Negative Home Equity and Household Labor Supply

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ABSTRACT

I find that negative home equity causes a 2%-6% reduction in household labor supply. I utilize U.S. household-level data and plausibly exogenous variation in the location-timing of home purchases with a single lender. Supporting causality, households are observationally equivalent at origination and equally sensitive to local housing shocks that don't cause negative equity. Results also hold comparing purchases within the same year-MSA, that differ by only a few months. Though multiple channels are likely at work, evidence of non-linear effects is broadly consistent with costs associated with housing lock and financial distress.

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Following the historic decline in house prices during the recent financial crisis more than 15 million U.S. mortgages, or approximately 1/3rd of mortgaged properties, had negative home equity[1]. At the same time, labor markets experienced a severe and prolonged deterioration, with not just employment, but also labor force participation rates, still below pre-recession levels for years after the crisis. While these declines may have been driven by common factors, previous work (ex. Mian and Sufi 2012; Verner and Gyongyosi 2017) suggests a causal link between employment and housing wealth where house price shocks affect equilibrium employment via local labor demand. What is less well understood is whether negative home equity, caused by house price shocks, may have altered not only labor demand, but also labor supply. If there is a significant relationship between negative home equity and labor supply it could improve our understanding of household financial decision making as well as provide potentially important implications for marcoprudential policies.

My primary contribution in this paper is to provide the first causal empirical estimates of the effect of negative home equity on overall household labor supply. I find that instrumented negative equity is associated with a 2%-6% reduction in household income. I utilize U.S. household-level data and plausibly exogenous variation in the location-timing of home purchases with a single lender. These results are consistent with a number of recent papers indicating that negative home equity could negatively affect labor supply. In particular, evidence suggests a reduction in home equity could reduce entrepreneurship (Adelino, Schoar, and Severino 2015 and Schmalz, Sraer, and Thesmar 2017), innovation and effort (Bernstein, McQuade, and Townsend 2017), employment

[1] According to First American CoreLogic as of June 30, 2009.

opportunities among impoverished households (Bos et al. 2015), labor mobility (Ferreira et al. 2010; Ferreira et al. 2012; Foote 2016; Bernstein and Struyven 2019), job search (Brown and Matsa 2017) and labor income among bankrupt households (Dobbie and Song 2015a). While these results are suggestive, the average net effects on labor supply are still ambiguous. Many of the effects are likely to be limited to only a select subset of homeowners, such as entrepreneurs, innovators, or bankrupt/impoverished[2] households, while the effects of others, such as housing lock and job search, are still heavily debated[3]. There are also other channels, such as wealth effects, which would predict the exact opposite behavior. For example, there is prior evidence that exogenous increases in wealth, via either lottery winnings (Imbens et al. 2001; Cesarini et al. 2017) or inheritance windfalls (Joulfaian and Wilhelm 1994) reduce labor supply. These would predict an increase, rather than a decrease, in labor supply from negative home equity, coming from a reduction in housing wealth. The multitude of potential channels mean the exact nature of the relationship, if it is significant, between negative home equity and labor supply is inevitably an empirical question. The findings in this paper of a positive

[2] For example, Bos et al. 2015 focuses on a sample of households who were delinquent on a loan from a pawnshop within the last two years. Not surprisingly this sample population has very low income. Only 43% are employed and only 6% are homeowners. Credit constraints that prevent this population from finding employment, such as being unable to use a credit card to buy a suit, seem unlikely to extend to the average U.S. homeowner.

[3] In these settings households are financially constrained by negative equity which prevents them from moving, also known as "housing lock". Due to the effectively non-recourse nature of mortgages in the U.S. the effect of housing lock on mobility is unclear and empirical evidence has historically been divided, with papers such as Schulhofer-Wohl (2012) and Mumford and Schultz (2014) finding no evidence of reduced mobility. Modestino and Dennett (2013) also point out that while non-pecuniary costs of immobility could be large, very few households in a given year have to move for employment, so the effect on aggregate labor supply may be limited.

relationship between housing wealth and labor supply, that occurs non-linearly for households with negative home equity, suggests prior evidence of labor market disruptions coming from housing market frictions have significant economic impacts on labor supply[4]. In particular, non-linear effects are most consistent with housing lock and financial distress as driving mechanisms between the observed relationship between negative home equity and household income.

Empirical identification of the effect of negative home equity on labor supply faces a number of challenges which I address in this paper. First of all, few datasets have comprehensive household-level panel information on income, assets and liabilities. The few databases that do, such as the American Housing Survey (AHS), tend to be surveys that suffer from self-reporting biases and small sample sizes that confound clean identification[5]. Even with appropriate data, simple regressions of labor income on negative home equity are unlikely to provide causal interpretation. A number of omitted variables drive both house prices and labor income (ex. local labor demand shocks) and reverse causality could be problematic since wealthier households are likely to invest more in home improvements.

[4] The findings in this paper are also related to recent findings in Sodini et al. (2017), who note that home ownership actually appears to increase labor income in Sweden among movers who take on more debt. In that setting the proposed explanation is that households respond to the need to service a higher level of monthly mortgage payments by working more, which comes from switching from owning to renting, not necessarily a change in home equity directly. The effects on labor supply of negative home equity are likely to differ in many ways from the effect of switching from renting to owning a home, but both may be a least partially driven by some of the aforementioned frictions that exist for homeowners with a significant amount of mortgage debt.

[5] For example, Cunningham and Reed (2012) use AHS data, but only have 652 household-year observations over the course of 9 years with negative equity, which is a very limited sample for something as noisy as self-reported household equity and labor income.

In this paper I overcome these challenges with a new transaction-level dataset with comprehensive information on assets, liabilities, and deposits for all customers of a major U.S. financial institution from 2010-2014, referred to hereafter as *MyBank*, and an empirical methodology based on variation in the timing of housing purchases. The transaction-level deposit information allows me to generate accurate high frequency measures of household income, while the data on assets and liabilities lets me determine which households have negative home equity. Since I observe actual deposits rather than reported values any estimated effects represent actual changes in deposit behavior rather than changes in household reporting in response to eligibility criteria[6].

To overcome issues of identification I exploit plausibly exogenous variation in home equity from the interaction of the location and timing of home purchases, relative to households in the same region, as an instrumental variable for the probability a household has negative home equity. In this empirical strategy households are exposed to identical time-varying local house price shocks, but differ in their home equity based on when they happened to purchase their home relative to their neighbors. Since variation in the timing of home purchases is not randomly assigned I address concerns that omitted variables could be related to the timing of purchase and future income in a way that violates the exclusion restriction of the instrumental variables methodology. First I show that for low levels of expected loan-to-value, house price shocks have little effect, but as the probability of having negative equity rises, labor supply falls, consistent with an explanation driven by negative home equity. I also show that the results are robust to

[6] Chetty et al. (2013) have shown that in the context of household response to the EITC individuals manipulate self-employment reported income.

including household fixed effects, controlling flexibly for national cohort trends, and including a number of time-varying non-parametric household-level controls for household characteristics that could be related to local demand shock sensitivity.

There is a growing body of evidence (ex. Mian and Sufi 2009; Palmer 2015) that lending standards may have changed in the run-up to the financial crisis, leading to potentially different sensitivities for households who bought earlier vs. later to local demand shocks. The empirical design in this paper circumvents these concerns by including both region-time and origination date-time fixed effects for a single lender in all specifications. In other words, I compare households that bought properties financed with the same lender at the same time, but did so in different regions and compare them with households who bought at different times in those areas. The key source of variation is that households bought their properties at relatively fortunate or unfortunate times in their specific MSA, relative to their neighbors, but not earlier or later overall. This flexible set of controls means that any observed relationship between the instrumented home equity and labor income, can't be spuriously driven by changes in nationwide lending standards by *MyBank* or the entry of subprime lenders during the boom.

One remaining potential violation of the exclusion restriction, and causal interpretation, could occur if borrowers differed systematically in the timing of entry by region in a manner that was correlated with differential household sensitivity of labor income to local demand shocks among these borrowers. If for example, *MyBank*, happened to increase lending more to low credit quality or subprime borrowers in areas that subsequently experienced larger house price declines, that could potential confound causal interpretation of the observed relationship. While I find that my instrument for negative home equity has a valid first stage and predicts lower household income, I find it does not predict statistically or economically significant differences in reported income, credit scores, or interest rates at the time of mortgage origination. If these borrowers were really more sensitive to local demand shocks it seems likely that would show up in the form of lower income, higher credit scores, or high interest rates at the time of initial origination of the loan. Given the relatively strong power I have for most of these tests, it appears unlikely there was any substantive difference in observable characteristics of these borrowers that is correlated with the instrument. Therefore, it is unlikely there were substantive differences in "hard information" lenders used at origination across these regions or observable characteristics of these borrowers. I also find no differences in the probability of a mortgage being "Alt-A" or using unverified income, and no difference in verified income at origination, suggesting no evidence of differential "soft-information" across these regions either.

While it seems unlikely, it is still possible that there exist some unobservable differences in these households that makes them more sensitive to local demand shocks. To address this concern I first include households fixed effects to flexibly control for any time-invariant differences in characteristics and take advantage of the panel nature of the data. I find that instrumented negative home equity is still associated with a decline in labor income. I then take advantage of the fact that most of the proposed theories for why reductions in home equity could reduce labor supply are based on frictions that occur non-linearly when households have negative home equity. I run a placebo test excluding all observations when a household actually has negative home equity and show that in reduced form changes in the instrument, that would normally increase the probability of negative home equity, are no longer associated with statistically significant changes in household income. In other words, once we exclude treatment, changes in local house prices, likely to be correlated with local demand shocks, have no differential effect on household income. This is also supported by non-linear forms of the analysis which show no relationship between instrumented home equity and income, even for large variation in instrumented home equity, except for circumstances when properties are likely to have negative equity. The placebo results show that these households are unlikely to differ even on unobservables that makes them more sensitive to local demand shocks, except for through the treatment of negative home equity. Supporting this causal interpretation, I also show my results hold after comparing only households who bought in the same MSA and year, but at different times of the year, just a few months apart. They also hold among the subset in my sample where I can observe student loans and control for the approximate date they enter the labor market.

One final concern I address is that households with *MyBank* mortgages and negative equity could be systematically hiding income from the institution they owe money. Since I measure only deposit inflows at *MyBank*, households who also have mortgages at *MyBank* could be closing accounts or reducing payroll inflows at that institution in order to appear less able to pay and receive more assistance. To partially alleviate this concern throughout my analysis I use multiple restrictions to be sure households in the panel have active retail accounts, taking advantage of the inflow and level information I have for all retail accounts at *MyBank*. Results are robust to all choices of filter and measures of income. I also rerun the analysis for households with a *MyBank* retail and credit card account, but have a mortgage where *MyBank* does not own or service the mortgage. In this case the household has no incentive to hide deposits and I find that negative equity still reduces income. Overall, these results are consistent with income shrouding playing little role in the observed decline in deposits, so that results represent actual declines in overall household income.

In Section 1 I begin by describing the unique household level financial information from a major U.S. financial institution used in this paper. In Section 2 I describe the empirical challenges for identification in more detail and the methods employed in this paper to overcome them. I discuss the empirical findings in Section 3. In Section 4 I discuss potential mechanisms that could explain the observed relationship between home equity and household labor supply. Section 5 concludes the paper.

I. Data description and validation

The majority of my data comes from a major U.S. financial institution but I also merge in zip-code level income data from the Internal Revenue Service (IRS) to validate my income measures and state-level judicial foreclosure law information. The data provider for this project is a major U.S. financial institution, who I refer to as *MyBank*, with transaction-level client account information on more than 1/4th of all U.S. households over the 5 years from 2010-2014[7]. For the purposes of this project I focus on households with sufficient *MyBank* relationships to estimate income and mortgage information and

[7] According to census.gov from 2009-2013 there were about 116 million U.S. households and *MyBank* has client accounts covering more than 31 million households (see Table A1 for details), which would be about 27% of all U.S. households. The coverage is lower when looking at individuals, which is likely because dependents are unlikely to have separate *MyBank* accounts (ex. children) and some households with multiple adults still may choose to list only one person in the account information. *MyBank* has consistently been one of the five largest U.S.-based banks, with borrowers across all 50 states. Mortgages originated by *MyBank* are often securitized and sold-off, but origination details remain available for analysis in my sample.

analyze income decisions at a monthly household level. Income is estimated using retail account deposit information and mortgage information is either derived from credit bureau data (only available for households w/ *MyBank* credit card accounts) or *MyBank* mortgage account information. In appendix A I detail how combining household information from multiple *MyBank* accounts alters the sample size.

