Household Debt Overhang and Labor Supply

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Abstract

For households with homes worth less than the mortgage I test the effect of "household debt overhang" on their labor supply decisions. I utilize 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. I then exploit plausibly exogenous variation in the timing of home purchases among households in the same region and time as an instrument for the probability of negative home equity and find that negative equity causes a 2%-6% reduction in household labor supply. These results are robust to the inclusion of time-varying national cohort fixed effects as well as using a life-event driven proxy for the timing of home purchase based on the date of college attendance. Income-contingent loss mitigation creates implicit marginal tax rates that provide a plausible channel by which household debt overhang acts. Consistent with this explanation I find that the labor supply decline is larger in regions where mortgage modifications are more prevalent, even if foreclosures occur less frequently. Taken together these results provide evidence that the moral hazard problem caused by mortgage debt overhang can exacerbate employment declines and highlights the potential unintended consequences of mortgage assistance programs.

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1 Introduction

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 employment still below pre-recession levels for years after the crisis[2]. A number of recent theoretical papers (Mulligan (2008, 2009, 2010), Herkenhoff and Ohanian (2011), Donaldson et al. (2014)) have shown that this co-incident movement in housing and labor markets may have been partially driven by perverse labor supply incentives caused by the unprecedented decline in household home equity. They show that house price declines can cause a "household debt overhang" problem, similar to the problem faced by highly levered firms, but where negative home equity exacerbates employment declines. In particular, if household income is transferred to mortgage lenders via increased liability repayment, then this transfer would incentivize households to reduce their labor supply.

In this paper I empirically test the effect of mortgage debt overhang on labor decisions and find that negative home equity causes a substantial reduction in household labor supply. In particular, instrumented negative home equity is associated with a 2.3%-6.3% reduction in household income. This reduction in labor supply appears to be driven by large changes in household labor decisions, such as reductions in employment, rather than effort supplied at existing jobs. Income-contingent loss mitigation strategies by lenders, such as mortgage modifications, create implicit marginal tax rates that provide a plausible channel by which

[1] According to First American CoreLogic as of June 30, 2009. In fact in some states more than half all mortgages were underwater.
[2] Bureau of Labor Statistics (BLS)

household debt overhang acts. Consistent with this explanation, I find that the reduction in labor supply for households with negative home equity is amplified in regions where mortgages are modified at a higher rate, even controlling for delinquency and foreclosure rates in those regions. Despite the potential economic importance of such a mechanism, to the best of my knowledge, this is the first paper to establish the role mortgage debt overhang played in reducing household labor supply following the crisis.

Empirical identification of the effect of household debt overhang 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[3]. 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.

In this paper I overcome these challenges by utilizing 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 home purchases. The transaction-level deposit information allows me to generate accurate high frequency measures of household income, while

[3] 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.

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[4]. I then use information on the timing of home purchase, 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.

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 including household fixed effects, controlling 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 could still be a concern that even within a region the timing of purchase could be related to future house price movements and income shocks in an unobservable way[5]. To reduce even that concern I instrument for negative equity using the age of student loans as a proxy for life-event driven home purchases and find that results are robust to

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

[5] For example, if real estate brokers were more likely to purchase homes in Nevada during the peak of the crisis than they were in say Nashville, they would experience larger house price declines and their labor income could be more exposed to local housing demand shocks.

this specification. This alleviates concerns that omitted variables such as industry choice drive both local demand sensitivity and the timing of home purchases.

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 deposits. This may not be that surprising since virtually all income-contingent loss mitigation programs require documentation of income, which would include income deposited at any institution.

These results complement a recent body of work that investigates how households respond to excess liabilities. A number of recent papers have looked at how indebtedness affects entrepreneurial activity (Adelino, Schoar, and Severino 2015), employment opportunities among impoverished households (Bos et al. 2015)[6], and labor income among bankrupt households

[6] The paper focuses on 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

(Dobbie and Song 2015b). Melzer (2015) has also shown that households with negative home equity reduce investments in their house, since they anticipate no longer being residual claimants. Mayer et al. (2014) found that households were aware of the announcement of a large scale mortgage modification program by Countrywide and responded by falling delinquent, despite the ability to pay. Taken together these results suggest that a significant number of households are aware of their home equity and loss mitigation programs, and are willing to respond strategically via their home investment and mortgage payment decisions[7]. This paper contributes to this literature by showing that households also reduce their labor supply in response to the incentives provided by negative home equity and mortgage assistance programs.

This paper also fits within a broader literature analyzing the relationships between household liabilities, assets, consumption, and labor decisions. This includes a broad and growing literature trying to understand how negative home equity interacts with labor mobility in the U.S. and abroad (Fredrick et al. (2014), Cohen-Cole et al. (2015), Demyanyk et al. (2013), Donovan et al. (2011), Goetz (2013), Modestino and Dennett (2013), Mumford and Schultz (2014), Schulhofer-Wohl (2012), Struyven (2014))[8], the effect of contract modifications including large scale loan modifications programs (Agarwal et al. (2010), Agarwal et al. (2012),

homeowners. Credit constraints that prevent this population from finding employment, such as being unable to use a credit card to buy as suit, seem unlikely to extend to the average U.S. homeowner.

[7] Even though the authors are unable to investigate the effects on income of the announcement of the countrywide program it is worth noting that settlement had debt-to-income targets of 34% for at least 5 years based on the previous 1 year of income, which like HAMP imply marginal tax rates in excess of 100%. A household willing to stop paying their mortgage and forgo an employment opportunity would be eligible for more than 100% of the forgone income in reduced monthly payments once they received a modification.

[8] 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 is divided. 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 is unlikely to be much larger than tenths of a percent, and certainly not the 2.3%-6.3% observed in this paper.

Calomiris et al. (2011), Chang and Weizheng (2013), Collins and Urban (2015), Dobbie and Song (2015a), Dobbie and Song (2015b), Goodman et al. (2011), Goodman et al. (2012), Goodman and Woluchem (2014), Lucas et al. (2011), Mayer et al. (2014), McCoy (2013), Mulligan (2009), Schmeiser and Gross (2014), Gerardi and Li (2010)), and how liabilities alter household consumption and investment decisions (Baker (2015), Bhutta et al. (2010), Adelino et al. (2015), Cunningham and Reed (2013), Foote et al. (2008), Fuster and Willen (2013), Gerardi et al. (2013), Guiso et al. (2013), Melzer (2015)).

The remainder of the paper is organized as follows: Section 2 begins with a discussion of household debt overhang and the relationship with mortgage modification programs. Section 3 precedes with a description of the data. In Section 4, I present the empirical methodology. I discuss the empirical results in Section 5. Section 6 concludes the paper.

2 Debt Overhang and Mortgage Modifications

For highly levered firms a reduction in firm wealth reduces the marginal incentives for investment in positive net present value projects because the benefits accrue disproportionally to existing debt holders (Myers 1977). Highly levered households face a similar 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 liability repayment, then this transfer to debt holders acts just like an implicit tax that incentivizes households to reduce their labor supply (Mulligan (2008, 2009, 2010), Herkenhoff and Ohanian (2011), Donaldson et al. (2014)).

While in practice income-contingent repayment for foreclosed properties in deficiency judgments are rare (Ghent and Kudlyak 2011), income contingent mortgage modifications were ubiquitous following the crisis (Goodman et al. 2011) and likely provide a major channel through which household debt overhang problems occur. In response to the substantial rise in mortgage delinquencies during the crisis, lenders engaged in large scale mortgage modification programs to help distressed borrowers. In fact from January 2008-May 2011 51% of all non-performing or re-performing subprime mortgages received a mortgage modification (Goodman et al. 2011)[9]. While these modifications may have been optimal collection strategies by lenders they may have also provided perverse labor supply incentives. Mulligan (2009) has shown that in theory and in practice lenders are more likely to engage in loss-mitigation actions for delinquent borrowers if they demonstrate a reduced ability to pay their liabilities. These income-contingent loss mitigations result in implicit marginal tax rates with strong moral hazard incentives for households to reduce labor supply. In the case of the majority of public mortgage modification programs debt-to-income targets create implied marginal tax rates in excess of 100% for households with negative equity, which as noted by Mulligan (2009) "is significant even from a macroeconomic perspective" and likely to "produce distortions that are large enough to be visible in the national employment data".

These income-contingent loss mitigations mean that for many households with negative equity the majority of benefits from additional time and effort invested in employment income accrue to the debt holders rather than the household. For example, if an average negative home equity household with $4,000/month in gross income and $1,500 in monthly mortgage payments

[9] For Prime, Alt A, and Option ARM, the modification rates were 23%, 31%, and 29% respectively.

was seeking a mortgage modification via the Home Affordable Modification Program (HAMP) and worked to earn an extra $500/month in income not only would all of the additional $500/month in income accrue to the lender, the household would actually end up losing at least $3,271 over the next 5 years despite the additional time/effort[10]. Just like in the classic corporate debt overhang problem faced by firms "the gain in the market value of debt acts like a tax on new investment [and] if that tax is high enough, managers may try to shrink the firm" (Myers 2001), where in the case of this household debt overhang problem the borrower reduces the "firm" by reducing their labor supply. This could mean that a fall in housing wealth, which via a wealth effect would normally suggest a rise (weakly) in household labor supply, could actually cause a reduction in labor supply via a substitution effect coming from the implicit marginal tax of the income-contingent loss mitigation by the lender.

3 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 from the Internal Revenue Service (IRS) to validate my income measures and state-level judicial foreclosure law information.

3.1 *MyBank* Data

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[11]. For the purposes of this project I focus on households with

[10] Calculations based on checkmynpv.com.

[11] 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

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 appendix A I detail how household information from multiple *MyBank* accounts are combined at a monthly frequency. Information on the change in sample size because of data requirements is shown in table A1.

3.1.1 Mortgage Accounts Data

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 2 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.

3.1.2 Credit Card Accounts Data

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

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 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 term, balance, monthly payments, and initial balance.

