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Economic Shocks and Household Decisions

A Dissertation submitted in partial satisfaction
of the requirements for the degree of

Doctor of Philosophy

in

Economics

by

Jennifer Milosch

Committee in Charge:

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May 2014

Economic Shocks and Household Decisions

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by

Jennifer Milosch

To my little sister, Kristin, who will always be my biggest fan and my love, Kyle, who brings me indescribable joy each and every day.

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Abstract

Economic Shocks and Household Decisions

Jennifer Milosch

This dissertation concerns various types of economic shocks and the implications of such shocks on the decisions of households. There has been a long history in the theoretical economics literature of modeling agents as forward-looking and thus in making their life-cycle decisions they will have accounted for the paths they expect their income, wealth, or economic opportunities to take. Therefore, these chapters will focus on households' responses to unexpected changes in economic factors. The two types of economic shocks to be explored are income shocks, a shock that will affect only one spouse, and house price shocks, a shock that affects both spouses. Particular care is given to trying to identify exogenous and unexpected changes in income or wealth for the households. The asymmetric responses to financial gains versus losses are explored for each type of shock.

Throughout the analyses are conducted using longitudinal data on individuals or households. These data allow for observations of the sample household through a long portion of its life cycle and through changes in their economic situation. In the first chapter, I explore the effects of unpredicted changes in permanent income of each spouse on the probability of divorce for the couple. I find that

if the husband experiences a negative income shock, the probability of divorce increases. If the wife experiences a negative income shock, this effect on divorce is only true if she had a switch into unemployment. In Chapter 2, I continue the analysis of economic shocks on probability of divorce by looking at responses to local house price shocks. These local housing prices give us changes in wealth for the households that are exogenous to many of the other decisions an individual household makes. In response to a positive house price shock, the risk of divorce decreases for couples. Finally in the third chapter, I analyze the effect of housing prices on another household behavior: labor supply choices. Married female homeowners are less likely to be employed following a positive house price shock in their metropolitan area. Conversely, older married male homeowners are more likely to be employed when there are negative house price shocks in their area.

Professor S. Lundberg
Dissertation Committee Chair

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Introduction

In the past few decades the United States and the rest of the world has experienced a great deal of economic volatility. These large and often unexpected changes in the nation's economy begs the question of how such changes have affected households in the United States. In particular, how do households adjust their behavior in response to changes in their economic situation? This dissertation attempts to address this question for different types of economic shocks and estimate how they affect the household's decisions on divorce and labor supply. The availability of long-lasting longitudinal data gives us the ability to observe households or individuals over a long portion of their married and working lives. This means we can continually observe the household's characteristics over time and see when and how they respond to changes in their economic situation.

Household decisions depend on a number of factors and characteristics, however arguably one of the most important of these is the economic environment they face which in turn helps to determine the household's budget constraint.

The wealth of a household comes from many different sources and in these chapters we will look at two contributing sources: labor earnings and owner-occupied housing.

A couple chooses to marry based on the information that they have available to them at the time of marriage. If the expected surplus of the marriage is positive, then it is beneficial for the couple to marry. As in Burdett and Coles (1997), we can consider that there is some set of characteristics of each spouse that determines their quality as a partner and thus the surplus of the marriage. It seems realistic to assume that the expected financial situation of the spouses and the household play a role in the gains to marriage. As the economic situation of the household changes, at some point the surplus of the marriage could dip below zero. This means that at a later date it is may no longer be optimal for the marriage to continue. The first two chapters will thus explore samples of married households and their changing economic situations.

Chapter 1 analyzes the effect of income shocks on marital stability by estimating unpredicted changes in permanent income in each year. Using a long cohort survey, the National Longitudinal Survey of Youth of 1979, we observe individuals from a young age through a long portion of their lives. The information available up until each year is used to generate a prediction of permanent income, and then update in each subsequent year with the new information revealed in the survey. In this chapter, a "shock" to income is defined as the difference of the prediction of permanent income this year as compared to the prediction at the time of marriage. The results show that the probability of divorce increases when the husband faces a negative income shock. The same is only true for the wife when her negative income shock is due to a switch into unemployment.

Chapter 2 concerns how shocks to housing prices affect the decision to divorce for homeowners. Compared to the previous chapter, this type of economic shock is something that occurs to both spouses, rather than affecting the earnings brought in by only one spouse. Residential housing has been the largest component of household wealth for the past several decades so shocks to housing prices likely represent large changes in wealth for these households. In this chapter household level data from the Panel Study of Income Dynamics is used, providing a broad sample of household types. Using variation in local housing prices while controlling for local labor market conditions, we find that the probability of divorce decreases in response to positive house price shocks, however no significant effect is found for negative shocks. This effect is strongest among households with lower socioeconomic status, perhaps because the wealth shock is relatively larger for them.

In Chapter 3 of this dissertation a different type of household decision is discusses: labor supply and labor force participation choices of households. Using the same metropolitan level house price shocks faced by the respondents of the Panel Study of Income Dynamics, we focus in on groups that are likely to be less attached to the labor force. First, the results show that married female homeowners decrease their hours of work in response to positive house price shocks. We can show that this effect is due to these women adjusting on the extensive margin of labor supply. Since the effect is strongest among women with young children it seems likely that these women are choosing to exit the labor market to care for their children at home. Older married males, on the other hand, increase their labor hours in response to negative house price shocks. This also is shown to be from the men choosing whether or not to work.

Through these research endeavors I have found evidence that economic factors, both individual and more aggregate ones, are important determinants of household decisions. In general prosperity increases marital stability whereas economic hardships destabilize the relationship. Changes in their economic opportunities also lead households to adjust their decisions regarding work in the labor market. An increase in housing wealth allows married women to exit the labor market and care for their children and a decrease in housing wealth means older males are more likely to remain in the labor market, likely through delaying retirement.

