Who Needs Liquidity, When, and Where?
Evidence from Penalized Withdrawals

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***Disclaimer**: The views expressed in this presentation are those of the authors and do not necessarily reflect the views of the Treasury or the U.S. government. Results are preliminary. Please do not cite without authors' consent.*

Motivation

- Marginal utility smoothing across time and states of nature is perhaps the most fundamental rule for economic efficiency
- Degree to which marginal utility of consumption differs between today and tomorrow is key moment of interest across fields in economics
  - Captures household's equilibrium demand for liquidity (interaction of supply/demand) = value of liquidity
  - Crucial for assessing market efficiency and how we should target policies toward highest welfare returns from allocation of the marginal dollar

Motivation

- Yet, assessing households' valuation of liquidity is a challenging task
- Requires:
  - Identifying preferences for consumption
  - Comprehensive consumption data on durable and non-durable goods
  - Information on household expectations about consumption tomorrow
  - Estimation of scale economies to translate utility into per capita terms
- Each of these steps entails a range of estimation and identification difficulties
- Recent important literature aims to tackle this challenge in a wide variety of methods (based on consumption or labor supply)

This Paper

- We offer an alternate approach to study the equilibrium demand for liquidity by leveraging a simple yet powerful intuition:

  Households who are willing to take up pricey borrowing – in the form of penalized withdrawals from savings accounts – reveal a high marginal rate of substitution between consumption today and consumption tomorrow

  ⟹ have higher demand for and valuation of liquidity

This Paper

- We use U.S. tax records on over 12 million households from 1999-2018 to analyze the anatomy of American households' demand for liquidity

- We study three levels of savings withdrawals behaviors across time and space:
  (1) Micro shocks using household events over time
  (2) Steady-state demand for liquidity across localities
  (3) Macro shocks using temporal variation in the Great Recession across local labor markets

- Analysis reveals significant responses and variation across the multiple margins
  - Underscoring the previously-overlooked effectiveness of penalized withdrawals as a prevalent tool to identify liquidity needs

- Motivates policies that target both households and locations

Our Object of Interest: Value of Liquidity

- From the household Euler Equation

$$\frac{u'(c_t)}{u'(c_{t+1})} = 1 + \theta_t$$

  - $\frac{u'(c_t)}{u'(c_{t+1})} =$ the relative marginal utility of consumption today
  - $\theta_t \equiv$ the implied price of moving one \$ from $t+1$ to t
    - **Excess valuation of a dollar today**

- Our goal is to characterize θ_t and study how it varies across time, space, and individuals
  - Useful to properly target policies

- We will refer to a high value of θ_t as high value for liquidity since it is the shadow price of one \$ of utility today

Measuring Value of Liquidity: Challenges

- Measuring θ_t directly is challenging:
  - We do not observe u'
  - We observe c_{t+1} only ex-post → too late for policy implementation

- Using income shocks to proxy for liquidity value provides, at best, an incomplete assessment, since the equilibrium value of liquidity depends on:
  - household demand for liquidity (could be captured by income shocks)
  - supply of liquidity, which depends on local credit market conditions faced by households

Measuring Value of Liquidity: Challenges

- One promising avenue is to rely on indirect measurement based on revealed preferences: observing the price at which individuals are willing to move \$ from $t+1$ to t would allow us to infer information about the valuation of liquidity
  - E.g.: observing individuals taking a loan at 5% real interest rate signals they value \$ today at least 5% more than tomorrow

- In practice, there are several challenges with this approach as well:
  - Data availability: to our knowledge, there is no data on the universe of interest rates charged to each household
  - Infra-marginality/exclusion problem: interest rates only provide information on individuals who have access to that particular liquidity tool (e.g. not everyone may be approved for a credit card, loans are denied)
  - Aggregation: hard to aggregate the multiple available financial instruments and quantify their true interest rate

Measuring Value of Liquidity: One Solution

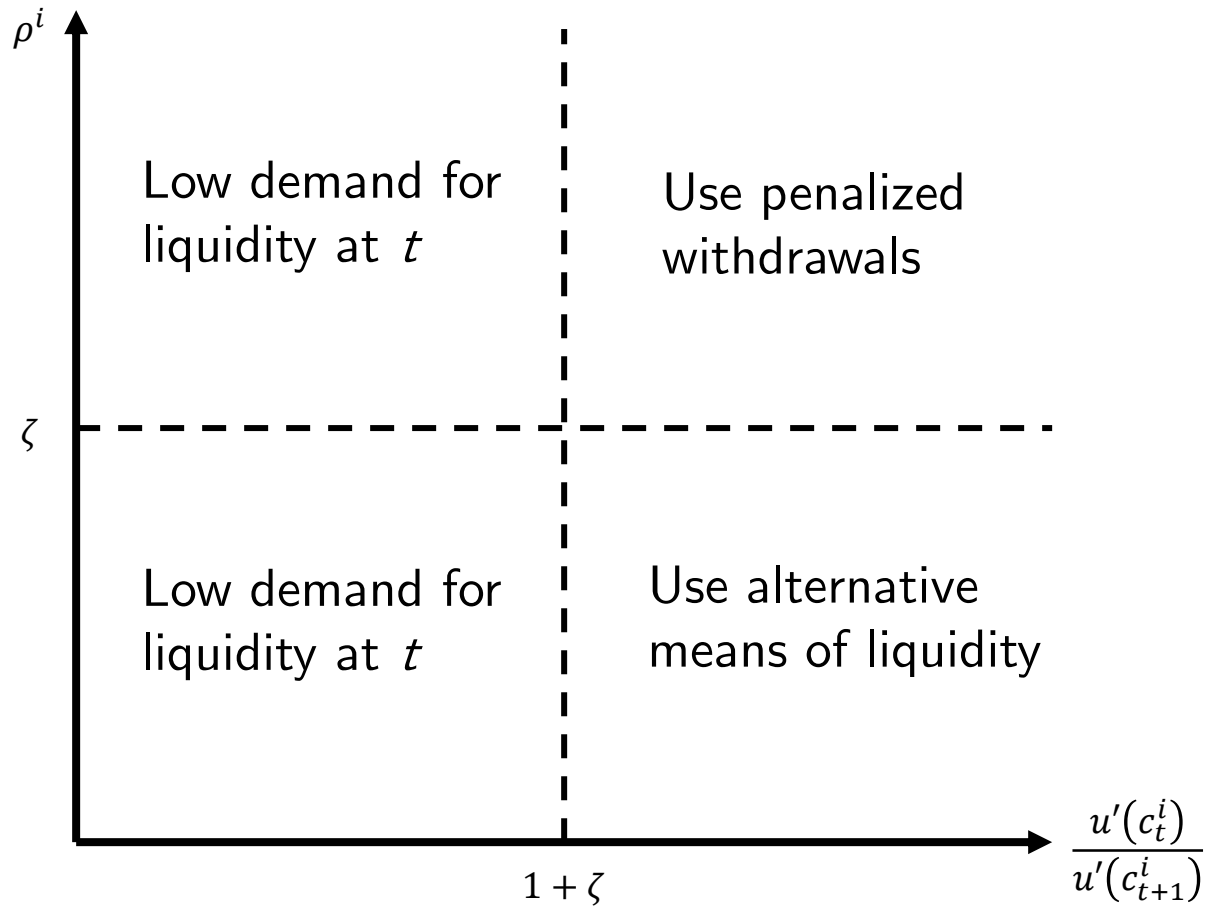
- Consequently, an ideal tool for indirect measurement of liquidity value would be a financial instrument with the following key characteristics:
  - Charge a constant price P across time, space, households for shifting resources from $t+1$ to t
  - Be widely available across time, space, households

- Observing take-up of such financial instrument would inform us that:
  - Individuals are willing to pay at least P to shift \$ to time t
  - Other available means of liquidity are more costly
  - → It will therefore capture the two motives (demand+supply) that determine household's valuation of liquidity in equilibrium

- Penalized withdrawals from 401(k)/IRA accounts provide an almost ideal tool
  - Conditional on funds, you can withdraw paying a uniform 10% penalty
  - Most prime-age households have access and available funds (as we show)

⇒ We use take-up of penalized withdrawals to measure demand for liquidity

Measuring Demand for Liquidity: Illustration



ρ^i is the liquidity cost of alternative means (i.e. not penalized withdrawals) for household i

ζ is the liquidity cost of a penalized withdrawal, that is constant for everyone

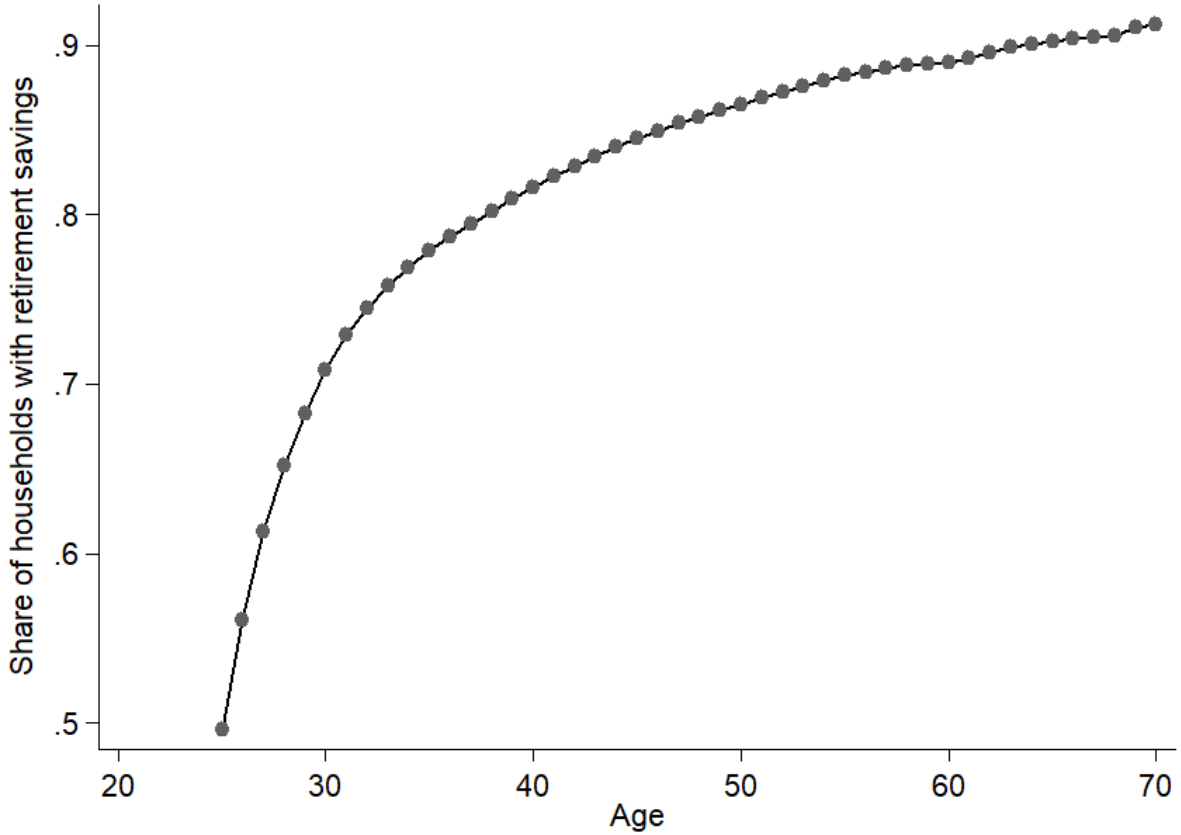
- Two shocks can lead to an increase in mass of penalized withdrawals
  - Credit crunch → upward shift in cost of alternative liquidity means
  - Negative income shock → rightward shift in MU of consumption today

