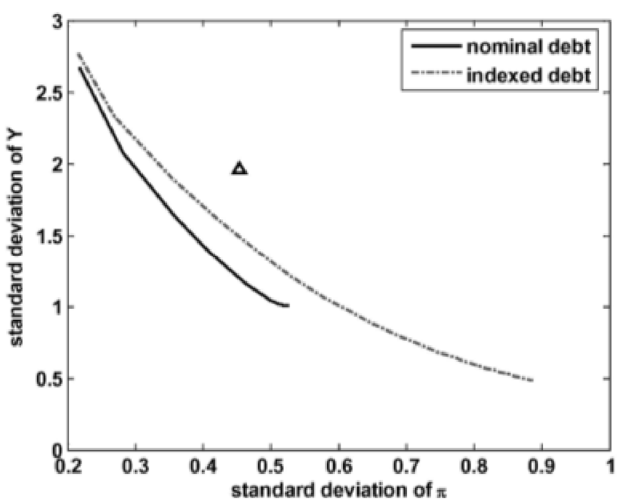
Question 2: ***Is there any gains for the central bank because of nominal debts assumption?*** Iacoviello's answer is **it depends on the objective function**

He finds that nominal debt yields an ***improved OUTPUT-INFLATION variance trade-off*** for the central bank for all ***supply-side shocks***

Monetary policy and debt contracts

- Consider a positive inflation surprise shock: it causes a stronger output decline in the indexed debt model since, while demand drops in both cases, borrowers do not get the benefit of lower real repayments as before.
- Therefore indexed debt stabilizes only the type of shocks that monetary policy can offset.
- If we consider a supply shock the Taylor curve in an economy with indexed debt lies all above that for an economy with nominal debt

Policy Frontiers and Debt Contracts



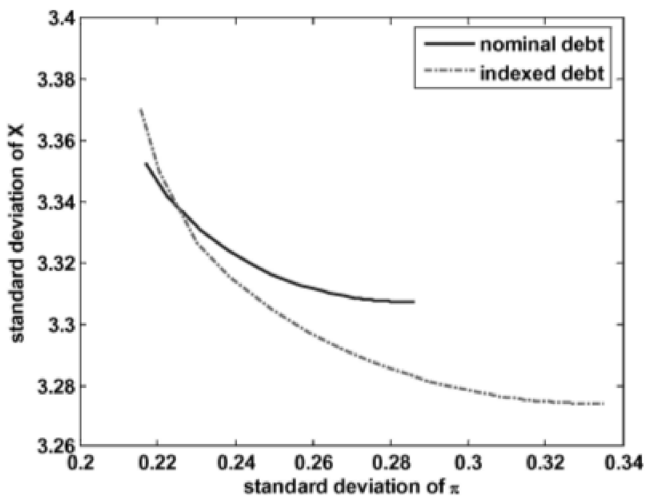
- This result is a consequence of two causes:
  (1) shocks that matter for the trade off are only those that move the target variables in opposite directions
  (2) the accelerator of demand shocks gives more leverage to the central bank and implies that smaller interest rate changes are needed to stabilize the economy for given demand disturbances

- Sources of trade-offs in model *not amplified*, since such shocks (ceteris paribus) ***transfer resources from lenders to borrowers during a downturn***. Debt-deflation amplifies *DEMAND* shocks but stabilizes *SUPPLY* shocks

He finds that nominal debt yields an ***improved OUTPUT GAP-INFLATION variance trade-off*** for the central bank for all ***supply-side shocks except TECHNOLOGY SHOCKS***

- It is interesting to consider how the results change when the *trade-off involves inflation and output gap*, defined as the shortfall of output from its equilibrium level under flexible prices (as proxied by X_t , the time-varying markup).
- If we consider a POSITIVE technology shock $\Longrightarrow$ for a given drop in prices, *output* $Y_t \uparrow$ less with *nominal debt* than with *indexed debt* because of the *negative deflation effect*; however, *output gap* $X_t \uparrow$ more with *nominal debt* than with *indexed debt* because, while in both cases $\downarrow$ price stickiness prevents aggregate demand from $\uparrow$ enough to meet the higher supply, debt-deflation implies that demand $\uparrow$even less if debt is not indexed.

Policy Frontiers and Debt Contracts



- If technology shocks were the only source of supply-side fluctuations, the gap is bigger under nominal debt and the trade off would be worsened under nominal debt. But
  (1) if the weight of π stabilization is large, central bank can offset technology shocks better than π shocks, nominal debts dominates
  (2) if the weight of output stabilization is large,the reverse is true, indexed debts dominates

NOTE: From Econ 202B, we know that when there is a positive DEMAND shock, the central bank *does not really face a trade-off between output and inflation stabilization* since inflation $\uparrow$ and output $\uparrow$. The central bank can easily just INCREASE interest rates to prevent overheating of the economy.

The central bank faces a non-trivial trade-off when it has to dampen SUPPLY shocks; when there is a positive SUPPLY shock, inflation $\uparrow$ but output $\downarrow$. If the central bank DECREASES the interest rate then inflation $\uparrow$ and output $\uparrow$; we have a trade-off here.

7.3 Auclert (JMP, 2015): *Monetary Policy and the Redistribution Channel*

Redistribution channel

- Traditional view: monetary policy affects household spending via a *substitution channel*
- A *redistribution channel* is also active when agents have correlated marginal propensities to consume and balance sheet positions
  - supported empirically: Johnson, Parker, Souleles 2006; Baker 2013
- Nominal interest rate changes impact balance sheets by:
  - redenominating nominal wealth (future inflation effect)
  - **redistributing between unhedged borrowers and savers (real interest rate effect)**
- This is expansionary if those agents whose balance sheets improve when interest rates fall have higher MPCs
- This project**:** understand and quantify the redistribution channel using model and micro data

No-uncertainty framework

- Consider an agent with arbitrary preferences, facing no uncertainty, earning real income $\{y_t\}$ and holding long-term contracts. Solves

$$\begin{aligned}
\max \quad & U(\{c_t\}) \\
\text{s.t.} \quad & P_t c_t = P_t y_t + ({}_{t-1}B_t) + \sum_{s\geq 1} ({}_tQ_{t+s})({}_{t-1}B_{t+s} - {}_tB_{t+s}) \\
& \quad + P_t({}_{t-1}b_t) + \sum_{s\geq 1} ({}_tq_{t+s}) P_{t+s}({}_{t-1}b_{t+s} - {}_tb_{t+s})
\end{aligned}$$

- Initial holdings:
  - Nominal assets: $\{{}_{-1}B_{t+s}\}_{s\geq 0}$ (deposits, long-term bonds, mortgages)
  - Real assets: $\{{}_{-1}b_{t+s}\}_{s\geq 0}$ (TIPS, price-level adjusted loans)
- Initial real term structure: $q_t = ({}_0q_t)$ and expected price level $\{P_t\}$
- No arbitrage between nominal and real bonds: Fisher equation for nominal term structure ${}_tQ_{t+s} = ({}_tq_{t+s}) \frac{P_t}{P_{t+s}}$

Present-value budget constraint

- Intertemporal budget constraint (using a TVC/TC)

$$\sum_{t\geq 0} q_t c_t = \sum_{t\geq 0} q_t \left(y_t + ({}_{-1}b_t) + \left(\frac{{}_{-1}B_t}{P_t} \right) \right) \equiv W$$

- All financial assets with same present-value are equivalent and can be restructured in each period
  - $\rightarrow$ **Initial balance sheets are arbitrary**
- Example: initial holding of a single real liability $\frac{D}{P_0}$ in form of:
  - Adjustable rate: ${}_{-1}B_0 = -D$
  - Fixed rate: ${}_{-1}B_t = -M$, $t = 1 \dots T$, $\sum_{t=0}^{T} Q_t M = D$
  - Price-level adjusted: ${}_{-1}b_t = -m$, $t = 1 \dots T$, $\sum_{t=0}^{T} q_t m = \frac{D}{P_0}$

Unexpected shock

- At $t = 0$ there is an unanticipated/uncontracted "shock" to monetary policy, resulting in a change in
  1. The price level $\{P_0, P_1 \dots\}$
  2. The real term structure $\{q_0 = 1, q_1, q_2 \dots\}$
  3. The agent's real income sequence $\{y_0, y_1 \dots\}$
- The Fisher equation still holds after the shock
- Consider the first-order change in consumption dc_0 and welfare dU that results from this change in the environment
- Consumer theory $\rightarrow$ $MPC = \frac{\partial c_0}{\partial W}$, $\epsilon_{0,t}^h = \frac{\partial c_0^h}{\partial q_t} \frac{q_t}{c_0}$ at initial $(\{q_t\}, W, \overline{u})$
- $\rightarrow$ **now balance sheets matter**: for example,

$${}_{-1}B_t = 0 \quad {}_{-1}b_t = c_t - y_t \quad \forall t$$

hedges against both the inflation and the real interest-rate shock

Unexpected one-time shock

- At $t = 0$ there is an unanticipated/uncontracted "shock" to monetary policy, resulting in a one-time change in
  1. The price level $\{P_0, P_1 \dots\}$ $\rightarrow$ $dP = Pd\pi$
  2. The real term structure $\{q_0 = 1, q_1, q_2 \dots\}$ $\rightarrow$ $dq = -qdr$
  3. The agent's real income sequence $\{y_0, y_1 \dots\}$ $\rightarrow$ dy_0
- The Fisher equation still holds after the shock
- Consider the first-order change in consumption dc_0 and welfare dU that results from this change in the environment
- Consumer theory $\rightarrow$ $MPC = \frac{\partial c_0}{\partial W}$, $\epsilon_{0,t}^h = \frac{\partial c_0^h}{\partial q_t} \frac{q_t}{c_0}$ at initial $(\{q_t\}, W, \overline{u})$
- Assuming separable utility,

$$\sum_{t\geq 0} \beta^t u(c_t) \qquad \sigma(c) \equiv -\frac{u'(c)}{cu''(c)} \qquad \epsilon_{0,0}^h = -\sigma(c_0)(1 - MPC)$$

Consumption and welfare response

Impulse response to the shock

To first order, the date-0 consumption and welfare change in response to the shock are

$$\begin{aligned}
dc_0 &= MPC d\Omega + c_0 \sum_{t\geq 0} \epsilon_{0,t}^h \frac{dq_t}{q_t} \\
dU &= U_{c_0} d\Omega
\end{aligned}$$

where $d\Omega = dW - \sum_{t\geq 0} c_t dq_t$, the net-of-consumption wealth change, is given by

$$\begin{aligned}
d\Omega \quad = \quad & \underbrace{-\sum_{t\geq 0} Q_t \left(\frac{{}_{-1}B_t}{P_0} \right) \frac{dP_t}{P_t}}_{\text{Revaluation of NNP}} \\
+ \quad & \underbrace{\sum_{t\geq 0} q_t \left(y_t + \left(\frac{{}_{-1}B_t}{P_t} \right) + ({}_{-1}b_t) - c_t \right) \frac{dq_t}{q_t}}_{\text{Real revaluation of future flows}} + \underbrace{\sum_{t\geq 0} (q_t y_t) \frac{dy_t}{y_t}}_{\text{Real income change}}
\end{aligned}$$

One-time change

One-time unexpected change

For a one-time change:

$$dc_0 = MPC d\Omega - \sigma(c_0)(1 - MPC)\, c_0 dr$$

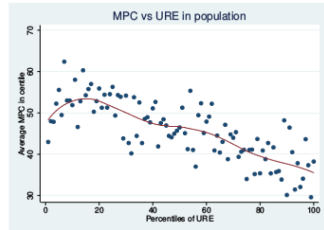
where $d\Omega$ comprises net nominal position (NNP) and unhedged rate exposure (URE):

$$d\Omega = \underbrace{-\sum_{t\geq 0} q_t \left(\frac{{}_{-1}B_t}{P_t}\right)}_{\text{NNP}} d\pi + \underbrace{\left(y_0 + \left(\frac{{}_{-1}B_0}{P_0}\right) + ({}_{-1}b_0) - c_0\right)}_{\text{URE}} dr + dy_0$$

- This formula continues to apply under forms of market incompleteness:
  - Uninsurable idiosyncratic risk $\rightarrow MPC = \frac{\partial c_0}{\partial y_0}$
    - (*consumption response to one-time transitory income shock*)
  - (In some cases) borrowing constraints $\rightarrow MPC = 1$

Correlations in the population

- Italian Survey of Household Income and Wealth 2010:
  - URE≡Non-financial Income - Consumption + Deposits - D (debt *payment* for fixed-rate and debt *liability* for adjustable-rate debt)



- Using these numbers, the redistribution and substitution channels have the same *sign*, and same magnitude if the EIS is around 0.025-0.05

Main Results: ***Redistribution channel*** depends on two factors: **(1)** $Cov\left(MPC^i, \underbrace{URE^i}_{\text{unhedged interest rate exposure}}\right)$ and **(2)** URE^i depends a lot on the *terms structure* of asset side and liability side of HHs.