Chapter 1

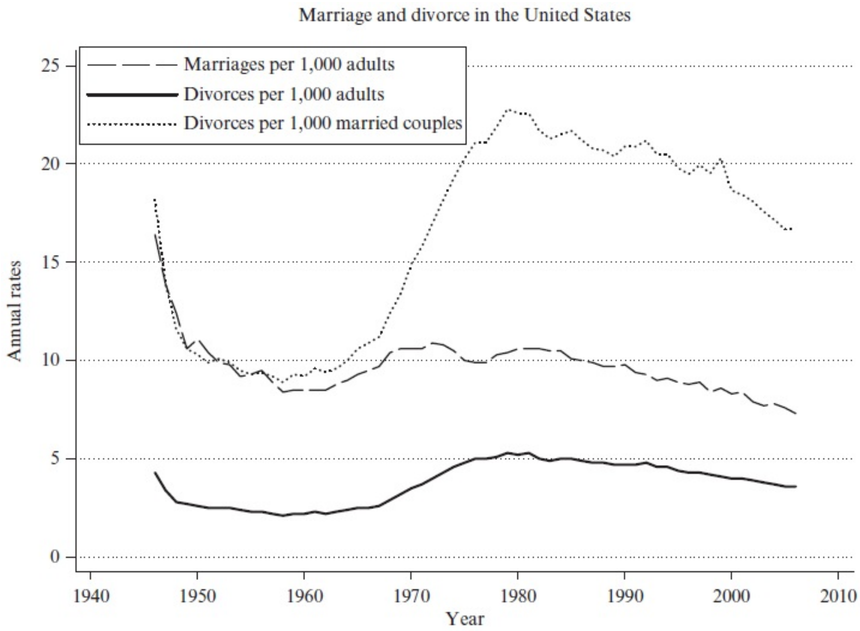
The Effects of Unpredicted Changes in Income on the Probability of Divorce

1.1 Introduction

A large number of studies have found that there has been rising income volatility at different times throughout the past several decades. There is evidence of this phenomenon from numerous data sources and this volatility has important implications for consumption smoothing, poverty, and consumer well-being.[1] During the same time period, there were large changes in the environment of marriage and divorce in the United States. According to Kreider and Ellis (2011) using data from the Survey of Income and Program Participation (SIPP), 21% of males and 23% of females 15 and older have ever been divorced. Figure 4.4 from Stevenson

[1] A few of these studies discussing income volatility are Gottschalk and Moffitt (2009) and Dynan et al. (2012) using PSID data, and Leete and Bania (2010) using SIPP data.

Figure 4.4 from Stevenson and Wolfers (2011)



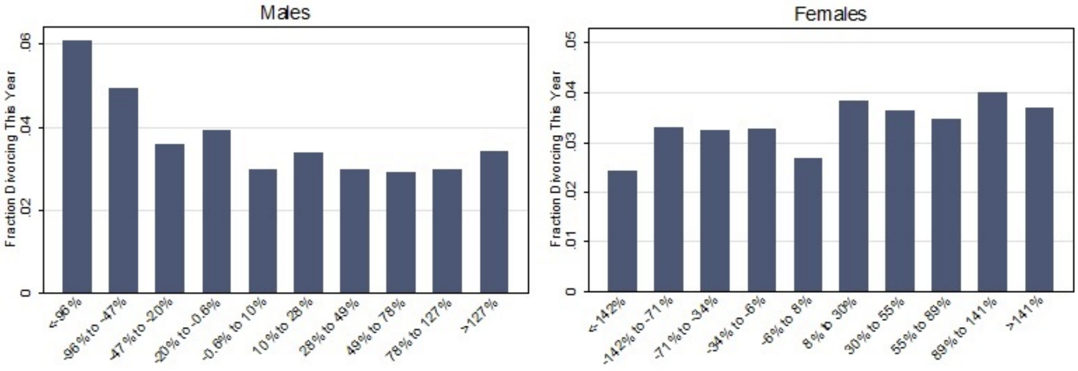
Source: Data from 1946–88 from Carter et al. (2006); 1999–2003 from U.S. Census Bureau (2007b); 2004–06 from Eldridge and Sutton (2007).

and Wolfers (2011) shows that the number of divorces per 1000 married couples has risen from about 8 in 1960 to a peak in the early 1980s of about 22 and has been falling slowly, but steadily, ever since. Since divorce is so widespread, it is potentially very costly, and the observed income volatility, the goal of this paper is to examine income shocks as one potential determinant of marital stability.

How do unexpected changes in income affect the probability of divorce? If high permanent income is a desirable characteristic in a spouse for both men and women, an increase in permanent income should make an individual a more attractive spouse than before, and a decrease in permanent income should decrease spousal quality. First I forecast the permanent income of both the respondent of the survey and his/her spouse at each year of marriage given all the information that is available up until that date. These forecasts can be viewed as what the couple expected permanent income to be at each year of their marriage. I assume that any changes in these predictions over time are "surprises" due to the new information learned in the past year. In this way, I analyze the effect of these unexpected changes on the divorce hazard. The evidence shown in this paper suggests that unexpected decreases in income for males increase the probability of divorce and is robust to many specifications. On the other hand, we see a similar effect on the divorce hazard only when the wife has a negative income shock due to a switch into unemployment. The effects of these shocks to income are explored across different subsamples. I explore who faces positive and negative changes in predicted permanent income to look for similarities among these groups. Finally, several models of marriage and matching are discussed. The empirical results are compared to the models' predictions on the effect of changes in permanent income.

To illustrate these results, Figure 1.2 shows the fraction divorcing in a given year across deciles of the income shocks for the husbands and the wives. The fraction divorcing in a given year is much higher for those males with large negative shocks, and relatively flat for males with positive income shocks. For women, there possibly a slightly positive trend across the figure but certainly not as clear as for

Figure 1.2: Fraction Divorcing by Income Shock Decile



the males. On both panels the fraction divorcing is the lowest for the decile including zero, which would be only very small changes in predicted permanent income.