3.1.3 Retail Accounts Data

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, such as "ACH direct deposit", 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 further restrict my analysis to households with active accounts[12] who appear to use their *MyBank* retail accounts to deposit the majority of their income[13].

To explore the validity of using deposits as an income measure I then focus on 376 million direct deposit transactions and utilize the fact that direct deposit paychecks tend to fall on a set of possible regular schedules. This allows me to explore to what extent my deposits are

[12] 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.

[13] 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.

consistent with what would be expected and create a "jobs algorithm" to try and assign paychecks to specifics regularly paying jobs. I find that consistent with bureau of labor surveys my paychecks peak on the 1st, 3rd, 15th and last day of the month[14]. Direct deposits tend to pay on Fridays, as expected, while physical deposits tend to post on the following Mondays. After running the "jobs algorithm" 90% of account-month observations have at least one job associated with them, where the assigned jobs paychecks can explain 84% of all observed deposits. In fact according to the Social Security Administration[15] the average monthly benefits for a beneficiary of social security is $1,223.45/month, which matches favorably with the $1,267.5/month I see per social security recipient in my sample based on the algorithm. For more details on the algorithm see appendix B.

Given the importance of this income measure for my analysis I also confirm the validity of my income measure by comparing the average annual income based on my deposit data at a zip code-level with those reported by the IRS Statistics of Income (SOI) over the period 2010-2013. In figure 1A 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 one measure does not appear to be systematically higher suggests that for the subset of households analyzed deposits represent an effective measure of household income.

3.1.3 Merging *MyBank* Data

[14] The peak on the 3rd is due to social security payments. For more details see Appendix B as well as Stephens (2003).
[15] www.ssa.gov

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 or 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 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 appendix A.

I analyze a broad range of characteristics for each sub-sample of *MyBank* in table 1. 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 A2 in appendix A.

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 1B 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 in come 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.

3.2 IRS Zip Code Level Income Data

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.

3.3 State-Level Judicial Foreclosure Data

As noted by Mian et al. (2015) states that don't require judicial procedures for mortgage lenders to foreclose on delinquent borrowers are twice as likely to foreclose. The increased ease and likelihood of foreclosure reduces the likelihood that non-performing mortgages will receive a modification. For example, the documentation for the net present value tests for mortgage modifications under HAMP includes "state-level foreclosure timelines" and "state-level average foreclosure costs" as major determinants of whether or not a mortgage modification should be undertaken. To explore this source of variation I merge in state-level judicial foreclosure requirements based on RealtyTrac's website, just as was carried out in Mian et al. (2015).

3 Empirical Methodology

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 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 simple panel regression

$$y_{icrt} = \alpha_i + \gamma_{rt} + \sum_k \delta_{1k} \cdot 1_{\{l_k \le LTV_{it} \le \mathrm{h_k}\}} + X'_{it}\beta + \epsilon_{icrt} \tag{1}$$

where for household *i* in month *t* in region *r* that originated their mortgage on date *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, household-level fixed effects, and a number of time-varying household level controls, X'_{it}. 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 region level, the inclusion of region x time fixed effects precludes the possibility that results are driven by variation in local demand shocks or individual variation in home investment. I also include multiple loan-to-value indicator buckets to see if, as would be predicted by household debt overhang, declines in income occur only for high loan-to-value ratios. In this specification I also include household fixed effects to rule out any time invariant omitted variables, as well as time-varying household-level controls such as the amount of mortgage pre-payment as well as non-linear controls for credit score, origination home equity, and origination income interacted with time fixed effects.

Despite the inclusion of all these controls time-varying household level variation in LTV still has the potential to confound casual 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.

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

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).

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

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 the 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 household having negative equity:

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

Variation in SLTV, after including all controls in equation (1), will be driven almost entirely by the timing of house purchase within a given region. Households that bought homes prior to relative local house price declines will have higher SLTVs relative to those who bought immediately afterward.

To formalize the instrumental variable approach define I run a 2SLS regression where the 1st stage is

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

,where I defined a household who has negative home equity (aka underwater) as $U_{it} \equiv 1_{\{LTV_{it} \geq 100\}}$, and the 2nd stage is[16]

$$y_{icrt} = \alpha_i + \gamma_{rt} + \phi_{ct} + \delta_2 \cdot \widehat{U}_{it} + X'_{it}\beta + \epsilon_{icrt} \tag{7}$$

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. To extent that all remaining variation in SLTV after all controls is driven by the timing of home purchases the exclusion restriction requires that the timing of home purchases is unrelated to other factors that could alter future income changes. To make this clear as a robustness check I

[16] 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.

also replace the 1st stage above with one that only includes house price changes at a region-cohort-time level explicitly.

This still leaves one possible confounding factor; the timing of house purchases within a region could violate the exclusion restriction. For example, if house price purchases by households with income more sensitive to local demand shocks could predict future house price declines then this could be potentially problematic. To address this I focus on life-event driven moves based on the time since a household attended college. In particular for each household rather than using the region-cohort-time percent change in house price I instead use the expected change in house price at the region-college attendance year-time as a proxy for the house price change.

4 Results

4.1 Negative Home Equity and Household Labor Supply

In this section I analyze the results of using variation in the timing of house purchases as a plausibly exogenous source of variation in the probability of having negative home equity among households living in the same region at the same time. I focus on the subset of households with sufficient deposit and mortgage information at *MyBank* to estimate current income, income at origination, and current loan-to-value. In table 2 column 1 I regress the % change in income, normalized by income reported at the time of mortgage origination, on indicators for varying loan-to-value ratio ranges, while including MSA x time fixed effects, household-level timing varying prepayment controls, income at origination, and 10% indicator buckets for original loan-to-value interacted with time fixed effects. Consistent with negative equity reducing labor supply

I find that for low values of loan-to-value buckets income does not fall, but for high LTVs income falls by 4-5%. One potential concern is that income at origination and the additional other household time invariant controls may not capture all differences in characteristics across cohorts that could later reduce income via omitted variables. To address that concern in column 2 I rerun the analysis using household fixed effects. Though there is a small increase in the income reduction for a lower tier of loan-to-value ratios, for all high loan-to-value ratios results are largely unchanged. The non-linear nature of the effect of loan-to-value ratio on changes in income is illustrated clearly in figure 3. In this figure the x-axis are 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 run I just described for column 2. The only difference, besides more granular buckets, is that I normalize the fixed effect so buckets less than 100% sum to zero, allowing us to cleanly observe any changes that occur for high loan-to-value buckets. What we see is that for low loan-to-value ratios changes in loan-to-value do not have significant effects on labor income, but for high values, especially those above 100% LTV we see a large and consistent reduction in income. These results are consistent with household debt overhang causing a reduction in labor supply[17]. If we were concerned that variation in moving date is generally correlated with sensitivity to local demand shocks we would expect differences in income changes even for low loan-to-value buckets. Restricting the analysis to only direct deposits on the left hand side in column 3 yields almost identical results, lending credibility to

[17] Note that for lenders the pertinent loan-to-value ratio would be the value after sale, including all costs. Since these house prices are computed at a region level and do not account for the costs of execution we would expect some reduction in income even for households with observed loan-to-value ratios just below 100%.

the fact that changes in deposits are being caused by a reduction in wages rather than some other form of account inflows.

As was mentioned previously there could still be a concern with the above procedure that time-varying household specific factors, including income, could influence the loan-to-value ratio. To address this concern in table 3 I set a dummy variable equal to 1 if the synthetic loan-to-value ratio, which is not based any household specific time varying factors, is greater than 100%. In column 1 I run a reduced form regression using the negative equity synthetic LTV as an instrument, after controlling for MSA x time and household fixed effects, and I find that it is associated with a statistically significant reduction in household labor income. To quantify the size of this effect and the validity of the IV I run a formal 1st stage in column 2 and find that a negative SLTV is associated with a 36.8% higher chance of a household having negative equity, after controlling for MSA x time and household fixed effects, and reveals that this is a strong instrument. The formal result of this IV is shown in column 3 and shows that estimated average effect of negative equity is a 3.63% reduction in household income. When re-running the analysis using raw $ deposits per month instead of normalizing by origination income I find that it reduces income by -$366/month or about 4% of mean monthly income in my sample.

In columns 5-7 I show the results are robust to the choice of instrument. In particular in columns 5 and 6 I use a non-linear 1st stage based on 10% SLTV buckets and find that income falls 2.34% and $305/month respectively. As noted previously, you may still be concerned that even the SLTV could be providing some variation in current LTV not driven solely by the timing of moving. To alleviate this concern I use 10% buckets for MSA level house price changes since mortgage origination as an instrument, after controlling for MSA x time and household fixed effects. The reduced form of this IV regression is shown in figure 4. Just as was the case with loan-to-value, for low or positive differences house prices based on the timing of moving relative to households in the same region at the same time there is no change in income, but when house prices are significantly lower income falls. Since I am controlling for MSA x time fixed effects and computing changes in house price since origination at an MSA level the only source of variation here is based on the timing of home purchase relative to home owners in the same region at the same time. I run this IV formally in column 7 and find that as expected negative equity is associated with a decline in household income.

In tables 5-7 I show that these declines are robust to the choice of measurement of changes in income and liabilities, clustering of standard errors, observational frequency of the analysis, and are not driven by costs associated delinquency. If my measure of income based on deposits falls systematically relative to reported income as loan-to-value rises then this would negate the debt overhang interpretation of results. To alleviate these concerns in columns 1-3 of table 4 I show that results are largely unchanged when I use current deposits divided by mean deposits over my whole sample, rather than the reported income at origination, or the log of deposits. In table 4 column 4 and table 5 I show that the significance of results is not driven by an underestimate of standard errors due to the high frequency level of monthly observations. In column 4 I show that results are still significant when clustering at the MSA instead of MSA-month level and in table 5 I show that results are robust to running all analysis at the quarterly or yearly frequency, where home equity is computed as either the average or maximum over the sample period. In table 6 I rerun the analysis among the subset of households that also have a *MyBank* credit card account, which allows me to observe all their credit bureau liabilities. In this specification I show that results are robust to using a measure of negative equity based on all liabilities not just those associated with the primary mortgage balance. Since households with negative home equity are more likely to fall delinquent, if the costs of delinquency itself, such as explicit costs, stress, or employer background checks, affect income this would be problematic for my interpretation. I show in table 7 though that the results are significant even looking at only all households that are current on all mortgage payments and so don't face costs associated with delinquency.