Institutional Details

- Many savings instruments require that money be held for an allotted time or until a certain date
  - IRA/401(k)
  - HSA
  - CDs
- Account holders may withdraw from these accounts early, but must pay a penalty (e.g., 10% penalty for IRA withdrawals before age 59.5)
- Some early withdrawals are exempt from tax penalties
  - Rollovers
  - Death/disability
  - Funds used for higher education
  - Unreimbursed medical costs over 10% of AGI
  - First time homebuyer
  - Separation from employment for those over age 55

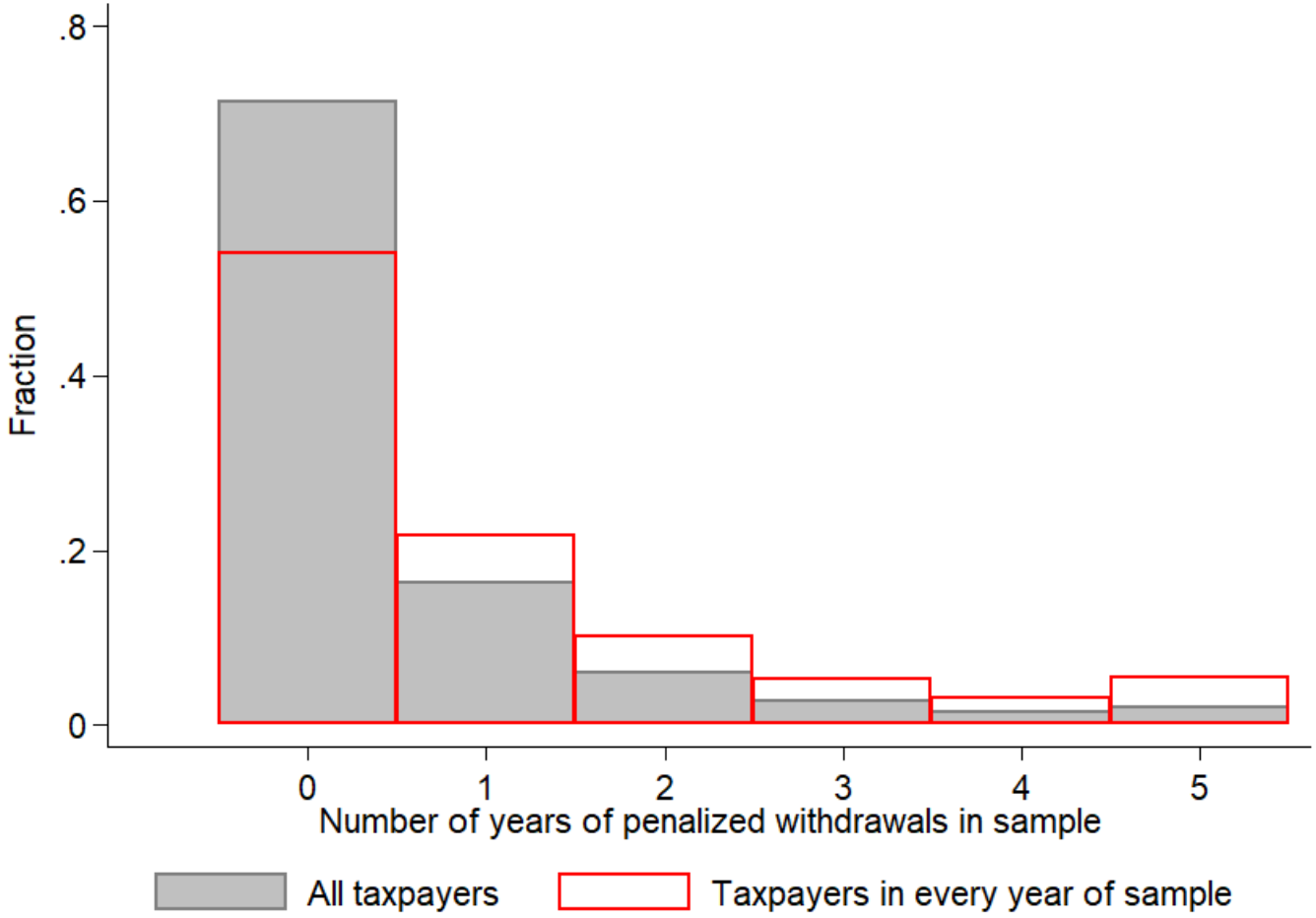
Data and Analysis Sample

- Tax records for filers and non-filers based on 10% sample of U.S. population from 1999-2018 aggregated to the household level
- Restrict sample to ages 45-59 to focus on prime-age households for whom this tool is more relevant (leads to sample of 12.6 million households)



Analysis Sample

- Average annual share of returns with a penalized withdrawal is 7.5%
  - 46% of households observed for 15 consecutive years report taking a penalized withdrawal in at least one year



Analysis Sample

- Taxpayers who have taken a penalized withdrawal have slightly lower household income and wages

	Have Taken Pen. Withdrawal	Never Take Pen. Withdrawal
HH AGI	$120,076	$135,558
HH Wage Income	$93,212	$101,642

Note: AGI and wages measured in 2018 for prime-age households (primary taxpayer aged 45-59)

Evidence on Demand for Liquidity

- Part I: Household Level Events (household over time)
- Part II: Spatial Differences (steady-state over space)
- Part III: Macro Shocks (space over time)

Part I: Household Level Events

Household Level Events

- Underlying hypothesis posits that individuals use withdrawals to self-insure
- We begin with verification exercises that study events which can lead to adverse income changes
  - Unemployment
  - Income loss
  - Job switch

Event Study Specification

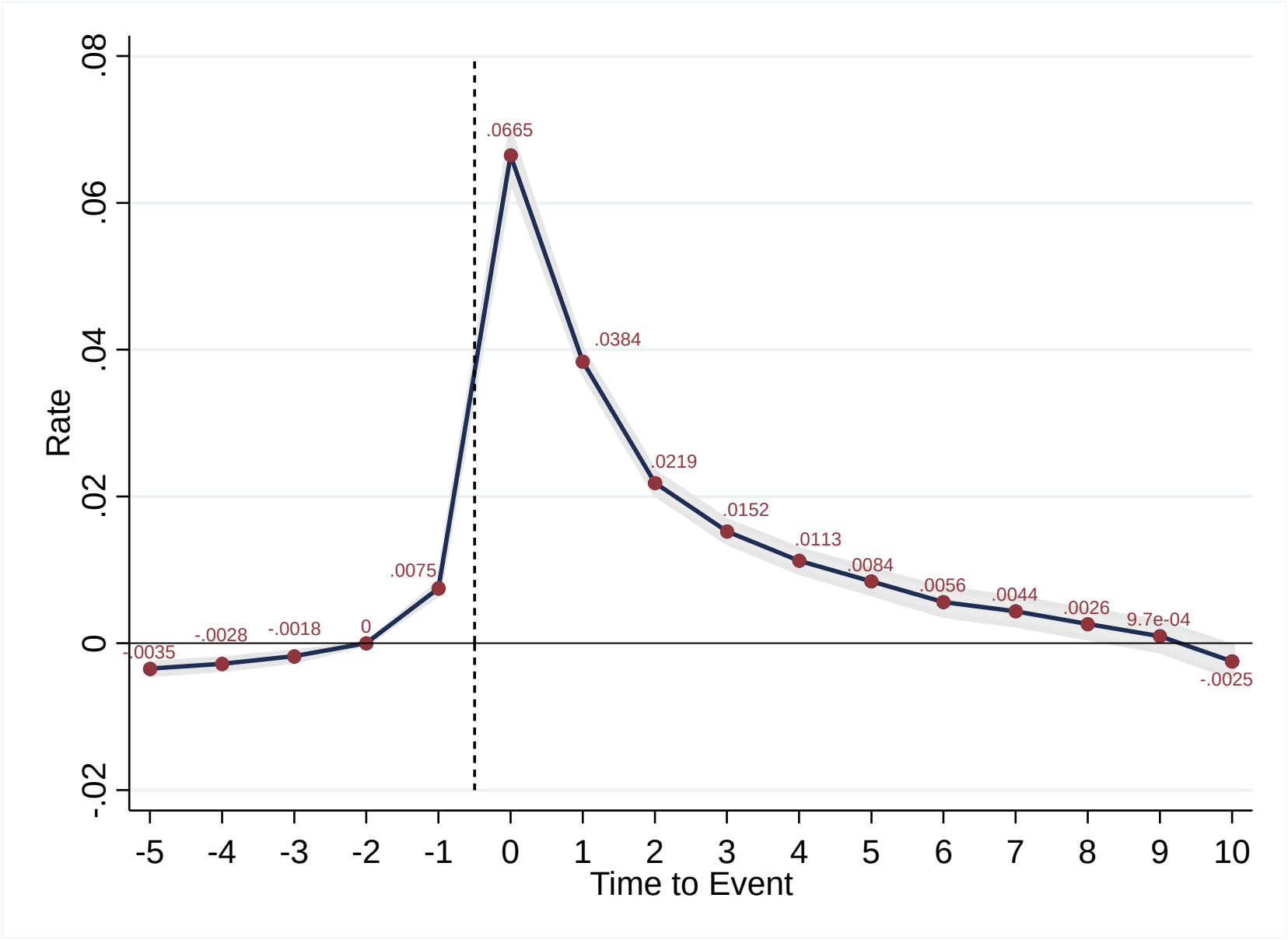
- Estimating equation:

$$y_{it} = \sum_{\tau} I_{\tau} \times \beta_{\tau} + GX_{it} + \alpha_i + \varepsilon_{it}$$