The analysis in this paper is most closely related to Weiss and Willis (1997) (hereafter WW). The results in WW show that when there is a positive shock to the woman's earnings, a marriage is more likely to end in divorce. Conversely, an unexpected increase in the man's earnings means the marriage is less likely to end in divorce. The authors note, however, that expected earnings at the time of marriage have no effect on the probability of divorce; it is only surprises that matter. The divorce hazard also rises for negative surprises to earnings. The event that causes the largest increase in the divorce hazard in their data is when the husband has a negative shock to earnings and the wife has a positive shock to earnings. They posit that an increase in the woman's earnings is more important when she is single than when she is married. Thus, higher earnings means she is more capable of living on her own and the divorce hazard rises. So the argument in WW is one of gains from marriage: an increase in the woman's earnings decreases gains from marriage, while an increase in the man's earnings increases the gains.

The paper fits into the literature in the following way. First, a panel data set more than twice as long with smaller gaps between interviews is used as compared to Weiss and Willis (1997). This means that the respondents are seen for a longer portion of their lives, and are significantly older in the most recent surveys. As the goal is to identify *permanent* changes in income, this is better established if we are able to see the individuals in their peak earnings years. Second, I attempt to more accurately identify changes in income that are "surprises" to the couple. The analysis is also expanded to explore potential non-linearities in the effects for positive versus negative income shocks, the direction of each spouse's shock, and across income and education levels.

1.1.1 Review of the Literature

Related to this paper, there are several paper that aim to estimate shocks to income and analyze the effect on divorce. Becker, Landes and Michael (1977) approaches this question using cross-sectional data, so there the researchers cannot see one couple learning about each spouse's quality over time. Böheim and Ermisch (2001) uses data from the U.K. that asks respondents about the financial situation of their spouses and expectations for next year about the financial situation of their spouses. Changes from expectations are recorded, and they find that positive changes in expectations decrease the divorce risk. Charles and Stephens (2004) finds that a spouse's job displacement increases the probability of divorce, however loss of job due to disability does not. The effect of job loss on divorce is further explored in Doiron and Mendolia (2012) using the British Household Panel Survey distinguishing between reasons for displacement. The authors find that job loss due to dismissals increase the risk of divorce. Nunley and Seals (2010) examine household income shocks and finds that transitory increases in household income decrease the likelihood of divorce, and decreases in household income increase the likelihood of divorce.

The theoretical literature on marriage and divorce goes back to *A Theory of Marriage: Parts I and II* in Becker (1973) and (1974), which focused on a static model with no frictions. He examines the attractive traits of a marriage partner in Part I and settings with different types of uncertainty for Part II in Becker (1974). We expect that some characteristics of individuals are complementary in marriage which leads to positive assortive matching and others that are substitutes leading to negative assortive matching. More recent papers use dynamic marriage models allowing for endogenous divorce to arise within the environemnt: Cornelius (2003) and Rasul (2006). Cornelius (2003) presents a model where divorce occurs as individuals continue to search for a better spouse while married. In this model, individuals will accept an early match that is not ideal, knowing that they can remarry once they find a better match. In Rasul (2006) there is learning about the quality of a marriage. First, an individual sees an imperfect signal about the match quality of a potential spouse. Once married, both learn the true quality of the match in the following period. In this way, divorce may be the optimal response for one or both parties once the true quality is realized. The relationship between income uncertainty and marriage is explored in Hess (2004) where individuals may marry for love or in order to hedge the risk of income shocks. The author finds that if income uncertainty is resolved later on in life, those couples who provide good income insurance for one another are more likely to stay together. On the other hand if income uncertainty is revealed relatively quickly, those couples are more likely to divorce if they do not have enough love in the marriage.

1.2 Data

The focus of this paper is on the effects of changes in income over time, and so the data used is a panel study that tracks individuals through a large portion of their life. The National Longitudinal Study of Youth (NLSY79)[2] had its initial interview in 1979 when the individuals were between the ages of 14-22. This initial

[2]Data obtained through the Bureau of Labor Statistics: NLSY (2012)

interview will allow us to see people as they are completing their educational choices and just entering into marriages and the labor force. The survey was administered annually from 1979 to 1994 and has since continued bi-annually. As of 2008, 61.2% of the original respondents were still participating in the survey. This survey is long lasting, so the respondents can be observed into their high income years, which the BLS estimates to be between 45-55 years of age. The final interview currently available is for 2010 when the respondents are between 45 and 53.

The NLSY79 is comprised of three sampling groups. First, there were 6,111 members of the cross-sectional sample designed to be nationally representative of the noninstitutionalized, civilian population in 1979. Second, there were 5,295 members of a supplemental sample that over-sampled black, Hispanic, and non-black/non-Hispanic disadvantaged individuals. Last, there were 1,280 members of a sample of active members of the military. The majority of the military sample and the whole of the non-black/non-Hispanic disadvantaged respondents were dropped from the survey in 1984 and 1990, respectively, and thus are not included in this study. The final sample contains a total of 9,735 respondents.

In a similar study, Weiss and Willis (1997) use data from the NLS High School Class of 1972 (NLS-72). This survey is similar in form to the NLSY79, however it is a much shorter and infrequent panel with only 6 interviews over 14 years from high school graduation until the respondents are age 32. While the NLS-72 used in WW has slightly better retention of respondents and more information on the spouses of respondents, the NLSY79 has a panel that spans 32 years which arguably makes it better suited to this endeavor. In addition, the NLSY79 has smaller gaps between interviews than the NLS-72 in which respondents were only surveyed in 1972, 1973, 1974, 1976, 1979, and 1986. The NLSY79 has respondents born between 1957-1965.