Overall these results are consistent with negative home equity causing an average labor income decline of 2.34%-6.34%. With some additional assumptions I can estimate the labor supply elasticity with respect to the implicit tax rate of mortgage modifications. In my mortgage data households with negative equity are 21 percentage points more likely to receive mortgage modifications than those without negative equity. From Mulligan (2009) we know that national mortgage modification programs create a substantial implicit tax, but lost income occurs immediately while lost benefits occur over the following 5 years. We know that total benefits over those 5 years are 1.2-1.5 times larger than the loss in income, so an implicit present value tax rate of 100% is consistent with reasonable discount rate benchmarks. Combining these we can say that the average household with negative equity faces an expected implicit marginal tax rate of 21% and since they reduce their labor supply by 2.34%-6.34% this implies an elasticity of 0.11-0.30. These estimates are lower than the large elasticities of 0.94 estimated by Dobbie and Song (2015b) among bankrupt households, but compare favorably with estimates of Hicksian elasticity of labor supply in the microeconomic literature, which are on average approximately 0.25 (Chetty 2012).

Using the estimated labor supply declines for negative equity we can also get some estimates of the potential macro-economic effects. If the average unemployed household on average earns half of their employed level of income and all changes in labor supply occur via the extensive margin then a 2.3%-6.3% reduction in labor income is consistent with a 4.6%-12.6% rise in unemployment among negative equity households. CoreLogic estimates that approximately 15 million households had negative equity following the crisis. Combining these estimates and aggregating the partial equilibrium results suggest a 0.69-1.89 million decline in job-equivalent labor supply because of household debt overhang. From the peak of 2008 to the trough in 2010 non-farm payrolls fell by about 8.6 million jobs, so the estimated decline from household debt overhang would be 8%-21% the size of the total general equilibrium employment decline following the crisis[18].

4.2 Additional Robustness Checks

One potential concern with these results is that the timing of purchase might be correlated with factors related to future house price changes and labor income declines, which would violate the exclusion restriction of the instrumental variable used. I attempt to address these concerns in Table 8. In columns 1 and 2 I rerun the analysis in columns 3 and 4 of table 3, but now also include cohort x time fixed effects. If the concern is that national trends in the timing of home purchases around the time of the crisis could be related to labor demand shock sensitivity this should capture any variation coming from national cohort effects. I find that effects are essentially unchanged by the inclusion of cohort x time fixed effects where estimated declines in labor income due to negative home equity are 3.47% and $298/month. In column 3 of Table 8 I include purchase cohort x time fixed effects, but also a large range of non-parametric household-specific time varying controls that might be expected to be correlated with labor demand sensitivity. These include declines for origination income and property value, mortgage original

[18] The actual total amount of reduced labor participation following the crisis that can be explained by household debt overhang will depend critically on labor demand curve and in particular the stickiness of wages.

interest rate by percentage buckets, and original credit score in bins of 50 all interacted with time fixed effects. These results show a 4.94% decline in household income, again consistent with overall results.

Even with all these controls, there is still the potential I am missing some omitted variable which varies within region relative to national trends, but that predicts both future relative house price performance in a region and local demand sensitivity. One possible story could be the industries that are related to real estate, such as construction, could perform well in regions when house prices rise, encouraging employees in those industries to purchase properties just before local house price declines. Since workers incomes are more exposed to house price declines this could lead to a violation of the exclusion restriction. To address even this concern I use the time since a household attended college, as proxied by the average origination date of all student debt[19], as an instrument for the likelihood of a household having negative equity. The idea is that the only driver of the timing of home purchases is life-event driven, such as moving after graduating college, rather than something like occupational choice. Consistent with all the previous results I find that this IV regression estimates that negative equity is associated with a 3.78% reduction in household income.

One final 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 their mortgage lender. If households hide income from their lender when they have negative equity this could mean that the reduction in deposits seen for households with negative equity is

[19] 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.

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 filter and measures of income. To be even more careful though in Table 9 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[20] as a proxy for the MSA the property is located in and information from the credit bureau data on mortgage origination dates. I then utilize the same synthetic LTV computed in the previous analysis based on those households with *MyBank* mortgages, which varies only at the region-time-cohort level. 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 of computing the synthetic LTV is likely to reduce the power of the regression, but the reduced form regression still finds that negative SLTV is associated with lower deposits, after including all region x time, cohort x time, and household fixed effects. The result holds 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. Overall these results suggest that hiding income is unlikely to explain the reduction in monthly deposit inflows seen for households with negative equity.

4.3 Extensive vs. Intensive Margin

To understand potential drivers of the decline in labor supply for households with negative equity I investigate how households change their income. Do they alter their labor decisions via

[20] 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.

the extensive margin, such as labor market participation, or the intensive margin, such as altering hours worked at existing jobs? Unfortunately since I do not observe occupational choice I cannot test this directly, what I can test is to what extent changes in income are driven by households making large employment decisions or a many households making marginal changes. In Table 10 I test this in columns 2 and 4 by excluding cases where income changes by more than 25% relative to either the income at origination or the mean income estimated in sample. I find that when excluding large employment decisions there is no longer statistically significant relationship between negative equity and labor supply. This suggests that small changes driven by say reduced ability to wage bargain with a monopsonist among households whose labor mobility is reduced by negative equity[21] is less likely to provide an alternative explanation for the labor supply results shown in this paper. In columns 1 and 3 I show that these results are not driven by households systematically leaving the bank. I exclude only cases where households deposit $0 into their accounts and results are still significant. In column 5 I also show that households are make large reductions in labor income, such as going on unemployment, but are also more likely to leave the labor market entirely. In particular I show that households with negative home equity are more likely to receive social security, which suggests that they are either more likely to retire or move onto disability.

4.4 Effect of Mortgage Modifications Rates

The magnitudes of the decline in labor supply for households with negative equity shown in this paper suggest that household debt overhang induced by income-contingent loss mitigation likely represent the most plausible channel for the relationship between negative equity and labor

[21] See for example Cunningham and Reed (2012).

supply. In figure 5 I show that households with negative equity are much more likely to fall delinquent on their payments and receive a mortgage modification. In fact among households with negative equity and who are 60+ days delinquent 44% receive a mortgage modification within the next 24 months. In figure 6 I take the difference in the distribution of debt-to-income ratios for households with negative equity relative to those with positive equity. Rather than a consistent decline in income across the distribution I find evidence consistent with households shifting above the 31% DTI threshold used by many mortgage modification programs and bunching in the DTI ranges above that threshold. In figure 7 I also find that household income rises dramatically in the months after a household receives a mortgage modification. While there exist multiple possible explanations for the behaviors observed in these figures, they are consistent with income contingent modifications playing a significant role in explaining the labor supply response to negative equity.

To try and analyze the relationship between negative equity, labor supply, and mortgage modifications more formally I rerun the main regressions, but focus on how the average treatment effect of negative equity on labor supply varies across regions that experience more and less mortgage modifications. If households that become delinquent are more likely to receive mortgage modifications in a given region, then if the reduction in labor supply is being driven by income contingent loss mitigation we would expect these households to see a larger reduction in income. In column 1 of Table 11 I test this explicitly by interacting an MSA’s modification rate, relative to the average in the sample, with the negative equity dummy. An MSA’s modification rate is a time invariant metric computed as the number of mortgages that ever receive a modification in a given MSA divided by the number of all mortgages ever in a region. I find that a one-standard deviation increase (1.54%) in the modification rate is associated with 0.72%

larger reduction in labor supply for households with negative equity. If we assume that this increased modification rate holds for negative equity households then this would suggest a point estimate for the elasticity of labor supply with respect to mortgage modifications of 0.47.

One concern with this analysis could be that areas with more modifications could also have more delinquencies, foreclosures, and generally worse economic conditions which could perhaps effect heterogeneity in the average treatment effect. To reduce this concern I show in column 2 that results are robust to the inclusion of the percent of all mortgages that are ever at least 60 days delinquent as a control. In column 3 I also show the effect of negative equity on labor supply is larger if the modification rate is higher among only mortgages that are at least 60 days delinquent. Similar to in column 1 I find that a one-standard deviation change in this measure of modification rate (3.91%) is associated with a 0.801% decline in labor supply. In column 3 I go one step further to reduce concerns about regional omitted variables driving heterogeneity in the treatment effect, rather than mortgage modification rates. In column 4 of Table 11 I include a dummy variable for the MSA being in a state that has judicial foreclosure requirements. Mian et al. (2015) and Ghent (2012) convincingly argue that state foreclosure laws differ based on historical path dependent exogenous events and there exists no significant differences in a number of characteristics for states with and without judicial foreclosure requirements. States with judicial foreclosure requirements though are twice as likely to foreclose on delinquent borrowers. The increased ease and likelihood of foreclosure reduces the likelihood that non-performing mortgages will receive a modification. For example, the documentation for the net present value tests for mortgage modifications under HAMP includes “state-level foreclosure timelines” and “state-level average foreclosure costs” as major determinants of whether or not a mortgage modification should be undertaken. Consistent with the higher likelihood of modification increasing the effect of negative equity on labor supply I find that states that require judicial foreclosure requirements are associated with larger declines in labor supply for negative equity. Another nice feature of this methodology is that Mian et al. (2015) find that the reduced foreclosures in states with judicial foreclosure requirements leads to smaller aggregate demand shocks. Therefore the larger response of labor supply, in partial equilibrium, that I find for households with negative equity in states with judicial foreclosure requirements exist despite the lower likelihood of foreclosure and improved local labor demand.