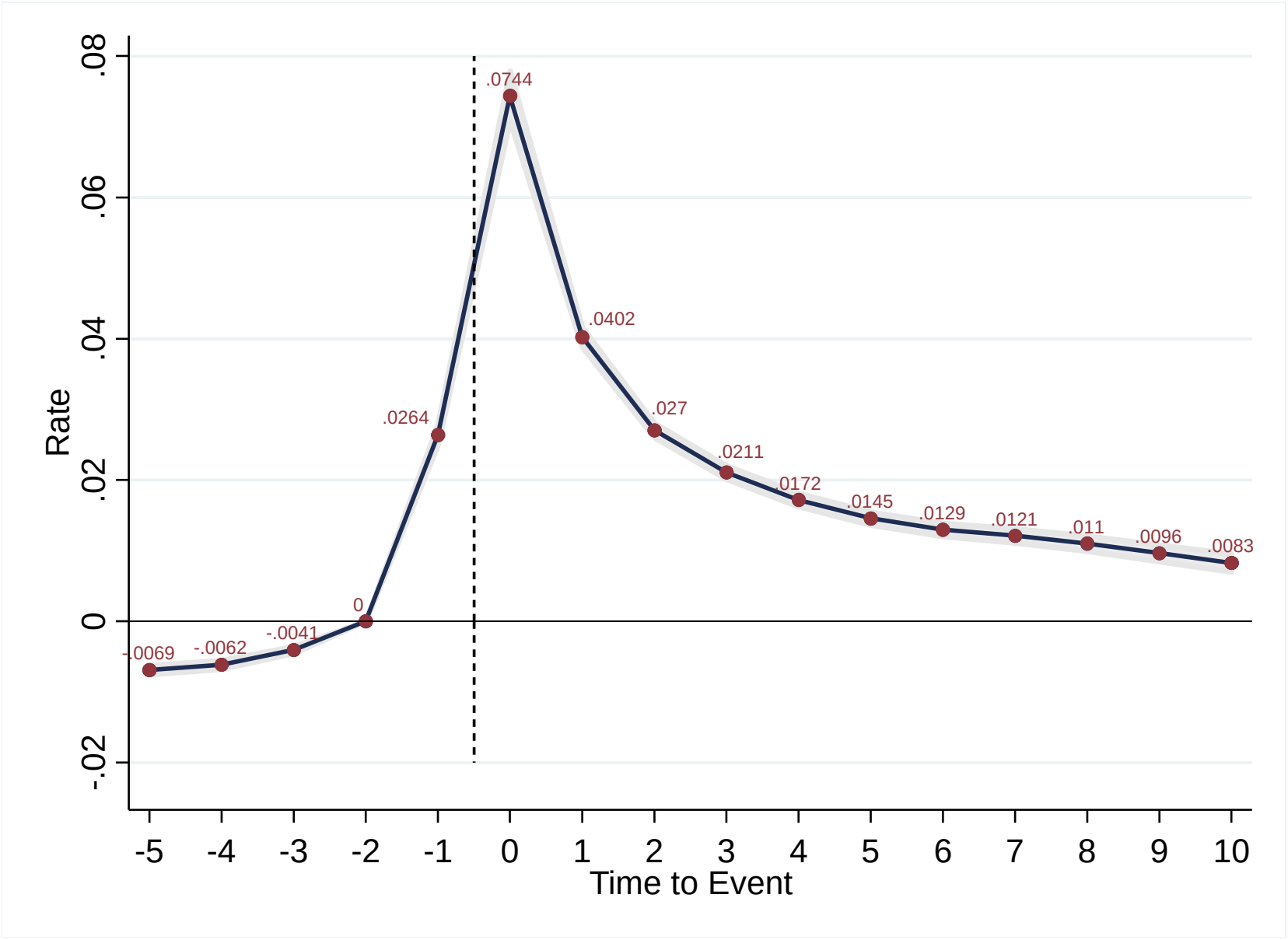
  - y_{it} – indicator for penalized withdrawal for household i at time t
  - τ – year relative to the event, I_{τ} set of indicators
  - X_{it} – full set of age and (cyclical) year dummies
  - α_i – household fixed effect

- We plot β_{τ} around different events to trace the evolution of households' withdrawal behavior

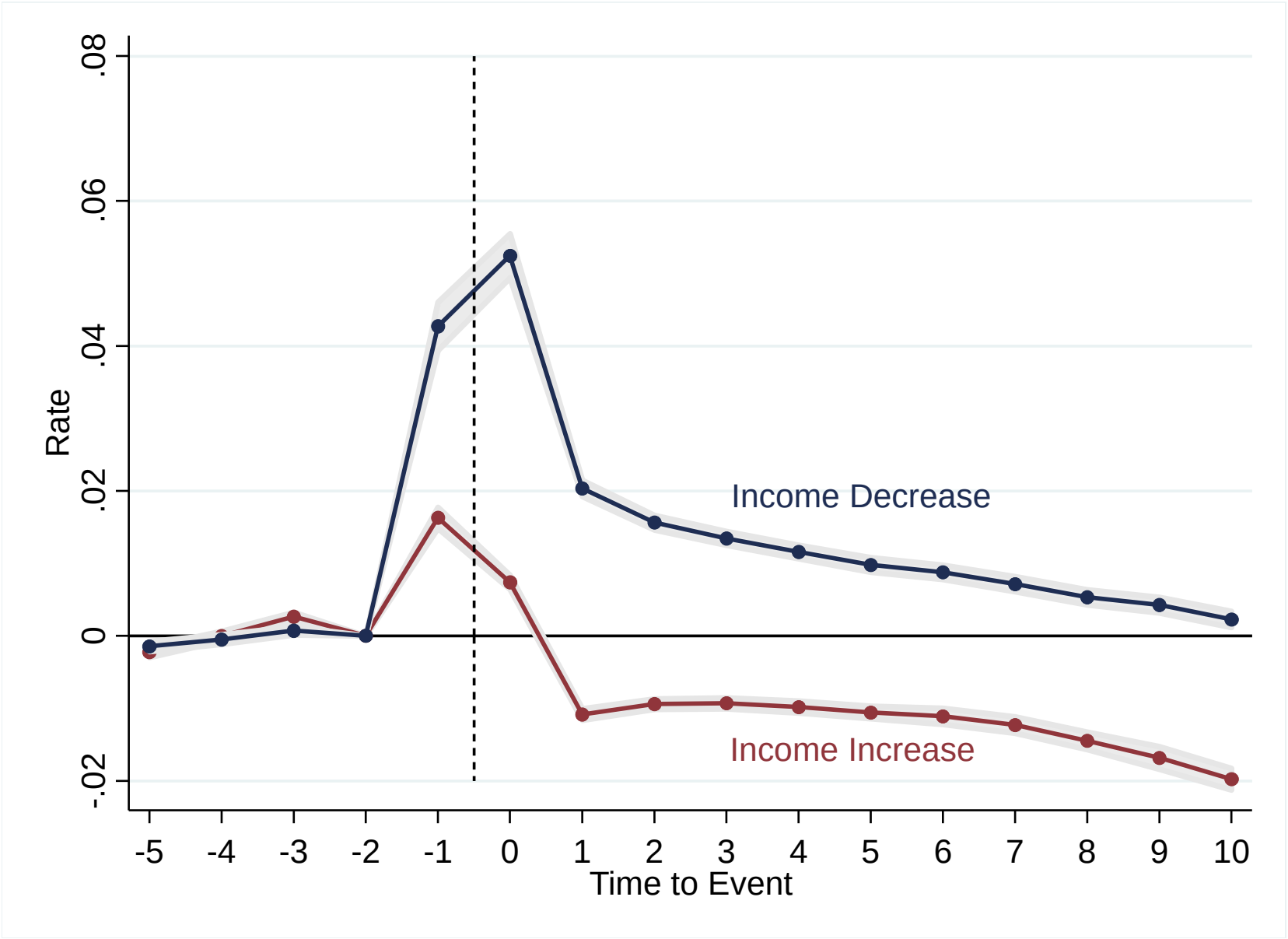
Unemployment Event



Income Loss Event



Job Switches



Short-Run Self-Insurance

Event Type:	Wage Earnings (1)	Gross Income (2)
Unemployment Event	-13,683***	-8,809***
	(358)	(353)
Drop in Income	-51,414***	-37,807***
	(1,697)	(1,655)
Penalized Withdrawal Event	-7,863***	305
	(256)	(487)

- Endogenous choice of withdrawals fully offsets wage loss in the short run

Part II: Differences across Locations

Differences across Locations

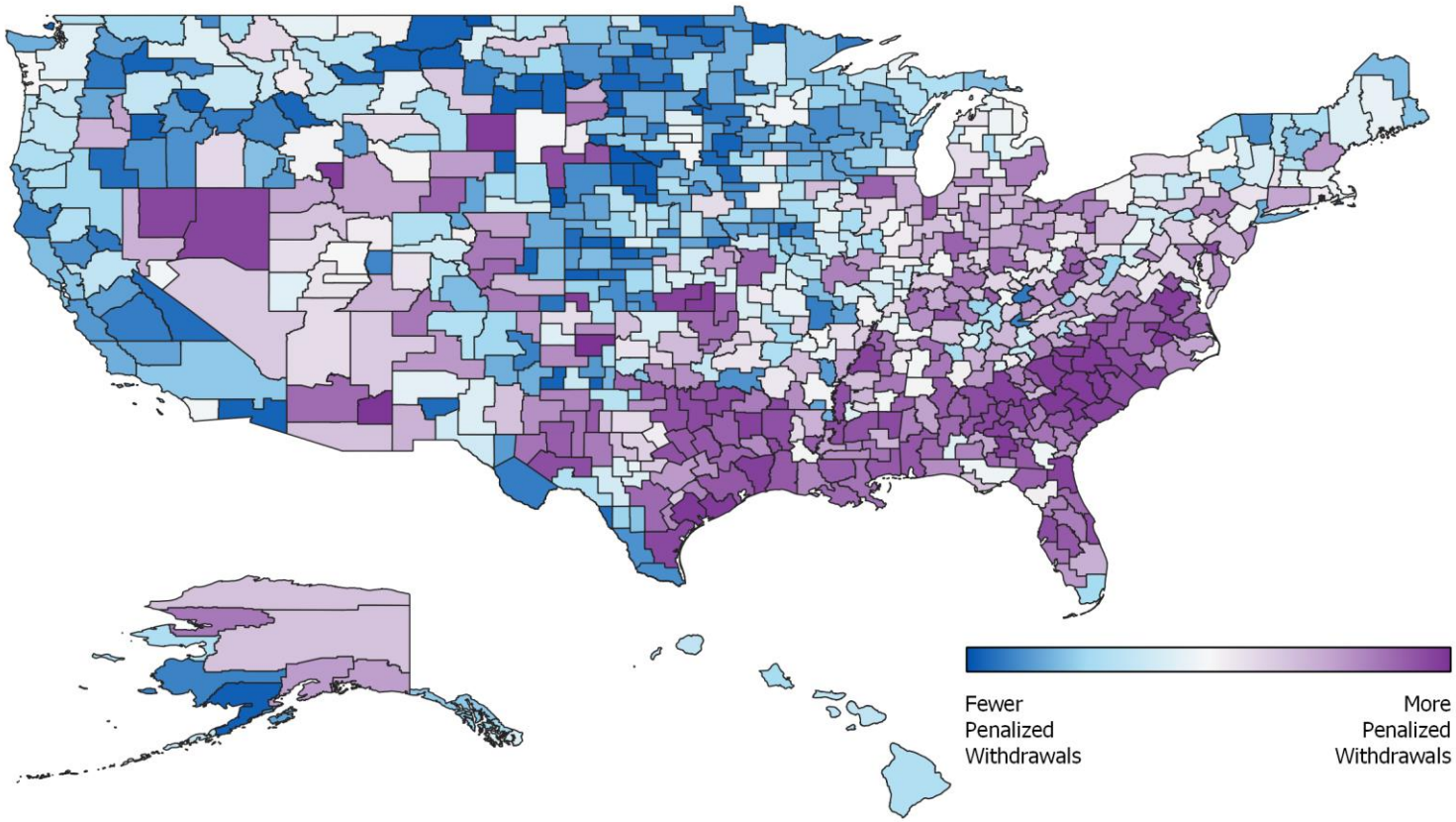
- We have established that individuals use penalized withdrawals to self-insure
  → penalized withdrawals signal liquidity needs