For each mortgage account I have detailed information on the mortgage type (ex. fixed rate 30 year), characteristics at origination including the date, reported income, credit score, interest rate, appraised loan-to-value, and ongoing monthly mortgage performance, characteristics, and actions, including delinquency status, current loan-to-value updated using internal LPS MSA-level HPI data, any loss mitigation actions taken, such as mortgage modifications, and current interest rates. Perhaps not surprisingly given the substantial coverage of this data provider, in Figure B3 in the appendix I show that the time series of delinquency rates for *MyBank* mortgage data matches closely with the levels and trends seen in national Federal Reserve economic mortgage data over the past 5 years.

By a substantial margin the largest population of households with a *MyBank* relationship are credit card customers. This should be expected since households very often only have one mortgage lender, but will have multiple credit cards. For each credit card account and month *MyBank* pulls credit bureau data on the associated customer liabilities. For the purposes of this paper this monthly frequency credit bureau data is the only information used from the credit card accounts. The credit bureau data includes comprehensive data on all customer liabilities across all lenders including mortgages, auto-loans, student loans, home equity lines of credit, credit cards, and installment credit as well as monthly updated credit scores. For each credit category the dataset includes information on the balance, monthly payments, and initial balance[8].

Retail accounts include any checking or savings accounts. The raw data includes every single transaction into these accounts (inflows and outflows) but to protect privacy include only the day a transaction occurred, the amount of the transaction, and very general transaction category types (ex. "ACH direct deposit"). The dataset includes billions of transactions over the period 2010-2014, but since my goal is to measure income I focus on the subset of transactions labeled as deposits, which include direct deposits, physical deposits including at the teller and ATM, and other deposit types including mobile RDC deposits. Since some of these accounts are not being used to deposit the majority of income I restrict my analysis to households with active accounts[9] that appear to contain the majority of their income[10].

To explore the validity of using deposits as an income measure I confirm the validity of my income measure by comparing the average annual income based on my

[8] Maturities and interest rates on these liabilities are estimated and validated for the subset of data where both are available. In particular, given the panel nature of the data I am able to observe total monthly payments in addition to changes in the outstanding balance for each account month over month. Assuming a fixed interest rate, maturity, and standard amortization schedule I numerically estimate what would be the implied interest rate and maturity from a selection of discrete interest rates and maturities that exist in the data for each set of back-to-back months. If less than 75% of estimated interest rates and maturities for given product do not match or I have less than 20 observed estimates, I do not include them in the sample. Even with sufficient information these could have floating rates, non-standard amortization schedules, or unusual pre-payment behavior which would confound clean identification of the underlying maturities and rates.

[9] A household is defined to have "active" accounts if across all accounts in a given month they deposit at least $100 or have $200 in financial assets.

[10] To be included in the panel all households must have at least 12 months with deposits across all accounts >=$100 & <=$25k, a mean and median level of deposits across all accounts >=$500 & <=$25k.

deposit data at a zip code-level with those reported by the IRS Statistics of Income (SOI)[11] over the period 2010-2013. In Figure B1 you can see a very strong correlation between these measures of income. Regardless of the type of income measure used and the subsample explored I find that zip code level correlations between my measure and the IRS SOI are very high and range from 0.736 all the way up to 0.911. The fact that the relationship is so strong between these two measures and neither appears to be systematically higher suggests that for the subset of households analyzed deposits represent an effective measure of household income. I also extract households receiving social security or disability checks. After excluding regularly schedule job-related deposits, I assign any remaining direct deposits that are paid on either the 3^{rd} of each month, or the 2^{nd}, 3^{rd} or 4^{th} Wednesday of each month as social security-related. According to the Social Security Administration the mean monthly benefit for a beneficiary is $1,223/month which matches closely with the mean of $1,268/month I find per social security recipient in my sample. This validates not only the data overall, but also this method of extracting social security payments.

For the majority of my analysis I focus on households with retail deposits that let me measure income, and mortgages at *MyBank* that let me see their level of home equity which include about 200k households in the final sample representing approximately 7.8 million household-month observations. For most of my analysis I focus on households with income at origination, loan origination date, and additional information which

[11] For the purposes of income validation, I utilize publicly available zip-code level income data from the IRS (Internal Revenue Service) Statistics of Income for 2010-2013. This data is based on administrative records of individual income tax returns (Forms 1040) from the IRS Individual Master File (IMF) system. More details about IRS SOI income data are available online at www.irs.gov.

restricts that to approximately 5.4 million household-month observations. I also consider households with *MyBank* retail and credit card accounts and mortgages with any lender as robustness check, which increases the sample to about 20.1 million household-month observations. For more details on the data merging see Table A1 in the appendix.

I analyze a broad range of characteristics for each sub-sample of *MyBank* in Table 1 and in more detail in Table B1 in the appendix.

[INSERT TABLE 1 HERE]

From the tables we can see that the median household income for households with mortgages is about $5-6k/month and as expected the majority of household liabilities are mortgage related. The median level of income, non-housing financial assets, mortgage leverage, and mortgage interest rates are similar to self-reported information collected by the Survey of Consumer Finance (SCF) for households with at least $1,000 in active mortgage balance in 2010 consistent with the representative nature of the *MyBank* national coverage and lends credibility to the external validity of the conclusions of this paper. For more details on this comparison see Table B2 in the appendix.

The *MyBank* mortgage data includes information on reported income at origination which provides a nice opportunity to test the validity of the cross-lines of business data matches as well as providing another check of the quality of my deposit-based income measure. In Figure B2 I plot the cumulative distribution function of income at origination and income based on deposits for a match sample of individual households who originated a mortgage in the same year when sufficient deposit information is available to estimate income. These distributions appear remarkably similar and the individual income correlations range from 0.378 to 0.449 depending on the measure of deposit income used, all of which lend substantial credibility to the internal matches across *MyBank* lines of business as well as validating my income measure across the income distribution.

II. Empirical method

To understand the effect of negative household equity on labor supply I run an instrumental variables regression using variation in the likelihood of negative equity based on the timing and location of home purchase relative to households living in the same region at the same time. To build intuition for the instrumental variables approach though I start by running the following regression

$$y_{icrt} = \alpha + \gamma_{rt} + \phi_{ct} + \sum_{k} \delta_{1k} \cdot 1_{\{l_k \leq LTV_{it} \leq \mathrm{h_k}\}} + \epsilon_{icrt} \quad (1)$$

where for household *i* in month *t* in region *r* that originated their mortgage in month *c*, this regresses household income, y_{icrt}, on a dummy variables which equals 1 only if the households loan-to-value ratio, LTV_{it} is greater than l_k and less than $\mathrm{h_k}$ for *k* loan-to-value buckets, region x time fixed effects, γ_{rt}, and cohort (month of mortgage origination) x time fixed effects, ϕ_{ct}. The problem with a naïve regression of income on home equity is that reverse causality or omitted variables are not only possible, but are likely to prevent confidence in any causal interpretation of the effect of negative equity on labor supply. For example, time varying local demand shocks and initial credit quality could affect both income and home equity, and households with higher income likely invest more in home maintenance. Since I compute changes in house prices at MSA level, the inclusion of MSA x time fixed effects precludes the possibility that results are driven by variation in local demand shocks or individual variation in home investment.

The cohort x time fixed effects means analysis is not confounded by changes over time in the nationwide composition of borrowers at *MyBank* or entry of subprime borrowers during the boom. I also include multiple loan-to-value indicator buckets to see if, as would be predicted by many of the theories of labor market frictions from housing wealth, declines in income occur only for high loan-to-value ratios.

Despite the inclusion of all these controls time-varying household level variation in LTV still has the potential to confound causal interpretation. In equation 2 I make this more transparent by decomposing the current household's LTV into three distinct components; (1) house prices changes, (2) changes in the balance of the mortgage, and (3) origination LTV.

$$LTV_{it} \equiv LTV_{ic} \times \frac{(1 + \%\Delta Loan_{it})}{(1 + \%\Delta HP_{rct})} \tag{2}$$

Since households with improved income are more likely to prepay their mortgage, reducing the LTV, prepayment poses an empirical challenge for identification. To circumvent this rather than using actual changes in loan amount, I compute what the loan reduction would be if the mortgage was a 30-year (360 months = T) fixed rate loan paying the median national monthly mortgage rate, r (I use 6.75% based on my sample statistics).

$$\%\Delta \text{Synth}Loan_{ct} \equiv -\frac{(1+r)^{t-c} - 1}{(1+r)^{T} - 1} \tag{3}$$

The resulting formula in equation (3) varies across mortgages based on the age of the loan, but no longer depends on any other source of household-specific variation. An additional concern is that origination LTV could be a function of household specific characteristics, such as income or credit quality. Since I include household-level fixed effects in specification (1), time-invariant factors, like LTV at origination, are only a concern when interacted with a time-varying factor, as is the case here. In particular, if high LTV at origination individuals are more sensitive to local demand shocks then this could be driving any simultaneous movement in income and household equity, rather than labor supply. To alleviate this concern I use the median national LTV at origination for each cohort for all households. Combining these I get a "synthetic" LTV, or *SLTV*, which only varies at the cohort-region-time level, and, controlling for all previously mentioned fixed effects, provides a plausible instrument for the probability of a household having negative home equity:

$$SLTV_{rct} \equiv LTV_c \times \frac{(1 + \%\Delta \text{Synth}Loan_{ct})}{(1 + \%\Delta HPI_{rct})} \tag{4}$$

Variation in SLTV, after including all controls in equation (1), will be driven almost entirely by how fortunate the timing of house purchase was for a household within a particular region relative to their neighbors. Households that bought homes prior to relative local house price declines will tend to have higher SLTVs relative to those who bought immediately afterward. While LTV, which will be the endogenous variable, is driven by time-varying household-specific factors, like the chosen origination loan-to-value for those individuals, SLTV which is instrumenting for it, will not have any variation coming from individual-level decisions.

To formalize the instrumental variable approach define I run the following 2SLS regression

$$U_{it} = \alpha + \gamma_{rt} + \phi_{ct} + \delta_1 \cdot 1_{\{SLTV_{rct} \geq 100\}} + X'_{it}\beta + \eta_{icrt} \tag{6}$$

$$y_{icrt} = \alpha + \gamma_{rt} + \phi_{ct} + \delta_2 \cdot \widehat{U}_{it} + X_{it}'\beta + \epsilon_{icrt}$$

where I defined a household who has negative home equity (aka underwater) as $U_{it} \equiv 1_{\{LTV_{it} \geq 100\}}$.[12] Since SLTV is computed using region-level house prices since origination, the remaining variation comes from the region x origination date interactions. In other words, a buyer is instrumented to have negative home equity via SLTV not because they bought early or later overall or in a region that saw worse declines, but bought at a specifically bad time in that region relative to those buying at that time in other regions. Once household fixed effects are included the resulting variation comes within a household during times when they are more likely to have positive vs. negative home equity, based on the timing of their home purchase within a given region. It takes advantage of not only the timing of home purchase, but also the non-linearity of the treatment effects. The necessary assumption for the exclusion restriction is that after controlling for all fixed effects the synthetic LTV only affects income via the probability the house has negative home equity. In my analysis I find support for exactly this, since after including all fixed effects negative SLTV is not correlated with observable, or even difficult to observe, measures of local demand sensitivity, but still relates to the probability of negative home equity and subsequent labor income. These results are also robust to a wide range of variations of specification (6) including the primary specification which controls flexibly for any time-invariant characteristics via household

[12] I run this using the 1st stage as a linear probability model using negative SLTV as the instrumental variable. For robustness I also show results using multiple loan-to-value bucket indicators in the 1st stage, but not probit or linear-linear models. As noted by many papers (ex. Greene 2004) probit estimates are inconsistent in a fixed effect panel regression as are purely linear models when the underlying treatment effect varies non-linearly.

fixed effects as well as comparing just those households who bought their homes within the same MSA and year, separated by only a few months.