Related literature

- Distributional effects of inflation:
  - Doepke and Schneider (2006), Berriel (2013)
- Monetary policy and inequality:
  - Coibion, Gorodnichenko, Kueng, Silvia (2012)
- Mortgages:
  - contract choice: Campbell and Cocco (2003)
  - monetary policy transmission: Calza, Monacelli, Stracca (2013), Garriga, Kydland, Sustek (2013),
- Interest rate risk and portfolio choice: Merton (1971), Campbell and Viceira (2002)
- Financial institution balance sheets: Brunnermeier-Sannikov (2012, 2013); Begenau, Piazzesi, Schneider (2013)
- MPC heterogeneity:
  - measurement: Johnson et al (2006), Parker et al (2013), Mian, Rao, Sufi (2013), Baker (2013)
  - aggregate demand effects: Mian-Sufi (2012), Farhi-Werning (2012, 2013), Korinek-Simsek (2013)

Lecture 8

Households Balancesheets and Monetary Policy: Empirics

8.1 Kashyap and Stein (AER, 2000): *What Do a Million Observations on Banks Say about the Transmission of Monetary Policy?*

Abstract: We study the monetary-transmission mechanism with a data set that includes quarterly observations of every insured U.S. commercial bank from 1976 to 1993. We find that the impact of monetary policy on lending is stronger for banks with less liquid balance sheets–i.e., banks with lower ratios of securities to assets. Moreover, this pattern is largely attributable to the smaller banks, those in the bottom 95 percent of the size distribution. Our results support the existence of a "bank lending channel" of monetary transmission, though they do not allow us to make precise statements about its quantitative importance.

Main Idea: Authors look only at the asset side and infer *balance sheet strength* in terms of "assets." Within different-sized banks, balance sheets differ a lot. ***Small-sized banks*** primarily depend on *deposits* as their source of funding while ***large-sized banks*** do rely on deposits, but not to the same extent as *small-sized banks*.

Interesting Question: Are *actual interest rates* or *expected future interest interest rates* more important for the *credit channel*?

- New-Keynesian "answer" : *expected future interest rate.*
- Classical "answer" only <u>addressed in this paper</u> : *actual interest rate*
- ***Answer:*** Depends on Bank and HH behavior but generally both are important; $\frac{2}{3}$ of *credit channel* effect comes from Δ*actual interest rate* and the other $\frac{1}{3}$ comes from Δ*expected future interest rate.* HHs may withdraw (invest) deposits due to changes in expected future interest rates. Banks may re-balance their portfolios in expectation of HHs withdrawing (investing) their deposits.
  - Some banks can partake in "*rational buffer stock*" behavior: Due to changes in *expected future interest rates*, banks can hold MORE liquid assets so once the change in interest rates happen, these banks don't have to cut their lending as much (relative to other bank that did not adjust accordingly ex-ante).

Data and Variables: Bank-level variables are the Consolidated Report of Condition and Income (known as the Call Reports) that insured banks submit to the Federal Reserve each quarter. Three measures of monetary policy shocks are used:

1. "narrative approach" measure of monetary policy: ***Boschen-Mills (1995)*** index
2. conventional measure: federal funds rate
3. ***Bernanke and Mihov (1998)*** measure.

Two-Step Regression:

1. In the first step, run the following cross-sectional regression *separately* for each bank size class i and each time period t:
   - $L_{i,t}$= bank-level measure of lending activity
   - $B_{i,t}$= measure of balance sheet strength

- $FRB_{i,k}$ = Federal Reserve-district dummy variable (i.e., a geographic control).

$$\Delta log\left(L_{i,t}\right) = \sum_{j=0}^{4} \alpha_{j,t} \cdot \Delta log\left(L_{i,t-j}\right) + \beta_t \cdot B_{i,t-1} + \sum_{k=1}^{12} \Psi_{k,t} \cdot FRB_{i,k} + \varepsilon_{i,t}$$

2. In the second step of procedure, take for each size class the β_t's, and use them as the dependent variable in a purely time-series regression:

$$\beta_t = \eta + \sum_{j=0}^{4} \phi_j \cdot \underbrace{\Delta M_{t-j}}_{\text{monetary policy shock}} + \delta \cdot TIME_t \left(+ \sum_{j=0}^{4} \gamma_j \cdot \Delta realGDP_{t-j} \right) + u_t$$

- β_t= measure of the intensity of liquidity constraints in a given bank size class at time t
- M_t = monetary-policy indicator (with higher values corresponding to easier policy).

Hypothesis is that, for the smallest class of banks, an expansionary impulse to M_t should lead to a reduction in β_t — i.e., the sum of the ϕ's should be NEGATIVE.

Main Result: In all six cases, the point estimates (sum of $\phi's$) are negative, consistent with the theory. An INCREASE in interest rates (*tightening* of monetary policy) DECREASES lending of small banks MORE than lending of larger banks. Variation in the cross-section is used for identification; results are generalized to the time series behavior.

TABLE 3—TWO-STEP ESTIMATION OF EQUATIONS (1), (2), AND (3): SUM OF COEFFICIENTS ON MONETARY-POLICY INDICATOR

Panel A: C&I Loans	Univariate	Bivariate
1. Boschen-Mills		
<95	−0.0438	−0.0131
	(0.0188)	(0.0187)
95–99	−0.0339	0.0094
	(0.0401)	(0.0303)
>99	0.0960	0.1411
	(0.0661)	(0.0428)
Small-Big	−0.1398	−0.1542
	(0.0611)	(0.0449)
2. Funds rate		
<95	−0.0267	−0.0151
	(0.0071)	(0.0089)
95–99	−0.0066	0.0097
	(0.0137)	(0.0112)
>99	0.0795	0.1175
	(0.0281)	(0.0314)
Small–Big	−0.1062	−0.1327
	(0.0296)	(0.0376)
3. Bernanke-Mihov		
<95	−1.8633	−0.5269
	(1.0933)	(1.2463)
95–99	0.7345	3.3461
	(2.1853)	(2.1119)
>99	4.7862	7.5911
	(3.5220)	(2.3927)
Small–Big	−6.6495	−8.1181
	(3.3966)	(3.0215)

Panel B: Total Loans	Univariate	Bivariate
1. Boschen-Mills		
<95	−0.0179	−0.0044
	(0.0110)	(0.0120)
95–99	−0.0129	0.0167
	(0.0236)	(0.0118)
>99	0.0516	0.0921
	(0.0522)	(0.0373)
Small–Big	−0.0695	−0.0965
	(0.0464)	(0.0348)
2. Funds rate		
<95	−0.0088	−0.0046
	(0.0037)	(0.0049)
95–99	−0.0126	−0.0040
	(0.0079)	(0.0060)
>99	0.0258	0.0460
	(0.0188)	(0.0152)
Small–Big	−0.0346	−0.0506
	(0.0182)	(0.0174)
3. Bernanke-Mihov		
<95	−0.1926	0.7827
	(0.5344)	(0.5780)
95–99	−0.2849	1.1191
	(1.1178)	(0.7766)
>99	3.6558	6.7373
	(2.5209)	(1.4636)
Small–Big	−3.8484	−5.9545
	(2.2180)	(1.5971)

Note: Standard errors are in parentheses.

8.2 Landier, Sraer, and Thesmar (Working Paper, 2014): *Banks Exposure to Interest Rate Risk and The Transmission of Monetary Policy*

Abstract: We show that banks' cash flow exposure to interest rate risk, or income gap, plays a crucial role in their lending behavior following monetary policy shocks. In a first step, we show that the sensitivity of bank profits to interest rates increases significantly

with their income gap, even when banks use interest rate derivatives. In a second step, we show that the income gap also predicts the sensitivity of bank lending to interest rates, both for commercial & industrial loans and for mortgages. Quantitatively, a 100 basis point increase in the Fed funds rate leads a bank at the 75^{th} percentile of the income gap distribution to increase lending by about 1.6 percentage points annually relative to a bank at the 25^{th} percentile. We conclude that banks' exposure to interest rate risk is an important determinant of the bank-level intensity of the bank lending channel.

Data: Use bank holding company (BHC) data available quarterly from 1986 to 2011.

Main Idea: Authors define "income gap" as:

$$\text{income gap} = \frac{(\text{\$ of the banks assets that reprice or mature within 1 Yr}) - (\text{\$ of liabilities that reprice or mature within 1 Yr})}{\text{\$ of total assets}}$$

- Δinterest rate $\implies$ Δasset prices and Δnet interest income $\implies$ Δincome gap. This is one way to capture *sensitivity* of net interest income to changes in interest rates

Interesting Question: Fixing a bank's ***income gap***, are *actual interest rates* or *expected future interest interest rates* more important here?

- Δshort-term assets: *actual interest rate (* here the *rate you charge lenders* and *pay to depositors* ACTUALLY change)
- Δlong-term assets: *expected future interest rate.*

Main Results: Δinterest rate $\uparrow \implies \Delta$income gap $\uparrow \implies \Delta$net interest income $\uparrow \implies$ Δbank's earnings (stock market values) $\uparrow$ $\implies$ lending resources $\uparrow \implies$ lending $\uparrow$

- Authors directly look at the sensitivity of each bank's revenue to interest rate movement and check whether it is related to the income gap. They find that banks revenue indeed depend on Income gap $\times$ Δr: This confirms their direct evidence that ***banks do not hedge out entirely their interest rate risk.***

8.3 Drechsler, Savov, and Schnabl (Working Paper, 2015): *The Deposits Channel of Monetary Policy*

Abstract: We propose and test a new channel for the transmission of monetary policy. We show that when the Fed funds rate *increases*, banks widen the interest spreads they charge on deposits, and deposits flow out of the banking system. We present a model in which imperfect competition among banks gives rise to these relationships. An increase in the nominal interest rate increases banks' market power, inducing them to increase deposit spreads and hence restrict deposit supply. *Households respond to the increase in deposit prices by substituting from deposits into less liquid, but higher-yielding assets*. Using branch-level data on the universe of U.S. banks, we show that following an increase in the Fed funds rate, deposit spreads increase by more, and supply falls more, in areas with less deposit competition. We control for changes in banks' lending opportunities by comparing branches of the same bank in the same state. We control for changes in macroeconomic conditions by showing that deposit spreads widen immediately after a rate change and even if this change is fully anticipated. Our results imply that monetary policy has a significant impact on how the financial system is funded, on the quantity of safe and liquid assets it produces, and on its provision of loans to the real economy

Data and Variables: Authors build a novel data set at the bank-branch level that includes information on deposits rates (by product), deposit holdings, branch ownership, bank characteristics, and county characteristics.

- data on *deposit holdings* is from the Federal Deposit Insurance Corporation (FDIC).
- data on *deposit rates* is from the private data provider Ratewatch
- data on *county characteristics* from several sources:
  - annual number of establishments, employment, and annual payroll are from the ***County Business Patterns survey***; data on quarterly wages are from the ***BLS***; data on annual population and county size are from the ***Census Bureau***; data on annual gross county tax revenues from the ***Internal Revenue Services***; data on annual median household income, the unemployment rate, and the poverty rate from the ***Census Bureau***.
- data on *bank characteristics* from the U.S. Call Reports, obtained from the Federal Reserve Bank of Chicago.

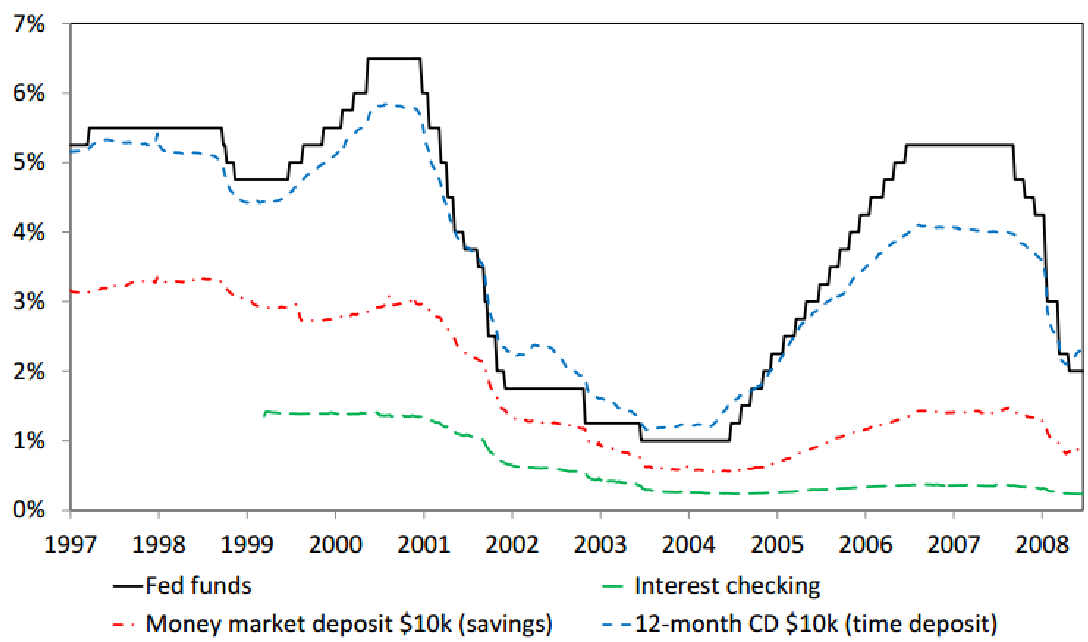
Main *measure of bank competition* is the ***deposit Herfindahl index*** at the county level: A Herfindahl of 1 indicates an extreme of complete concentration of county deposits within a single bank, whereas lower values indicate greater competitiveness.