- Next, we explore the regional differences in liquidity needs
  - To investigate the potential role of location

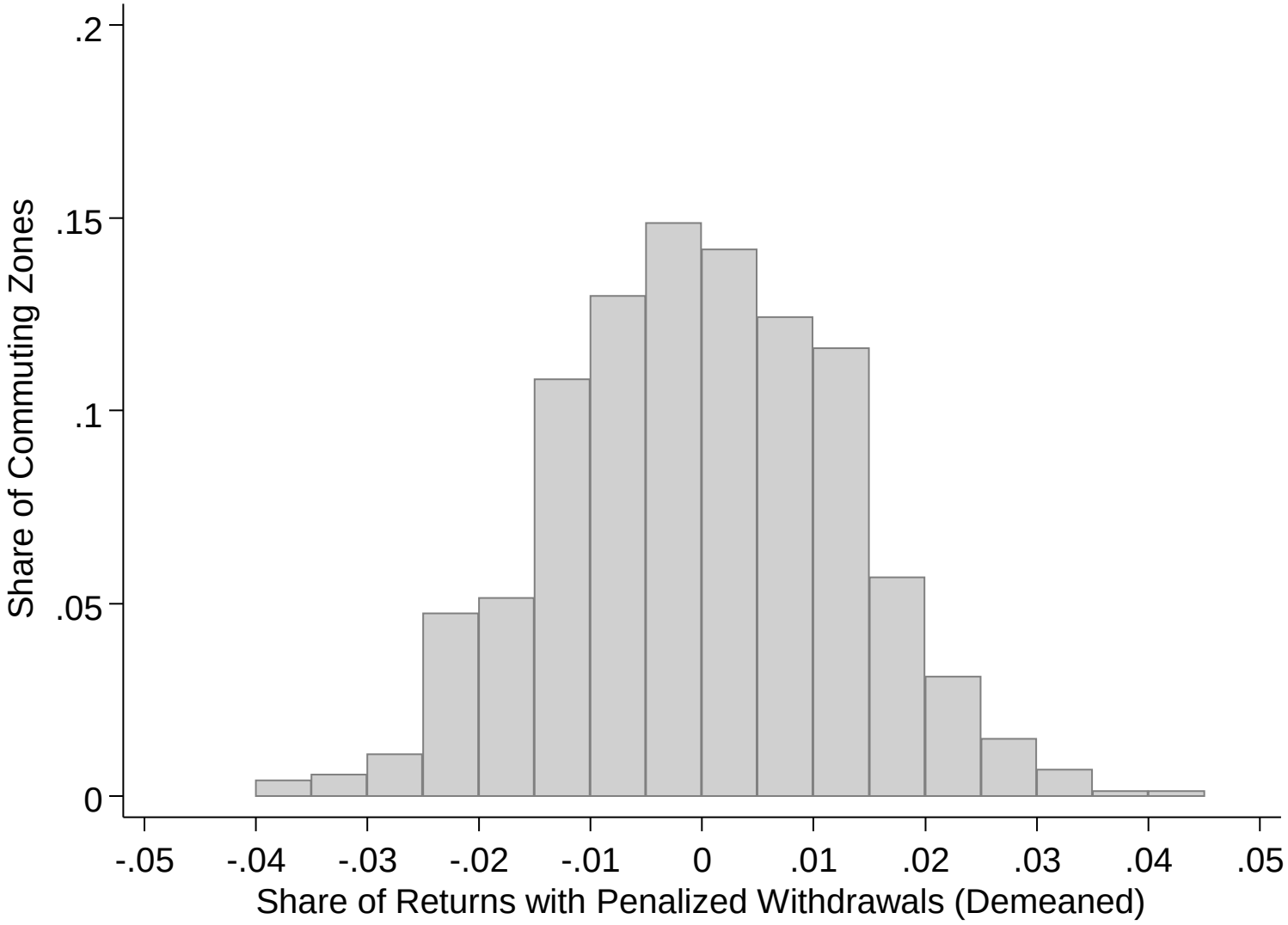
Location-Based Withdrawals

- As a starting point, we plot a map of average annual share of households that have a penalized withdrawals by commuting zones (CZs)

- The map shows large differences across regions



Location-Based Withdrawals - Distribution



Location-Based Withdrawals

- Next, we add controls to further isolate the location "effects"

- Estimating equation:

$$y_{itc} = \xi_c + GX_{it} + \alpha_i + \varepsilon_{itc}$$

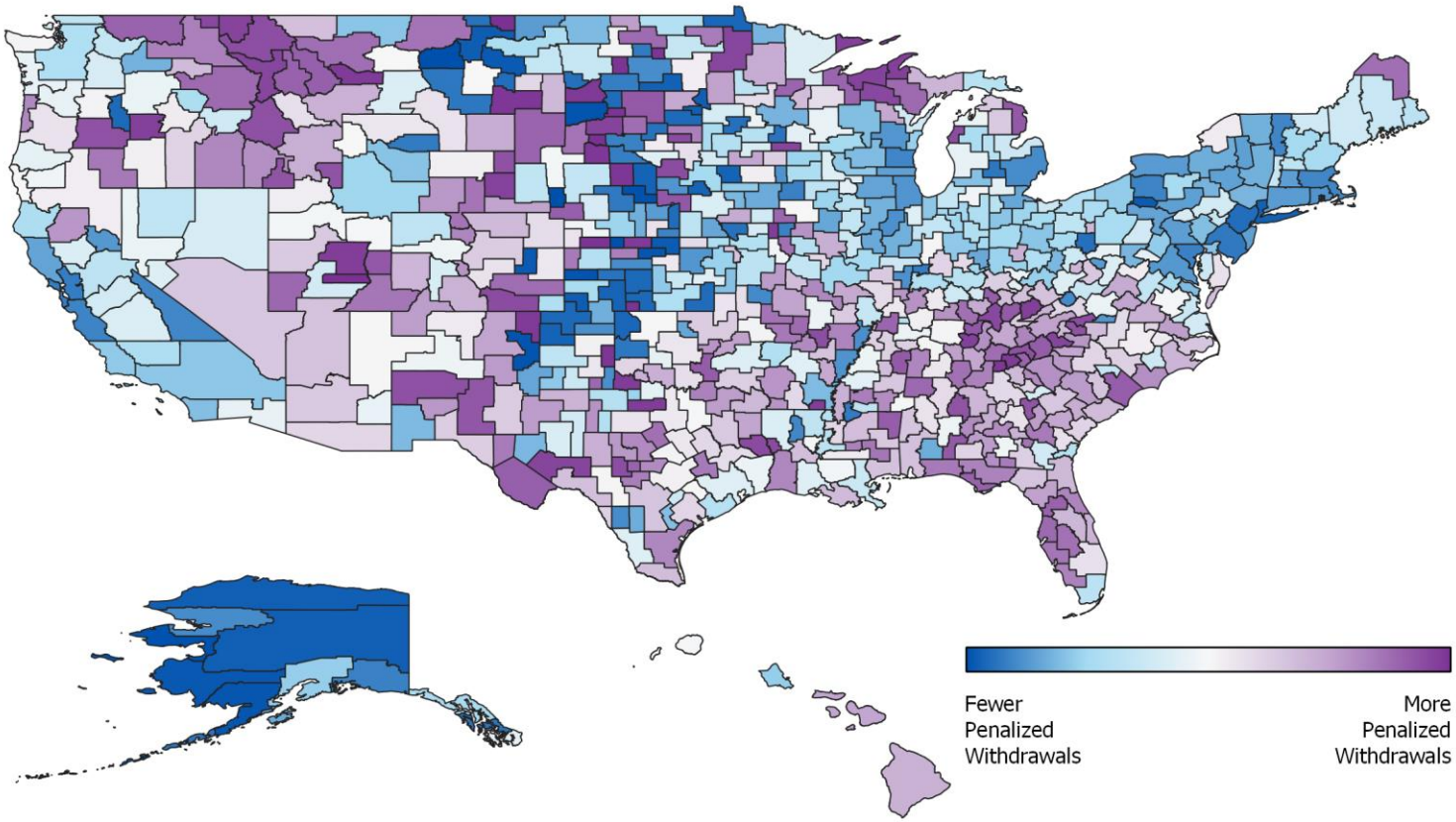
  - y_{itc} – outcome for household i at time t in CZ c
  - X_{it} – full set of age and (cyclical) year dummies
  - α_i – household fixed effect
  - ξ_c – CZ fixed effect
    - Parameters of interest