III. Results

A. Validity of the Instrument

Since negative home equity and household labor supply are likely to be jointly determined, to assess the causal effect of negative home equity on labor supply I employ the instrument outlined in the two stage least squares regression of specification 6. In particular, I use a dummy variable equal to one if the SLTV is greater than 1, after controlling for region-time and origination date-time fixed effects as an instrument. As detailed in section 2, SLTV is a measure of home equity based on the timing of home purchase in a given MSA, that doesn't depend on household-specific behaviors or characteristics.

[INSERT TABLE 2 HERE]

In Table 2 column 1 I show that this instrument meets the relevance criterion for a valid instrument. After including MSA x time and origination date x time fixed effects if the SLTV is greater than 1 a mortgage is a statistically significant 62.3 percentage points more likely to actually have negative home equity. In fact, throughout the analysis the first stage f-statistics are always very strong, because SLTV is mechanically related to LTV. The timing of home purchase is almost certainly going to be a strong predictor of current LTV, even with a broad set of fixed effects. Since SLTV meets the relevance criterion of being a valid instrument, if there is a relationship between negative home equity and labor supply, we would expect to observe it in reduced form between negative SLTV and household income. I find exactly this relationship in Table 2 columns 2 and 3. Negative SLTV is associated with a statistically significant reduction in the percent change in income per month, relative to income reported at origination, as well as raw observed household income/month. These are already suggestive of a potential causal link between negative home equity and labor supply. The remaining concern for causal interpretation would be a violation of the exclusion restriction.

Since the timing of home purchase, even from a single lender, within a region, relative to that same timing in other regions is not fundamentally randomly assigned, it is reasonable to be concerned that this region-specific timing could violate the exclusion restriction. If *MyBank* engaged in regional variation in the timing of different lending policies, that predicted future changes in house prices, and differences in local demand sensitivity of these borrowers, that would confound causal interpretation of these findings. Since the specifications in Table 2 don't include household fixed effects, I can test explicitly for any evidence of observable differences in these borrowers at the time of origination correlated with the instrument. In Table 2 columns 4-6 I show that negative STLV doesn't predict statistically or economically significant differences in reported income, credit scores, or interest rates at the time of mortgage origination, despite the fact that these households' current income is lower in columns 2 and 3. In other words, there is no evidence that *MyBank* was lending to borrowers with income more sensitive, ex-ante, to house price movements. The borrower reported incomes at origination weren't lower, the credit agency determination of credit quality or sensitivity to future economic shocks wasn't higher, and even a proxy for bank's internal measure of risk, the mortgage interest rate charged to the borrower, didn't differ for these households. The finding of no differences in borrower characteristics and in particular no differences in origination interest rates are especially helpful for causal interpretation in light of evidence from Hsu et al. (2014). Di Maggio and Kermani (2014) and Hsu et al. (2018) find that unemployment insurance can be a stabilizing force for housing markets that reduces defaults and Hsu et al. (2014) present evidence that this can cause lenders to provide easier credit in states with larger unemployment benefits. They find that for a "$3,600 increase in maximum UI benefits, [they] estimate that interest rates for first-lien mortgage loans decline by about 10 basis points". This makes sense if lenders are aware ex-ante of regional variation in employment risks for mortgage default and incorporate those into costs of borrowing. My finding of a fairly precise null for the effects of the proposed instrument on origination interest rates suggests any effects of the instrument are unlikely to be driven by systematic differences in labor market conditions or regulations at the time of origination, while the inclusion of region x time fixed effects alleviate concerns about ex-post differences in local labor market outcomes.

One limitation of looking at self-reported characteristics, such as income at origination, is that the borrowers might be misreporting these values systematically (Mian and Sufi 2017). To alleviate that concern I show in Table 3 columns 1-3 that these borrowers aren't any more likely to originate a mortgage that is Alt-A ("liar loans") or without income documentation, and focusing on only verified income still reveals no income difference at the time of origination.

[INSERT TABLE 3 HERE]

Despite finding no evidence of differences on important observable characteristics at origination, it may not be probable, but it is still possible that the borrower's differed on some unobservable qualities that makes them more sensitive to local demand shocks. To deal with even this concern I first show in Table 3 column 4 that negative SLTV is still associated with a decline in income after including household fixed effects to control flexibly for any time-invariant component in any unobservable differences. This still doesn't deal with any differences in unobserved household sensitivity to time-varying shocks. To address that concern I use the fact that the likely theories explaining a positive relationship between housing wealth and labor supply, predict effects concentrated among households with negative home equity. In Table 3 column 4 I show that omitting household-month observations with negative home equity there is no relationship between negative SLTV and household income. This placebo test shows that once the source of treatment, actual negative home equity, is omitted there is no relationship between house price changes and household income. In other words, these households are not generally more sensitive to local demand shocks, but only when it also happens to cause them to have negative home equity. The non-linearity of this sensitivity is also confirmed in Figure 1, which shows the relationship between non-linear categorical dummies for LTV and the percent change in household income since origination, after controlling for MSA x time, origination date x time, and household fixed effects.

[INSERT FIGURE 1 HERE]

As can be seen in the figure for low levels of LTV, but large variation in relative terms, there is no relationship between LTV and household income. Only when households approach negative home equity is there a decline that occurs non-linearly in household income[13], and remains low for households with negative equity. Figure 2 panel A repeats

[13] It is worth noting that since actual home value is estimated from MSA-level indices it is possible that some households with LTVs of 90% to 100%, or even 80% to 90%, would actually have negative home equity if they tried to sell their home. Given that we would expect some decline in income even for households measured as having some small amount of positive equity.

this analysis with the same fixed effects, but looks at interactions with 10% buckets of house price movements since origination.

[INSERT FIGURE 2 HERE]

Just like with SLTV this eliminates concerns that the overall effects could be driven by household choices at origination or during the life of the mortgage. The direct non-linear effects for the first stage and reduced form are presented explicitly in Figure 3.

[INSERT FIGURE 3 HERE]

What you see is no change in income for large changes in SLTV, if SLTV is relatively low. It is only once SLTV approaches 100% that income begins to fall. This happens to coincidence almost exactly with when we see increases in the probability a household actual has negative home equity – the first stage. Again, for cases where households are unlikely to have negative home equity, but large relative variation in housing wealth, there is no change in household income. Only when housing wealth declines are likely to lead to increased probability of negative home equity is there a non-linear and persistent decline in household income. This is made clearer in Figure 2 Panel B which includes only homes with positive home equity. Again, for large and even negative changes in home equity I see no evidence of reduction in income. In an additional and related placebo test in column 6 in Table 3 I also find that among households with only positive home equity those with higher SLTV are not associated with more sensitivity of income to changes in local unemployment rates. Again, these provide evidence that estimated effect sizes are not contaminated by reverse causality of job losses or local conditions to housing. Taken together these provide compelling evidence that negative SLTV leads to declines in household income, only through the increased probability of negative home equity, and a causal link from negative home equity to reduced household labor supply.

B. Negative Home Equity and Household Labor Supply

In Subsection A of Section 3 I provide evidence that strongly supports the validity of negative SLTV as an instrument for negative home equity. Using that instrument in Table 4 column 1 and 2 I show that instrumented negative home equity is associated with a $298/month or 3.47% decline in household labor supply.

[INSERT TABLE 4 HERE]

While the previous section provided substantial support for causal interpretation of this estimate, it focused primarily on the lack of any evidence of observable differences in the borrowers correlated with negative SLTV. By contrast in the remainder of Table 4 I further the confidence in the causal interpretation by showing that baseline findings are robust to a wide variety of additional controls. In column 3 I address concerns that the timing of home purchase and location even within a given MSA may have been correlated in a way that exposed these households to larger local demand shocks for the same MSA-level shock. In this specification I include zip code x time fixed effects, instead of MSA x time fixed effects, and again I find similar declines in labor supply, suggesting selection within MSA is not driving the observed results. In column 4, I also include a large range of non-parametric household-specific time varying controls that might be expected to be correlated with labor demand sensitivity. These include deciles for origination income and property value, mortgage original interest rate by percentage buckets, and original credit score in bins of 50 all interacted with time fixed effects.

These results show a 4.9% decline in household income, again consistent with overall findings and suggest results are not driven by any non-linear selection at origination.

In the appendix in Table B2 I re-run all these analyses, but excluding household fixed effects. These estimated effects are very similar to those with household fixed effects suggesting again that omitted time invariant co-variates are unlikely to be confounding causal interpretation of my findings. On the other hand, this may come as a surprise when looking at the reduced form estimates for SLTV greater than 100% in Table 2 without household fixed effects and Table 3 with them. The reduced form estimates are substantially larger in Table 2. Why then are the two-stage least squares estimates so similar? The reason becomes clearer when examining Figure 3. As I describe in more detail above it shows the non-linear first stage and reduced form as a function of SLTV. What you see is no change in income for large changes in SLTV, if SLTV is relatively low. It is only once SLTV approaches 100% that income begins to fall. Then as SLTV rises after that point income continues to fall, but importantly is matched by a rise in the probability of having negative home equity in the 1st stage. In fact, if you multiply these you get a relatively smooth effect as SLTV rises in the effect of instrumented negative home equity on income. The reason is that an increased probability of having negative home equity tends to vary closely with the amount of negative home equity. These are very hard to disentangle, not just for the econometrician, but also for borrowers and lenders. Prior to selling a property all parties only have some noisy measure of the true value of a property and so as the household becomes more and more underwater by my estimates they are more likely to actually be underwater if a transaction were to occur and simultaneously have a larger amount of negative home equity if they do have negative home equity. It is worth noting then that these results represent the combined effects of an increased probability of having negative home equity and increases in the amount of negative home equity conditional on being underwater. This is important since most predictions from channels discussed in section 1 suggest the latter, rather than the former, may be the driving force behind the observed increases in the magnitude of household income effects as SLTV rises.

Unfortunately, in this data I don't see when workers enter the labor force and it is possible that those who buy earlier or later in specific markets also entered the labor market in a systematically different ways and may be more likely to be laid off. To partially mitigate that concern in column 5 I show that instrumented negative home equity is associated with a 2.2% decline in labor supply, even controlling for the origination year interacted with the MSA and time. That means my identification is coming from comparing households who bought in the same MSA and year, but at different times of the year, just a few months apart. Given the proximity of these purchases it is very unlikely that there are large systematic differences between these buyers. That being said it is still possible, though significantly less likely, that even within a given year later buyers also entered the labor market later, making them more exposed to economic downturns. While I don't see the year people enter the labor force, for the subset with student debt I can estimate the time since a household attended college, as proxied by the average origination date of all student loans[14]. In column 6 I

[14] For a small subsample of households with credit cards I have information on when they graduated college. This sample is too small to use as an instrument, but has provided credibility that as would be expected, average origination date of student loans is highly correlated with the timing of college graduation.

use this same sample of households with information on approximate college graduation date, but now include fixed effects for MSA x time x college graduation year. This allows me to control flexibly for the duration of time the household head has been in the local labor market, which is likely to be correlated with age and more likely to be related to job duration. Even with this more stringent level of controls I find a valid first stage and a statistically significant decline of 5.6% in household labor supply in response to instrumented negative home equity.

One additional potential concern with all the analysis up to this point could be that I measure deposits at only one institution and in particular I use deposits from the same institution that is the household's mortgage lender. If household hides or shifts deposits away from their lender when they have negative equity this could mean that the reduction in deposits seen for households with negative equity is actually just movement of deposits to another institution rather than an actual decline in overall deposits from income. With this concern in mind throughout my analysis I use multiple restrictions to be sure households in the panel have active retail accounts, taking advantage of the inflow and level information I have for all deposit accounts at *MyBank* and results are robust to all choices of filters and measures of income. In particular, in appendix Table B4 column 2 I show that results are robust to including only direct deposits instead of all deposits as the measure of income[15]. To address the concern more directly I show in Table 5 column 1 that results are unchanged excluding cases where households deposit $0 into their accounts.