Descriptive Analysis:

This figure below plots the time series of the Fed Funds rate and the average rate paid by *three deposit products*: interest checking, money market saving account, and 12-month certificate of deposits (CD). These three products proxy respectively for the three major classes of bank deposits: *checking deposits*, *savings deposits*, and *time deposits*, which accounted for \$1.6 trillion, \$6.5 trillion, and \$2.1 trillion in 2014, respectively. **The figure shows *two striking regularities*:**

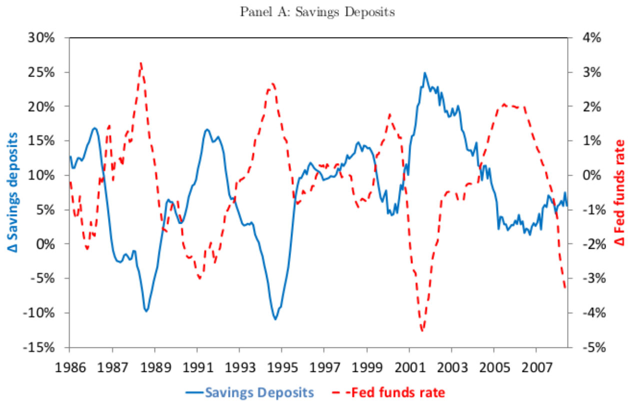
- The *spreads between the Fed funds rate* and the *three deposit rates* are often very large, especially for checking and savings deposits. In particular, the spread on savings deposits, which constitutes almost half of all deposits, is greater than 2% on average over this period, and at times exceeds 3%. Checking deposits incur a substantially larger spread still, whereas the spread on time deposits is relatively small.
- Second, deposit spreads covary strongly positively with the Fed funds rate. When the Fed funds rate ↑, banks' deposit rates ↑, but less than one-for-one, so that spreads widen. In contrast, when the Fed funds rate ↓, deposit spreads ↓. For instance, as the Fed Funds rate dropped from 6.5% in 2000 to 1% in 2004, the spread on savings deposits shrank from 3% to 0.25%. As with average spreads, the pattern in checking deposits is even more pronounced, whereas it is less dramatic for time deposits.

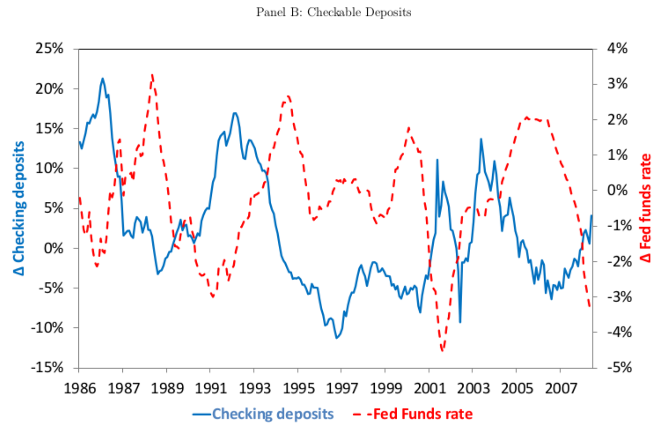
Figure 1: **Deposit rates and monetary policy**
This figure plots deposit rates by product, as well as the Fed funds rate target. The data is weekly from RateWatch. The sample is from January 1997 to June 2008.

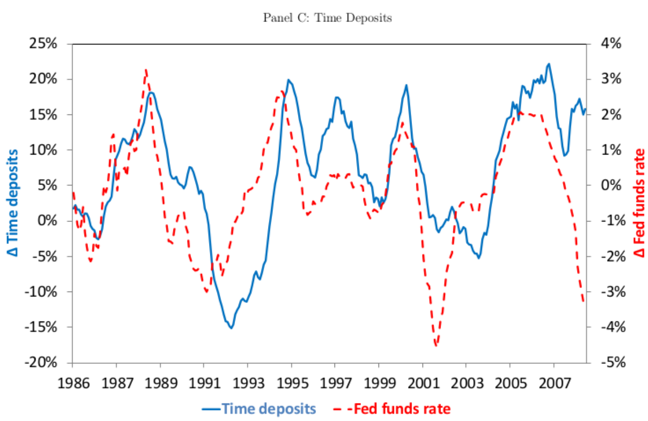


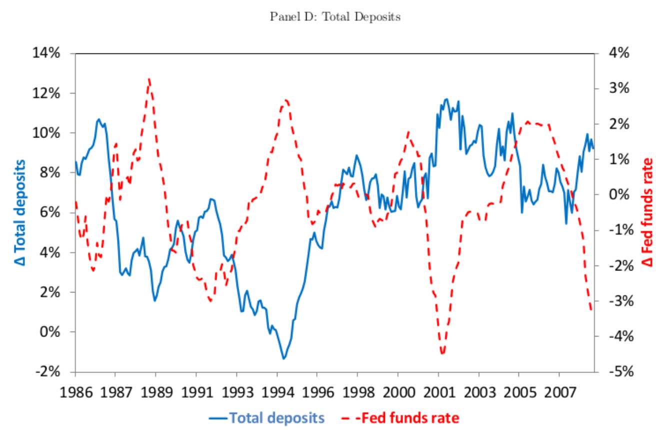
These figures below shows what happens due to the widening of these three deposit rate spreads and the resulting adjustment for the "equilibrium" quantities of deposits. There is an OUTFLOW from *checking and savings deposits* (i.e. *liquid deposits*) (Panels A and B) and an INFLOW to time deposits (Panel C). The ***net effect is an aggregate outflows of deposits from the banking system*** (Panel D). Hence, when the Fed funds rate ↑, total deposits shrink and the composition of deposits *becomes less liquid*.

- Hence, when the Fed funds rate ↑, the spreads on *liquid deposits* widen relative to time deposits, and depositors ***substitute away*** from liquid deposits and toward less liquid time deposits.









Their paper's theoretical *partial equilibrium* model predicts that an INCREASE in the Fed funds rate leads to higher deposit spreads in areas where competition is low (see their Proposition 1). Hence, they test the deposit channel by comparing banks in concentrated (uncompetitive) areas with banks in less concentrated (competitive) areas. They do find this model prediction present in the data.

ISSUE: There could be something that drives changes in HHs withdrawing of liquid deposits *not directly related* to changes in spreads (through changes in interest rates) and the ***Herfindahl index***. For example, different regions or counties could experience different changes in income levels due to changes in interest rates, which drive the HHs withdrawing of liquid deposits. These effects would be unrelated to spreads or the competitiveness of banks in the region.

Empirical Strategy: Authors test the *deposit channel* by examining whether the variation in deposits also coincides with variation in lending. They construct a bank-level measure of deposit competition using the weighted average of county-level Herfindahl indices using branch deposits as weights. This bank-level Herfindahl proxies for the average level of competition in the markets in which a bank is active. They estimate the bank-level analog to the branch-level results using the following OLS regression:

$$\Delta y_{i,j.c,t} = \alpha_i + \delta_t + \beta \cdot HHI_{i,t} + \gamma \cdot \Delta FF_t \times HHI_{i.t} + \varepsilon_{i,j,c,t}$$

where $\Delta y_{i,j.c,t}$ is s the change in a bank-level outcome (e.g., log growth of assets, deposits, loans, interest spread) of bank i from time t to $t+1$, ΔFF_t is the change in the Fed funds rate from time t to $t+1$, HHI it is the average deposit Herfindahl of bank i at time t, α_i are bank fixed effects and δ_t are time fixed effects. They cluster standard errors at the bank level.

Table 6: **Bank liabilities and market power**

This table examines the effect of monetary policy on bank liabilities. The sample consists of commercial banks from the Call Reports from January 1, 1994 to June 30, 2008. The bank-level Herfindahl is calculated as the weighted average of county-level Herfindahl indices using branch-level deposits lagged by one quarter as weights. The quantity-based dependent variables are calculated as log growth over a quarter. The deposit spread is the change in the Fed funds rate minus the change in the deposit rate over a quarter. The main effects (Herfindahl, Equity/Assets, Securities/Assets) are included as control variables in the regressions (coefficients not shown). All regressions include bank and quarter fixed effects. Standard errors are clustered by bank.

	Total deposits		Demand deposit		Savings deposit		Time deposit		Δ Spread	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ FF x Herfindahl	-1.498***	-1.098***	-0.665**	-0.453*	-1.061***	-0.831***	-2.843***	-2.250***	0.023***	0.024***
	(0.170)	(0.162)	(0.272)	(0.271)	(0.280)	(0.276)	(0.253)	(0.243)	(0.004)	(0.004)
Δ FF x Sec./Assets		-0.020***		-0.009***		-0.009***		-0.031***		0.000***
		(0.002)		(0.003)		(0.003)		(0.003)		(0.000)
Δ FF x Equ./Assets		-0.011		0.028*		0.058***		-0.055***		0.000
		(0.010)		(0.017)		(0.015)		(0.012)		(0.000)
Quarter f.e.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank f.e.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.168	0.231	0.089	0.099	0.082	0.101	0.16	0.206	0.81	0.81
Observations	443,591	443,591	441,761	441,761	439,551	439,551	441,282	441,282	443,612	443,612

Table 7: **Bank lending and market power**

This table examines the effect of monetary policy on bank lending. The sample consists of commercial banks from the Call Reports from January 1, 1994 to June 30, 2008. The bank-level Herfindahl is calculated as the weighted average of county-level Herfindahl indices using branch-level deposits lagged by one quarter as weights. The quantity-based dependent variables are calculated as log growth over a quarter. The main effects (Herfindahl, Equity/Assets, Securities/Assets) are included as control variables in the regressions (coefficients not shown). All regressions include bank and quarter fixed effects. Standard errors are clustered by bank.

	Assets		Real Estate Loans		C&I Loans		Securities	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ FF x Herfindahl	-1.026***	-0.694***	-0.711***	-0.599***	-0.878**	-0.717*	-0.903**	-0.477
	(0.136)	(0.128)	(0.229)	(0.219)	(0.378)	(0.374)	(0.356)	(0.358)
Δ FF x Securities/Assets		-0.019***		0.000		-0.008**		-0.014***
		(0.001)		(0.002)		(0.004)		(0.004)
Δ FF x Equity/Assets		-0.01		0.017		0.039**		0.037**
		(0.007)		(0.012)		(0.018)		(0.016)
Quarter f.e.	Y	Y	Y	Y	Y	Y	Y	Y
Bank f.e.	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.174	0.218	0.168	0.211	0.054	0.069	0.057	0.088
Observations	443,748	443,748	439,803	439,803	438,467	438,467	439,322	439,322

- 100 basis points $\uparrow$ in the Fed funds rate *raises* deposit outflows by 1.5% for banks in uncompetitive deposit markets relative to banks in competitive deposit markets: effect is *negative* and *statistically significant* for all types of deposits and across all specifications.

- 100 basis points $\uparrow$ in the Fed funds rate *reduces* assets by 1.0% for banks in uncompetitive deposit markets relative to banks in competitive deposit markets: effect is *negative* and *statistically significant* for all types of deposits and across all specifications. Similar results for ***real estate loans*** (Columns 3 and 4), ***C&I loans*** (Columns 5 and 6), and ***securities*** (Columns 7 and 8). Intuition: HHs withdrawing depoits from banks $\Longrightarrow$ banks have less liquid assets and thus cut their lending .

Results: Banks can't easily replace deposit financing and increases in the Fed funds rate affects banks' supply of loans to the real economy. They are consistent with the central mechanism of our model, which is that the Fed funds rate affects the trade-off banks face between limiting deposit supply in order to maximize the rents from market power and financing a large balance sheet to maximize revenues. It also consistent with the large literature on the *bank lending channel*, which argues that banks amplify changes in monetary policy through changing the supply of credit to firms.

8.4 Jiménez, Ongena, Peydró, and Saurina (Econometrica, 2014): *Hazardous Times for Monetary Policy: What Do Twenty-Three Million Bank Loans Say About the Effects of Monetary Policy on Credit Risk-Taking?*

Abstract: We identify the effects of monetary policy on credit risk-taking with an exhaustive credit register of loan applications and contracts. We separate the changes in the composition of the supply of credit from the concurrent changes in the volume of supply and quality, and the volume of demand. We employ a two-stage model that analyzes the granting of loan applications in the first stage and loan outcomes for the applications granted in the second stage, and that controls for both observed and unobserved, time-varying, firm and bank heterogeneity through *time×firm* and *time×bank* fixed effects. We find that a lower overnight interest rate induces lowly capitalized banks to grant more loan applications to ex ante risky firms and to commit larger loan volumes with fewer collateral requirements to these firms, yet with a higher ex post likelihood of default. A lower long-term interest rate and other relevant macroeconomic variables have no such effects

Motivation: Authors study the impact of monetary policy on the credit risk-taking by banks. They look at how changes in interest rates affect whether banks expand (contract) their lending, but also to whom they expand (contract).

Data and Variables: Exhaustive bank loan data comes from the *Credit Register of the Banco de España* (CIR), which is the supervisor and regulator in Spain of the banking system.

There are *three key interaction variables*: **(1)** overnight rate; **(2)** bank's capital ratio; **(3)** firm's credit risk. The triple interaction of these variables is the key variable of interest.