- This specification is identified off movers across commuting zones

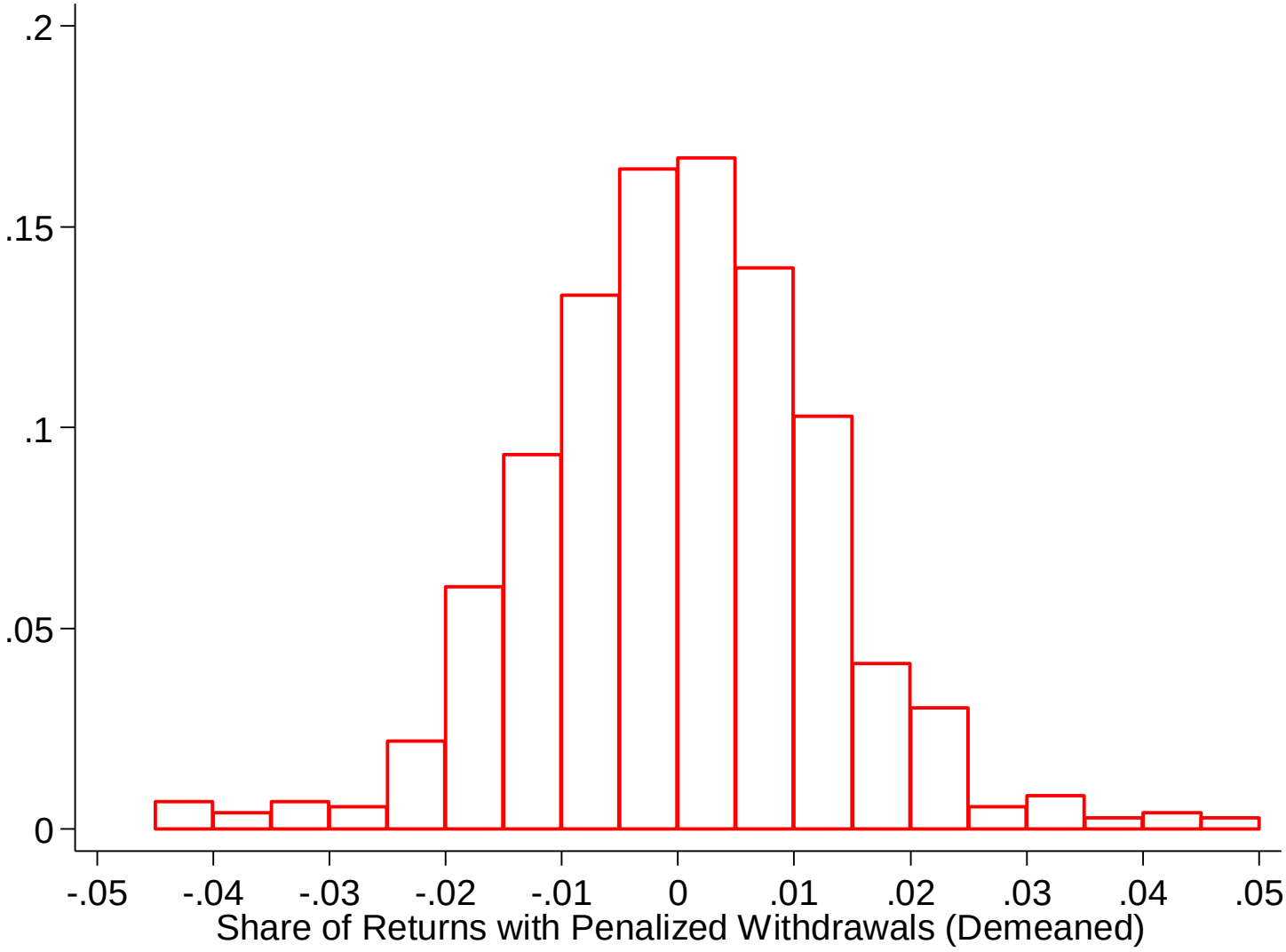
- We plot the location fixed effects ξ_c on a map
  - Normalized to be comparable to raw means (by demeaning toward to the overall average)

Location-Based Withdrawals – CZ Fixed Effects

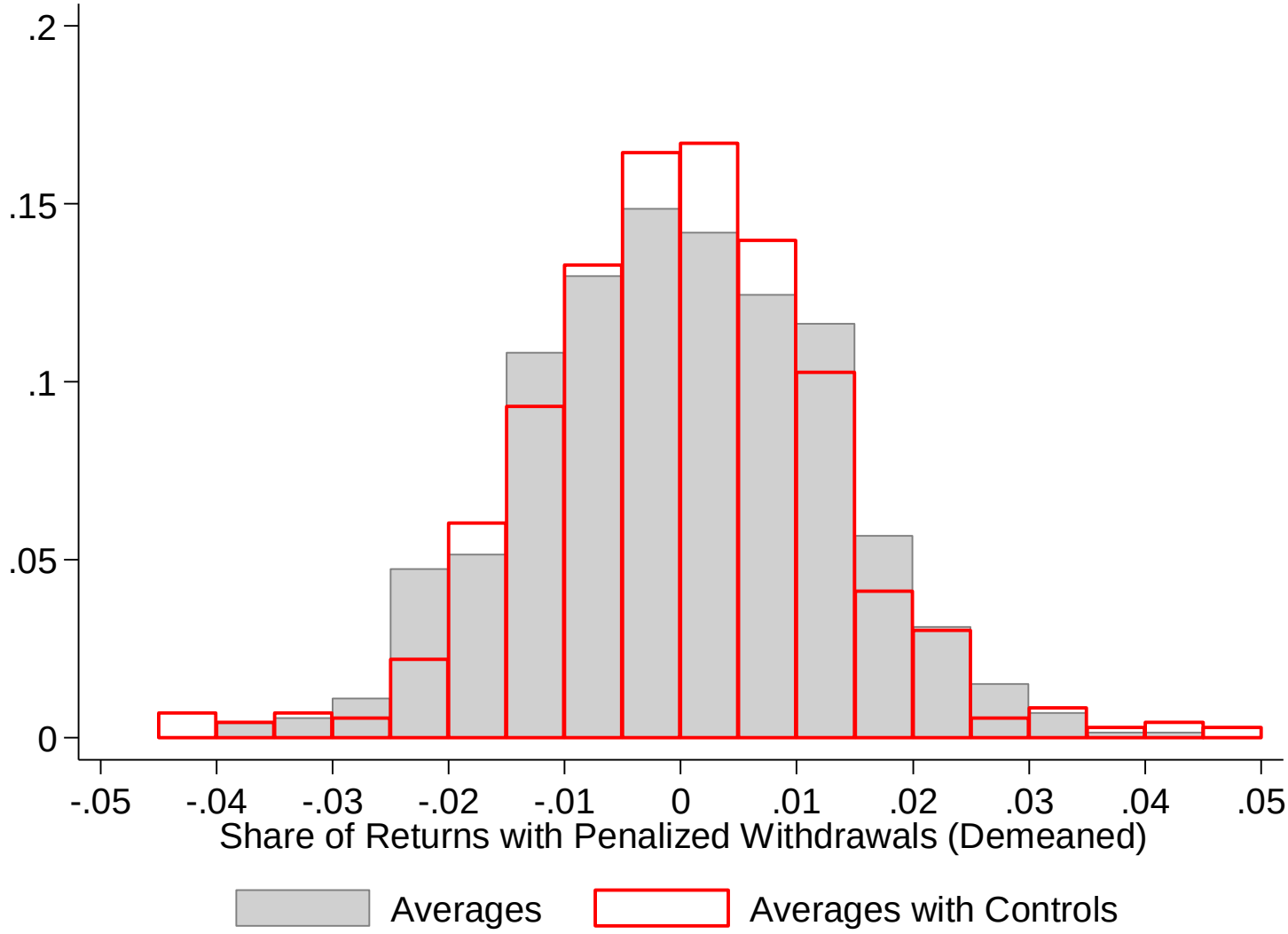
- Even accounting for individual characteristics and controls, large differences across space remain



Location-Based Withdrawals - Distribution



Location-Based Withdrawals - Comparison



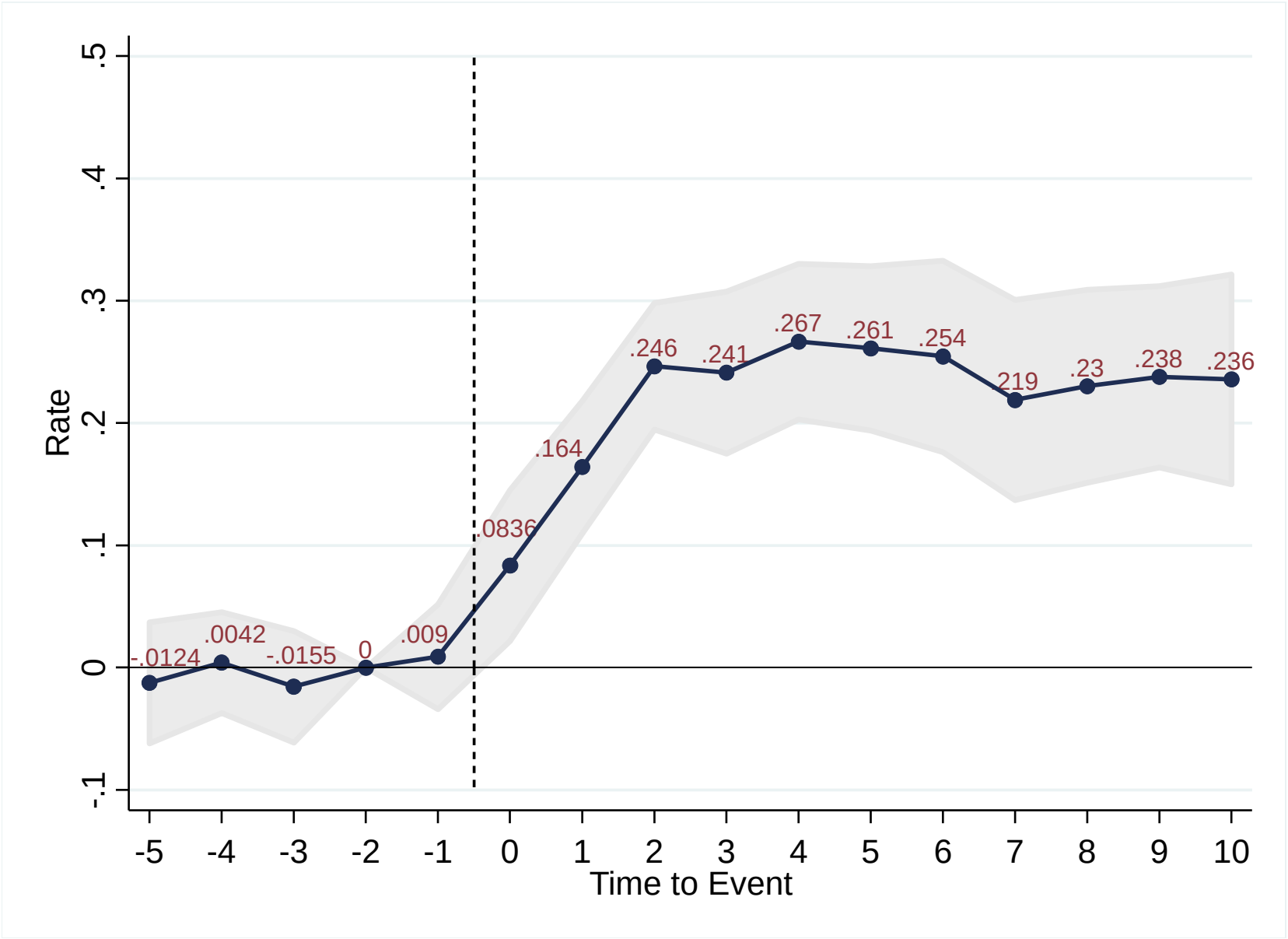
Movers Design

- Using the same variation, direct movers design allow quantifying the average share of variation attributed to location
- Estimating equation:

$$y_{itc} = \sum_{\tau} I_{\tau} \times \delta_{\tau} + \sum_{\tau} I_{\tau} \times \Delta_i \times \beta_{\tau} + \xi_c + GX_{it} + \alpha_i + \varepsilon_{it}$$