[15] Columns 1, 3 and 5 also show that results are not altered by normalizing percent changes in deposits by the mean of the household over the whole sample, focusing on just the log of deposits, or using *MyBank*'s internal measure of a household.

[INSERT TABLE 5 HERE]

This suggests results are not driven by households systematically leaving the bank. This is despite the fact that Table 5 column 2 shows results are driven entirely by declines of greater than 25% in household income. This suggests households make large extensive margin changes in labor income, say by increasing search duration. It also makes it unlikely results are driven by household systematically moving deposits into retirement savings accounts prior to depositing. Shifts in this kind of long-run savings behavior would cause small pervasive changes in deposit inflows rather than large concentrated reductions of the magnitude observed. This is also supported by the results in Table 5 column 3. Despite the overall reduction in deposit income shown previously, in column 3 I show that households are actually more likely to receive social security or disability checks. This suggests again that these households are either more likely to retire or move onto disability and in doing so reduce their labor supply by reduced labor force participation. The fact that we observe an increase in social security or disability checks again suggests there isn't a systematic shift of deposits away from *MyBank* in response to the instrumented negative home equity.

To be even more careful though, I rerun my analysis focusing on *MyBank* retail customers with a mortgage from another lender. Since I no longer have detailed mortgage information I use the zip code households enter in their retail accounts[16] as a proxy for the MSA the property is located in and information from the credit bureau data on mortgage origination dates. I then regress the $ amount of deposits per month on the

[16] For households with multiple zip code I use the zip code of the largest account and the date closest to the origination of the most recently originated mortgage.

percent of mortgages in that estimated zip code x origination year x time with negative home equity, after including MSA x time, origination date x time, and household fixed effects. Note that in this case these are reduced form regressions since current LTV is not available in credit bureau data to run the 1st stage. This method is likely to reduce the power of the regression, but the reduced form regression shown in column 4 still finds that a higher probability of negative home equity due to the timing of home purchase is associated with lower current deposits, after including all region x time, cohort x time, and household fixed effects. The result holds in column 5 when analyzing households with mortgages at any lender or for the subset of households where *MyBank* is not a servicer or owner of the mortgage. Since in these cases *MyBank* is not the lender there is no reason for the borrower to systematically shift deposits away from the institution. Overall these results suggest that hiding income is unlikely to explain the reduction in monthly deposit inflows seen for households with negative equity.

In subsequent work, Gopalan et al. 2019, build on the analysis carried out in my paper by replicating the identification strategy developed in this paper in an entirely new dataset based on verified employer income records, rather than deposits at MyBank, and also find a negative relationship between instrumented negative home equity and labor income. These results provide additional confidence that results are not driven by income hiding at MyBank and support the general external validity of the findings in this paper. I am unable to observe detailed employer information in my sample, but in their replication and extension Gopalan et al. (2019) are, which allows them to run additional robustness tests. They show that a matched set of renters living in the same zip code and working with the same job title at the same employer as a homeowner assigned the same loan-to-value as that homeowner has no reduction in income for lower home equity. This provides another strong placebo test consistent with the causal interpretation presented in my paper.

While a complete assessment of the macroeconomic implications of this labor supply response is beyond the scope this paper, it is worth noting just how many households were likely to have been affected in the recovery following the Great Recession. In appendix Figure B4 panel A I show separate estimates of the percent of residential properties with near zero or negative home equity by quarter over my sample period by both Zillow and CoreLogic. In both cases they find similar overall levels and trends, with approximately 30.7% of all households with negative home equity in every quarter of 2010, before falling considerably as markets recovered. At the same time according to Federal Reserve Economic Data (FRED) the rate of homeownership, as measured by owner occupancy per household and shown in panel B, were at 67.1% at the beginning of 2010 and fell thereafter. Putting these together it plausible that as many as 1 in 5 U.S. households were being directly affected by negative home equity in the first quarter of 2010, before falling to as low as 8.4% by the tail end of 2014. If 1/5th of households were experiencing negative effects to their labor income of 2.2-5.6% this would certainly suggest the potential for substantial macroeconomic effects. According to CoreLogic as of the first quarter of 2010 there was over $820 trillion in negative home equity, making it the single largest category of unsecured household liability[17].

[17] Based on data from the New York Federal Reserve as of the first quarter of 2010 the outstanding principal balance of student loans, credit cards, auto-loans, and other liabilities were approximately $0.76, $0.76, $0.7, and $0.36 trillion respectively.

This is made even clearer when examining regional heterogeneity in treatment. In panel C I plot the proportion of properties with negative home equity for MSAs two standard deviations above ("high") and below ("low") the national MSA-level average. While in the second quarter of 2011 in the median MSA about 22% of households had negative home equity, for "low" MSAs this was only 4%, but for "high" MSAs it was around 60%. For example, according to Zillow's estimates, in areas of Las Vegas as many as three-quarters of all households had negative home equity. Holding constant local economic conditions and selection, this would suggest that an equivalent household in "high" underwater MSAs were 56 percentage points more likely than those in "low" MSAs to have negative home equity in early 2010. The estimated effect of negative home equity on labor income from Table 4 column 1 is about $298/month of treatment. Based on this estimated labor income treatment effect and under the assumption of a ratio of income to consumption of 0.85 as in Hurst et al. (2016), this could equate to a $137/month/household expected loss in consumption in the "high" underwater MSAs relative to the "low", or $1,641/household on an annualized basis. Annual effects in just 2010 could be comparable in size to the $1,860 per household cross-region transfers caused by constant interest rate mortgage policy found in Hurst et al. (2016) and the size of tax rebate checks authorized by the U.S. congress during the 2001 and 2008 recessions which tended to range from $500 to $1,000 per household. While useful to gain a general understanding of the potential size of the microeconomic effects, unfortunately this simple exercise brings with it a myriad of important caveats. We have also ignored any other effects of home equity within this simple exercise, despite evidence it would be likely to alter consumption and in doing so potentially influence local labor demand

(Mian and Sufi 2012). More broadly speaking we have ignored all general equilibrium effects either of negative home equity overall and of course within the context of the estimated effects on labor income. For “high” underwater MSA areas, with such a substantial portion of the local labor market affected, it certainly seems reasonable to expect that these labor market distortions may have been more than just a microeconomic considerations. Quantifying the exact general equilibrium effects of such distortions is likely to fall outside the scope of this paper though, since regardless of the channel any local general equilibrium effects are likely affected by responses of wages, in-migration, and firm competitiveness as illustrated in Donaldson et al. (2019). Also as has been noted by more generally by Chetty et al. (2011), macroeconomic estimated labor supply elasticities tend to exceed microeconomic estimates and typically cannot be easily recovered without the benefit of an underlying structural model.

IV. Discussion: Potential Mechanisms

Overall these results are consistent with negative home equity causing an average partial equilibrium labor income decline of 2.2%-5.6%, not driven by changes in labor demand. While an exact comprehensive decomposition of the underlying channels is beyond the scope of this paper, but likely to be an important area of inquiry for future researchers, non-linearities in the treatment effects would be consistent with housing lock and/or financial distress altering household labor supply.

A. Housing Lock

Households who are financially constrained and have negative equity may be prevented from moving, also known as “housing lock”. To extent that reduced mobility reduces labor market opportunities, this could cause a reduction in income via longer periods of unemployment, worse labor market matches, or monopsony power on the part of employers aware of the limited searching ability of a worker[18]. Due to the relatively weak recourse nature of mortgages in the U.S. the effect of housing lock on mobility is unclear and empirical evidence has historically been divided, with papers such as Schulhofer-Wohl (2012) and Mumford and Schultz (2014) finding no evidence of reduced mobility. Modestino and Dennett (2013) also point out that while non-pecuniary costs of immobility could be large, relative few households in a given year have to move for employment, so the effect on aggregate labor supply may be limited.

By contrast, more recent research leveraging the empirical design developed in this paper have shown significant reductions in moving rates among households with negative home equity in the Netherlands and United States (Bernstein and Struyven 2019; Gopalan et al. 2019). In addition, Brown and Matsa (2017) provide recent evidence that job seekers appear to engage in more geographically constrained search in more depressed housing markets, which could be consistent with mobility constraints from housing lock altering labor market search. Though not mortgage liabilities, Maggio et al. (2019) also find evidence that the discharge of student loans improves borrower mobility and labor income, consistent with debt playing a role in constraining employment search.

In the case of mortgage liabilities these sorts of constraints are unlikely to bind when a household has positive home equity, since the home could in theory be sold

[18] Technically weaker wage bargaining caused by negative home equity leading to a reduction in wages with no other action wouldn't be household labor supply, but by far the most reasonable mechanism through which an employer could know that an employee has weaker bargaining in this situation is via reduced outside offers or search, which would constitute a change in labor supply. In this setting just like in Brown and Matsa (2017) negative home equity could lower search, even among employed individuals, who then generate slower wage increases in bargaining even with their existing employer.

without needing substantial additional resources. On the other hand, negative home equity requires the homeowner to either use financial assets to pay down the liability, default, or rent out the property in order to facilitate moving, which is often not feasible. Given that we would expect non-linear effects of home equity on mobility that increase starting near negative home equity, which is exactly what is shown in (Bernstein and Struyven 2019), and a matching prediction for labor income distortions. It should be noted though that since in the U.S. setting strategic default becomes more likely as negative home equity increases it is possible that effects on mobility and income could asymptote as default incentives rise. Lenders in these settings may also have incentives to encourage short sales, which would force movement on the part of the homeowners, which may also cause behaviors to curtail for high levels of negative home equity.

B. Financial Distress

Households with reduced wealth, and especially low home equity, are much more likely to experience financial distress when faced with an income or liquidity shock (Foote et al. 2008; Fuster and Willen 2017; Gerardi et al. 2018). This is because even if a household experiences an income shock, but has positive equity in the house, they should be able to access that value in order to avoid default. Even if market frictions preclude the ability to access that wealth as liquidity, households have a strong incentive to avoid default, since the lender would seize the house and they would lose all their positive housing wealth. In the case of negative home equity households appear to engage in "strategic" default, which may be a value-maximizing decision (Foote et al. 2008; Adelino et al. 2013; Mayer et al. 2014), but even this form of default may bring with it increased energy, time, and stress, which could reduce worker productivity or job search among the unemployed (Deaton, 2012; Currie and Tekin, 2015; Dobbie and Song, 2015; Bos et al. 2015; Engelberg and Parsons, 2016)[19]. Di Maggio et al. (2019) find substantial labor income effects of student loan dischargement, but the particular set of borrowers examined were already not paying these loans. While there could be any number of reasons borrowers not paying would respond to debt relief, when asked for an interpretation of this result Ben Miller, the senior director for post-secondary education at the Center for American Progress, said he thought “it suggests there might be some sort of psychological benefit to this relief that goes beyond the household balance sheet”[20]. This interpterion could be consistent with effects of stress associated with financial distress highlighted previously. It is also plausible that such mechanisms could be important within the context of mortgage liabilities and home equity decisions more generally. Guiso et al. (2013) and Bhutta et al. (2017) provide evidence that the decision to default among underwater households is often one driven more by emotional and behavior factors than specific costs or benefits, such as lender recourse. To the extent that these forms of distress have significant effects on the labor markets, a non-linear effect of home equity concentrated in households with negative equity would be consistent with this mechanism.

Another way in which financial distress could alter labor markets is through incentives caused by household protection under limited liability, which I call the “household debt overhang” channel. As is well known, for highly levered firms a reduction in firm wealth reduces the marginal incentives for investment in positive net

[19] It could also be that direct effects on credit scores from distress could hurt labor market outcomes, but Dobbie et al. (2017) show that removal of bankruptcy flags and subsequent increases in credit scores and access to credit don’t substantially alter labor income.