Table 1.1: Summary Statistics for NLSY79

	1979-1985		1986-1992		1993-2000		2002-2010	
Variable	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Time Invariant:[(a)]								
Black-R	0.15	0.35	0.15	0.35	0.15	0.35	0.15	0.36
Hispanic-R	0.07	0.25	0.07	0.25	0.07	0.25	0.07	0.25
Female-R	0.50	0.50	0.51	0.50	0.51	0.50	0.52	0.50
Years of Educ Father-R	11.9	3.59	11.9	3.59	11.9	3.58	11.9	3.59
Years of Educ Mother-R	11.7	2.78	11.7	2.77	11.6	2.76	11.6	2.77
Age First Married-R	24.6	5.69	24.6	5.71	24.6	5.77	24.5	5.85
Age First Married-Sp	24.9	5.73	24.9	5.74	24.9	5.81	24.8	5.75
Length of First Marr.[(b)]	9.28	6.87	9.31	6.89	9.42	6.92	9.54	6.98
Time Varying:								
Age-R	20.6	3.05	28.0	3.12	35.1	3.43	44.9	3.53
Age-Sp	22.5	5.73	29.5	5.44	36.6	5.71	46.5	5.80
Years of Educ-R	11.9	2.08	13.1	2.35	13.4	2.47	13.6	2.53
Number of Children-R	0.28	0.66	0.97	1.14	1.55	1.31	1.85	1.37
Own Property	0.13	0.34	0.36	0.48	0.60	0.50	0.72	0.45
Weeks Worked-R	31.8	20.0	39.6	18.8	41.6	18.5	41.5	19.2
Weeks Worked-Sp	39.9	18.0	41.3	18.2	41.4	18.6	41.2	19.4
Income-R	$13,510	$13,378	$26,360	$21,433	$34,088	$31,545	$42,498	$46,670
Income-Sp	$23,335	$18,566	$31,018	$25,009	$35,021	$32,936	$43,735	$50,423
Currently Married-R	0.23	0.42	0.53	0.50	0.63	0.48	0.64	0.48
Currently Divorced-R	0.02	0.14	0.08	0.27	0.13	0.34	0.18	0.38

(a) Changes in time-invariant variables are due to respondents dropping out of the survey over time.

(b) This is tenure for marriages that have ended. This is the length until separation or divorce. Marriages that continue beyond the final interview will not affect these values.

NOTES- R indicates values are for the respondents of the survey, Sp indicates values are for the current spouses of the respondents. Sample weights are used.

Summary statistics for the NLSY79 are broken down into four time periods and are reported in Table 1.1 for the years of 1979-1985, 1986-1992, 1993-2000, and 2002-2010. The initial sample is almost exactly 50% female and has 15% blacks and 7% Hispanics. The average years of education for a respondent is increasing from 11.9 to 13.6 over the length of the sample indicating that some individuals continued their schooling through at least part of the survey. Both males and females obtain similar amounts of schooling on average at 12.4 years and 12.6 years respectively. As expected, female respondents earn less than male respondents throughout the sample. Among the respondents who are working, women earn 22% less in hourly wages and 45% less in income. The discrepancy in these percentages is likely due to the fact that women also work fewer hours during their childbearing years. Interestingly, the gap between men and women in income worsens over time going from 40.6% before 1995 and 57.7% after amongst men and women who were working. A similar change is noted in wages where the wage gap increases from 18.7% to 27.3% over the same intervals.

The averages for the marriage and divorce variables give a quick look into the family structures of the respondents. We see that on average, first marriages that end within the 32 years of the sample last about 9 years and the median length is 7 years when considering the end of marriage to be either divorce or separation, whichever happens first. The legal process of divorce can often take several years, so to more accurately measure the end of the relationship the date of legal separation is used, if the couple separates before divorcing. In comparison, the median length of time from marriage to the final date of divorce is 8 years in the NLSY79. As expected we see that the percentages of respondents who are married or divorced is increasing over time, and by the end of the sample 64% are currently married and 18% are currently divorced.

1.3 Empirical Methods

The first step in the empirical estimation is to create a measure of permanent income for the respondents. WW use income at age 32 as a proxy for permanent income, as it is the age of the respondents in the last year of the NLS-72 survey. They assume that income at age 32 is a good indicator for an individual's permanent income. However, according to Solon (1992), there is significant errors-in-variables bias associated with using a single year's income as a measure of the permanent component of income. To mitigate some of this bias, the measure of permanent income used is as follows. Let Y_i^{perm} be the average of log of incomes of respondent i across three years, a proxy for permanent income. The incomes that are used are those at the ages of 41, 43, and 45 or the ages of 42, 44, and 46.[3] This average is a better estimate of permanent income since the respondents

[3]These are for every other year as the survey was only conducted bi-annually after 1994. Because of this fact, I may miss some respondents if I only use income at the ages of 41, 43,

are closer to their peak earnings years and taking the average of incomes works to reduce the potential for an unusual income in one year to be driving the shocks. Several authors including Solon (1992) and Mayer (1997) have suggested that an average of variables across years reduces the errors-in-variables bias associated with measuring permanent income.