Empirical Strategy: Authors include $time * firm$ and $time * bank$ fixed effects account for any observed and unobserved time- varying heterogeneity in almost all firms and banks (comprising almost the entire economy). Their estimated equation is:

$$\begin{aligned}\Delta log\left(LOAN_{b,i,t}\right) =&\alpha + \beta \cdot \Delta IR_{t-1} + \gamma \cdot \Delta IR_{t-1} \times log\left(CAPITAL_{b,t-1}\right)\\ &+ \delta \cdot \Delta IR_{t-1} \times log\left(CAPITAL_{b,t-1}\right) \times \mathbf{1}_{\{DOUBTFUL_{i,t}\}} + \Omega \cdot Controls_{b,i,t} + \varepsilon_{b,i,t}\end{aligned}$$

- $\Delta log\left(LOAN_{b,i,t}\right)$= change in the logarithm of the committed credit (in thousands of Euros) granted by bank b to firm i during quarter t
- $CAPITAL$ = *capital ratio* variable defined as the logarithm of the ratio of bank equity and retained earnings over total assets (in percent) of bank b at time $t-1$
- $\mathbf{1}_{\{DOUBTFUL_{i,t}\}}$= 1 if firm i had doubtful loans in the previous four years prior to t (t: 1988:II $\rightarrow$ 2008:IV), and = 0 otherwise
- ΔIR_{t-1}= annual change in the Spanish overnight interest rate at $t-1$

Result: Overnight rate $\downarrow$ $\Longrightarrow$ for a *less healthy* bank looking to lend to a given *risky* firm, lending to that firm $\uparrow$

TABLE 1

MONETARY CONDITIONS, BANK RISK, FIRM CREDIT HISTORY, AND THE INTENSIVE MARGIN OF LENDING: EXPLAINING THE QUARTERLY CHANGE IN OUTSTANDING CREDIT GRANTED BY A BANK TO A FIRM

Model	I		II		III		IV		V		VI		VII		VIII		IX	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Macroeconomic Variables																		
ΔGDP_{t-1}	0.613	0.072 ***	0.615	0.072 ***														
ΔCPI_{t-1}	-0.168	0.070 **	-0.167	0.070 **														
ΔIR_{t-1}	-0.124	0.052 **	-0.215	0.235														
ΔIR_{t-1}*LN(CAPITAL RATIO$_{bt-1}$)			0.044	0.123	0.101	0.104	0.088	0.090	0.028	0.115								
ΔIR_{t-1}*I(DOUBTFUL LOANS IN THE PREVIOUS 4 YEARS$_{ft}$)			-0.510	0.224 **	-0.349	0.221												
ΔIR_{t-1}*LN(CAPITAL RATIO$_{bt-1}$)*I(DOUBTFUL LOANS IN THE PREVIOUS 4 YEARS$_{ft}$)			0.316	0.124 **	0.221	0.121 *	0.240	0.117 **	0.284	0.156 *	0.314	0.123 **	0.326	0.121 ***	0.256	0.152 *	0.253	0.147 *
$\Delta IRLT_{t-1}$*LN(CAPITAL RATIO$_{bt-1}$)*I(DOUBTFUL LOANS IN THE PREVIOUS 4 YEARS$_{ft}$)															0.119	0.180	0.149	0.177
Bank and Firm Variables																		
LN(CAPITAL RATIO$_{bt-1}$)	-0.001	0.002	-0.001	0.002	-0.006	0.004 *	-0.008	0.003 ***	0.000	0.005								
I(DOUBTFUL LOANS IN THE PREVIOUS 4 YEARS$_{ft}$)	-0.035	0.001 ***	-0.039	0.004 ***	-0.027	0.004 ***												
LN(CAPITAL RATIO$_{bt-1}$)*I(DOUBTFUL LOANS IN THE PREVIOUS 4 YEARS$_{ft}$)			0.003	0.002	-0.002	0.002	-0.003	0.002	-0.002	0.004	-0.004	0.002 *	-0.005	0.002 **	-0.004	0.002 *	-0.005	0.002 **
ΔLN(LOAN CREDIT$_{bft-1}$)													-0.246	0.002 ***			-0.246	0.002 ***
Year * Quarter Fixed Effects	no		no		yes		-		-		-		-		-		-	
Bank Fixed Effects	no		no		yes		yes		-		-		-		-		-	
Firm Fixed Effects	no		no		yes		-		-		-		-		-		-	
Bank * Firm Fixed Effects	no		no		no		no		yes		no		no		no		no	
[Year * Quarter * Bank] Fixed Effects	no		no		no		no		no		yes		yes		yes		yes	
[Year * Quarter * Firm] Fixed Effects	no		no		no		yes		yes		yes		yes		yes		yes	

NOTE. – The estimates in this table come from linear models using ordinary least squares and 6,564,964 observations from the 1988:II - 2008:IV period. The dependent variable is ΔLN(LOAN CREDIT$_{bft}$) which is the change in the logarithm of committed credit granted by bank b to firm i during quarter t. The definition of the independent variables can be found in the Appendix. Where possible a constant is included but its coefficient is left unreported. Fixed effects are either included ("yes"), not included ("no") or spanned by another set of effects ("-"). Coefficients (Coeff.) are listed in the first column, (robust) standard errors (S.E.), that are corrected for clustering at the [Year * Quarter * Bank] level (15,248 clusters) following Arellano (1987), are reported in the second column, and the corresponding significance levels are in the third column. *** Significant at 1%, ** significant at 5%, * significant at 10%.

- Bank-firm credit growth that follows a decrease in the short-term interest rate is strongest for firms with higher credit risk and, especially so, when granted by banks with a lower capital ratio.

8.5 Bernanke and Kuttner (JF, 2005): *What Explains the Stock Market's Reaction to Federal Reserve Policy?*

Abstract: This paper analyzes the impact of changes in monetary policy on equity prices, with the objectives of both measuring the average reaction of the stock market and understanding the economic sources of that reaction. We find that, on average, a hypothetical unanticipated 25-basis-point cut in the Federal funds rate target is associated with about a 1% increase in broad stock indexes. Adapting a methodology due to Campbell and Ammer, we find that the effects of unanticipated monetary policy actions on expected excess returns account for the largest part of the response of stock prices.

Motivation: This paper is an empirical study of the relationship between monetary policy and one of the most important financial markets, the market for equities. The authors have two principal objectives.

1. Measure and analyze in some detail the *stock market's response to monetary policy actions*, both in the aggregate and at the level of industry portfolios.

2. Try to gain some insights into the *reasons for the stock market's response.*

Data and Variables: Use market-based way to identify *unexpected funds rate changes,* which relies on the *price of federal funds futures contracts*, which embody expectations of the effective federal funds rate, averaged over the settlement month. This is motivated by ***Krueger and Kuttner (1996)***, which found that the *federal funds futures rates* yielded efficient forecasts of funds rate changes.

Empirical Strategy: The author's baseline estimated equation involves a regression of the CRSP value-weighted return on the raw change in the federal funds rate target:

$$H_t = a + b \cdot \Delta i_t + \varepsilon_t$$

where there is *no distinction* between surprise and expected changes in the Fed funds rate changes.

- H_t= CRSP value-weighted return

- Δi_t = actual change in the fed funds rate target

The authors also estimate the equation that distinguishes between surprised and expected changes:

$$\begin{aligned} H_t =& a + b^e \cdot \Delta i_t^e + b^u \cdot \Delta i_t^u + \varepsilon_t \\ \Delta i_t^u =& \frac{D}{D-d} \left(f_{m.d}^0 - f_{m,d-1}^0 \right) \\ \Delta i_t^e =& \Delta i_t - \Delta i_t^u \end{aligned}$$

- Δi_t^u= the *unexpected* ("surprise") target funds rate change for an event taking place on day d of month m. It is calculated from the change in the rate implied by the current month futures contract. Because the contract's settlement price is based on the *monthly average federal funds rate*, the change in the implied futures rate must be scaled up by a factor related to the number of days in the month affected by the change.
- Δi_t^e = the *expected* component of the rate change, which is defined as the actual change - surprise change.

In both specifications, error term ε_t represents factors "other than monetary policy" that affect stock prices on event days.

Results:

1. The stock market reacts fairly strongly to *surprise* funds rate changes.

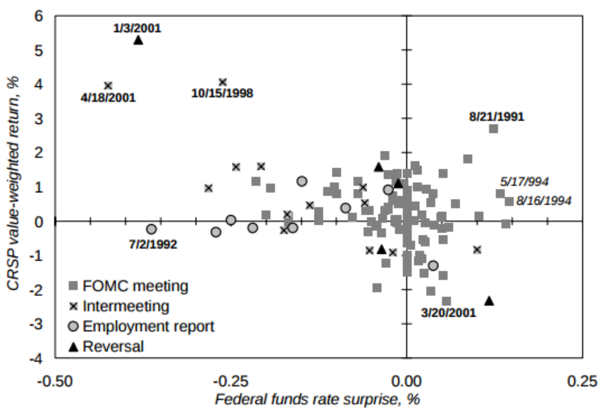


Table 2
The response of equity prices to federal funds rate changes

The table reports the results from regressions of the one-day CRSP value-weighted equity return on changes in the federal funds rate (columns a and c), and on the surprise and expected components of the funds rate change (columns b and d). All variables are expressed in percentage terms. The full sample consists of the 55 target rate changes and the 77 FOMC meeting dates over the period from June 1989 through December 2002, excluding the 17 September 2001 observation, for a total of 131 observations. The outliers excluded from the regressions in columns c and d correspond to the six observations with influence statistics in excess of 0.3, leaving 125 usable observations. Parentheses contain *t*-statistics, calculated using heteroskedasticity-consistent estimates of the standard errors.

	Full sample		Excluding outliers	
Regressor	(a)	(b)	(c)	(d)
Intercept	0.23	0.12	0.17	0.11
	(2.58)	(1.35)	(2.14)	(1.37)
Raw funds rate change	−0.61	…	−0.11	…
	(1.06)		(0.31)	
Expected change	…	1.04	…	0.67
		(2.17)		(1.62)
Surprise change	…	−4.68	…	−2.55
		(3.03)		(2.79)
$\bar{R}^2$	0.007	0.171	−0.007	0.049

- The NEGATIVE relationship between funds rate surprises and stock returns is readily visible in the figure above. Also apparent, however, are a number of observations characterized by very large changes in equity prices — some exceeding three standard deviations in magnitude. The authors investigate which observations might have an unduly large effect on the regression results and exclude such outliers in a separate analysis.
- The table above shows that when the target rate change is broken down into its *expected* and *surprise* components the estimated stock market response to the ***surprise*** component is *negative* and *highly significant* while the estimated stock market response to the ***expected*** component is *positive* and *not significant*. Otherwise, in the baseline regression the response to the raw target rate change is small and insignificant.

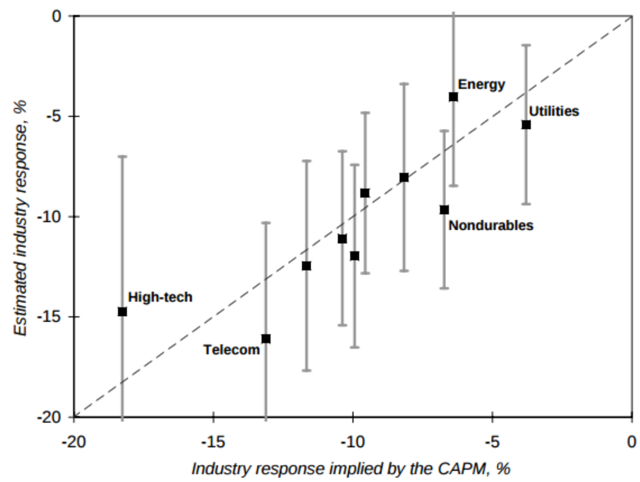
2. When estimating the impact of federal funds surprises on *expected future dividends*, *real interest rates*, and *expected future excess returns*, it turns out that the largest effects come from revisions to expectations of future excess returns, and to expectations of future dividends; real interest rates have a very small direct impact. The main finding is that policy's impact on equity prices comes predominantly through its effect on *expected future excess equity returns*. Specifically, they find that while an unanticipated rate cut (for example) generates an

immediate rise in equity prices, it tends to be associated with an extended period of lower-than-normal excess returns. One interpretation of this result is that monetary policy surprises are associated with changes in the *equity premium*.

3. When estimating the impact of federal funds surprises on disaggregated indexes, specifically the 10 industry portfolios constructed from CRSP returns as in Fama and French (1988), the responses vary drastically across industries (see table below to the left). Also, the pattern of responses of the industry portfolios is consistent with the implications of the CAPM — the observed responses are somewhat proportional to the industries' market "betas".