[20] https://finance.yahoo.com/news/student-debt-loans-cancel-forgive-142422120.html

present value projects because the benefits accrue disproportionally to existing debt holders (Myers 1977). As shown in theoretical work by Donaldson et al. (2019) highly levered households face a similar debt overhang problem when deciding to invest in the effort needed to earn labor income. If a portion of any marginal income earned by an indebted household is transferred to a lender via increased expected liability repayment, then this transfer to debt holders acts just like an implicit tax that incentivizes households to reduce their labor supply. This doesn't mean households necessarily purposefully leave existing employment, but could suggest, as in Donaldson et al. (2019), that already unemployed workers could be incentivized to prolong job search in an effort to find a better match. Empirically, Dobbie and Song (2015a) show evidence consistent with households responding to such incentives with their labor decisions. Using random assignment to judges they show that bankruptcy protection causes an increase in labor supply. The proposed mechanism of the authors is that households with limited liability don't always expect to fully repay outstanding liabilities and bankruptcy protection reduces the likelihood of a larger implicit tax from wage garnishment outside the bankruptcy system. This is functionally the same underlying premise as the debt overhang mechanism proposed in this paper and modeled in Donaldson et al. (2019). In the context of home equity, Donaldson et al. (2019) show that if the house value is sufficiently high, relative to the outstanding mortgage, there are no distortionary effects since a household can use the collateral to fully repay all liabilities. When collateral values are low though, such as cases of low or negative home equity, limited liability causes labor supply distortions, just like the case of unsecured liabilities. Therefore, in their framework debt overhang would predict a non-linear relationship between housing wealth and labor income, with no relationship between housing wealth and labor supply until home equity is sufficiently low[21].

C. Wealth Effects

There is broad prior evidence that increases in non-housing wealth can cause reductions in labor supply (Joulfaian and Wilhelm 1994; Imbens et al. 2001; Cesarini et al. 2017) consistent with households establishing a reference level of wealth or liquidity, supporting smoothed consumption growth, and working at only the level required to maintain it (Rizzo and Zeckhauser, 2003). By contrast, Bernstein, McQuade, and Townsend (2018) show that declines in housing wealth are associated with lower innovation among workers, suggestive of reduced productivity. One proposed channel for this response put forth by the authors is that declines in housing wealth could cause reductions in consumption (Mian et al. 2013) and specifically decreased spending on labor-augmenting goods and services (Becker, 1965; Baxter and Jermann, 1999; Aguiar et al., 2013). For example, if innovative workers with higher levels of wealth are more likely to pay for home services that may free up additional time they can engage in working or even just thinking about inventions, that may be more likely to increase their productivity. This may also be consistent with findings in He and Maire (2018) who show that the relaxation of liquidity constraints from extracting home equity have labor market consequences in Denmark. To the extent that labor-augmenting consumption is

[21] It is not clear though that these ex-ante costs of financial distress are plausibly first-order in practice. For mortgage debt, unlike the setting of Dobbie and Song, lenders either legally cannot or in practice do not obtain deficiency judgements and garnish wages. While income-contingent renegotiations, such as mortgage modifications, could provide another observable channel it isn't obvious that households are aware and willing to alter their behaviors in response to such incentives.

the prevailing channel, it is not clear ex-ante that these effects should be asymmetric or non-linear. On the other hand, Bernstein, McQuade, and Townsend (2018) demonstrate a non-linear response of worker innovation to housing wealth shocks, where increases in housing wealth have no effect, while large declines, especially among those more likely to have low or negative home equity, drive the observed response. Housing wealth is the primary form of savings for many households (Campbell 2006) and the marginal propensity to consume out of housing wealth has sharp non-linearities around negative home equity (Baker 2019; Ganong and Noel 2019), so this could be driven by non-linearities in the response of consumption to housing wealth. That being said, the finding of no response of household income in my setting to large increases in housing wealth feels at least somewhat at odds with this interpretation and suggests that perhaps other mechanisms, many of which do contain starker non-linearities in home equity, may provide more likely explanations.

D. Collateral Channel & Entrepreneurship

Another channel through which home equity could affect labor market decisions are entrepreneurial endeavors. Adelino et al. (2015) and Schmalz et al. (2017) have shown that due to information asymmetries between banks and entrepreneurs collateral value from positive home equity is a critical driver of the entry and success of entrepreneurs and small business development. To the extent that entrepreneurship is an income maximizing labor opportunity, a reduction in home equity would then be expected to reduce labor income. While just like with many of the other channels discussed the relationship would be expected to be non-linear, the predicted pattern of the non-linearity is likely to be quite different in this setting. For households with positive home equity we would expect a reduction in home equity to reduce collateral value and in doing so alter entrepreneurial income, but for households with negative home equity we would expect little-to-no effect for changes in home equity since the collateral already has no value for lenders to use. That being said, entrepreneurship may bring with it non-pecuniary benefits that act as a compensating differential in equilibrium. In that case it may be that even though home equity matters as collateral for entrepreneurship it is not clear that it will necessary be an important driver for total household income.

V. Conclusions

In this paper, I provide the first empirical evidence of the causal effect of negative home equity on household labor supply. I use a new comprehensive dataset with information on household-level liabilities, assets, and all deposit transactions for all customers of a major U.S. financial institution from 2010-2014 and variation in home equity based on the timing of home purchases among households in the same region at the same time from the same lender, controlling for any aggregate origination cohort trends. I find that instrumented negative home equity causes an average reduction of 2.2%-5.6% in household labor income, even when comparing households who bought their homes in the same region in the same year. These results shed new light on the role house price declines played in exacerbating employment declines following the crisis. Mian and Sufi (2012) have examined how house price shocks affect equilibrium employment via local labor demand, but this is the first paper to demonstrate the role house price declines played in labor markets via the supply channel. While identifying the aggregate general equilibrium response to home equity is beyond the scope of this paper, my results do suggest that it has a role to play in understanding how household balance sheets can exacerbate financial crises.

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Table I. Summary Statistics

This table includes simple summary statistics for *MyBank* data. To be included in the panel all households must have at least 12 months with deposits across all accounts >=$100 & <=$50k and a mean and median level of deposits across all accounts >=$500 & <=$25k. For direct deposits the HH must have at least 12 months of direct deposits >=$100 & <=$25k, a mean and median level of direct deposits across all accounts >=$500 & <=$25k and >=75% of all deposits must be via the direct deposit channel. All data winsorized at 99th percentile. This sample includes only households that have retail and mortgage accounts at *MyBank* from 2010-2014.

	Mean	Median	Std. Dev	# Obs (mil)	# HHs (mil)
A. Households w/ *MyBank* Retail & *MyBank* Mortgage 2010-2014					
Retail Data					
Income (All)	$7,663	$5,315	$8,439	7.835	0.200
Income (Dir. Dep.)	$4,142	$2,826	$4,742	7.835	0.200
Income (Dir. Dep. w/ Filter)	$6,470	$5,172	$5,226	2.291	0.058
Savings	$35,370	$10,100	$60,626	7.835	0.200
Card/Credit Bureau Data (w/ *MyBank* Credit Card Account)					
All Liabilities	$266,300	$225,000	$210,610	5.158	0.144
Has Auto loan	30%			5.158	0.144
Bal Used/Available All Credit	20%	10%	29.3%	5.158	0.144
FICO Bank Credit Score	767	782	74.4	5.158	0.144
Mortgage Data					
Primary MTG Balance	$199,900	$170,700	$137,130	7.835	0.200
MTG Interest Rate @ Origination	5.373	5.375	1.227	7.835	0.200
MTG Age (Months)	64	58	49	7.835	0.200
Income @ Origination	$7,494	$6,237	$5,171	5.419	0.147
Origination Loan-to-Value (%)	64	68	22.1	7.835	0.200
Current Loan-to-Value (%)	58	58	31.5	7.835	0.200
Is Owner Occupied	92.0%			7.835	0.200
Subprime	10.2%			7.835	0.200
Jumbo	19.3%			7.835	0.200
Stated Income	13.3%			7.835	0.200
Single-Family Residential	88.7%			7.835	0.200
Is Fixed Rate	83.9%			7.835	0.200

Table II. Validity of SLTV Instrument and Observables

This table provides evidence that after controlling for region-time and origination date-time fixed effects a household's synthetic loan-to-value ratio (SLTV) greater than 100% is a valid instrument to look at the effect of negative home equity on household labor supply, based on observable characteristics. SLTV is an instrument for loan-to-value that does not depend on household specific factors, except the timing-location of moving, and varies at the region-time-cohort level. Column 1 regresses a dummy equal to 1 if a household's current loan to value is greater than 100% on a dummy which equals 1 if the household's SLTV is greater than 100%, after including MSA x time, and origination date x time fixed effects. This is the 1st stage estimate of an IV regression. Column 2 is the same as 1, but the % change in deposits, where the numerator is the monthly deposit inflows and the denominator is the household's income at the time of mortgage origination, is the dependent variable. Column 3 is the same as column 1, but includes raw monthly deposit inflows as the dependent variable, without any normalization. Column 4 is the same as column 1, but monthly gross reported income at origination is the dependent variable. Column 5 is the same as column 1, but credit score at origination is the dependent variable. Column 6 is the same as column 1, but initial mortgage interest rate at origination is the dependent variable. All standard errors are clustered at the MSA level. P-Values: * 10%; ** 5%; ***1%.

	1st Stage	Reduced Form		@Origination Placebo tests		
	(1)	(2)	(3)	(4)	(5)	(6)
	LTV>1	%ΔDep	$Dep	$ Mo. Income	Credit Score	Int. Rate
SLTV>1	0.623***	-4.42***	-436.8***	-64.8	1.03	-0.0003
	(0.028)	(0.775)	(128.5)	(151.9)	(1.66)	(0.0003)
MSA x Time FE	Y	Y	Y	Y	Y	Y
Orig. Date x Time FE	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.587	0.072	0.045	0.045	0.152	0.727
Observations (mil)	5.375	5.375	5.375	5.375	5.375	5.375

Table III. Robust to Selection on Unobservables

This table provides evidence that after controlling for region-time, origination date-time, and household fixed effects a household's synthetic loan-to-value ratio (SLTV) greater than 100% is a valid instrument to look at the effect of negative home equity on household labor supply, focusing on tests that reveal differences in difficult to observe or unobservable characteristics. SLTV is an instrument for loan-to-value that does not depend on household specific factors, except the timing-location of moving, and varies at the region-time-cohort level. Column 1 regresses a dummy equal to 1 if a household's mortgage at origination was "Alt-A" or a "Liar Loan" on a dummy which equals 1 if the household's SLTV is greater than 100%, after including MSA x time, and origination date x time fixed effects. Column 2 is the same as column 1, but a dummy variable equal to one if the mortgage has no documentation at origination is the dependent variable. Column 3 is the same as column 1, but monthly gross verified income at origination is the dependent variable. Column 4 is the same as column 1, but the % change in deposits, where the numerator is the monthly deposit inflows and the denominator is the household's income at the time of mortgage origination, is the dependent variable and the regression includes household fixed effects. Column 5 is the same as column 4, but excludes any observations where a household actually has negative home equity. Column 6 is the same as column 5, but includes an interaction between negative SLTV and demeaned monthly percent changes in aggregate deposits by MSA. All standard errors are clustered at the MSA level. P-Values: * 10%; ** 5%; ***1%.