  - y_{itc} – outcome for household i at time t in CZ c
  - τ – year relative to the move, I_{τ} set of indicators
  - X_{it} – full set of age and year dummies; additional: financial outcomes
  - α_i –household fixed effect
  - Δ_i – difference in average propensity of taking penalized withdrawals between the destination CZ and the origin CZ
- β_{τ} is the parameter vector of interest
  - Variation in household behavior across CZs attributable to location itself

Movers Design



Movers Design

- Findings support the identifying assumption of no differential selection into differential intensity locations (lack of pre-trends)
- Clear change upon the move with very high degree of persistence
  - 25% of total steady-state variation can be attributed to location
- Mover designs cannot account for shocks that both differ across households with varying Δ_i *and* align exactly with the timing of moves
  - Can the results be explained by differential changes to household economic conditions interacted with timing of moves to differential intensity locations?
- Two pieces of evidence inconsistent with this notion:
  1) High degree of persistence (10 years) whereas direct effects of household shocks have been shown above to be transitory
  2) Directly accounting for household-level economic conditions:

Movers Design: Controls

	(1)	(2)	(3)
After x Intensity	0.215***	0.239***	0.240***
	(0.0305)	(0.0292)	(0.0294)
After	0.0015*	0.0006	0.0028***
	(0.0008)	(0.0008)	(0.0008)
Constant	0.0749***	0.0713***	0.0703***
	(0.0003)	(0.0004)	(0.0004)
Age FE	X	X	X
Year FE	X	X	X
Household FE	X	X	X
Household-Level Controls		X	X
Interactions			X
Number of Observations	6,465,594	5,219,429	5,219,429
Number of Clusters	741	741	741
R-squared	0.317	0.356	0.356

- Estimates hardly change when we flexibly account for unemployment, wage earnings, gross income

Movers Design: Level of Locality

- Can results be explained by state-level variation alone?

	(1)	(2)	(3)
After x Intensity	0.227***	0.242***	0.246***
	(0.0257)	(0.0279)	(0.0279)
After x Intensity x	-0.128**	-0.099*	-0.111**
Same state	(0.0521)	(0.0537)	(0.0543)
Combined	0.099*	0.143***	0.135***
	(0.0526)	(0.0505)	(0.0513)
Age FE	X	X	X
Year FE	X	X	X
Household FE	X	X	X
Household-Level Controls		X	X
Interactions			X
Number of Observations	6,465,594	5,219,429	5,219,429
Number of Clusters	741	741	741
R-squared	0.244	0.2425	0.2425

- 45% (=1-(0.135/0.246)) of share of spatial variation attributable to location still exists across CZs within states

Understanding Spatial Heterogeneity

- We have shown two facts about spatial heterogeneity in withdrawals which capture different drivers of liquidity needs

  1) Large differences in withdrawals across locations

  - Captures both average demand for liquidity of households living in that location (e.g., more income shocks in a region) + supply of alternative means of liquidity in the location (e.g. presence of banks that offer loans at low interest rate)

  2) Location effects can explain around 1/4 of the overall variance

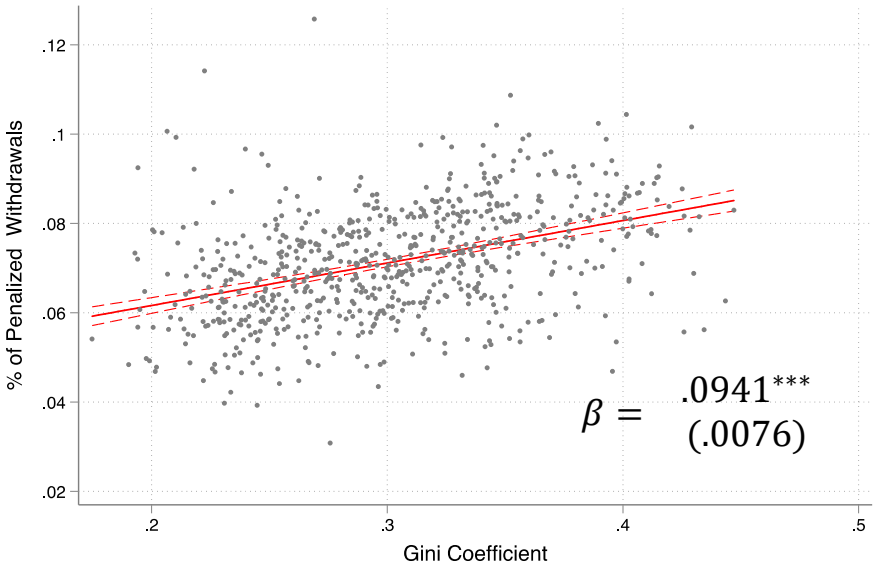
  - Narrows in on supply since model accounts for individual characteristics through fixed effects (and time varying controls)

- Next, we explore the correlates of these regional differences using CZ-level indicators of prosperity, inequality, and social cohesion [Chetty et al. 2006]

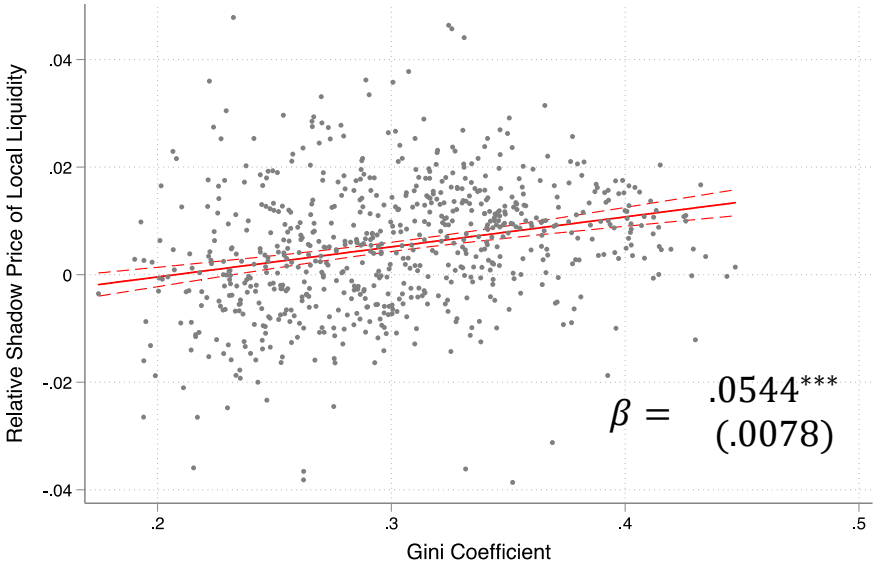
Correlate: Inequality

- CZs with more inequality have more withdrawals
  - True for both (i) raw averages, and (ii) controlling for individual FEs, age, and year

i. Raw Averages



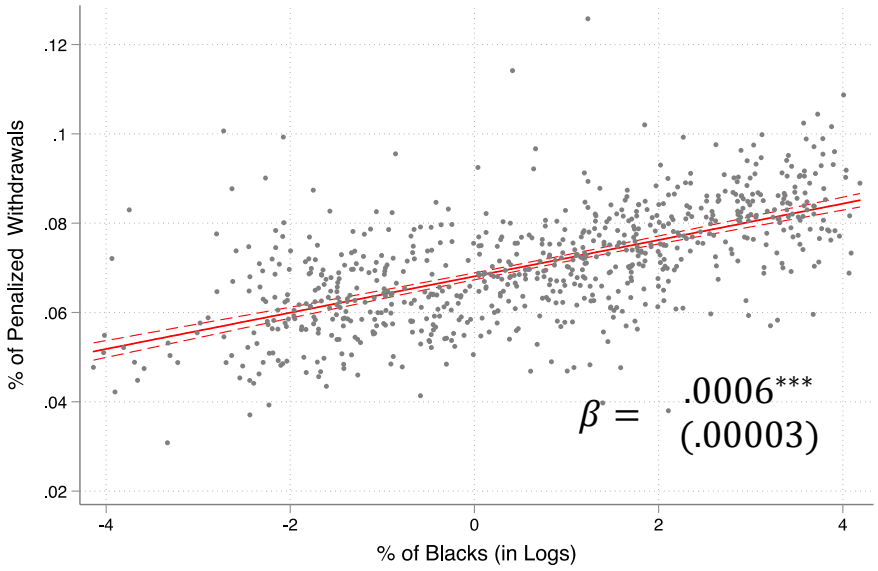
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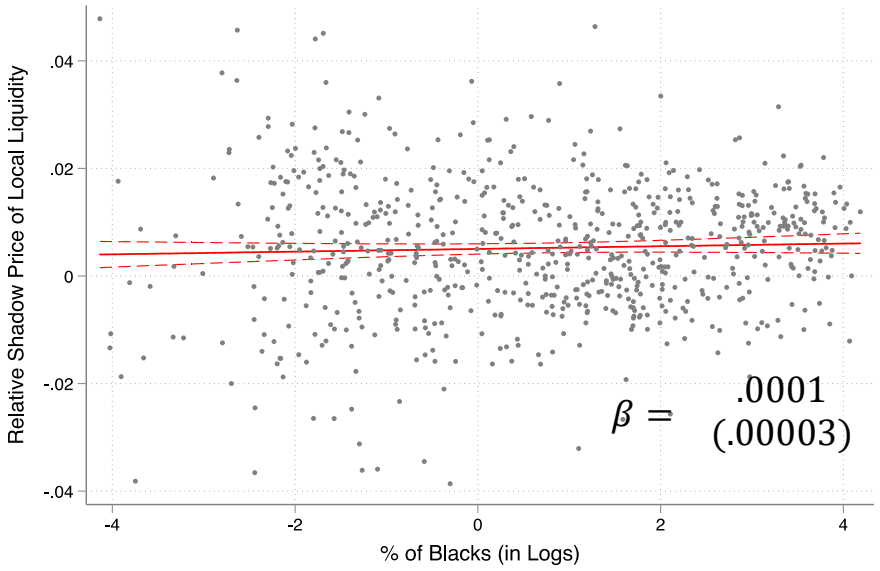
Correlate: Percent Black