In each year, beginning at age 20, I predict permanent income of the respondent using the information available up until that year. Once the respondent marries, the couple must decide in every year whether to stay in the marriage or not. To see the effects of surprises in predicted permanent income on this decision, all of the relevant new information available in the data is incorporated into the predictions in each year. This is an attempt to capture expectations about their future financial state, perhaps much like the couple would do themselves. As the effects of the variables could be different for men and women, they are estimated separately. First we estimate:

$$log(Y_i^{perm}) = \alpha_{20} * z_i + \beta_{20}' * x_{i,20} + \delta_{20} * log(Y_{i,20}) + v_{i,20} + u_i^{perm} \tag{1.1}$$

z_i are characteristics that do not change over time, such as race and parents' education. $x_{i,20}$ are time-varying characteristics, like marital and employment

and 45. For example, if an individual was 42 in 2002, 44 in 2004, and 46 in 2008, I would never observe income at the ages of 41, 43, and 45.

status, at age 20. $log(Y_{i,20})$ is log of income at age 20. Finally in the error term is $v_{i,20}$, the portion of permanent income not explained by the information at age 20, and u_i^{perm}, the unexplained variation in permanent income. Several controls are added that are not included in the analysis by WW in an attempt to more accurately capture surprises. One of the difficulties for measuring surprises for women in the sample involves fertility decisions. For instance, a couple may choose to have a child and so the woman stops working suddenly. Since this is not a "surprise" change in her income, we want to account for this in the predictions of permanent income. Control variables are included for the presence of young children in the household (less than 5 years old), and for the wife being pregnant (an indicator variable equal to 1 in the year before a birth occurs).[4] Using Equation 1.1, I generate fitted values of the log of permanent income with the information at age 20, $log(Y_{i,20}^p)$. To generate the prediction of permanent income at age 21, we include $log(Y_{i,20}^p)$ in the regression. Thus, the age 21 prediction includes the new information observed at age 21 and the past history prior to that age through $log(Y_{i,20}^p)$. Note that the time-invariant characteristics are no longer included in this regression as their effects will have been incorporated into

[4]The full set of control variables used in the income regressions for respondents are: year fixed effects, race, religion, parent's educations, AFQT scores, family poverty status, education, expected educational attainment, region of residence, an indicator for the presence of young children, an indicator for the wife being pregnant, employment status, hours per week working, indicator for married, occupation by 3-digit census code, and income.

the prediction from age 20.

$$log(Y_i^{perm}) = \gamma_{i,t-1} * log(Y_{i,t-1}^p) + \beta_t' * x_{i,t} + \delta_t * log(Y_{i,t}) + v_{i,t} + u_i^{perm} \quad (1.2)$$

for t=21,...,40

This is repeated in each year using the the new values of the control variables and the previous year's predicted permanent income. The variable $log(Y_{i,t-1}^p)$ is the log of the previous year's predicted permanent income and $log(Y_{it})$ is the log of the current year's income. By including the previous prediction and any new information, we construct a measure that captures the cumulative innovations to permanent income. This is then repeated for the ages of 22-40. The goal with these estimations is to control for as many variables as possible that may affect the respondent's forecasts of their own permanent income at a given point in time. Once we control for these variables, both for the current year and their past values reflected in $log(Y_{i,t-1}^p)$, any remaining variation in the predicted permanent income is taken to be a surprise change in income for the respondent.

The set of predictions for every age, $log(Y_{i,20}^p)$-$log(Y_{i,40}^p)$, are used to estimate the effect of income shocks on divorce. What is the relevant reference point for the couple in determining what is surprise that can affect their decision to divorce? One natural way of thinking of a "shock" to the couple is how different the predicted permanent income is in the current year, compared to what it was when the couple married.

$$\Delta log(Y_{i,t}^{perm}) = log(Y_{i,t}^{p}) - log(Y_{i,M}^{p})$$

Positive differences would indicate the respondent expects permanent income to be larger than was expected at the time of marriage, and negative differences indicate expected permanent income has decreased. Thus an income shock in this paper is defined as a change in predicted permanent income compared to the predicted permanent income at the date of marriage.

1.4 Results

A probit model is used to estimate the effects of changes in predicted permanent income on the divorce hazard in each year after the start of the first marriage. The dependent variable equals zero in years where the couple is married, one in the year the couple divorces (if ever), and then missing for the rest of the sample. Since this is a divorce hazard model, the marginal effects will be interpreted as their effect on the probability the dependent variable equals one (the couple divorces) in a particular year. The regressions are pooled across years so observations are in the person-year format. The interpretation of the coefficients are the effect on the probability of divorce in a particular year, conditional on the couple reaching a particular year of marriage. Also, since the income at age 41, 43, and 45 or 42, 44, and 46 is used in constructing the permanent income variable the following analysis is performed only for respondents who are younger than 41.

Two different approaches are used in the analysis. In Section 1.4.1, the predicted income of the spouse is not controlled for; this leads to unbiased estimates only if the spouse's income shocks are orthogonal to the respondents. This initial methodology is used because data on the spouses is somewhat limited in the NLSY79. So, the results in this first section have a larger sample size. In Section 1.4.2, changes in both the husband and the wife's predicted permanent income will be included to the best extent possible. In all regressions, standard errors are clustered on the respondent ID number as each person appears in the data multiple times. The number of categories for clustering that appears at the bottom of each table describes the number of marriages the analysis is based on.

1.4.1 Respondents' Permanent Income Changes

Table 1.2 shows the marginal effects of the variables of interest from various specifications of a probit regression. The specification includes other controls that may affect the quality of marriage and probability of divorce. To allow for the possibility that positive and negative shocks to income do not have symmetric effects on the divorce hazard, the income shock variable is separated into its positive and negative components. For example, households may exhibit what is known as loss aversion in the behavioral economic literature where agents dislike losses more than they like gains. The equations to be estimated are variations of:

$$div_{i,t} = \gamma_{1,t} * Pos.\ \Delta Perm.\ Inc + \gamma_{2,t} * Neg.\ \Delta Perm.\ Inc + \alpha_t' * x_{i,t} + u_{i,t} \quad (1.3)$$

Where $log(Y^p_{i,t})$ is the log of predicted permanent income in year t and $log(Y^p_{i,M})$ is the predicted permanent income at marriage, and $x_{i,t}$ are various other control variables. Define
$Pos.\ \Delta Perm.\ Inc= \left[log(Y^p_{i,t}) - log(Y^p_{i,M})\right] * \mathbb{1}(Positive)$ to be the change in predicted permanent income if that change is positive and zero if the change is non positive. Likewise, define
$Neg.\ \Delta Perm.\ Inc= \left[-(log(Y^p_{i,t}) - log(Y^p_{i,M}))\right] * \mathbb{1}(Negative)$ to be the absolute change in predicted permanent income if the change is negative and zero if the change is non negative. This way, we can directly analyze the potentially different effects of a negative change in predicted permanent income and a positive one.