	@Origination Placebo tests			HH FEs	Placebo No Neg Eq	
	(1)	(2)	(3)	(4)	(5)	(6)
	Alt-A	No Income Docs	Verified $ Mo. Income	%ΔDep	%ΔDep	%ΔDep
SLTV>1	0.0002	-0.004	-6.1	-1.37***	0.08	0.08
	(0.0037)	(0.013)	(122.5)	(0.42)	(0.61)	(0.61)
SLTV>1 x %ΔMSA Dep						0.17
						(0.24)
MSA x Time FE	Y	Y	Y	Y	Y	Y
Orig. Date x Time FE	Y	Y	Y	Y	Y	Y
HH FE	N	N	N	Y	Y	Y
Sample	All	All	All	All	Eq>0	Eq>0
Adjusted R^2	0.110	0.107	0.056	0.480	0.529	0.531
Observations (mil)	5.375	5.375	4.144	5.375	4.753	4.753

Table IV. Negative Home Equity and Labor Supply

This table shows the average change in household income associated with negative household home equity using variation in the timing of home purchase as an instrument for the probably of having negative equity. The instrument is a dummy variable equal to one if a household's synthetic loan-to-value ratio (SLTV) is greater than 100% after controlling for MSA-time, origination date-time, and household fixed effects. Column 1 shows the results of running the two-stage least squares procedure of regressing raw monthly deposit inflows as the dependent variable, without any normalization, on instrumented negative home equity. Column 2 is the same as column 1 but the dependent variable is the % change in deposits, where the numerator is the monthly deposit inflows and the denominator is the household's income at the time of mortgage origination. Column 3 is the same as column 2, but includes zip-time instead of MSA-time fixed effects. Column 4 is the same as 2, but includes time varying non-parametric household-level controls. These include deciles for origination income and property value, mortgage original interest rate by percentage buckets, and original credit score in bins of 50 all interacted with time fixed effects. Column 5 is the same as 2, but includes MSA x time x origination year fixed effects. Column 6 is the same as 2, but instead of origination date x time fixed effects it includes graduation year x MSA x time fixed effects among the subset of borrowers with outstanding student loans. All standard errors are clustered at the MSA level. P-Values: * 10%; ** 5%; ***1%.

			Zip FE	X_{it} Controls	Orig Yr x MSA FE	Grad Yr FEs
	(1)	(2)	(3)	(4)	(5)	(6)
	$Dep	%ΔDep	%ΔDep	%ΔDep	%ΔDep	%ΔDep
LTV>1	-298.1***	-3.47***	-3.77***	-4.94***	-2.20**	-5.63**
(IV: SLTV>1)	(61.3)	(1.18)	(1.13)	(1.03)	(0.89)	(2.97)
Region x Time FE	Y/MSA	Y/MSA	Y/ZIP	Y/MSA	N/A	Y/MSA
Orig. Date x Time FE	Y	Y	Y	Y	N/A	N
HH FE	Y	Y	Y	Y	Y	Y
HH Time Varying Controls	N	N	N	Y	N	N
MSA x Time x Orig Yr FE	N	N	N	N	Y	N
MSA x Time x Grad Yr FE	N	N	N	N	N	Y
F-Stat	2440.4	2440.4	2109.6	2304.8	110.25	126.1
Adjusted R^2	0.380	0.490	0.529	0.492	0.620	0.550
Observations (mil)	5.375	5.375	5.271	5.219	5.219	0.665

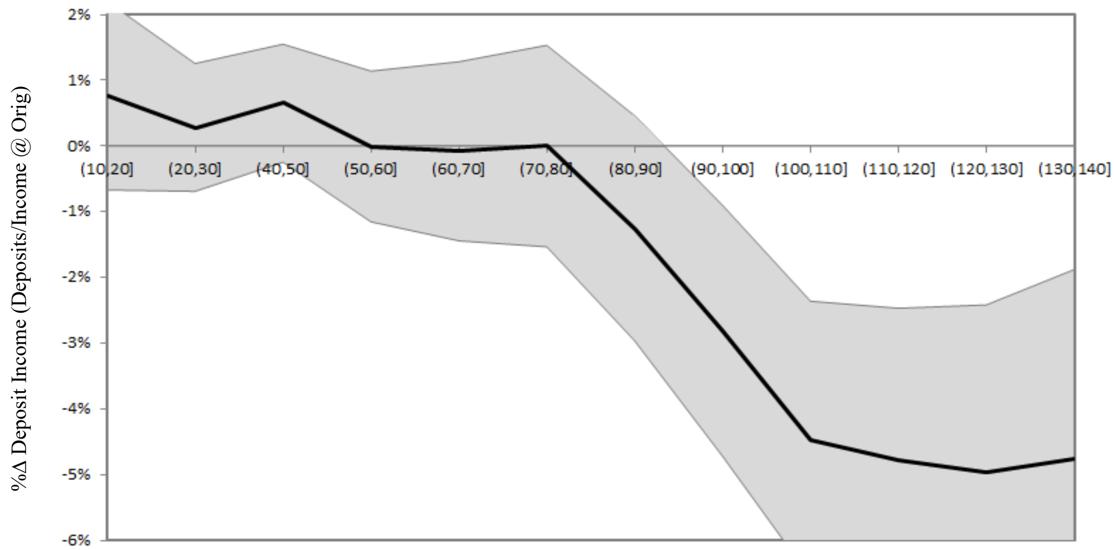
Table V. Robust to Income "Hiding"

This table explores the drivers of the negative effect of mortgage loan-to-value (LTV) on labor supply and show it is not driven by "hiding" of deposits with other institutions. Just as in the main specifications Column 1 regresses the % change in deposits, where the numerator is the monthly deposit inflows and the denominator is the household's income at the time of mortgage origination, on an instrumented dummy equal to one if current mortgage loan to home value is greater than 100%, MSA x time, origination date x time, and household fixed effects. A dummy which equals 1 if my synthetic loan to value ratio (SLTV) measure is greater than 100% is used as an instrument for the likelihood that a household has negative home equity. SLTV is an instrument for loan-to-value that does not depend on household specific factors, except the timing of moving, and varies at the region-time-cohort level. In this case though cases with 100% decline in deposits are completely excluded from the analysis. Column 2 is the same as column 1 but excludes any changes larger than 25%. Column 3 is the same as column 1, but does not exclude any deposits and the dependent variable is a dummy equal to 1 if the household receives any social security checks. These are defined as direct deposits received on the 3rd of the month, or the 2nd, 3rd, or 4th Wednesday that are not explained by regularly scheduled labor related direct deposits. Column 4 restricts the sample to the subset of borrowers with credit cards and associated credit bureau data. For this subset, I don't rely on mortgage data, so I know the approximate timing and zip code of origination (see text for more detail), but not the actual loan-to-value at or income at origination. I therefore regress the $ amount of deposits per month on the percent of mortgages in that estimated zip code x origination year x time with negative home equity, after including MSA x time, origination date x time, and household fixed effects. Column 5 is the same as column 4, but restricts the analysis to only households with mortgages not serviced or owned by *MyBank*. All standard errors are clustered at the MSA level. P-Values: * 10%; ** 5%; ***1%.

	(1) %ΔDep	(2) %ΔDep	(3) %GetSS	(4) $Dep	(5) $Dep
LTV>1	-3.35***	-0.07	0.91***		
(IV: SLTV>1)	(1.12)	(0.55)	(0.32)		
%NegEq				-48.8***	-65.0***
(Region x Cohort x Time)				(10.4)	(15.0)
Region x Time FE	Y	Y	Y	Y	Y
HH FE	Y	Y	Y	Y	Y
Orig. Date x Time FE	Y	Y	Y	Y	Y
Normalization	Orig Inc	Orig Inc	No	N/A	N/A
Dep/Mo Constraint	>$0	>-25%	N/A	N/A	N/A
Mortgage Servicer/Owner	All	All	All	All	Not *MyBank*
Orig Location/Date Method	Actual	Actual	Actual	Derived	Derived
Adjusted R^2	0.621	0.430	0.548	0.344	0.348
Observations (mil)	4.794	3.888	5.375	20.113	15.018

Figure 1. LTV vs. Income: Variation Primarily from Timing of Purchase

This figure shows the relationship between income and current household mortgage loan to property value (LTV) after controlling for household specific factors and local demand shocks. This figure shows the coefficients of regression where I regress the % change in deposits, where the numerator is the monthly deposit inflows and the denominator is the households' income at the time of mortgage origination, on dummies for various ranges of current (LTV) ratios, where house price is computed using original property value and changes in LPS MSA-level house price indices used by *MyBank* internally, MSA x time, origination date x time, and household fixed effects. In this figure the x-axis indicator dummies for each household-month that appears in a given 10% LTV bucket and the right hand side are the co-efficients from the regression (bold line). LTVs of 30-40% are the omitted group for comparison. 95% confidence intervals computing standard errors clustered at the MSA level, are shown in the shaded regions. P-Values: * 10%; ** 5%; ***1%.

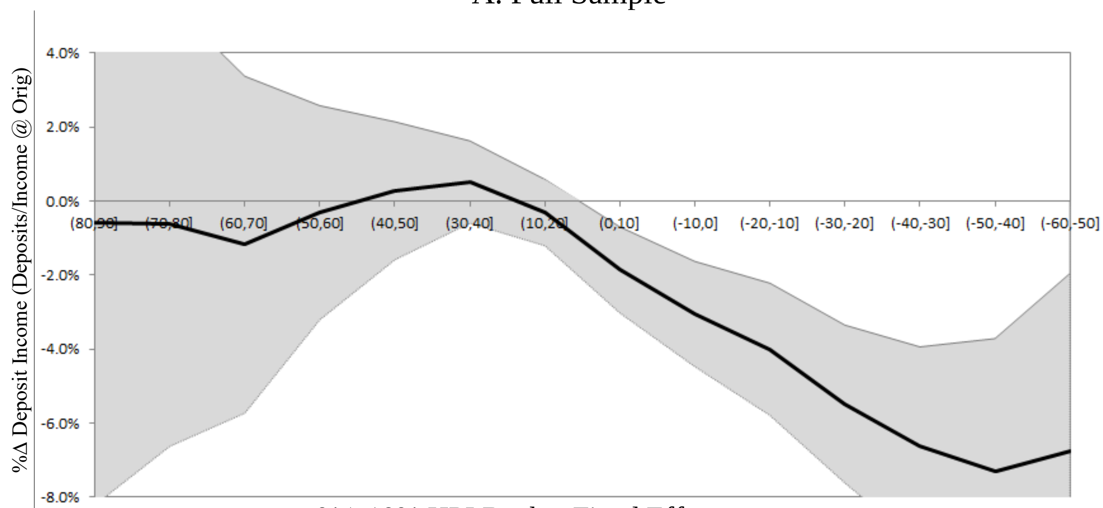


10% LTV Bucket Fixed Effects

Figure 2. LTV vs. Income: Identification Based HPI IV Reduced Form

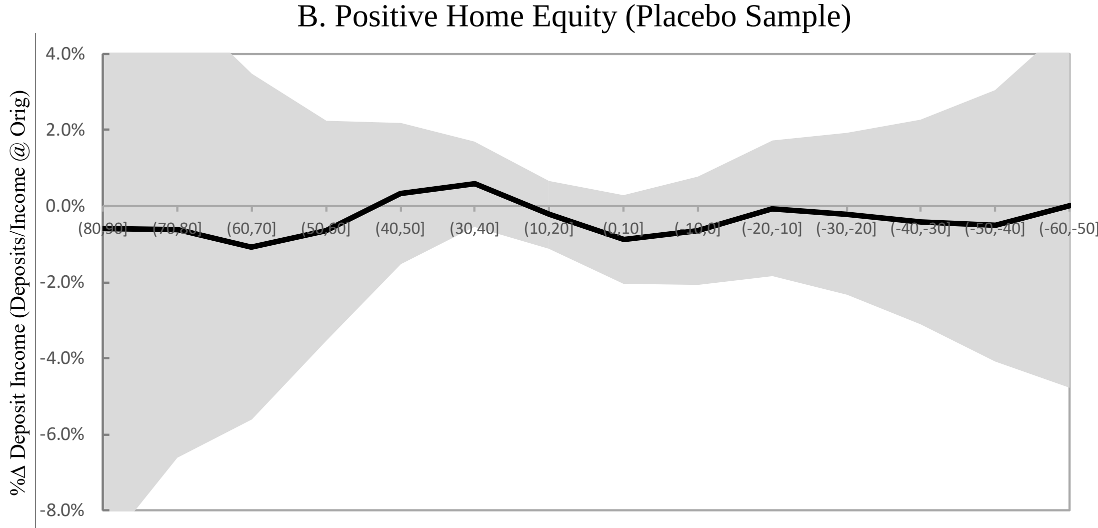
This figure shows the average change in household income associated with negative household home equity using variation in the timing of home purchase as an instrument for the probably of having negative equity. In this figure Panel A shows the coefficients of regression where I regress the % change in deposits, where the numerator is the monthly deposit inflows and the denominator is the households income at the time of mortgage origination, on dummies for various ranges of MSA-level house price index changes since mortgage origination, where house price is computed using original property value and changes in LPS MSA-level house price indices used by *MyBank* internally, MSA x time, origination date x time, and household fixed effects. In this figure the x-axis are indicator dummies for each household-month that appears in a given 10% HPI change bucket and the right hand side are the co-efficients from the regression (bold line). HPI changes of 20-30% are the omitted group for comparison. 95% confidence intervals computing standard errors clustered at the MSA level, are shown in the shaded regions. Panel B is the same as panel A, but includes only households with positive home equity as a placebo test. P-Values: * 10%; ** 5%; ***1%.