    - Although the fit is not perfect, a ***one-factor CAPM*** does a good job of explaining the observed industry variation (see figure below to the right)

Index	Response to federal funds rate changes: anticipated	unanticipated	$\bar{R}^2$	SE	DW	Market beta
CRSP value weighted	−1.11	−11.43	0.065	4.28	2.02	1
	(0.37)	(3.95)				
Nondurables	−0.85	−9.65	0.046	4.17	2.00	0.60
	(0.25)	(2.88)				
Durables	−1.47	−12.45	0.048	5.56	1.97	1.02
	(0.38)	(3.04)				
Manufacturing	−2.02	−8.82	0.035	4.26	2.03	0.85
	(0.61)	(2.81)				
Energy	0.20	−4.03	−0.003	4.71	2.12	0.55
	(1.02)	(1.24)				
High tech	0.06	−14.73	0.025	8.22	2.00	1.61
	(0.01)	(2.72)				
Telecommunications	0.35	−16.10	0.065	6.16	1.85	1.16
	(0.60)	(3.31)				
Wholesale/retail	−4.75	−11.97	0.056	4.85	1.95	0.90
	(1.47)	(3.64)				
Health care	−1.04	−8.04	0.017	4.96	2.15	0.72
	(0.29)	(1.80)				
Utilities	−1.24	−5.42	0.006	4.21	1.97	0.32
	(0.48)	(1.55)				
Other	−1.21	−11.08	0.051	4.62	2.09	0.92
	(0.35)	(3.61)				



8.6 Ippolito, Ozdagli, and Perez (Working Paper, 2015): *The Transmission of Monetary Policy through Bank Lending - The Floating Rate Channel*

Abstract: We find that *outstanding* bank loans are vital for the transmission of monetary policy because, unlike other debt, most bank loans have floating rates that are mechanically tied to monetary policy rates. This novel *floating rate channel* is potentially as important as the widely studied bank lending channel through new loans. Firms that use more bank debt and do not hedge it display a stronger sensitivity of their stock price, profitability, cash holdings, and inventory investment to monetary policy. The effect is more powerful for financially constrained firms, consistent with the idea that changes to floating rates induced by monetary policy have an impact on the liquidity of these firms. Moreover, this effect disappears when policy rates hit the zero lower bound, revealing a new limitation of unconventional monetary policies.

Motivation: Authors address the following questions: Does monetary policy have a strong impact on firms' liquidity positions and their ability to finance future projects by causing changes in the debt service burden of existing floating rate bank loans?

Firm-Level Data and Variables: The sample for their main analysis consists of US firms covered by Capital IQ (CIQ), CRSP, and Compustat from 2003 to 2008, excluding utilities (SIC codes 4900–4949) and financials (SIC codes 6000–6999). They focus on this period because of the lack of wide coverage of bank debt data in CIQ before 2003, and because the federal funds target rate hit the zero lower bound in 2008, after which the quantitative easing program of the Federal Reserve replaced the federal funds target rate as the main monetary policy tool.

Following ***Bernanke and Kuttner (2005)***, the authors focus on the *surprise element in the target rate change* and use it as the measure of monetary policy shocks, which relies using on the price of the current month 30-day federal funds futures contracts, a price that encompasses market expectations of the effective federal funds rate.

Empirical Strategy: First, the authors analyze whether firm i's stock price change $Ret_{i,t}$ over the day t in which a monetary policy shock $Surprise_t$ occurs and the day after depends on the importance of bank debt as a source of financing, $\left(\frac{BankDebt}{At}\right)_{i,t-1}$. The following regression is estimated:

$$\begin{aligned} Ret_{i,t} =& \beta_0 + \beta_1 \cdot Surprise_t + \beta_2 \cdot \left(\frac{BankDebt}{At}\right)_{i,t-1} + \beta_3 \cdot Surprise_t \times \left(\frac{BankDebt}{At}\right)_{i,t-1} \\ &+ \gamma \cdot Controls_{i,t-1} + \lambda \cdot Surprise_t \times Controls_{i,t-1} + \varepsilon_{i,t} \end{aligned}$$

- $Controls_{i,t-1}$= vector of firm characteristics
- $Ret_{i,t}$ = stock returns surprise at the FOMC announcement date t
- $Surprise_t$ = monetary policy surprise at the FOMC announcement date t
- $\left(\frac{BankDebt}{At}\right)_{i,t-1}$ = *main measure of bank debt usage*, defined as total bank debt calculates as drawn credit lines (CL) plus term loans (TL), divided by the total value of book assets.

Second, the authors look to provide evidence for the *floating rate channel* by exploiting the variation across firms in their floating-to-fixed interest rate hedging of their bank debt or floating rate debt. If the floating rate channel is quantitatively relevant, then one should observe that the effect of bank debt usage on the sensitivity of stock prices to monetary policy should diminish significantly for firms that engage in floating-to-fixed interest rate hedging. The we interact all regressors in baseline regression with a *hedging dummy* in order to assess statistical significance of the difference between hedgers and non-hedgers using the following regression. They also repeat baseline exercise by replacing *bank debt* with *floating rate debt*:

$$\begin{aligned} Ret_{i,t} =& \beta_0 + \beta_1 \cdot Surprise_t + \beta_2 \cdot \left(\frac{BankDebt}{At}\right)_{i,t-1} + \beta_3 \cdot Surprise_t \times \left(\frac{BankDebt}{At}\right)_{i,t-1} \times Hedge_t \\ &+ \lambda \cdot Surprise_t \times Controls_{i,t-1} \times Hedge_t \\ &+ \text{Uninteracted terms and second order interactions} + \varepsilon_{i,t} \end{aligned}$$

Results:

1. Bank debt is special for the transmission of monetary policy to stock prices, specifically bank debt usage increases the responsiveness of firms' stock prices to monetary policy significantly: If you have MORE bank debt (relative to other firms) and surprise $\uparrow$ in interest rate $\implies$ stock market price $\downarrow$ MORE since firm has more interest expense and investment $\downarrow$ MORE.

Table A4

Is Bank Debt Special for the Transmission of Monetary Policy?

This table examines how the reaction of firm equity prices to surprise changes in the federal funds rate varies with their level of bank dependence. The sample consists of U.S. firms covered by Capital IQ, CRSP and Compustat from 2003 to 2008, excluding utilities (SIC 4900-4949) and financials (SIC 6000-6999). We focus on firms with December fiscal year end to avoid asynchronous balance sheet items and use 2-day returns in order to allow the effect of bank-debt to be fully incorporated in stock prices. We remove firm-year observations with negative revenues, missing information on total assets, or a value of total assets under 10 million. We also discard penny stocks, defined as those with a price of less than $5. The sample comprises 43 monetary policy events from 2003 to 2008. Firm characteristics are demeaned and are lagged by one year and winsorized at the 1% level. The regression specification is as in equation (1). Unreported terms include a constant and non-interacted coefficients. In specification (6) we add undrawn credit lines to bank debt and normalize the resulting ratio to have the same standard deviation as the original BankDebt/At. Standard errors are clustered at the date level in specifications (1)-(2) and two-way clustered at the date and industry levels in specifications (4)-(7). Industries are Fama-French 48 industries. Square brackets around the estimates of the coefficient of surprise in columns (4)-(7) are introduced to indicate that, due to the interaction of surprise with industry fixed effects, these estimates cannot be interpreted as the estimate applicable to the average firm. Parentheses contain t-statistics. The asterisks denote *** for p<0.01, ** for p<0.05, * for p<0.1. Hadlock and Pierce (2010) measure given by HP = -0.548*Size+0.025*Size^2-0.031*Age.

	(1) No Controls	(2) CAPM Control	(3) Other Controls	(4) Industry FE & Event-Industry Clustering	(5) Inc. Undrawn Credit Lines	(6) Other Controls	(7) Firm Fixed Effects	(8) Instrumental Variable	(9) Floating Rate Debt
Surprise	-4.97***	1.28***	-8.02***	[-7.44]	[-8.07]	[-9.83]	-8.04***	-8.07***	-8.81***
	(-13.03)	(3.66)	(-17.72)	(-0.83)	(-0.90)	(-1.10)	(-3.33)	(-17.12)	(-3.63)
Surprise*(BankDebt/At)	-14.10***	-10.52***	-16.34***	-16.77***	-14.62***	-15.22***	-16.37***	-14.50	-13.79**
	(-4.35)	(-3.54)	(-4.17)	(-3.82)	(-3.10)	(-3.30)	(-2.69)	(-0.58)	(-2.48)
Surprise*LnAssets			-0.95***	-1.12***	-1.06***	-0.07	-0.94***	-1.00**	-1.01**
			(-3.67)	(-4.19)	(-3.99)	(-0.15)	(-2.64)	(-2.06)	(-2.53)
Surprise*Book Leverage			3.28**	3.83*	2.59	4.24**	3.15	2.44	4.49*
			(1.96)	(1.85)	(1.32)	(1.98)	(1.28)	(0.40)	(1.71)
Surprise*Profitability			-16.10***	-11.49**	-11.08**	-8.16	-15.36**	-15.68***	-16.54
			(-6.10)	(-2.19)	(-2.13)	(-1.33)	(-2.08)	(-4.06)	(-1.45)
Surprise*M/B			-0.02	-0.41	-0.41	-0.71	0.01	0.10	0.43
			(-0.08)	(-0.77)	(-0.78)	(-1.31)	(0.01)	(0.25)	(0.42)
Surprise*Int Rate Sensitivity						-7.05**			
						(-2.24)			
Surprise*Cash-Flow Volatility						-77.57			
						(-0.55)			
Surprise*Beta						1.47**			
						(2.16)			
Surprise*Cash Holdings						3.37			
						(0.96)			
Surprise*HP						4.22***			
						(3.42)			
Firm FE	NO	NO	NO	NO	NO	NO	YES	YES	YES
FF48 Industry FE	NO	NO	NO	YES	YES	YES	NO	NO	NO
Year FE	NO	NO	YES	YES	YES	YES	YES	YES	YES
Surprise*FF48 Industry FE	NO	NO	NO	YES	YES	YES	NO	NO	NO
Cluster (Fed event*IndustryFF48)	NO	NO	NO	YES	YES	YES	YES	NO	YES
Observations	64,682	64,557	64,428	62,871	62,746	55,506	64,428	63,626	41,710

2. A significant part of the effect of bank debt (mentioned in 1.) is driven by the floating rate nature of bank debt, a transmission mechanism they call the *floating rate channel*.

Table II

The Role of Bank Debt Usage and Interest Rate Risk Exposure in the Transmission of Monetary Policy

This table examines how bank and floating rate debt usage impacts the effect of monetary policy on stock prices, and how this impact varies with their hedging activity. Hedgers are defined on a yearly basis as those firms that report having hedged their interest rate risk from floating to fixed in their 10-K annual reports. Only firms with floating rate debt constituting more than 1% of total assets are included. Bank Debt/At is defined as bank debt (term loans plus drawn revolving credit) over book value of assets (At). FloatingRateDebt /At is defined as floating rate debt over book value of assets (At). All regressions also include an unreported constant term, as well as ln(assets), book leverage, profitability, market-to-book, interest rate sensitivity, and their interaction with surprise. All firm characteristics are lagged by one year and winsorized at 1%. Parentheses contain t-statistics. The asterisks denote *** for p<0.01, ** for p<0.05, * for p<0.1.

	(1) Non-Hedgers	(2) Hedgers	(3) Non-Hedgers	(4) Hedgers	(5) Non-Hedgers	(6) Hedgers	(7) Non-Hedgers	(8) Hedgers
Surprise	-4.10***	-8.62***	-5.08*	-6.83**	-4.59***	-8.22***	-5.76**	-6.34**
	(-4.07)	(-9.05)	(-1.91)	(-2.35)	(-4.76)	(-8.96)	(-2.20)	(-2.16)
BankDebt/At	0.35	0.26	0.13	1.94***				
	(0.86)	(1.14)	(0.13)	(3.12)				
FloatingRateDebt /At					0.25	0.21	0.77	1.19**
					(0.65)	(0.96)	(0.84)	(2.14)
Surprise *(BankDebt/At)	-25.18***	1.41	-38.02***	3.45				
	(-3.04)	(0.26)	(-3.09)	(0.38)				
Surprise *(FloatingRateDebt /At)					-20.81***	-2.72	-30.79**	-3.71
					(-2.60)	(-0.53)	(-2.36)	(-0.40)
Surprise*(BankDebt/At)*Hedging	26.71***		41.46***					
	(2.71)		(2.85)					
Surprise*(FloatingRateDebt /At)*Hedging					17.78*		27.07*	
					(1.90)		(1.74)	
Firm Controls	NO	NO	YES	YES	NO	NO	YES	YES
Firm FE	NO	NO	YES	YES	NO	NO	YES	YES
Surprise*Firm Controls	NO	NO	YES	YES	NO	NO	YES	YES
Cluster (Fed event*IndustryFF48)	NO	NO	YES	YES	NO	NO	YES	YES
Observations	11,796	12,335	11,788	12,335	11,796	12,335	11,788	12,335

8.7 Di Maggio, Kermani, and Ramcharan (R&R AER, 2015): *Monetary Policy Pass-Through: Household Consumption and Voluntary Deleveraging*

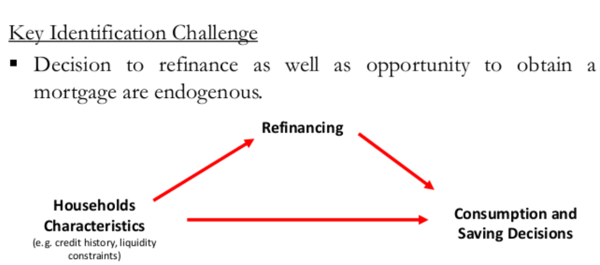
8.7.1 Motivation

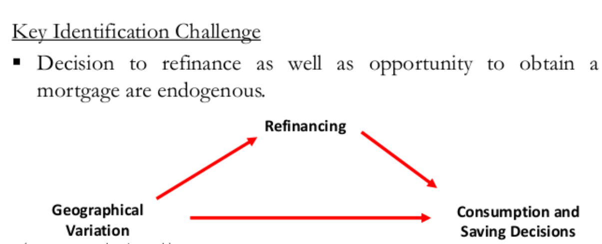
HHs' mortgage debt is the *largest* component of private debt in the US. Monetary policy can work through the changes in the monthly mortgage payments of HHs, assuming that borrowers have ***higher MPC*** than lenders. If Monetary Policy works through the ***income channel***, effectiveness of monetary policy depends on:

1. HHs consumption reaction to changes in their monthly mortgage payment: INCREASE in HHs *precautionary saving* motivations (for example due to higher uncertainty) can lower effectiveness of monetary policy.