- CZs with higher % of black residents have more withdrawals
  - Result is only driven by composition, does not hold with controls

i. Raw Averages



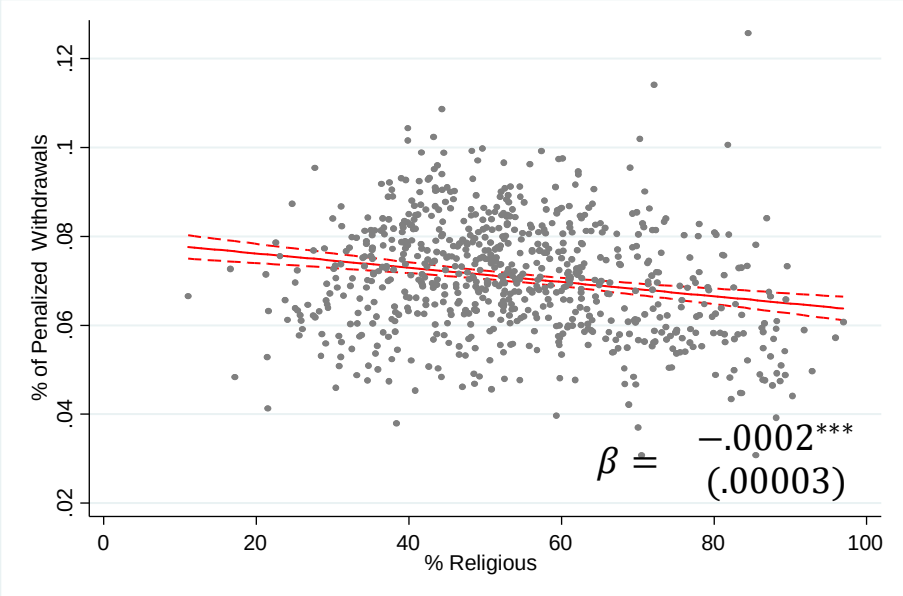
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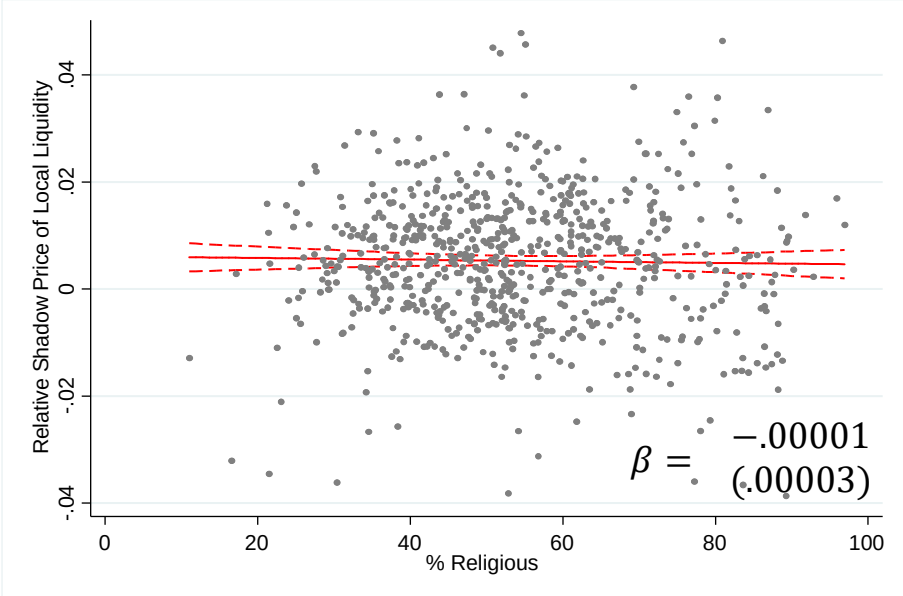
Correlate: Religiosity

- CZs with higher religiosity have less withdrawals
  - Result is only driven by composition, does not hold with controls

i. Raw Averages



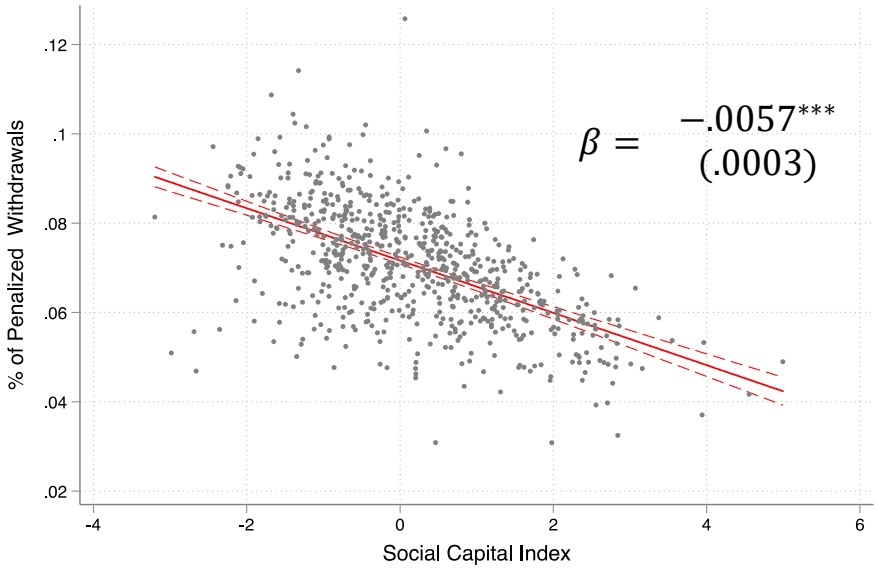
ii. Controlled



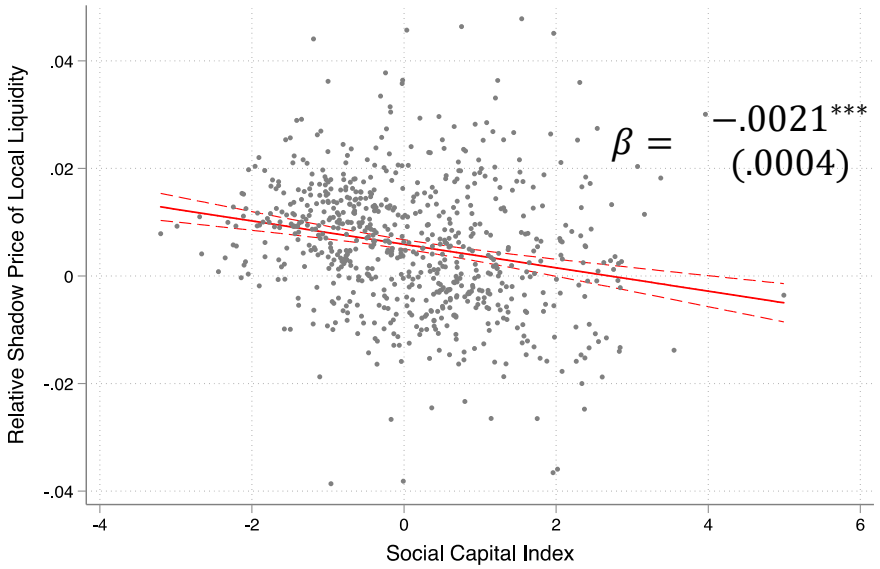
Correlate: Social Capital

- CZs with more social capital have less withdrawals
  - True for both raw averages, and with controls

i. Raw Averages



ii. Controlled



CZ-Differences in Event Elasticity

- We further investigate the determinants of CZ heterogeneity by estimating a richer specification that allows for shocks to have heterogeneous effects

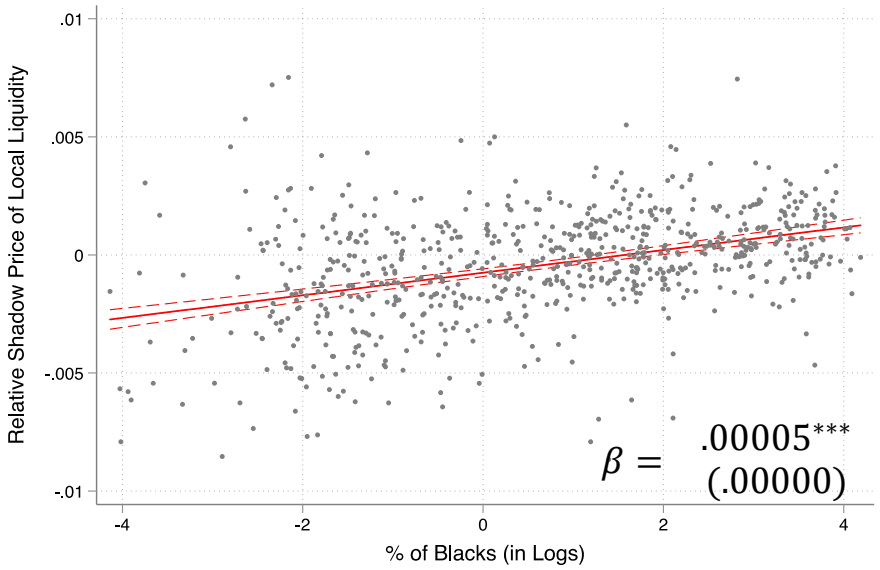
- Estimating equation:

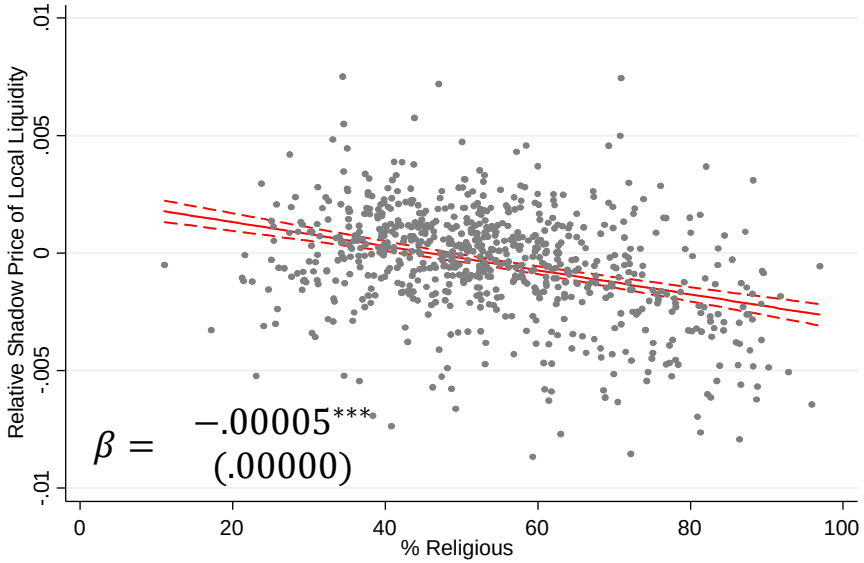
$$y_{itc} = \sum_{c} I_{\tau} \times (\beta_0 + \beta_c) + GX_{it} + \xi_c + \alpha_i + \varepsilon_{it}$$