5 Conclusion

In this paper I investigate the effect of mortgage debt overhang, in particular 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. Instrumenting for home equity, I find that negative equity causes an average reduction of 2.3%-6.3% in household income, consistent with households responding to the incentives created by negative equity and income-dependent mortgage assistance programs by reducing their labor supply. These declines are driven by large employment decisions, such as labor force participation. I also find that the labor supply decline is larger in regions where mortgage modifications are more prevalent, even if foreclosures occur less frequently, highlighting potential unintended consequences of mortgage assistance programs.

These results shed new light on the role mortgage-induced debt overhang played in exacerbating employment declines following the crisis. Mulligan (2008, 2009, 2010) has shown that negative home equity acts like an implicit tax on household labor income that provides strong incentivizes for them to reduce their labor supply. 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, and subsequent household debt overhang, play in reducing labor supply. Herkenhoff and Ohanian (2011) and Donaldson, Piacentino, and Thakor (2014) have modelled the implications of these incentives and shown that household debt overhang can raise equilibrium unemployment and could explain some of the sluggish recovery of labor markets after debt-driven financial crises. While identifying the aggregate general equilibrium response to household debt overhang is beyond the scope of this paper, my results do suggest that debt overhang has a role to play in understanding how household balance sheets can exacerbate financial crises.

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Table 1A. 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 winsorised 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	#Observations (mil)	#Households (mil)
A. Households w/ *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
B. 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 1B. Summary Statistics (cont.)

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 winsorised at 99th percentile. This sample includes only households that have retail and mortgage accounts at *MyBank* from 2010-2014.

	Mean	Median	Std. Dev	# Observations (mil)	# Households (mil)
C. 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 Autoloan	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
Is Fixed Rate	83.9%			7.835	0.200

Table 2. Income vs. LTV

This table shows the relationship between income and current household mortgage loan to property value (LTV) after controlling for household specific factors and local demand shocks. Column 1 regresses 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), region x time fixed effects, origination buckets interacted with time fixed effects, controls for household level mortgage pre-payments, mortgage age, and income at origination. Column 2 is the same as column 1, but instead of a variety of household specific controls includes household fixed effects. Column 3 is the same as 2, but the numerator in the dependent variable proxy for income is direct deposit inflows rather than all deposit inflows. All standard errors clustered at the MSA x Cohort level. P-Values: * 10%; ** 5%; ***1%.

	(1) %ΔDeposits	(2) %ΔDeposits	(3) %Δ Direct Deposits
50 < LTV < 90	-0.83	-2.60***	-3.97**
	(0.91)	(0.45)	(0.32)
90 < LTV < 100	-4.15***	-4.48***	-4.55***
	(1.40)	(0.64)	(0.42)
100 < LTV < 110	-4.98***	-5.46***	-5.01***
	(1.69)	(0.75)	(0.48)
110 < LTV	-4.46***	-4.15***	-5.51***
	(2.08)	(0.88)	(0.60)
Region x Time FE	Yes	Yes	Yes
Orig LTV x Time FE	Yes	No	No
Prepay/Amort Control	Yes	No	No
HH FE	No	Yes	Yes
Loan Age FE	Yes	No	No
Income @ Origination	Yes	No	No
Adjusted R^2	0.124	0.486	0.686
Observations (mil)	5.375	5.375	5.375

Table 3. Income vs. Synthetic LTV: An IV Approach

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. Column 1 regresses 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 a dummy which equals 1 if my synthetic loan to value ratio (SLTV) is greater than 100%, region x time fixed effects, and household fixed effects. 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. Column 2 is the same as 1 but includes a dummy equal to 1 if a household's current loan to value is greater than 100%. This is the 1st stage estimate of the IV regression. In column 3 I present the results of using the IV in column 2 on the % change in deposits normalized by origination income. Column 4 is the same as 3 but includes raw monthly deposit inflows as the dependent variable, without any normalization. Column 5 is the same as 3 but uses dummies for SLTV 10% bandwidth buckets as an IV. Column 6 is the same as 5 but looks at raw deposits. Column 7 is the same as 5, but uses 10% buckets of MSA level house price changes since mortgage origination as non-linear IV. All standard errors clustered at the MSA x Cohort level. P-Values: * 10%; ** 5%; ***1%.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	%ΔDep	LTV>100	%ΔDep	$ΔDep	%ΔDep	$ΔDep	%ΔDep
LTV>100			-3.63***	-366.4***			
(IV: SLTV>100)			(0.55)	(58.1)			
LTV>100					-2.34***	-305.3***	
(IV: SLTV 10% Bkts)					(0.51)	(50.4)	
LTV>100							-6.34***
(IV: HPI 10% Bkts)							(1.36)
SLTV>100	-1.34***	0.368***					
	(0.20)	(0.007)					
Region x Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HH FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.488	0.783	0.623	0.377	0.623	0.377	0.623
Observations (mil)	5.375	5.375	5.375	5.375	5.375	5.375	5.375

Table 4. Robust to Normalization

This table shows that the negative effect of mortgage loan-to-value (LTV) on labor supply is robust to the choice of normalization and method of clustering standard errors. 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 fixed effects, 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. 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. 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 column 3 of table 3, but standard errors are clustered at the MSA instead of MSA x cohort level. P-Values: * 10%; ** 5%; ***1%.

	(1) %ΔDep	(2) %ΔDirDep	(3) log(Dep)	(4) %ΔDep
LTV>100 (IV: SLTV>100)	-4.87*** (0.73)	-2.23** (1.10)	-4.50** (1.85)	-3.69*** (0.84)
Region x Time FE	Yes	Yes	Yes	Yes
HH FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.027	0.087	0.572	0.619
Denominator	Mean Dep	Mean DirDep	N/A	Orig Income
SE Clustering-Level	MSA-Mo	MSA-Mo	MSA-Mo	MSA
Observations (mil)	5.375	4.788	5.375	5.375

Table 5. Robust to Observational Frequency

This table shows that the negative effect of mortgage loan-to-value (LTV) on labor supply is robust to the choice of observational frequency. 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 fixed effects, 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 deposits are the average deposits over an entire quarter (3 months) negative equity is actually the % of times a mortgage has negative equity over that 3 month period. Column 2 is the same as column 1, but negative equity is not the % of the time a mortgage has negative equity over the period, but just a dummy equal to 1 if it ever has negative equity over the 3 month period. Column 3 is the same as column 1 but aggregated over calendar year (12 months) instead of quarterly (3 months). Column 4 is the same as column 2 but aggregated over calendar year (12 months) instead of quarterly (3 months). All standard errors are clustered at the MSA x cohort level. P-Values: * 10%; ** 5%; ***1%.

	(1)	(2)	(3)	(4)
	%ΔDep	%ΔDep	%ΔDep	%ΔDep
LTV>100	-6.02***	-5.39***	-6.33***	-5.28***
(IV: SLTV>100)	(0.80)	(0.72)	(1.08)	(0.90)
Region x Time FE	Yes	Yes	Yes	Yes
HH FE	Yes	Yes	Yes	Yes
Negative Equity	Period Mean	Period Max	Period Mean	Period Max
Frequency	Qtrly	Qtrly	Yrly	Yrly
Adjusted R^2	0.042	0.042	0.026	0.026
Observations (mil)	1.867	1.867	0.558	0.558

Table 6. Income vs. LTV: Current vs. Delinquent Borrowers

This table shows that the effect of negative equity on household income is driven by households that are not delinquent on their mortgage payments. 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 fixed effects, 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. The dependent variable is all deposits each month normalized by the reported income at origination. The sample analyzed is restricted to only mortgages that are current on all payments. Column 2 is the same as column 1, but run on the sample of households who are delinquent or foreclosed on their mortgage. All standard errors clustered at the MSA x Cohort level. P-Values: * 10%; ** 5%; ***1%.

	(1)	(2)
	%ΔDep	%ΔDep
LTV>100	-3.97***	2.44
(IV: SLTV>100)	(0.57)	(1.53)
Region x Time FE	Yes	Yes
HH FE	Yes	Yes
Delinquency Status	Current	Delinquent
Adjusted R^2	0.624	0.623
Observations (mil)	4.957	0.247

Table 7. Income vs. LTV: All Liabilities

This table shows that the effect of negative equity on household income is robust to including all liabilities as reported by the credit bureau. Similar to the main specifications Column 1 regresses the % change in deposits on an instrumented dummy equal to one if all outstanding liabilities divided by the home value is greater than 100%, region x time fixed effects, 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. The dependent variable is all deposits each month normalized by the reported income at origination. The sample analyzed is restricted to only households that have *MyBank* mortgage, credit card, and retail accounts. Column 2 is the 1st stage of the instrumental variable regression run in column 1. All standard errors clustered at the MSA x Cohort level. P-Values: * 10%; ** 5%; ***1%.

	(1)	(2)
	%ΔDep	LTV>100
LTV>100 (IV: SLTV>100)	-6.67*** (1.61)	
SLTV>100		0.159*** (0.004)
Region x Time FE	Yes	Yes
HH FE	Yes	Yes
Measure of Equity	All Liabilities	All Liabilities
Adjusted R^2	0.623	0.798
Observations (mil)	3.555	3.555

Table 8. Controlling for Cohort Effects

This table shows the decline 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, is not driven by differential cohort sensitivity to local demand shocks. Column 1 regresses 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 an instrumented dummy equal to one if current mortgage loan to property value is greater than 100%, region x time fixed effects, household fixed effects, and purchase date cohort x time 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. Column 2 is the same as 3 but includes raw monthly deposit inflows as the dependent variable, without any normalization. Column 3 is the same as 1 but also 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 4 uses the time since a household attended college, as proxied by the average origination date of all student debt as an instrument for the likelihood of a household having negative equity. All standard errors clustered at the MSA x Cohort level. P-Values: * 10%; ** 5%; ***1%.