2. Pass-Through of lower interest rates to HHs: Contractual frictions combined with underwater HHs can reduce pass-through of monetary policy to HH.

8.7.2 Interest Rate Changes and Consumption





8.7.3 Research Design

Key observation is that during the period 2004-2007 an important part of the mortgages originated were ARMs. Authors consider ***5-1 ARMs*** originated between ***2005 and 2007*** featuring: **(1)** Fixed interest rate for the first 5 years; **(2)** Interest-only payment for the first 10 years; **(3)** Automatic adjustment of the interest rate 5 years after origination.

- Reset driven by contract structure (not *endogenous*)
- Restricting attention only to the HHs with this type of mortgage limits potential concerns about the *endogeneity* of the choice between FRM and ARM.
- ARMs originated in 2005 were able to take advantage in 2010 of an average reduction of >3% in the interest rate.

Authors exploit the ***timing*** of the change in the interest rate and the ***automatic reset*** for these ARMs as a positive income/cash-flow shock for HHs holding these mortgages. Under this analysis, the authors estimate the local average treatment effect (LATE) since the average treatment effect (ATE) is impossible to estimate.

The *expectations channel* is killed by the timing difference of when HHs (who contracted a 5-1 ARM at a different point in time) anticipate the change in interest rates; only the *cash-flow channel* is captured.

Interest Rate
Adjustment (A)

Interest Rate
Adjustment (A)

Identification Strategy

Estimation methodology employed for the individual level is a version of the ***difference-in-differences*** estimator (DD).

- Each month t the ***treatment group*** includes all HHs holding 5-year ARMs who have their mortgages reset in month t, while the ***control group*** comprises those with the same type of mortgage, but that did not experience the change in their interest rate; estimate the consumption response of HHs who *experienced a reduction in the interest payment*, relative to that of HHs holding the same mortgage, but with a *different* reset date.
- **Main DD specification**:

$$Y_{i,t,g,\tau} = \sum_{\theta=-4}^{4} \beta_\theta \cdot 1_{\{\tau=\theta\}} + \beta_5 \cdot 1_{\{\tau \geq 5\}} + \lambda_i + \eta_{g,t} + \Gamma \cdot X_{i,t} + \varepsilon_{i,t,\tau}$$

  - Indices: i = HHs, g = county, t = month or the quarter, and τ = quarter since the interest rate adjustment.
  - Main outcome variables: $Y_{i,t,g,\tau}$ = INCREASE in ***consumption of durables*** (proxied by the purchase of a car) and ***partial mortgage prepayments*** as measure of deleveraging

- λ_i = HHs fixed effects, $\eta_{g,t}$ = county-month fixed effects
- $X_{i,t}$= vector of *borrower's characteristics* designed to capture any residual individual heterogeneity not already captured by λ_i

8.7.4 HH Data

Two main sources of information:

1. mortgage loans originated every month from 2005-2013 through ***Blackbox Logic***.
   (a) Information on the mortgages and the borrowers at origination, such as **(i)** the loan type, **(ii)** the initial interest rate, **(iii)** the initial FICO score and **(iv)** the amount of the loan
   (b) *Monthly updates* about **(i)** the status of each mortgage, **(ii)** the monthly payments, **(iii)** the current balance and other important information.
2. loans are then matched with credit bureau reports from Equifax.
   (a) Detailed information on ***HHs' balance sheets***: the monthly information on all loans that a borrower has, such as credit cards, auto loans, mortgages, and home equity line of credit, but also on current FICO score.

Only consider households for whom their mortgage is *not* in **foreclosure** nor is **repaid or re-financed**.

Mortgage Characteristics

	Our Sample	All Mortgages 2005-2008	FRMs	**ARMs**
FICO	**736.2**	703.76	705.16	687.97
Balance	**357,949**	239,043	196,125	312,466
Loan-to-Value Ratio	77.11	74.53	74.23	76.06
Interest Rate	6.449	6.27	6.30	6.06
Average Monthly Payment	1,921	1,654	1,485	1,765
Interest Rate After Adjustment	3.096			
Monthly Payment After Adjustment	915.8			

8.7.5 Measures of Consumption and Deleveraging

Can observe the *change in the monthly mortgage payments*.

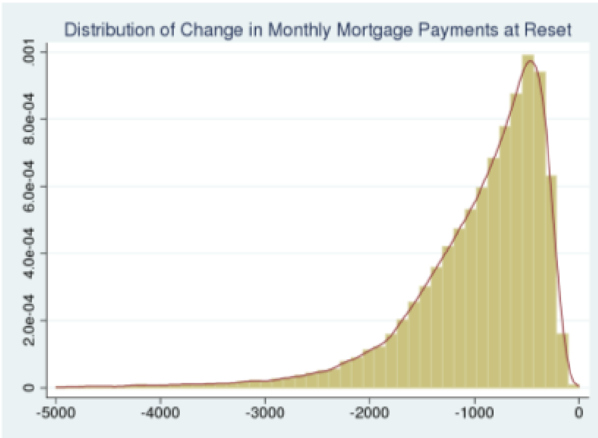


Figure 1 –Change in the Monthly Payment

This figure shows the average change in the monthly payment at the time of the interest rate adjustment, for our sample of hybrid ARMs with an interest-only period of 10 years and a reset date 60 months after origination.

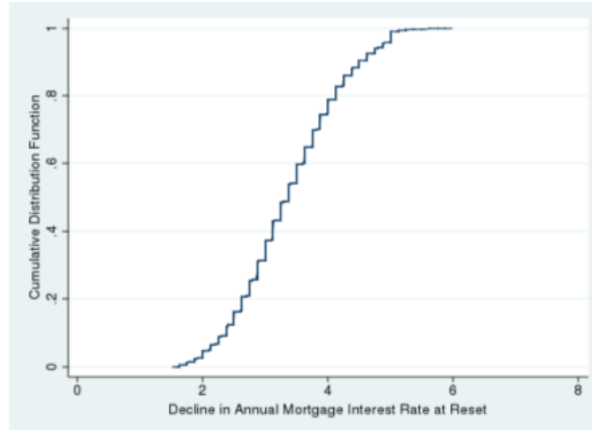


Figure 2 – Change in the Mortgage Interest Rate

This figure shows the cumulative distribution for the change in the mortgage interest rate between origination and the date of the adjustment, for our sample of 5-year ARMs with an interest-only period of 10 years and a reset date 60 months after origination. On average the interest rate declines by 3.3%.

Consumption: Main measure: *auto sales, computed using changes in auto loans.* Additional measures: balance of the borrowers' credit cards issued by both stores (e.g. Best Buy card, Macy's card, etc.) and banks (e.g. Chase, BoA, etc...).

- Financed car purchases account for about 80% of total car sales.
- Measure in car purchases = change in the auto loan balance at the time of purchase

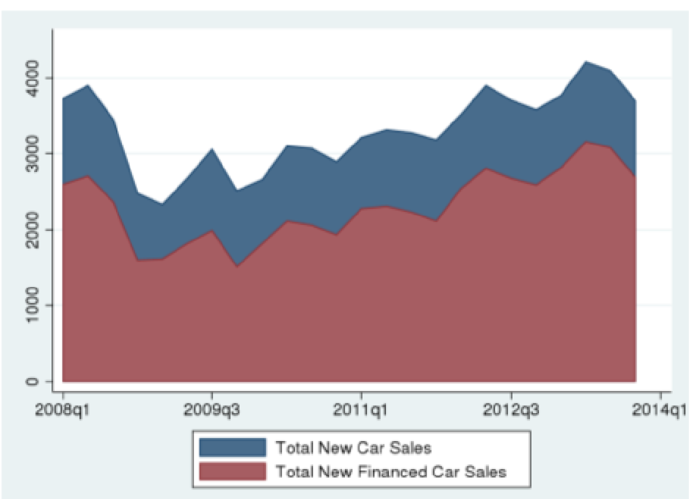


Figure 3 –Total Auto Sales

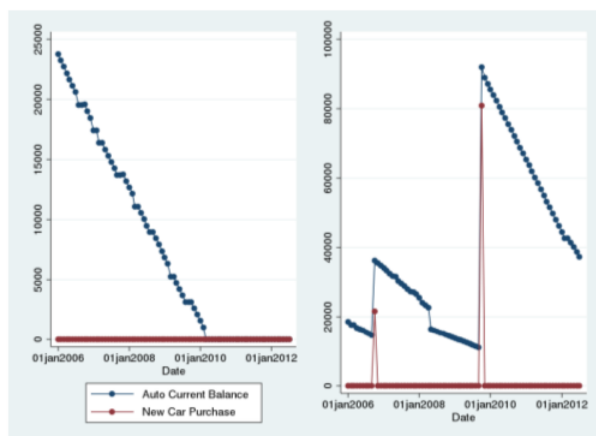
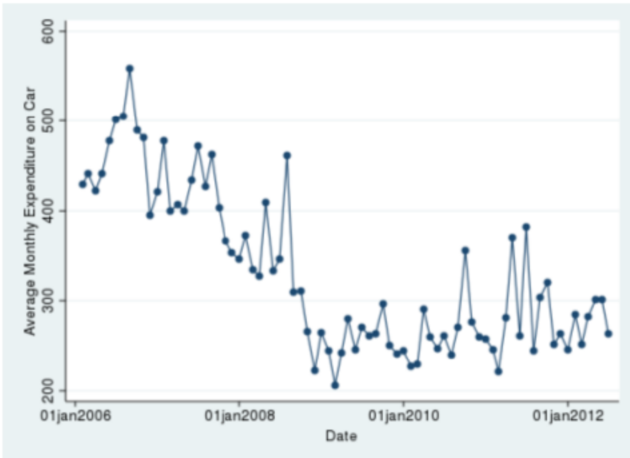
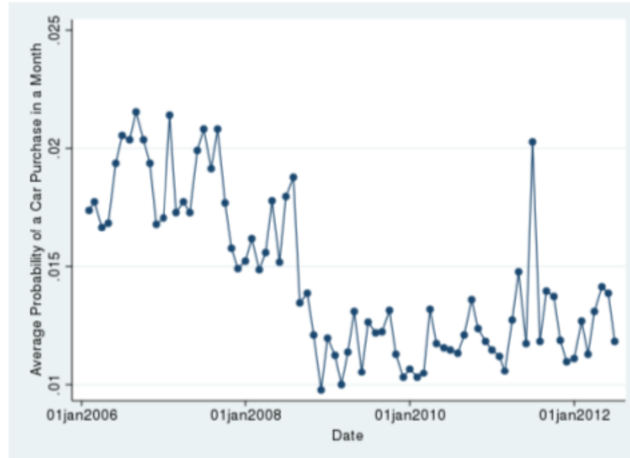


Figure 4 –Households Auto Loan Balances and Construction of Auto Sales Measure

The left panel is an example of individual who purchased her car before January 2006 and did not purchase any car until July 2012. The household in the right panel purchased two cars during the period. We assumed the value of the new car to be equal to the change in the auto loan balance at the time of purchase.

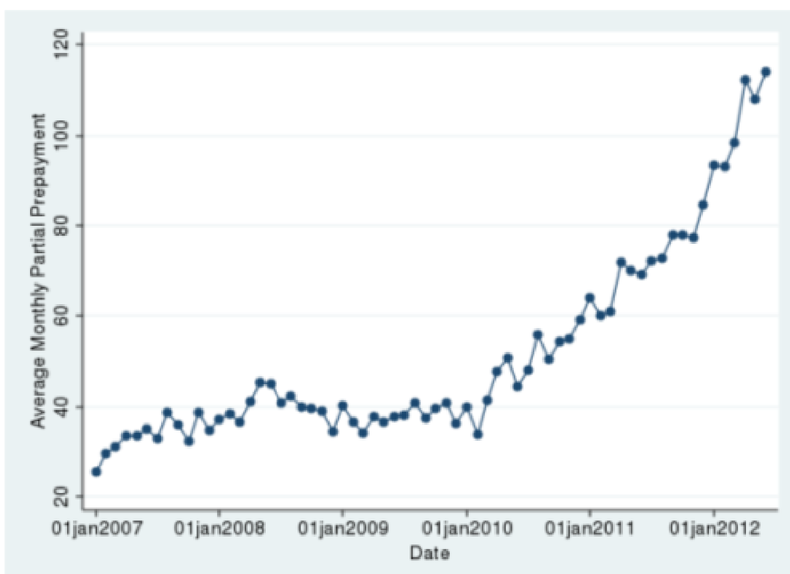
- ***Figure 5 – Car Purchases of Households with 5 ARMs over Time***: The left panel shows the average monthly car expenditure from January 2006 to July 2012 for those HHs who had a 5-year ARM mortgage originated between 2005 and 2007. The left panel shows the fraction of these HHs who purchased a car in each single month.