A. Full Sample



%Δ 10% HPI Bucket Fixed Effects

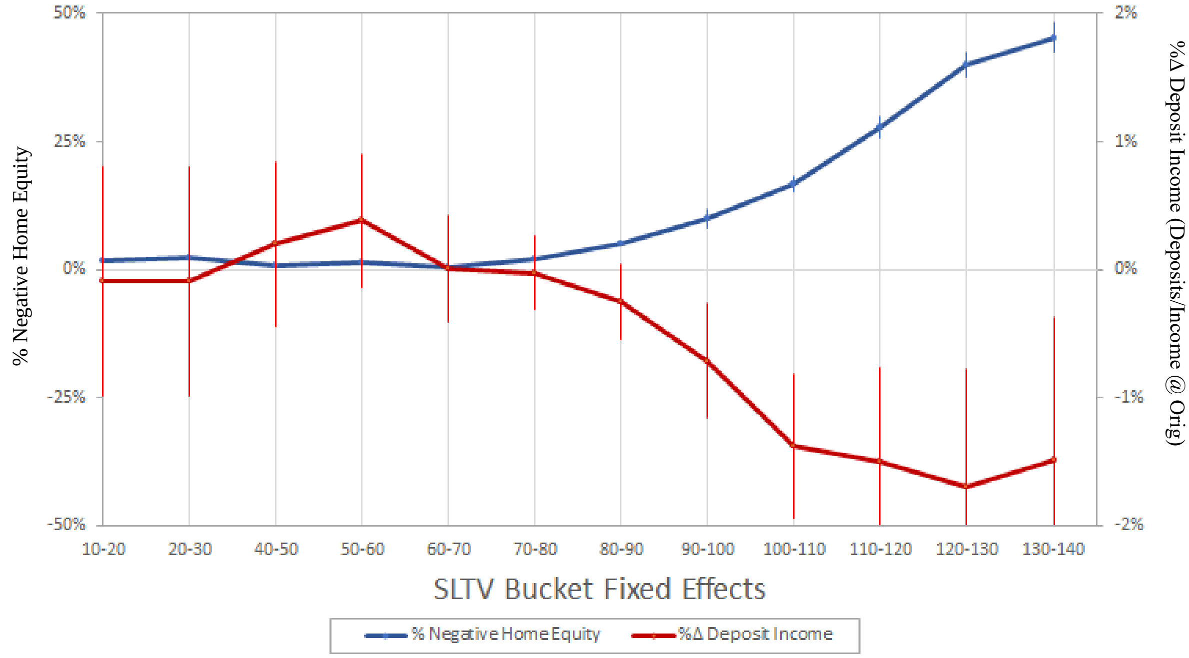
B. Positive Home Equity (Placebo Sample)



%Δ 10% HPI Bucket Fixed Effects

Figure 3. SLTV, Negative Home Equity, & Income

This figure shows the relationship between income/negative home equity and current household mortgage "synthetic" loan to property value (LTV) after controlling for household specific factors and local demand shocks. This figure shows the coefficients of regression where I regress the % change in deposits, where the numerator is the monthly deposit inflows and the denominator is the households' income at the time of mortgage origination, or a dummy for having negative home equity, on dummies for various ranges of current (SLTV) ratios, where house price is computed using original property value and changes in LPS MSA-level house price indices used by *MyBank* internally, MSA x time, origination date x time, and household fixed effects. In this figure the x-axis indicator dummies for each household-month that appears in a given 10% SLTV bucket and the right hand side are the co-efficients from the regression (bold line). 95% confidence intervals computing standard errors clustered at the MSA level, are shown in the shaded regions. P-Values: * 10%; ** 5%; ***1%.



Internet Appendix for

“Negative Home Equity and Household Labor Supply”

ASAF BERNSTEIN[22]

ABSTRACT

This Internet Appendix provides additional tables and figures supporting the main text.

[22] Citation format: Bernstein, Asaf, Internet Appendix for “Negative Home Equity and Household Labor Supply,” *Journal of Finance* [DOI String]. Please note: Wiley-Blackwell is not responsible for the content or functionality of any additional information provided by the authors. Any queries (other than missing material) should be directed to the authors of the article.

Appendix A: Panel Data Construction

The data provider for this project is a major U.S. financial institution, who I refer to as *MyBank*, with transaction-level client account information on more than 1/4th of all U.S. households over the 5 years from 2010-2014. For the purposes of this project I focus on households with sufficient *MyBank* relationships to estimate income and mortgage information and analyze income decisions at a monthly household level. Income is estimated using retail account deposit information and mortgage information is either derived from credit bureau data (only available for households w/ *MyBank* credit card accounts) or *MyBank* mortgage account information. In table A1 I detail the effect on sample size and household characteristics when multiple *MyBank* accounts are combined at a monthly frequency.

Table AI. Effect of Panel Data Construction on Sample Size

Merging is done at HH-level. To be included in the panel all households must have at least 12 months with deposits across all accounts >=$100 & <=$25k, a mean and median level of deposits across all accounts >=$500 & <=$25k. To be "active" a HH must have at least $200 aggregated across all accounts in a month or at least $100 in deposits across all accounts. For direct deposits and assigned to jobs direct deposits the same restrictions apply as with deposits, but for direct deposits and assigned direct deposits only respectively, and >=75% of all deposits must be via the channel of interest. 1st row includes no filters, but all others that include retail include the filter.

	Median Ann. Deposits	Median MTG Bal	# HH-Mo Obs (mil)	# Acct (mil)	# Cust (mil)	# HHs (mil)
MyBank Retail Acct (*Raw*)	$23,556					
MyBank Retail Acct	$37,166					
MyBank Credit Card Acct		$152,268				
MyBank Mortgage		$116,255				
MyBank RTL & MTG	$63,780	$170,726	7.83	1.40	0.70	0.20
MyBank RTL & CC & Any MTG	$66,301	$222,626	24.42	4.84	1.99	0.62
MyBank RTL & CC & No MTG	$39,982	$0	30.13	6.22	2.43	0.96
MyBank RTL, CC, MTG	$73,011	$177,631	4.36	1.32	0.49	0.13
MyBank RTL, CC, & Non-*MyBank* MTG	$67,506	$228,569	16.58	4.30	1.75	0.54
MyBank RTL & CC & Non-*MyBank* & Direct Deposit Req.	$72,587	$224,421	5.52	1.14	0.45	0.17
MyBank RTL & CC & Non-*MyBank* & Assigned Direct Deposit Req.	$63,837	$210,748	0.88	0.15	0.06	0.03

Appendix B: Additional Tables/Figures

Table BI. Additional Summary Statistics

To be included in the panel all households must have at least 12 months with deposits across all accounts of >=$100 & <=$50k and a mean and median level of deposits across all accounts of >=$500 & <=$25k. For direct deposits the HH must have at least 12 months of direct deposits >=$100 & <=$25k, a mean and median level of direct deposits across all accounts >=$500 & <=$25k and >=75% of all deposits must be via the direct deposit channel. All data winsorized at 99th percentile. Group A look at only households that have retail and credit card accounts at *MyBank* and a mortgage with any lender. Group B examines only the subset of households with mortgages either owned or serviced by *MyBank* from 2010-2014.

	Mean	Median	Std. Dev	#Obs (mil)	#HHs (mil)
B. *MyBank* Retail & Credit Card Accounts & Any Bank Mortgage 2010-2014					
Retail Data					
Income (All)	$7,856	$5,525	$8,547	24.42	0.622
Income (Dir. Dep.)	$6,632	$5,358	$5,305	7.81	0.195
Savings	$33,440	$9,782	$58,140	24.42	0.622
Bank Card/Credit Bureau Data					
All Liabilities	$294,600	$258,600	$204,585	21.74	0.568
MTG Balance	$250,900	$222,600	$165,344	20.94	0.554
MTG Interest Rate	6.96%	6.75%	3.33%	21.60	0.565
Has Autoloan	30.4%			21.74	0.568
Has *MyBank* MTG	32.1%			24.42	0.622
Bal Used/Available All Credit	21.9%	7.0%	29.3%	20.49	0.550
FICO Bank Credit Score	768	782	73.1	21.74	0.568
C. Households w/ MyBank Mortgage					
Mortgage Data (@ origination)					
MTG Balance (000s)	169.7	139.5	113.0		
MTG Interest Rate (%)	5.88	5.75	1.30		
Income @ Origination	7,054	5,730	5,025		
Combined Loan-to-Value	73.1	77.47	19.9		
Is Fixed Rate	91.2%				

Table BII. *MyBank* Summary Stats vs. Survey of Consumer Finance

To be included in the panel all households must have at least 12 months with deposits across all accounts >=$100 & <=$50k and a mean and median level of deposits across all accounts >=$500 & <=$25k. For direct deposits the HH must have at least 12 months of direct deposits >=$100 & <=$25k, a mean and median level of direct deposits across all accounts >=$500 & <=$25k and >=75% of all deposits must be via the direct deposit channel. All data winsorized at 99th percentile. This sample includes only households that have retail and mortgage accounts at *MyBank* from 2010-2014. Data from Survey of Consumer Finance (SCF) comes from 2010 and includes all households with a primary mortgage outstanding balance of at least $1,000 (13,580 households).

	SCF Median (2010)	*MyBank* Median	*MyBank* Std. Dev
Households w/ *MyBank* Retail & *MyBank* Mortgage 2010-2014			
Retail Data			
Income (All)	$5,083	$5,315	$8,439
Income (Dir. Dep. w/ Filter)	--	$5,172	$5,226
Savings	$7,850	$10,100	$60,626
Mortgage Data			
Current Loan-to-Value (%)	58.6	58.0	31.5
MTG Interest Rate	5.39	5.38	1.23
Is Fixed Rate	87.4%	83.9%	

Table BIII. Negative Home Equity and Labor Supply w/o HH Fixed Effects

This table shows the average change in household income associated with negative household home equity using variation in the timing of home purchase as an instrument for the probably of having negative equity. The instrument is a dummy variable equal to one if a household's synthetic loan-to-value ratio (SLTV) is greater than 100% after controlling for MSA-time, origination date-time, and household fixed effects. Column 1 shows the results of running the two-stage least squares procedure of regressing raw monthly deposit inflows as the dependent variable, without any normalization, on instrumented negative home equity. Column 2 is the same as column 1 but the dependent variable is the % change in deposits, where the numerator is the monthly deposit inflows and the denominator is the household's income at the time of mortgage origination. Column 3 is the same as column 2, but includes zip-time instead of MSA-time fixed effects. Column 4 is the same as 2, but includes time varying non-parametric household-level controls. These include deciles for origination income and property value, mortgage original interest rate by percentage buckets, and original credit score in bins of 50 all interacted with time fixed effects. Column 5 is the same as 2, but includes MSA x time x origination year fixed effects. Column 6 is the same as 2, but instead of origination date x time fixed effects it includes graduation year x MSA x time fixed effects among the subset of borrowers with outstanding student loans. All standard errors are clustered at the MSA level. P-Values: * 10%; ** 5%; ***1%.