	(1) %ΔDeposits	(2) $ΔMonthly Deposits	(3) %ΔDeposits	(4) %ΔDeposits	(5) %ΔDeposits	(6) %ΔDeposits
LTV>100 (IV: SLTV>100)	-3.47*** (1.18)	-298.1*** (61.3)	-4.94*** (1.03)		-5.63** (2.97)	-3.26*** (0.56)
LTV>100 (IV: College Grad Yr)				-3.78** (1.77)		
MSA x Time FE	Yes	Yes	Yes	Yes	Yes	No
Zip Code x Time FE	No	No	No	No	No	Yes
HH FE	Yes	Yes	Yes	Yes	Yes	No
Cohort x Time FE	Yes	Yes	Yes	No	No	No
HH Time Varying Controls	No	No	Yes	No	No	No
Region x Time x College Grad Yr FE	No	No	No	No	Yes	No
Adjusted R^2	0.490	0.380	0.492	0.547	0.550	0.623
Observations (mil)	5.375	5.375	5.219	0.665	0.665	5.271

Table 9. Mortgages at Non-*MyBank* Lenders

This table shows the relationship between income and current household mortgage loan to property value (LTV) after controlling for household specific factors and local demand shocks is not driven by households who deposit and lend at the same institution hiding income. I do this by using credit bureau data to look at households with *MyBank* retail and credit card accounts but who get mortgages from another lender. Column 1 monthly deposit inflows on an dummy equal to one if my synthetic loan to value ratio (SLTV) measure is greater than 100%, region x time fixed effects, household fixed effects, and home purchase cohort date x time fixed effects. 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. Column 2 is the same as column 1 but restricts the analysis to only households with mortgages not serviced or owned by *MyBank*. P-Values: * 10%; ** 5%; ***1%.

	(1)	(2)
	$ΔMonthly Deposits	$ΔMonthly Deposits
SLTV>100	-48.8***	-65.0***
	(10.4)	(15.0)
Region x Time FE	Yes	Yes
HH FE	Yes	Yes
Cohort x Time FE	Yes	Yes
Mortgage Servicer/Owner	All	Not *MyBank*
Adjusted R^2	0.344	0.348
Observations (mil)	20.113	15.018

Table 10. Extensive vs. Intensive Margin

This table explores the drivers of the negative effect of mortgage loan-to-value (LTV) on labor supply. 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 households 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%, region x time fixed effects, 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 the dependent variable is the average of all monthly deposits over the whole time period for each household rather than the income at origination. Column 4 is the same as column 3 but excludes any declines larger than 25%. Column 5 is the same as column 1, but does not exclude any deposits and the dependent variable is a dummy equal to 1 if the jobs algorithm identifies that the household receives any social security checks. All standard errors are clustered at the MSA x cohort level. P-Values: * 10%; ** 5%; ***1%.

	(1) %ΔDep	(2) %ΔDep	(3) %ΔDep	(4) %ΔDep	(5) %GetSS
LTV>100 (IV: SLTV>100)	-3.28*** (0.54)	0.09 (0.25)	-4.83*** (0.71)	-0.23 (0.17)	0.65** (0.31)
Region x Time FE	Yes	Yes	Yes	Yes	Yes
HH FE	Yes	Yes	Yes	Yes	Yes
Normalization	Orig Inc	Orig Inc	Mean Income	Mean Income	No
%ΔDep Range	>-100%	>-25%	>-100%	>-25%	N/A
Adjusted R^2	0.621	0.597	0.042	0.188	0.549
Observations (mil)	4.794	3.888	4.961	3.076	5.375

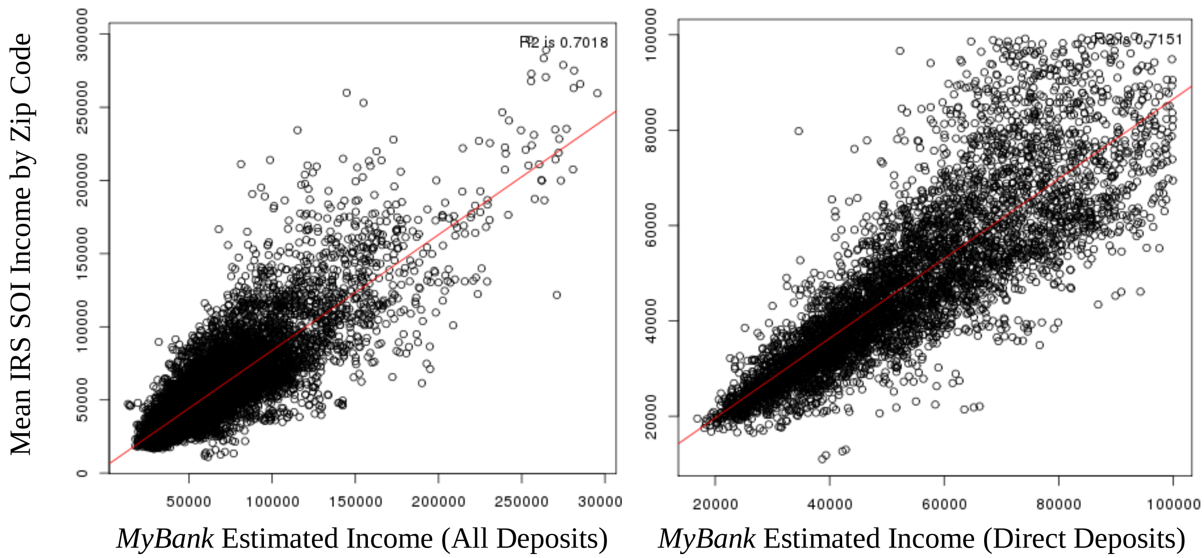
Table 11. Income vs. Negative Equity: Effects in High Modification Regions

This table shows how the relationship between income and current household mortgage loan to property value (LTV), after controlling for household specific factors and local demand shocks, varies in regions when mortgage modifications are more likely. Column 1 regresses 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 an instrumented dummy equal to one if current mortgage loan to home value is greater than 100%, region x time fixed effects, 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. This is also interacted with the level of excess modifications per mortgage in a given MSA. This modification rate is the number of mortgages ever modified from 2010-2014 divided by the number of all outstanding mortgages over the same time period. The excess modification rate is the rate in a given MSA minus the average rate for all MSAs in the sample, weighted by the number of observations in the sample. Column 2 is the same as column 1, but also interacts the excess delinquency rate with the instrument for having negative home equity. The delinquency rate is the number of mortgages ever 60 or more days past due from 2010-2014 divided by the number of all outstanding mortgages over the same time period. The excess delinquency rate is the rate in a given MSA minus the average rate for all MSAs in the sample, weighted by the number of observations in the sample. Column 3 is the same as column 1, but instead of the modification rate for all mortgages I use just the modification rate among delinquent mortgages. The modification rate in this case is the number of mortgages ever modified from 2010-2014 divided by the number of mortgages ever 60 or more days past due over the same time period. The excess modification rate is again the rate in a given MSA minus the average rate for all MSAs in the sample, weighted by the number of observations in the sample. Column 4 is the same as column 1 but includes a dummy variable equal to 1 if the state the property is located in requires judicial foreclosure requirements interacted with the instrumented dummy for negative equity. P-Values: * 10%; ** 5%; ***1%.

	(1) %ΔDep	(2) %ΔDep	(3) %ΔDep	(4) %ΔDep
LTV>100	-3.63***	-3.63***	-3.63***	-3.20***
	(0.55)	(0.55)	(0.55)	(0.46)
LTV>100 x MSA Excess Mod Rate (%)	-0.721**	-1.123**	-0.205**	
	(0.322)	(0.521)	(0.090)	
LTV>100 x MSA Excess DQ Rate (%)		0.161		
		(0.261)		
LTV>100 x Jud Foreclosure State				-1.72*
				(1.01)
Region x Time FE	Yes	Yes	Yes	Yes
HH FE	Yes	Yes	Yes	Yes
IV	SLTV>100	SLTV>100	SLTV>100	SLTV>100
MSA Excess Rate	Ever Mod /MTG	Ever DQ60+ /MTG	Ever Mod / Ever DQ60+	N/A
1SD Excess Mod Rate	1.54%	4.05%	3.91%	N/A
Adjusted R^2	0.619	0.619	0.619	0.619
Observations (mil)	5.375	5.375	5.375	5.375

Figure 1. Validity of Income Measure
1A. Zip-Code Level Mean Income IRS SOI vs. MyBank (2010-2013)

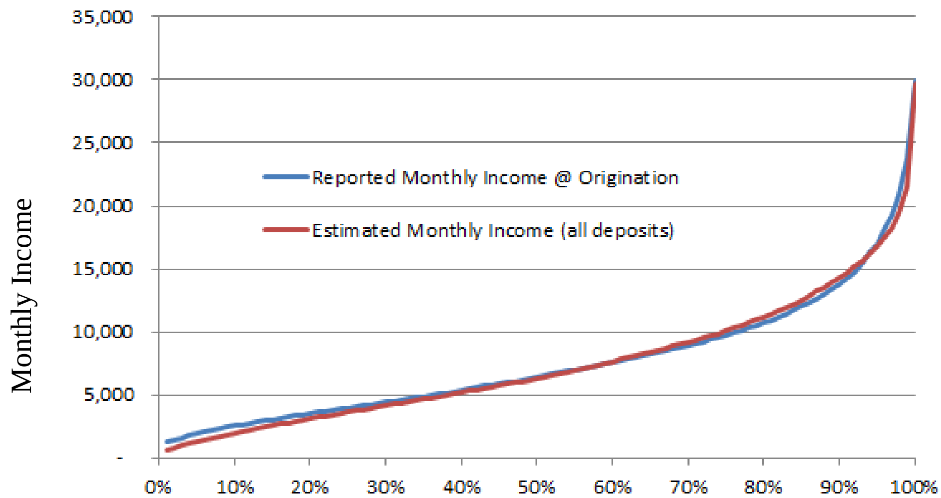
These figures compare the mean incomes by zip code from 2010-2013. To be included there must be at least 4,000 IRS SOI returns and at least 1,000 *MyBank* observations per zip-code year w/ filters applied. To be included in the panel all households must have at least 12 months with deposits across all 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

1B. 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 2. 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.