Deleveraging: Main measure: *borrowers' mortgage payments each month*. Additional measures: payment to Equity Loans and HELOC.

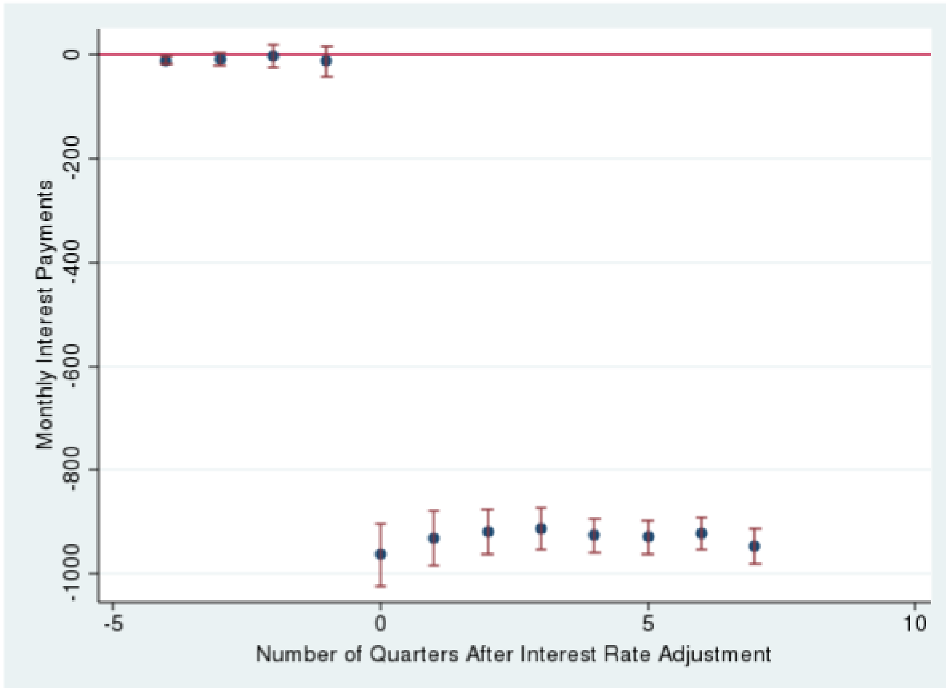
- Measures UNDERESTIMATE the *increase* in consumption: cannot capture purchases made by cash, check or other means not recorded in Equifax.
- At the same time, we cannot observe the decision of the households to save part of the reduction in the monthly payment in their checking or saving accounts.
- ***Figure 6 – Mortgage Partial Prepayment*:** This figure shows the average monthly prepayment of the mortgage for borrowers holding 5-year ARMs originated during the 2005-2007 period.



8.7.6 Main Result 1: *The cash-flow shock*

Positive Income Shock: At the moment of the interest rate reset, the monthly payment DECREASES on *average* by **$900** (50%). This figure also highlights one important feature of the setting, namely that the reduction in the payment is *not temporary*, but lasts for the whole post period. Why? even though these ARMs usually reset the interest rate every year after the initial fixed-rate period, the *low interest rate regime* that was set in Dec 2008 is still in place.

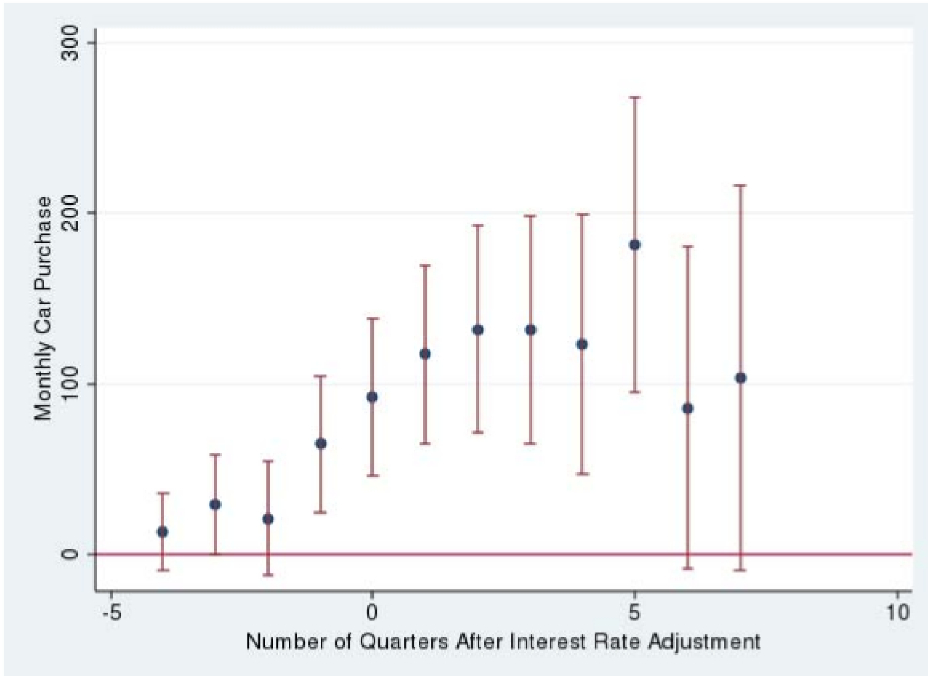
The automatic reset of the interest rates constituted a *major positive disposable income shock* for these HHs.



8.7.7 Main Result 2: *The consumption response*

Consumption: HHs INCREASE their consumption (car purchases and credit card balances) on *average* by **$150-$400** (>40% increase). This figure shows that HHs increase their car consumption starting one quarter before the interest rate reset, allocating on *average* **$50** to it. This suggests that HHs were *anticipating* the mortgage payment reduction and began to increase their car purchasing before the reset date. However, effect increases in the subsequent quarters to an *average* of as much as **$200** one year after the interest rate adjustment.

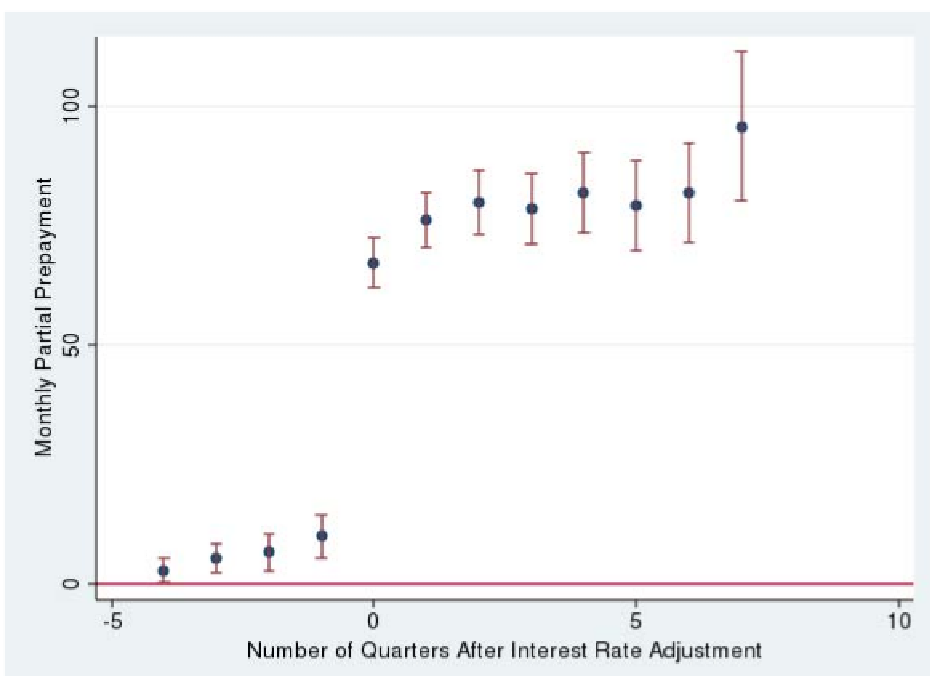
Mian and Sufi (2012a) estimate the impact of the 2009 "Cash for Clunkers" program on short and medium-run auto purchases and show that the resulting boost in aggregate demand is quite short-lived. Here, the reduction of the monthly payment *significantly INCREASED* aggregate demand, with no evidence of intertemporal substitution**;** the effect increases over time.



8.7.8 Main Result 3: *Voluntary Deleveraging*

If HHs are liquidity-constrained, a DECREASE in debt service will be associated with an INCREASE in consumption. But the magnitude of this effect can be a function of their incentive for *precautionary saving*. That is, the greater the income risk, the smaller the consumption response.

Voluntary Deleveraging: On *average* **\$100-\$120** (>100% increase) is allocated to repay their debts faster. This figure shows that HHs allocate on *average* **\$60** per month to a faster repayment of their mortgage, and the amount increases in the following quarters.



Volunatary deleveraging heterogeneous in LTV: The incentive for HHs to build equity in their homes crucially depends on their *current LTV*, because for HHs with LTV closer to 100 percent, the option to default is less attractive than for deeply underwater households, who might then have lower incentives to deleverage.

8.7.9 Main Result 4: *Heterogeneous Responses across Households*

There is heterogeneity in HHs' consumption and saving decisions in response to the *positive income shock*. Zeldes (1989a) shows that an important source of heterogeneity is the *tightness of HHs' liquidity constraint*. Several measures capturing *liquidity constraints* are used.

8.7.9.1 Liquidity Constraint Measure 1: Borrower Income

High income = 1 if the HHs' income is larger than the median one (i.e. larger than **$55,000** a year)

Low Income vs. High Income Households

	Interest Payment	Car Purchase	Prepayment
One Year Before	-0.00554***	0.0273**	6.86e-05
	(0.000523)	(0.0112)	(0.00135)
One Year After	-0.543***	0.0706***	0.0369***
	(0.000787)	(0.0169)	(0.00201)
Two Years After	-0.545***	0.137***	0.0435***
	(0.00121)	(0.0260)	(0.00305)
One Year Before X Household Group	0.00358***	-0.0405***	0.00165
	(0.000581)	(0.0125)	(0.00151)
One Year After X Household Group	0.0303***	-0.0529***	0.00967***
	(0.000835)	(0.0179)	(0.00216)
Two Years After X Household Group	0.0307***	-0.124***	0.00183
	(0.00124)	(0.0266)	(0.00317)

Results:

1. High-income HHs' cash flow shock is about 5% smaller, (see ***Column 1***), which could reflect the fact that these high-income households had better credit scores at origination and, therefore, their initial interest rate was slightly lower.
2. Low-income HHs tend to have a *higher* MPC (see ***Column 2***)
3. Low-income HHs tend to have a significantly *lower* marginal propensity to deleverage (see ***Column 3***) in the first year after the interest rate reset.

8.7.9.2 Liquidity Constraint Measure 2: LTV

High LTV = 1 if current LTV $\geq$ **120%**

Low LTV vs. High LTV Households	Interest Payment	Car Purchase	Prepayment
One Year Before	0.00132**	-0.00850	0.000969
	(0.000609)	(0.0115)	(0.00140)
One Year After	-0.520***	0.0303*	0.0417***
	(0.000929)	(0.0176)	(0.00211)
Two Years After	-0.525***	0.00982	0.0438***
	(0.00155)	(0.0293)	(0.00346)
One Year Before X Household Group	-0.00958***	0.0339**	0.000368
	(0.000745)	(0.0141)	(0.00176)
One Year After X Household Group	-0.0377***	0.0485**	-0.00814***
	(0.00110)	(0.0209)	(0.00259)
Two Years After X Household Group	-0.0398***	0.111***	-0.000578
	(0.00179)	(0.0338)	(0.00410)

Results:

1. Borrowers with a high LTV experience a monthly income gain only *slightly higher* than the other borrowers (see ***Column 1***), which could reflect the fact that these HHs, who purchased their houses in 2006, had the highest initial interest rate, and experienced the largest decline in the value of their houses.
2. High-LTV borrowers spend more than twice as much on durable goods as low- LTV households (have a *higher* MPC) (see ***Column 2***)
3. High-LTV borrowers tend to have a significantly *lower* marginal propensity to deleverage (see ***Column 3***) in the first year after the interest rate reset. Intuitively, borrowers who are deep underwater have little incentives to use the reduction of the monthly payment to repay their debt, because they do not expect to be able to build equity in their homes any time soon.