In Column (1) of Table 1.2, the specification has a linear function in the change in permanent income for both the positive and the negative changes, and Column (2) has a quadratic function in the change in permanent income. Column (3) and column (4) separate between female and male respondents. In Column (1) and Column (2), we see some evidence that positive changes in permanent

Table 1.2: Effect on Divorce Probability

	All Respondents		**Females**	**Males**
	(1)	(2)	(3)	(4)
Pos. ΔPerm. Inc.$_{t-1}$	0.0060**	0.0187***	0.0094***	0.0016
	(0.0025)	(0.0060)	(0.0031)	(0.0039)
Neg. ΔPerm. Inc.$_{t-1}$	-0.0011	0.0018	-0.0030	0.0050
	(0.0021)	(0.0049)	(0.0024)	(0.0033)
Pos. ΔPerm. Inc.$^2_{t-1}$	-	-0.0066**	-	-
	-	(0.0028)	-	-
Neg .ΔPerm. Inc.$^2_{t-1}$	-	-0.0005	-	-
	-	(0.0013)	-	-
Year Controls	Y	Y	Y	Y
N (Person-Year)	23,670	23,670	11,685	11,985
Couples	2,647	2,647	1,240	1,407
R^2	0.061	0.062	0.081	0.065

Custom weights constructed for the NLSY79 are used. Standard errors are in parentheses, clustered by person ID. Marginal effects are reported. *,**,*** indicate significance at the 10%, 5%, and 1% level.

income increase the probability of divorce, however the separation of men and women may to be important. In Column (3) for the females, the coefficient on the positive changes in predicted permanent income is positive and significant. This suggests that positive income shocks for women increase the probability of divorce, assuming their income shocks are orthogonal to their husbands. In Column (4), without including any measure of income shocks for the wives, the male respondents do not show any significant effect of income shocks.[5]

[5] All of the specifications have the other control variables shown in Table A.2 in the Appendix.

1.4.2 Controlling for Spouse Predictions

There are many reasons why we might believe that surprises to permanent income of the spouses are related to those of the respondents. For example, local labor market conditions might affect both individuals. If the respondent and his/her spouse's shocks to permanent income are not orthogonal, we must control for the predicted permanent income of both. The NLSY79 and other cohort surveys are focused on the respondent rather than the household. Therefore, information on a spouse of a respondent is not observed until the couple marries, and information is no longer observed once the marriage ends. This presents a problem with predicting the permanent income of the first spouse of each respondent. Again, for the respondents, the proxy for permanent income used is the average of income in the data across three specific years: when the respondents are 41, 43, and 45, or 42, 44, and 46. For the respondents' first spouses, however, income will only be observed in these years if the first marriage was still intact at that time. The income data the spouses will be missing if they have divorced before those ages.

To address this issue, Weiss and Willis (1997) use an alternative strategy to construct predicted permanent income for the spouses. For the male *spouses* of the female *respondents*, we use the estimated coefficients from the regressions for the male respondents. By taking these coefficients and multiplying them by the explanatory variables of the male spouses of the female respondents, predicted permanent income at each age is constructed. A second set of restricted permanent income regressions are estimated for the respondents, including only variables that are also available for spouses in the NLSY79. The set of explanatory variables used in these regressions that are available for both the respondents and the spouses are: race, education[6], income, weeks employed, family poverty status, weeks unemployed, hours per week, a dummy variable for young children, a dummy variable for a woman being pregnant, occupation by 3-digit census code, region of residence, and religion.

Recall that for the respondents the prediction of permanent income was generated using Equation A.3. In these regressions the important feature is the calculations of innovations to expectations of permanent income given the new information in the current year controlling for the previous year's predicted permanent income. Given that an income shock is the cumulative change in predicted permanent income since marriage, we want to ensure the prediction in the year of marriage is as accurate as possible. Since there is no information prior to marriage about the spouses we will not have any measure of last year's predicted

[6]Education of spouse is not reported in the NLSY79, so multivariate matching on race, education, and income by age and sex of the respondent is used to predict the education level of the spouses. Census and ACS data from the relevant cohorts is used (Ruggles et al. (2010))

permanent income for the spouses in the year of marriage. To obtain a measure of the past history of the spouses prior to marriage, multivariate matching from respondents to spouses is used to generate a variable $log(YSp^{p}_{i,M-1})$ for each spouse for the year prior to marriage. Essentially this constructs the unknown past history of the spouses whose information is not observed before marriage. We match respondents to spouses separately by age and sex over the variables of region of residence, education, race, presence of young children, and the woman being pregnant. Thus, the predictions of permanent income for the spouses begins at the age of first marriage, and the effect of past history on permanent income in the year of first marriage is $log(YSp^{p}_{i,M-1})$. For a more detailed description of the methodology used, see equations A.1 and A.3 in the appendix. This yields the predicted permanent income for the male spouse of female respondent i in at each age they are married between the ages of 20-40, $log(YSp^{p}_{i,20}), ..., log(YSp^{p}_{i,40})$ and an equivalent set of predictions for the female spouses of the male respondents. As was done for the survey respondents, the cumulated change over time in predicted permanent income is calculated so the variable of interest will be

$$\Delta log(YSp^{perm}_{i,t}) = log(YSp^{p}_{i,t}) - log(YSp^{p}_{i,M})$$

or what we will refer to as Δ *Perm. Inc.*[7]