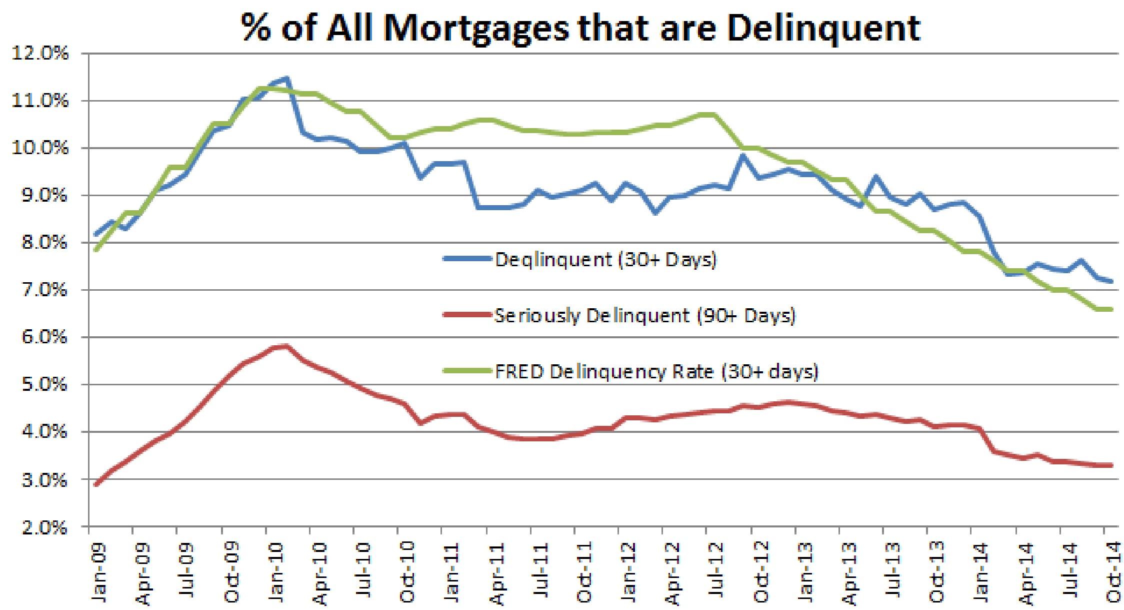


Figure 3. LTV vs. Income: Identification Based on Timing of Moving

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, region x time fixed effects, 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 (shown in red). I normalize the fixed effect so buckets less than 100% sum to zero, allowing us to cleanly observe any changes that occur for high loan-to-value buckets. 95% confidence intervals computing standard errors clustered at the MSA x cohort level, are plotted with dotted lines on either side.

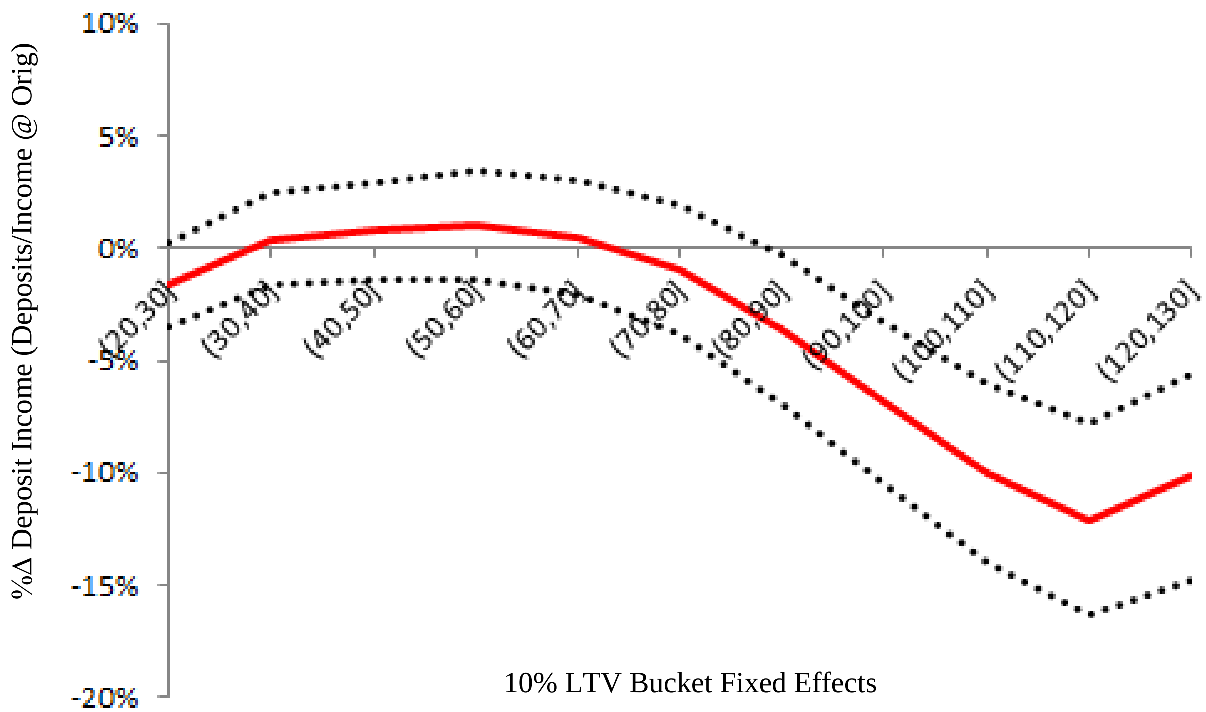


Figure 4. LTV vs. Income: Identification Based HPI IV Reduced Form

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. 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 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, region x time fixed effects, 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 (shown in red). I normalize the fixed effect so buckets greater than 0% sum to zero, allowing us to cleanly observe any changes that occur for negative house price differences. 95% confidence intervals computing standard errors clustered at the MSA x cohort level, are plotted with dotted lines on either side.

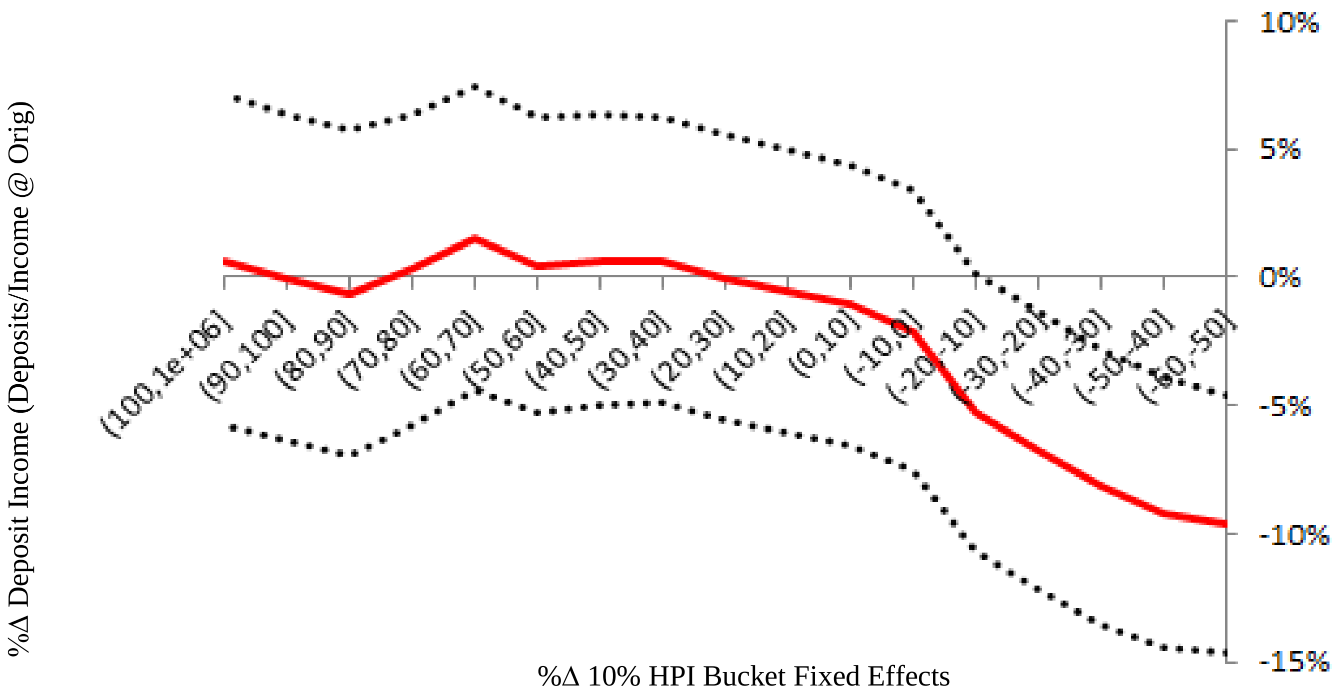


Figure 5. Modification and Delinquency Rates vs. LTV

This figure shows how delinquency and modification rates vary with a household's mortgage loan to home value (LTV) ratio by 10% LTV buckets over the time period 2010-2014. Each unit of observation is at the household month level. The black line represents the % of households with a LTV ratio in a given month with the 10% range that will receive a mortgage modification in within the next year. The red dashed line is the percent who are ever at least 60 days past due on any mortgage interest payments.