8.7.9.3 Liquidity Constraint Measure 3: FICO Score

High FICO = 1 if current FICO Score $\geq$ **660**

	(1)	(2)	(3)
	Interest Payment	Car Purchase	Prepayment
One Year Before	-0.00547***	-0.00532	0.000264
	(0.000575)	(0.0124)	(0.00150)
One Year After	-0.548***	0.00312	0.0247***
	(0.000867)	(0.0186)	(0.00223)
Two Years After	-0.547***	0.0255	0.0326***
	(0.00138)	(0.0297)	(0.00350)
One Year Before X High FICO	0.00324***	0.0178	0.00125
	(0.000611)	(0.0131)	(0.00159)
One Year After X High FICO	0.0317***	0.0592***	0.0263***
	(0.000888)	(0.0191)	(0.00230)
Two Years After X High FICO	0.0290***	0.0648**	0.0176***
	(0.00135)	(0.0290)	(0.00346)
FICO	-1.99e-05***	0.00105***	7.72e-05***
	(1.60e-06)	(3.45e-05)	(4.18e-06)
Log(House Prices)	-5.26e-05***	-7.81e-05	2.86e-05***
	(4.26e-06)	(9.14e-05)	(1.09e-05)
Households Fixed Effects	Yes	Yes	Yes
Origination Cohort X Time Fixed Effect	Yes	Yes	Yes
High FICO X Time Fixed Effects	Yes	Yes	Yes
Low FICO X Time Fixed Effects	Yes	Yes	Yes
Observations	2,212,779	2,213,325	2,029,757
R-squared	0.781	0.026	0.155

Results:

1. HHs with high FICO scores have a monthly payment reduction only 6% lower than those with low FICO (see ***Column 1***), which could reflect the fact that these HHs, who purchased their houses in 2006, had the highest initial interest rate, and experienced the largest decline in the value of their houses.

2. Borrowers with high FICO consume ***13% more*** than those with less access to the credit market (have a *higher* MPC) (see ***Column 2***), which is consistent with interpretation that low FICO households face higher borrowing costs and poorer access to credit,

3. Significant differences in the deleveraging behavior of HHs with different FICO scores, because the *more creditworthy* deleverage by 30% more than the less creditworthy (see ***Column 3***).

SUMMARY: Heterogeneity in results on the ***marginal propensity to consume*** and ***deleverage*** in different types of HHs suggest the importance of *liquidity constraints*. Fiscal stimulus identified is likely to operate through *wealth* and *liquidity mechanisms*. This has implications for the effectiveness of monetary policy; the central bank's policies should primarily target those HHs that will boost aggregate demand MORE (e.g. direct *allocation of credit*).

8.7.10 Further Evidence and Robustness Checks

8.7.10.1 Attrition

Authors examine possible sources of attrition, given sample period covers the crisis and that the **5-1** ARMs considered might have had an even harder time during the Great Recession than less risky mortgage types. This figure shows number of ***active loans*** (blue solid line), ***liquidated loans due to foreclosure, bankruptcy or real estate owned*** (green dash line) and ***paid off mortgages due to prepayment or refinancing*** (dash-dot line) over time**.** This paper's analysis only considers ***active loans***, comparing the consumption and savings decisions of borrowers benefiting from the interest rate adjustment at different points in time. results.

Excluding HHs who defaulted or prepaid their loan doesn't hurt the results ; if anything it *probably biases the results downwards* (underestimates them).

8.7.10.2 Difference-in-Differences Results

Authors further test the validity of their identification strategy. ***Potential concern***: mortgage-specific trend that could affect the results

- Main specification doesn't control for the *age of the mortgage*, which might be correlated with the household's consumption or prepayment behavior. In order to correct for this possibility, we consider as ***control group*** the mortgages that have the interest rate reset 10 years after origination, i.e. 10-year ARMs.
- This table shows results for sample including both 5-year and 10-year ARMs originated between 2005 and 2007 as provided by BlackBox Logic.

	1	2	3
	Interest Payment	Car Purchase	Prepayment
Four Quarters Before	-10.75***	40.11*	8.442**
	(3.135)	(21.58)	(3.206)
Three Quarters Before	-19.75***	26.13	6.935
	(4.852)	(31.32)	(4.462)
Two Quarters Before	-23.72***	48.57	12.12***
	(5.342)	(34.26)	(4.511)
One Quarter Before	-20.74***	99.45***	10.61**
	(7.376)	(33.88)	(4.931)
One Quarter After	-922.3***	146.7***	66.26***
	(43.58)	(46.24)	(6.329)
Two Quarters After	-848.7***	162.3***	75.30***
	(33.86)	(46.17)	(6.956)
Three Quarters After	-793.6***	187.3***	71.74***
	(33.06)	(42.69)	(7.501)
Four Quarters After	-750.6***	186.1***	67.25***
	(33.88)	(60.19)	(8.844)
Two Years After	-713.5***	137.7*	62.21***
	(34.58)	(80.01)	(9.658)
FICO Score	-0.0266***	1.803***	0.152***
	(0.00495)	(0.0564)	(0.0101)
Log(House Prices)	-0.141***	0.157	0.129***
	(0.0262)	(0.139)	(0.0165)
Household Fixed Effect	Yes	Yes	Yes
Origination Cohort X Loan Type X Time Fixed Effect	Yes	Yes	Yes
Mortgage Age Fixed Effect	Yes	Yes	Yes
Observations	4,530,401	4,596,110	4,294,354
R-squared	0.977	0.030	0.243

Results: similar to the baseline results that *only use* 5-year ARMs.

8.7.10.3 Unexpected Rate Reduction and the Role of Uncertainty

Authors investigate the effect of an *unexpected interest rate reduction* by analyzing ARMs that reset during the period January 2007-March 2008. This covers the *first time* the LIBOR declined and a relatively quiet period for the US economy. This table reports both the least squares and the instrumental variable estimates, controlling for *time*- and *HH fixed-effect*

8.7.10.4 Alternative Consumption and Deleveraging Measures

Authors investigate the impact of monetary policy on different measures of consumption and deleveraging. Analyzing a different measure of consumption and the repayment behavior for the case of other two types of debt confirms and reinforces the main results.

Results: SMALLER in magnitude but similar to the baseline results: consistent with the interpretation that this interest rate reduction ***came more unexpected*** that the one considered in the previous sections of the paper.

	(1)	(2)	(3)
		OLS	
	Interest Payment	Prepayment	Car Purchase
Post Rate Adjustment	-252.7***	87.65***	127.7*
	(5.039)	(33.00)	(74.88)
Monthly Payment$_{t+3}$			
Monthly Payment$_t$			
Time Fixed Effects	Yes	Yes	Yes
Household Fixed Effect	Yes	Yes	Yes
Observations	104,177	82,461	119,792
R-squared	0.976	0.199	0.174

Authors use the VIX index as a measure of uncertainty and find that over the period from Nov 2008 - Dec 2009 and find that as proposed by the existing theoretical literature, HIGHER *uncertainty* might lead to a significantly HIGHER *precautionary savings* motive.

8.7.10.5 Alternative Consumption and Deleveraging Measures

This table shows the coefficient estimates of OLS regression relating the amount spent on *retail credit cards* with the interest rate reset.

	Store Credit Cards	Bank Credit Cards
Four Quarters Before	1.170	19.34
	(2.649)	(26.00)
Three Quarters Before	3.174	19.09
	(3.194)	(31.94)
Two Quarters Before	0.451	46.02
	(3.760)	(44.86)
One Quarter Before	10.01**	87.69
	(4.324)	(54.99)
One Quarter After	14.25***	129.0**
	(4.926)	(61.27)
Two Quarters After	15.32***	125.3*
	(5.564)	(71.48)
Three Quarters After	15.22**	140.4
	(6.191)	(89.33)
Four Quarters After	20.87***	275.6***
	(6.919)	(98.48)
Two Years After	27.85***	330.0**
	(7.877)	(123.4)
Observations	1,158,492	289,562
R-squared	0.060	0.365

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R-squared	0.060	0.365

Results: Similar spending pattern, with HHs starting to INCREASE their consumption one quarter *before* the interest rate reset and keep consuming more after it. Analyzing a different measure of consumption and the repayment behavior for the case of other two types of debt confirms and reinforces the main results.

8.7.11 Main Result 5: *Aggregate-Level Evidence*

Authors use *county level* data to gauge the extent to which results might generalized across a broader sample of HHs and to better understand their ***local general equilibrium*** implications. Methodology cannot estimate the ***aggregate general-equilibrium effect***, such as an economy-wide multiplier of interest rate policy, as for instance we do not observe the lenders' response to such changes in interest rates.

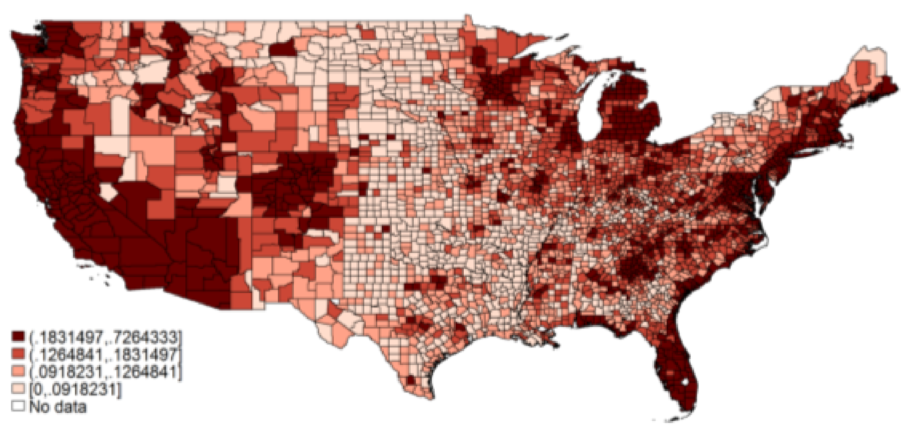
Garriga et al. (2013) develop a general equilibrium model showing that monetary policy affects decisions through the *cost of new mortgage borrowing* and the *value of payments on outstanding debt*. The transmission is found to be stronger under ***adjustable-*** than ***fixed-rate*** contracts, suggesting that mortgages are an important example of a persistent nominal rigidity.

County-Level Data:

- LPS: provides loan-level information collected from the major mortgage servicers in the US, covering about 60% of the mortgage market. We use these data to construct the total stock of outstanding mortgage debt in each county, disaggregating the principal balance by whether the mortgage is fixed rate or adjustable rate.
- Car sales data provided by Polk: sales of new vehicles at quarterly frequency by county.
- New York Fed Consumer Credit Panel: balances by county.

This figure shows the fraction of ARMs originated in each country in 2006 using data from LPS.

Fraction of ARMs in 2006



ARMs are relatively more frequent along the coast, where housing costs are generally higher.

MP Pass-Through *Results*: Fraction of ARMs is a *strong predictor* of pass-through of changes in monetary policy to households' mortgages rates and monthly payment (9-11 bps/sd) As the interest rate declines, counties with a higher fraction of ARMs display a *more significant reduction* in the average mortgage rate and in their average monthly payments, which suggests higher pass-through of changes in monetary policy and in LIBOR to these counties.

Monetary Policy Pass-Through

	Mortgage Interest Rate		Average Monthly Payment	
Fraction of $ARMs_{2006}$ X Six-Month LIBOR	0.172*** (0.0113)	0.197*** (0.0117)	0.0587*** (0.00813)	0.0332*** (0.00689)
County Controls	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
State X Time Fixed Effects		Yes		Yes
Observations	24,204	24,176	24,204	24,176
R-squared	0.342	0.245	0.143	0.145
Number of Counties	865	864	865	864

Economic Stimulus *Results*: A decline in interest rates like that of 2007-2013 leads to a *significant consumption response* in counties with a higher share of ARMs in 2006. The point estimates suggest that a one-standard-deviation increase in the fraction of ARMs is associated with about 2.5-3% increase in car sales in that county.

Voluntary Deleveraging *Results*: A decline in interest rates is associated with a *more significant deleverage* in counties with more AMRs in 2006. A one-standard-deviation increase in the fraction of ARMs is associated with about 1.5% decline in mortgage balances.

Reduced Form

	Car Sales	Credit Card Balance	Mortgage Balance	Car Sales	Credit Card Balance	Mortgage Balance
Fraction of $ARMs_{2006}$ X Six-Month LIBOR	-0.0592*** (0.0140)	-0.0729*** (0.0176)	0.0262*** (0.00995)	-0.0459*** (0.0157)	-0.0473*** (0.0171)	0.0967* (0.0496)
County Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State X Time Fixed Effects				Yes	Yes	Yes
Observations	23,980	24,204	24,204	23,980	24,176	24,176
R-squared	0.072	0.088	0.461	0.031	0.095	0.259
Number of Counties	857	865	865	857	864	864

IV Estimates

	Log(Car Sales)	Log(Credit Card Balance)	Log(Mortgage Balance)	Log(Car Sales)	Log(Credit Card Balance)	Log(Mortgage Balance)
Mortgage Interest Rate (Instrumented by Fraction of ARMs2006 X Six-Month LIBOR)	-0.340***	-0.424***	0.152***			
	(0.0806)	(0.103)	(0.0589)			
Average Monthly Payment (Instrumented by Fraction of ARMs2006 X Six-Month LIBOR)				-1.009***	-1.243***	0.447***
				(0.272)	(0.349)	(0.146)
County Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,981	24,204	24,204	23,980	24,204	24,204
R-squared	0.059	0.075	0.439	0.000	0.020	0.567
Number of Counties	858	865	865	857	865	865

SUMMARY: Aggregate results highlight the importance of ***debt rigidity*** in determining the aggregate effects of monetary policy transmission: The effects of a decline in the interest rate differ according to the concentration of ARMs in different areas.

APPENDIX

A.1 Final Examination (Spring 2013)

A.2 Field Exam Question ([August] 2014)