Figure 1.3: Size of Change in Predicted Permanent Income

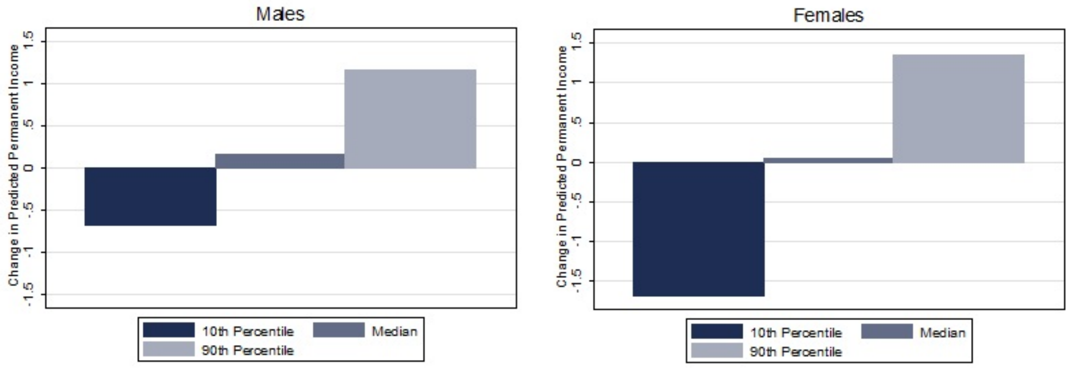


Figure 1.3 shows the relative size of the change in permanent income from one year to the next for all of the males and females. Note, from the figure it appears that females have a larger spread of changes in predicted permanent income than males. This may suggest that the methodology used does a slightly worse job predicting permanent income for women. If this procedure on average is predicting permanent income correctly the means of the change in predicted permanent income is very close to zero for both men and women, which is exactly what we see in this figure.

Table 1.3 shows the averages for some of the variables used to construct permanent income predictions for spouses in the data set. Comparing columns one

[7]Some respondents fail to report information on variables for their spouses covering the past calender year (income, weeks worked, weeks unemployed), so in those cases the second year of marriage is used as the reference point: Δ Perm. Inc. $= log(YSp^p_{i,t}) - log(YSp^p_{i,M+1})$.

Table 1.3: Comparing Spouse-Respondent Populations by Sex (Means)

	Males			**Females**		
	Respondents	Spouses	Diff.	Respondents	Spouses	Diff.
log(Income)	10.51	10.28	0.23***	8.22	7.68	0.54***
Predicted Perm. Inc.	10.56	10.48	0.08**	8.69	8.43	0.26***
Δ Perm. Inc.	0.26	0.13	0.14***	-0.02	-0.13	0.11***
Employed	0.89	0.93	-0.05***	0.69	0.67	0.02**
Unemployed	0.02	0.01	0.01	0.02	0.02	0.00
West	0.17	0.15	0.03***	0.15	0.17	-0.03***
South	0.29	0.32	-0.03***	0.32	0.29	0.03***
Central	0.35	0.31	0.04***	0.31	0.35	-0.04***
Black	0.08	0.07	0.01	0.07	0.08	-0.01
Hispanic	0.05	0.05	0.00	0.05	0.06	-0.01***
# of Children	1.30	1.30	0.00	1.30	1.30	0.00
Child $\leq$ 5yrs	0.52	0.51	0.01	0.51	0.52	-0.01
Pregnant				0.06	0.06	0.00
N (Person-Years)	9118	8549		8549	9118	

and two, we see sample means of various explanatory variables for the population of male respondents and the male spouses of the female respondents. In columns three and four, we compare the populations of female respondents and the female spouses of male respondents. For most of the control variables the population of male spouses and respondents and the population of female spouses and respondents the differences are quite small, though some are significantly different from zero. In addition, the procedure described above generates predicted permanent that are very close across the populations of respondents and spouses. We see some differences the mean of income shocks of spouses and respondents, but overall the distribution of shocks are very similar.[8]

The analysis in WW posits that the divorce hazard is a quadratic function in current predicted permanent income and controls for predicted permanent income in the year of marriage. From the equations above, this would be equivalent to for couple i, husband H, and wife W:

$$\begin{aligned} div_{i,t} = \beta_{1,t} * log(Y^p_{H,t}) + \beta_{2,t} * log(Y^p_{H,t})^2 + \beta_{3,t} * log(Y^p_{H,M}) + \beta_{4,t} * log(Y^p_{W,t}) \\ + \beta_{5,t} * log(Y^p_{W,t})^2 + \beta_{6,t} * log(Y^p_{W,M}) + \alpha'_{1,t} * x_{H,t} + \alpha'_{2,t} * x_{W,t} + u_{i,t} \end{aligned} \quad (1.4)$$

Where $x_{H,t}$ and $x_{W,t}$ are other control variables and $u_{i,t}$ is the error term. From Equation 1.4, for a person with a particular value of $log(Y^p_{H,M})$ the estimated coefficient $\hat{\beta_{1,t}}$ would describe the effect on divorce of a larger positive surprise for a respondent compared to another respondent with a smaller surprise and the same $log(Y^p_{H,M})$. In other words, comparing two individuals with the same expectations at marriage, $\hat{\beta_{1,t}}$ is the effect on divorce for one of them having a positive surprise. So, the specification compares changes in predictions for across people who looked the same at the time of marriage.