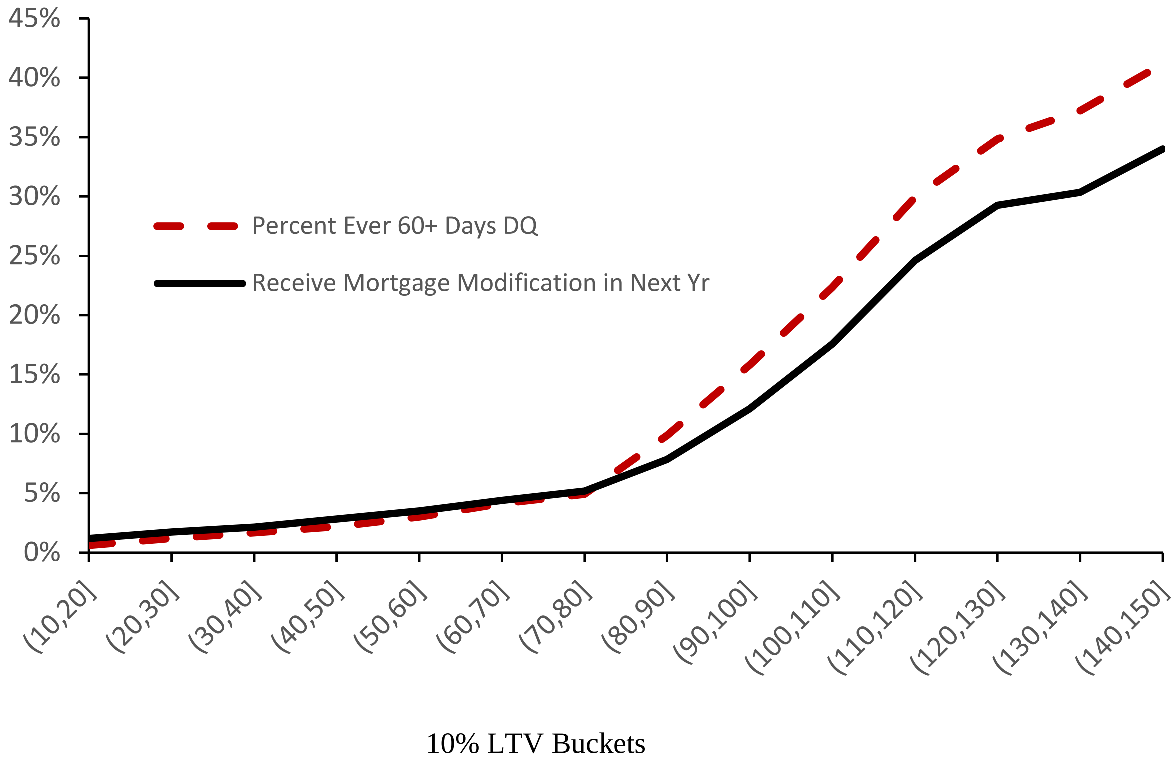


Figure 6. Bunching at Program Kink Points

This figure shows to what extent it appears that distribution of households with negative equity is consistent with bunching above the typically 31% debt-to-income (DTI) threshold of many mortgage modification programs. For all households with retail, credit card, and mortgage account at *MyBank* I compute the probability distribution function of the front end DTI ratio for each household-month observation from 2010-2014 for those households with and without negative home equity. I then take the difference between these distributions and plot tem here as a function of 1% DTI buckets.

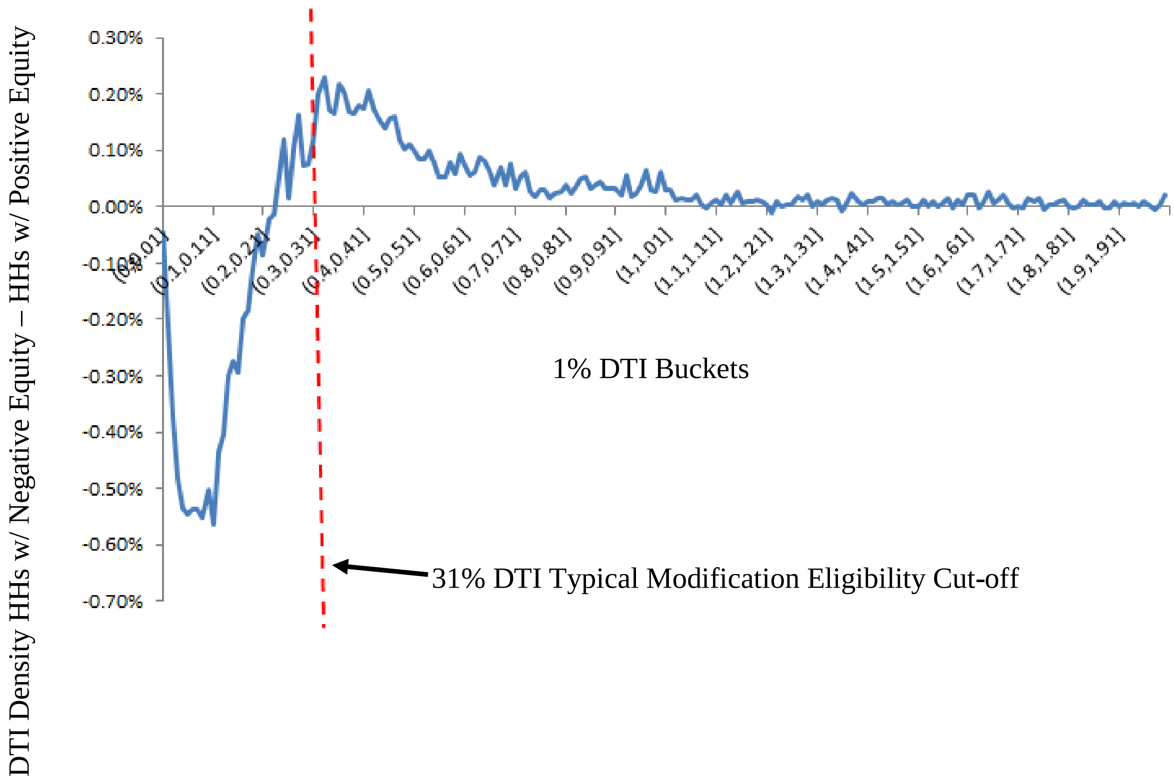
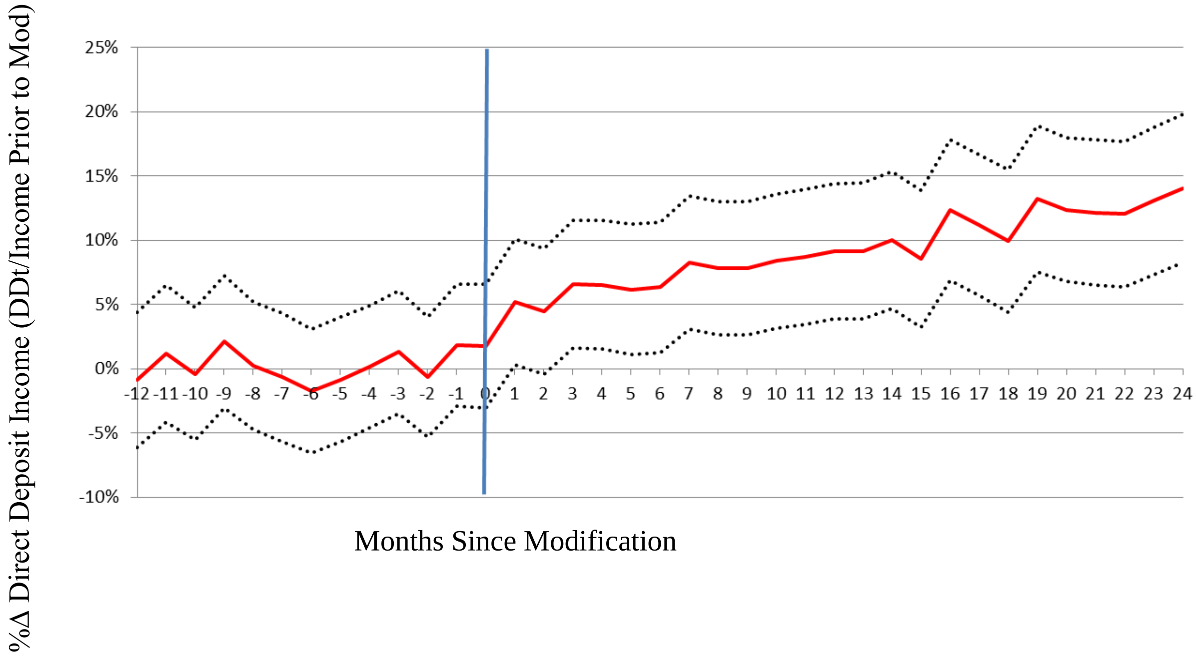


Figure 7. Mortgage Modifications and Labor Supply Event Study

In this figure I look at how household income changes for households who receive mortgage modifications around the dates they receive modifications. This figure plots the results from a regression of 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 dummies for event time relative to the month a mortgage is modified, with time, loan, and household fixed effects. The red line is the estimated coefficients from the event time dummies, normalized to zero for the pre-event period, and the dotted lines represent 95% confidence internals for these estimates, using standard errors clustered at the household level.



Appendices

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. In table A2 I also compare simple summary statistics from this primary sub-sample of households with *MyBank* mortgages and retail accounts with self-reported information collected by the Survey of Consumer Finance (SCF) for households with at least $1,000 in active mortgage balance in 2010. I find that my sample of households has similar levels of income, non-housing financial assets, mortgage leverage, and are charge comparable mortgage interest rates consistent with the representative *MyBank* national coverage and lending credibility to the external validity of the conclusions of this paper.

Table A1. 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)	#Accts (mil)	#Custs (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

Table A2. *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 winsorised 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%	

Appendix B. Jobs Algorithm

Of the billions of transactions from 2010-2014 there are 731,219,999 transactions into accounts at MyBank which are labeled as "deposits". Of these ~376m (51%) are direct deposits (denoted by "ACH direct deposit"), 327m (45%) are physical deposits, which include teller and ATM deposits, and the remaining ~28m (4%) include other deposit types such as "Mobile RDC Deposits". Excluded from these transactions are all transfers, outflows, et al. Besides a broad classification the dataset also includes account IDs and the date they were made. Table B1 below illustrates a hypothetical set of deposits in the data files provided[22].