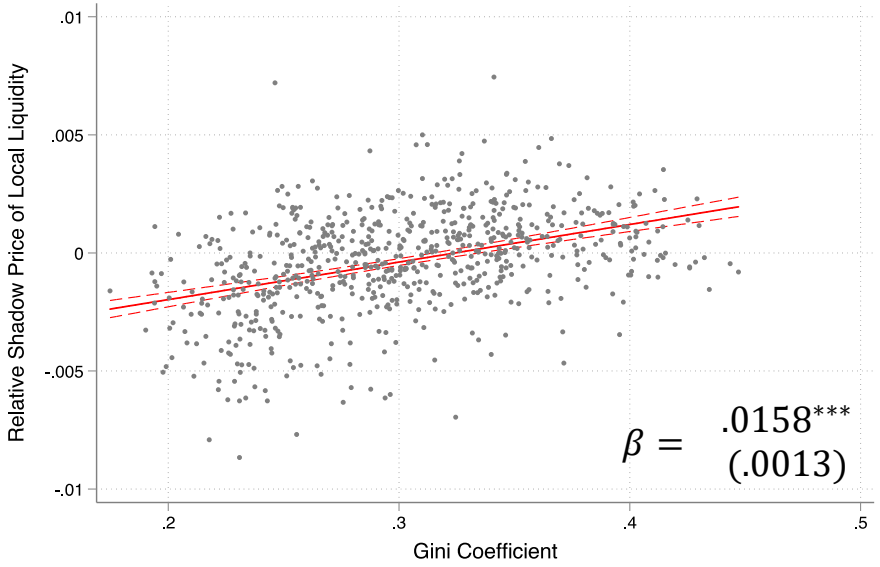
  - y_{itc} – outcome for household i at time t in CZ c
  - I_{τ} – a dummy equal to 1 for the three years post-event
  - X_{it} – full set of age and (cyclical) year dummies
  - α_i – household fixed effect
  - ξ_c – CZ effect capturing average differences in withdrawals across locations
  - β_c – the relative effect of the event in CZ c
    - Coefficients of interest

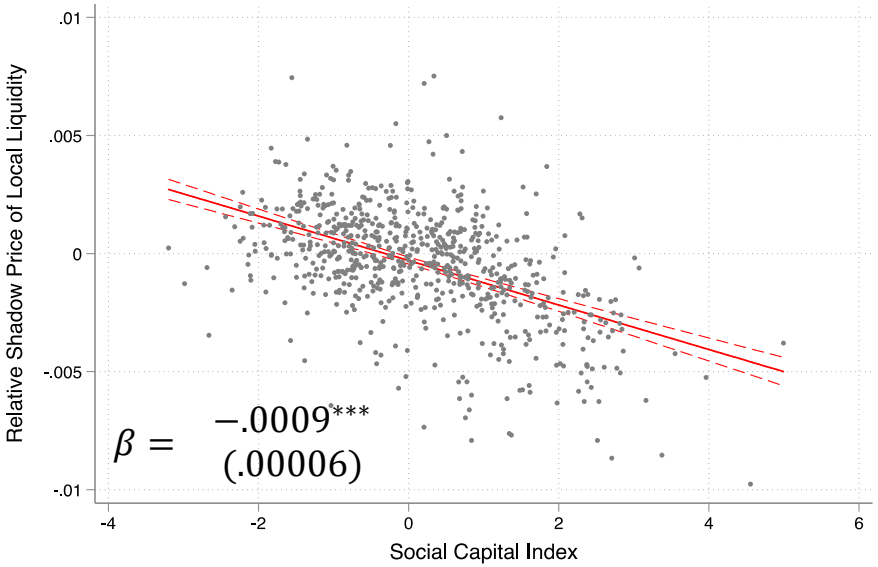
- We next plot β_c as a function of local inequality/social indicators for an income loss event

CZ-Differences in Event Elasticity: Correlates









Understanding Spatial Heterogeneity

- Local valuation of liquidity seems to be lower in CZs where there is the potential for local informal means of insurance
  - Social capital (importance of social connections) as a leading example
- High inequality may also make it harder to provide local credit
  - Consistent with literature which finds that low-income households face higher credit prices and reduced access to credit in higher inequality regions [Coibion et al. 2019]

Part III: Aggregate Shocks across Locations

Shocks to Location Demand for Liquidity

- We have shown large average differences in liquidity needs across locations
- We next show that demand for liquidity is affected by local economic conditions
  - Study the heterogeneous effect of an aggregate macro shock, the Great Recession (2008)

Shocks to Location Demand for Liquidity

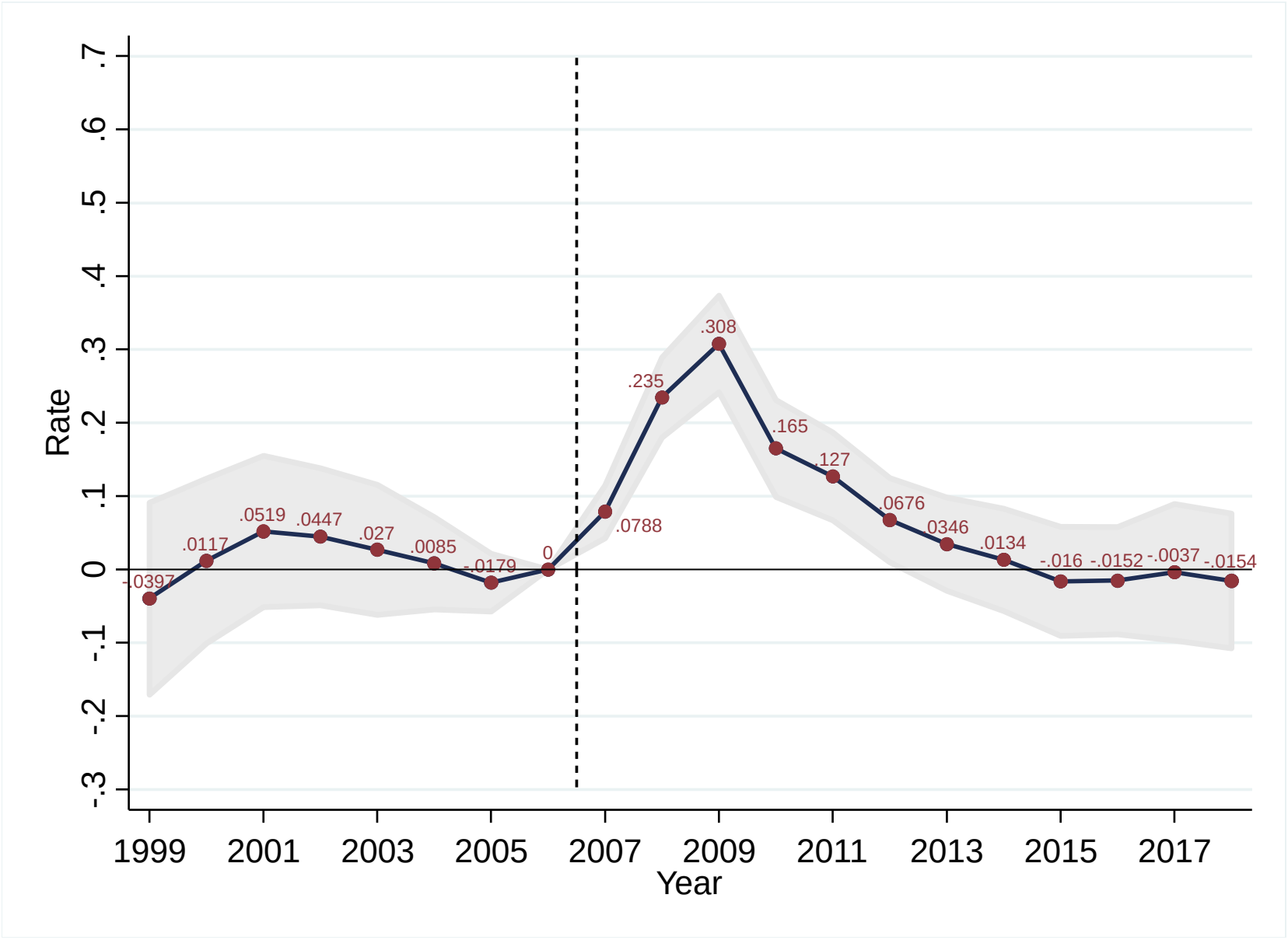
- Estimating equation:

$$y_{itc} = \sum_{\tau} I_{\tau} \times \delta_{\tau} + \sum_{\tau} I_{\tau} \times Treat_{c} \times \beta_{\tau} + \xi_{c} + GX_{it} + \alpha_{i} + \varepsilon_{it}$$

  - y_{itc} – outcome for household i at time t in CZ c
  - τ – year relative to 2006, I_{τ} set of indicators
  - X_{it} – full set of age and (cyclical) year dummies
  - $Treat_{c}$ – captures the treatment intensity for location c in terms of unemployment shock [Yagan 2018]
  - ξ_{c} – commuting zone fixed effect
  - α_{i} – household fixed effect

- We plot β_{τ} relative to a 1 pp local unemployment shock

Shocks to Location Demand for Liquidity



Shocks to Location Demand for Liquidity

- Commuting zones more severely affected by the great recession, as measured by unemployment increase, have seen a larger increase in withdrawals
  - Peaks at 0.3 pp increase in local penalized withdrawals per 1 pp local unemployment shock
  - Cumulative effect from 2007-2012 on probability of taking a penalized withdrawal for a 1 percentage point rise in CZ unemployment is 0.98 pp

Shocks to Location Demand for Liquidity

- Flow effect is over 4 times as large as effect of unemployment event (=0.30/0.067)
- Breakdown of cumulative impact into direct and indirect effects by accounting for households' unemployment status:

Model	Increase in Penalized Withdrawals (pp)
Baseline	0.98***
	(0.16)
Control for UI status	0.74***
	(0.15)
Control for UI x Year	0.72***
	(0.15)

- Indirect effect represents 73% (=.72/.98) of total
  - The great recession is a leading example for how the location effect, through market spillovers, can have an important role

Conclusions

- Despite the theoretical prominence of withdrawal penalties (e.g., Amador et al., 2006), the literature has overlooked the use of penalized withdrawals as a powerful tool for identifying the value of liquidity
- We use penalized withdrawals to characterize liquidity needs across three dimensions:

1) Household-level shocks lead to an increase in the demand for liquidity
2) Beyond the household, certain localities have persistently higher demand for liquidity (25% of variation is explained by location)
3) One way in which local demand for liquidity is shaped and may change over time is through aggregate economic shocks
    - The Great Recession had a direct impact on individuals (e.g., through unemployment), leading to higher demand for liquidity
    - But it had a larger equilibrium effect on localities beyond this individual impact (e.g., through spillovers into local credit markets)

Conclusions

- Policy implications:
  - Within retirement savings:
    - Supports the use of exemptions for household events and suggests further expansions to this policy
    - Suggests there may be room for more persistent location-based targeting through exemptions or penalty reductions
  - More broadly, policy levers that provide liquidity can be better targeted along these two dimensions – households and locations – by using the patterns of penalized withdrawals we have identified
    - Which reveal the underlying needs for liquidity