		Zip FE	X_{it} Controls	Orig Yr x MSA FE	Grad Yr FEs
	(1)	(2)	(3)	(4)	(5)
	%ΔDep	%ΔDep	%ΔDep	%ΔDep	%ΔDep
LTV>1	-7.06***	-6.24***	-6.43***	-3.89**	-4.56**
(IV: SLTV>1)	(2.18)	(2.13)	(1.22)	(1.04)	(2.42)
Region x Time FE	Y/MSA	Y/ZIP	Y/MSA	N/A	N/A
Orig. Date x Time FE	Y	Y	Y	N/A	N/A
HH FE	N	N	N	N	N
HH Time Varying Controls	N	N	Y	N	N
MSA x Time x Orig Yr FE	N	N	N	Y	Y
MSA x Time x Grad Yr FE	N	N	N	N	N
F-Stat	495.1	485.2	492.0	65.3	68.7
Adjusted R^2	0.073	0.084	0.074	0.104	0.095
Observations (mil)	5.375	5.271	5.219	5.219	5.219

Table BIV. Additional Robustness

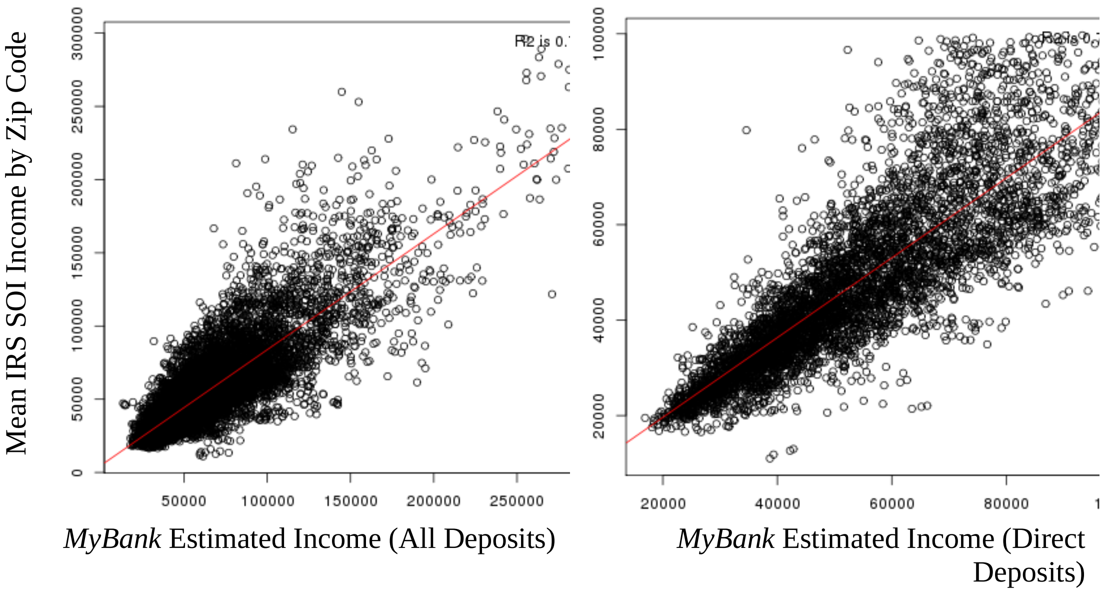
This table shows that the negative effect of mortgage loan-to-value (LTV) on labor supply is robust to the choice of measuring income and the household. Just as in the main specifications Column 1 regresses the % change in deposits on an instrumented dummy equal to one if current mortgage loan to home value is greater than 100%, region x time, origination date x time, and household fixed effects. A dummy which equals 1 if a household's synthetic loan to value ratio (SLTV) measure is greater than 100% is used as an instrument for the likelihood that a household has negative home equity. SLTV is an instrument for loan-to-value that does not depend on household specific factors, except the timing of moving, and varies at the region-time-cohort level. As in the primary specifications the numerator is still the monthly deposit inflows, but in this case the denominator is the households average monthly deposit inflows over the entire sample period. Column 2 is the same as column 1, but includes direct deposits instead of all deposits and normalizes by the income at origination just as in the main specification. Column 3 is the same as column 1 but the dependent variable is the log of all monthly deposit inflows, with nothing in the denominator. For households with 0 deposits in a given month, but with a still active account $1 was included instead. Column 4 is the same as the main specification, but households are defined based on an internal *MyBank* identifier instead of using those people with a shared mortgage liability. All standard errors are clustered at the MSA level. P-Values: * 10%; ** 5%; ***1%.

	(1) %ΔDep	(2) %ΔDirDep	(3) log(1+Dep)	(4) %ΔDep
LTV>100 (IV: SLTV>100)	-4.08*** (0.76)	-5.28*** (1.26)	-3.69** (1.89)	-3.38*** (1.15)
Region x Time FE	Y	Y	Y	Y
HH FE	Y	Y	Y	Y
Cohort x Time FE	Y	Y	Y	Y
Adjusted R^2	0.030	0.397	0.572	0.475
Define HH	Shared MTG	Shared MTG	Shared MTG	Internal
Denominator	Mean Dep	Orig Income	N/A	Orig Income
Observations (mil)	5.375	5.375	5.375	5.670

Figure B1. Validity of Income Measure – Part 1

Zip-Code Level Mean Income IRS SOI vs. MyBank (2010-2013)

These figures compare the mean incomes by zip code from 2010-2013. To be included there must be at least 4,000 IRS SOI returns and at least 1,000 *MyBank* observations per zip-code year w/ filters applied. To be included in the panel all households must have at least 12 months with deposits across all accounts >=$100 & <=$25k, a mean and median level of deposits across all accounts >=$500 & <=$25k. For direct deposits the HH must have at least 12 months of direct deposits >=$100 & <=$25k, a mean and median level of direct deposits across all accounts >=$500 & <=$25k and >=75% of all deposits must be via the direct deposit channel.

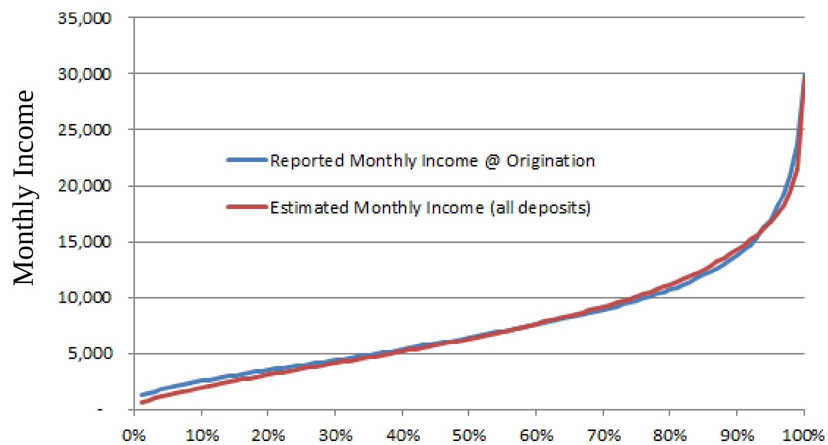


Correlations	All Deposits	All Direct Deposits	All Jobs
MyBank Retail Acct	0.832	0.886	0.911
MyBank RTL, CC, & Any MTG	0.838	0.777	0.736

Figure B2. Validity of Income Measure – Part 2

Estimated Income vs. MyBank @ Origination Distribution

This figure compares the cumulative distribution of reported income at mortgage origination for *MyBank* mortgages with the estimated income based on retail deposits for all households in the same calendar year for all households with data available for both, who meet the filter requirements. To be included in the panel all households must have at least 12 months with deposits across all accounts and years >=$100 & <=$25k, a mean and median level of deposits across all accounts and years >=$500 & <=$25k. For direct deposits the HH must have at least 12 months of direct deposits >=$100 & <=$25k, a mean and median level of direct deposits across all accounts >=$500 & <=$25k and >=75% of all deposits must be via the direct deposit channel. The table below includes the pair-wise individual correlations for each household for all three measures of income.



Correlation	All Deposits	Direct Deposits	Job Direct Deposits
MyBank RTL & CC & Any MTG	0.378	0.511	0.449

Figure B3. Validity of Delinquency Measure

This figure compares a time series of mortgage delinquency rates for households with mortgage at *MyBank* using *MyBank's* internal mortgage data with national seasonally adjusted quarterly mortgage delinquency rates published by Federal Reserve Economic Data (FRED) from 2009-2014. Quarterly data from are interpolated between quarters to provided monthly estimates. The green and blue top lines for both FRED and *MyBank* represent the percent of all mortgages that are at least 30 days past due. The red bottom line represents all *MyBank* mortgages that are at least 90 days past due.

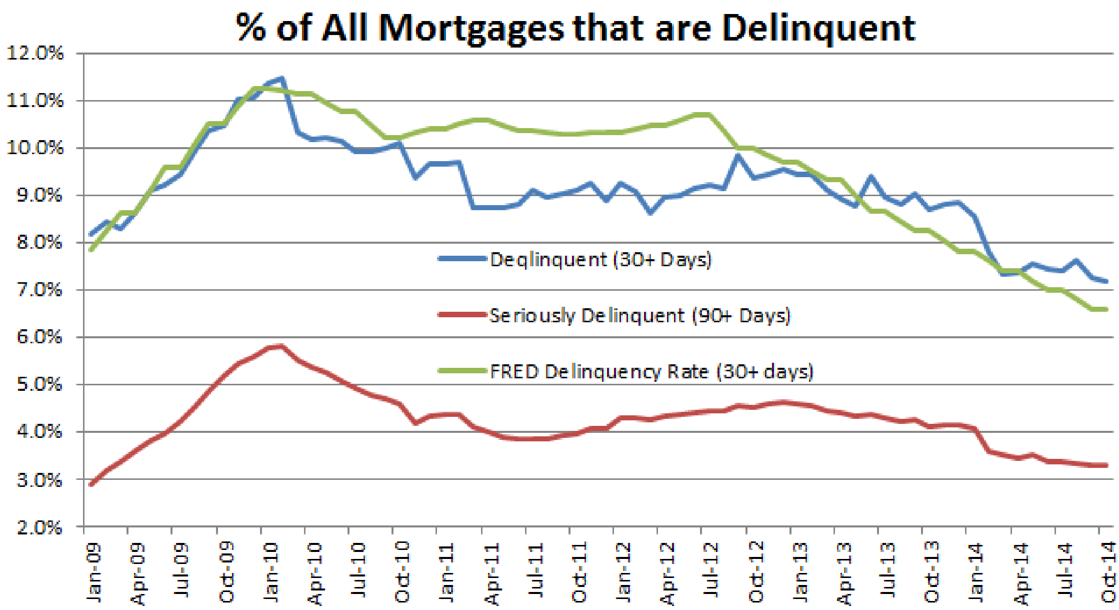
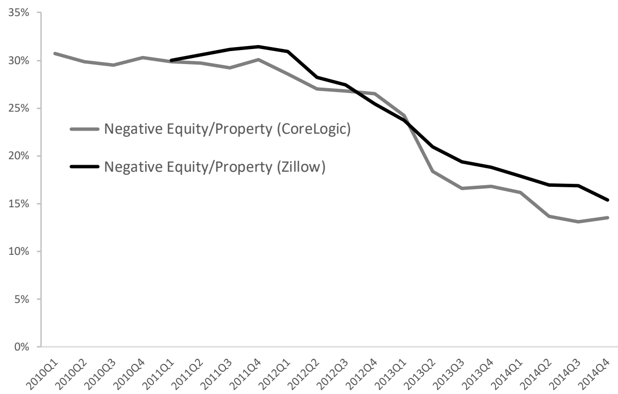


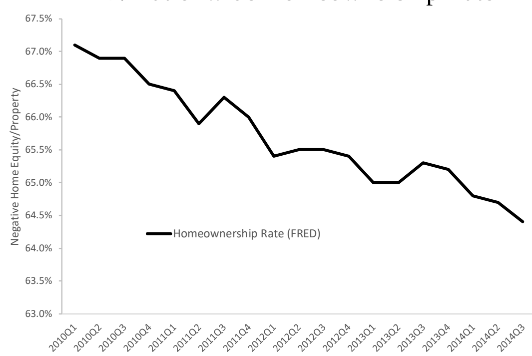
Figure B4. Time Series Statistics on Negative Home Equity

This figure provides aggregate statistics on the nationwide percent of properties with negative home equity based on data from CoreLogic and Zillow (Panel A), the nationwide homeownership rate from FRED (Panel B), and the difference in negative home equity rates for MSAs two standard deviations above and below the average according to data from Zillow (Panel C).

A. Nationwide Negative Home Equity Rate



B. Nationwide Homeownership Rate



C. Negative Home Equity Rate Variation by MSA