Table B1. Hypothetical Example of Transaction Dataset

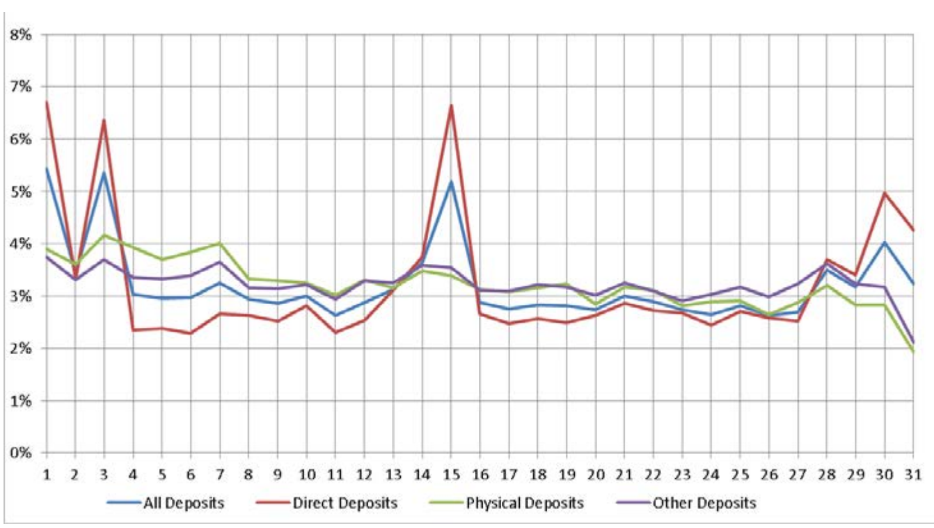
Date	**Acct ID**	**Description**	**Amount**
1/15/2011	1032101	ATM Deposit	130.00
1/15/2011	1032101	ACH Direct Deposit	652.21
1/30/2011	1032101	ACH Direct Deposit	652.21
1/3/2011	2031411	Mobile RDC Deposit	78.32

Since no information is provided on the reason for the transaction or the provider of the funds, to determine the number of jobs associated with an account and the $/job I focus only on direct deposit transactions >=$100 and <=$25,000, leaving ~333m transactions, and utilize the fact that direct deposit paychecks tend to fall on a set of possible regular schedules.

[22] These are for illustration purposes only to show data structure. All values are fabricated for this example and do not depict actual transactions in the database.

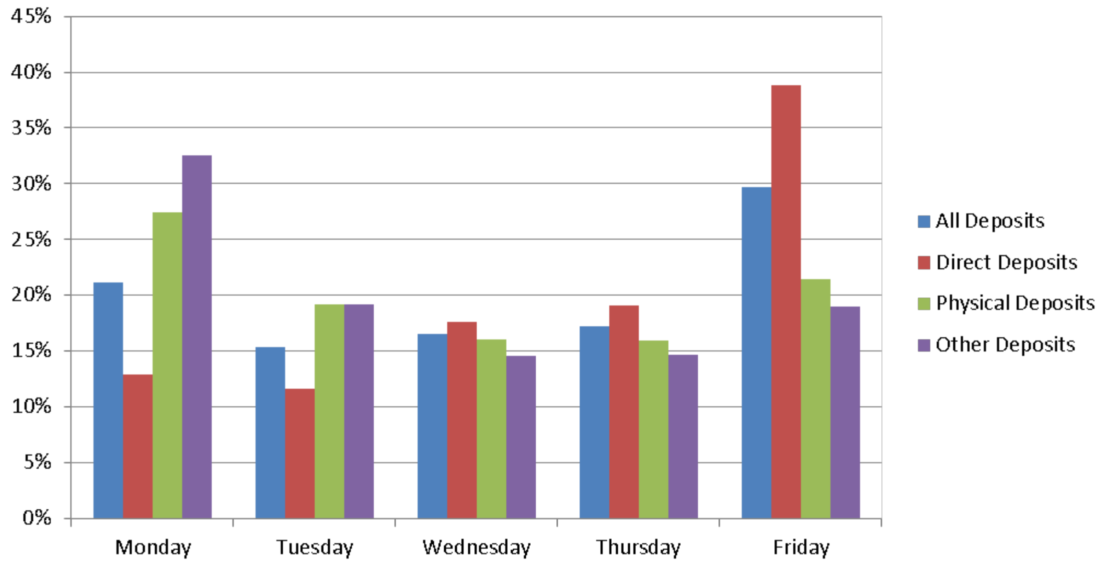
As noted by the Bureau of Labor Statistics (BLS)[23] employers can be characterized as weekly, bi-weekly, semi-monthly, and monthly payers. Adjusting for holidays, weekly payers pay every week on the same day, bi-weekly payers pay every two weeks on the same day, semi-monthly pay on the 1st and 15th or 15th and 30th, and monthly payers tend to pay on the last or first day of the month. Only one major employer type is absent from the BLS characterization, the U.S. government. About 1/4th of households have a social security recipient and depending on the type of program, the date filed, and birthdate of the individual social security checks are paid on either the 3rd of each month, or the 2nd, 3rd or 4th Wednesday of each month[24]. As can be seen in figures B1 and B2 the majority of direct deposits tend to fall on Fridays and on 1st, 3rd, 15th, or end of the month, where the exact day depends on the length of the month and any holidays.

Figure B1. Deposits by Type and Day of the Month



[23] http://www.bls.gov/opub/btn/volume-3/how-frequently-do-private-businesses-pay-workers.htm
[24] www.ssa.gov

Figure B2. Deposits by Type and Day of the Week



Using this information I assign paychecks to jobs using a *minimum jobs* algorithm, which assumes that the smallest number of jobs is likely to explain the paychecks seen. For example, if a HH receives 4 checks in a month, one say each Weds, and there are only 4 Weds in the month, then this is assigned as a weekly paycheck, rather than 2 bi-weekly paychecks or 2-3 social security paychecks. To achieve this I first assign all possible paychecks to weekly paying jobs, then bi-weekly, semi-monthly, monthly, and social security payments in order respectively, adjusting for holidays and non-business days (ex. If 15th is a Saturday and HH is paid semi-monthly then HH is paid on the 14th instead). Any paychecks which don't fit into one of these pay schedules is then left "unassigned". If multiple paychecks for a given account appearing on the same day the amounts are assigned equally to each job associated with those dates[25].

[25] Note that since all analysis is done at the average $/job level the precise allocation among jobs doesn't affect the data analyzed substantively.

Since my analysis is run at a monthly frequency one final concern is that some payment schedules pay unequal number of times each month. For example, if a HH receives weekly paychecks every Friday, then in July-2015 they would have received 5 paychecks while in August-2015 they would only have received 4. This could add a lot of noise to the income estimates since ceterus paribus this would make it appear that the HHs income fell 20% in August. The recently created JP Morgan Chase Institute also uses in-house proprietary deposit data to estimate and analyze income and in their inaugural report they noted that one of their three major findings was that one of the "drivers of monthly [income] volatility includes months with five Fridays, when employees may be paid three times instead of two". Since this is an artifact of the panel construction rather than fundamental changes income I create an adjusted income measure which takes the raw total income from all paychecks for a job each month and multiplies it by (# of paychecks per year)/ ((# paychecks received this month) x (12 months per year)) which creates an annualized income measure, adjusting for differences in the number of paychecks, and then divided by 12 to get a monthly measure. This adjusted measure only works for paychecks which have been assigned to a job and pay schedule, but for this subset it should prevent noise caused by difference in the number of paychecks per month.

Though any algorithm based solely on pay schedules is going to miss a few job-related paychecks[26] this methodology is able to assign most paychecks to regularly paying jobs. More than 90% of account-month observations have at least one job associated with them, and as can be seen in table B2, the assigned to jobs paychecks represent 84% and 61% of all direct deposit

[26] For example if the HR office accidentally pays checks a day late because of operational issues, the company has a non-standard holiday schedule, et al.

paychecks by number and dollar amount received respectively[27]. According to the Social Security Administration[28] the average monthly benefits for a beneficiary of SS is $1,223.45/month, which matches favorably with the $1,267.5/month I see per SS recipient in my sample.

Table B2. Breakdown of Deposits from Jobs Algorithm

	All Deposits	Direct Deposits	Direct Deposits (Assigned)	Direct Deposits (SS)
# >0 HH-Mo Obs (mil)	35.64	35.31	24.49	12.47
Total $ (bil)	205.01	175.45	107.74	20.66
# Paychecks (mil)		105.91	88.86	
$/Paycheck (mean)		$1,657	$1,212	
# Households	757,205	757,205	757,205	757,205
$/Job (mean)			$3,506.4	$1,267.5
$/Job Adj. (mean)			$3,502.1	

In table B3 I breakdown the assigned jobs by pay schedule type. Consistent with Bureau of Labor Statistics (BLS) Current Employment Statistics (CES) surveys[29] the majority of jobs are

[27] Non-reoccurring payments, like bonuses or yearly incentives, are more likely to be excluded by the jobs algorithm, which may explain why the # of paychecks picked up by the algorithm is smaller than the amount ($).
[28] www.ssa.gov
[29] http://www.bls.gov/opub/btn/volume-3/how-frequently-do-private-businesses-pay-workers.htm. About 36% of businesses pay on a bi-weekly basis and this is even higher among large businesses (1,000+ employees) where it is upwards of 70%, so the majority of jobs are paid bi-weekly.

associated with bi-weekly pay schedules, while semi-monthly pay schedules are associated with the highest paying jobs[30].

Table B3. Job Assigned Direct Deposits by Pay Schedule Type

Direct Deposits (Assigned)	Weekly	Bi-Weekly	Semi-Monthly	Monthly
# Obs (mil)	3.34	14.75	4.89	6.99
Total $ (bil)	11.54	61.05	25.14	15.93
$/Job (mean)	$3,228.6	$3,603.1	$4,700.1	$1,671.0
$/Job Adj. (mean)	$3,254.8	$3,612.9	$4,627.2	$1,671.0

Overall these results are consistent with the jobs algorithm effectively assigning direct deposits to jobs in a manner that captures most direct deposit income.

[30] Based on the CES survey monthly payers are concentrated among very small businesses (<10 employees), which may explain, at least partially, the lower $/job seen for the monthly paycheck receivers.