Instead, the specification in Equation 1.5 uses the difference between the current year and the time of marriage. The specifications used in this analysis include

[8] A histogram of the income shocks for these four groups can be found in the Appendix.

the difference of predicted permanent income compared to the start of the marriage. For example, for the husband's: $log(Y^p_{H,t}) - log(Y^p_{H,M})$. In order to test for potentially different effect for positive and negative surprises, this variable is divided into its positive component, $\left[log(Y^p_{H,t}) - log(Y^p_{H,M})\right] * \mathbb{1}(Positive)$, and the absolute value of its negative component $\left[-(log(Y^p_{H,t}) - log(Y^p_{H,M}))\right] * \mathbb{1}(Negative)$. The estimated equation is:

$$\begin{aligned} div_{i,t} = {} & \gamma_{1,t} * \left[log(Y^p_{H,t}) - log(Y^p_{H,M})\right] * \mathbb{1}(Pos.) + \gamma_{2,t} * \left[-(log(Y^p_{H,t}) - log(Y^p_{H,M}))\right] * \mathbb{1}(Neg.) \\ & + \gamma_{3,t} * \left[log(Y^p_{W,t}) - log(Y^p_{W,M})\right] * \mathbb{1}(Pos.) + \gamma_{4,t} * \left[-(log(Y^p_{W,t}) - log(Y^p_{W,M}))\right] * \mathbb{1}(Neg.) \\ & + \alpha'_{1,t} * x_{H,t} + \alpha'_{2,t} * x_{W,t} + u_{i,t} \end{aligned} \tag{1.5}$$

In some of the specifications the square of the difference is used, however it is not significant. If we compare this to the linear term in Equation 1.4, $\beta_{1,t}$ is essentially forced to be equal to $-\beta_{3,t}$ by construction. The estimated coefficient $\hat{\gamma_{1,t}}$ is the effect on the probability of divorce for a positive change of size $\Delta(Perm.Inc.) = log(Y^p_{H,t}) - log(Y^p_{H,M})$ for a respondent. So rather than comparing a movement in levels from a predicted value at marriage, the second specification estimates the effect for the absolute change in predicted permanent at any level of starting predicted permanent income. This is arguably the more intuitive way to study the effect of income shocks on divorce, and perhaps similar to how the couple themselves may think about surprises to their financial situation.

Table 1.4: Effect on Divorce Probability-With Spouse Predictions

Model	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
W: Pos.ΔPerm. Inc.$_{t-1}$	-0.0005	-0.0014	-0.0004	-0.0003	0.0009	0.0010	0.0002
	(0.0023)	(0.0023)	(0.0020)	(0.0019)	(0.0019)	(0.0019)	(0.0019)
W: Neg.ΔPerm. Inc.$_{t-1}$	-0.0024	-0.0028	-0.0027	-0.0027	-0.0021	-0.0023	-0.0012
	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0016)	(0.0016)	(0.0017)
H: Pos.ΔPerm. Inc.$_{t-1}$	0.0044	0.0034	0.0005	0.0003	-0.0004	-0.0004	-0.0014
	(0.0031)	(0.0031)	(0.0029)	(0.0029)	(0.0029)	(0.0029)	(0.0030)
H: Neg.ΔPerm. Inc.$_{t-1}$	0.0062***	0.0060***	0.0039**	0.0040**	0.0036**	0.0037**	0.0027
	(0.0021)	(0.0021)	(0.0019)	(0.0019)	(0.0018)	(0.0018)	(0.0020)
Wife's*Husband's$_{t-1}$	-	-	-	-	-	-0.0093	-0.0101
	-	-	-	-	-	(0.0071)	(0.0076)
Year Controls	N	Y	Y	Y	Y	Y	Y
Demographic Controls	N	N	Y	Y	Y	Y	Y
Duration/Age at Marr.	N	N	N	Y	Y	Y	Y
Fertility Controls	N	N	N	N	Y	Y	Y
Emp. Status	N	N	N	N	N	N	Y
N (Person-Year)	20,243	20,243	17,745	17,744	17,744	17,744	16,373
Couples	2,789	2,789	2,299	2,299	2,299	2,299	2,257
R^2	0.002	0.010	0.044	0.053	0.063	0.063	0.067

Custom weights constructed for the NLSY79 are used. Standard errors are in parentheses, clustered by person ID. Marginal effects are reported. *,**,*** indicate significance at the 10%, 5%, and 1% level.

Table 1.4 shows the results of probit regressions using the methods described above to calculated the predicted permanent income of the spouses. The variables of interest are *Pos.* Δ*Perm. Inc* for each spouse, the positive change in predicted permanent income, and *Neg.* Δ*Perm. Inc* for each spouse, the absolute negative change in predicted permanent income. Each column adds in more covariates to the regression. The first regression includes only the variables of interest and shows a strong correlation between the divorce hazard and negative income shocks for the husband. The regressions in Columns (6) and (7) add in year fixed effects and various demographic controls. The effect of the negative realization of predicted permanent income remains significant and appear to increase the probability of divorce. Column (8) includes controls for the duration of the marriage and the age of the husband at marriage. In Column (9) is the baseline regression[9] used throughout the paper for robustness checks and alternative samples and I include controls for fertility such as the number of children and if there are young children present in the household, however fertility decisions may be endogenous with the decision to divorce. Column (10) also controls for the wife's change in permanent income times her husband's, to see if there are any differences in the divorce hazard when the shocks are moving in the same or opposite direction. In addition, this variable captures information about the size of total changes within the household, however it is not significant in this specification. Finally, in Column (11) I include controls for the employment status of the husband and wife which decreases the marginal effect, however these are likely endogenous with the dependent variable as people adjust their labor market behavior in anticipation of a divorce. Table 1.4 strongly suggests that negative changes in predicted permanent income increase the probability of divorce for men. The coefficient on the husband's *Neg.* Δ*Perm. Inc* is positive in all specifications, so larger (or more negative) changes will increase the probability of divorce. As the previous literature has found, these baseline regressions suggest

[9]The full specification can be seen in Table A.2 in the Appendix.

there is not a symmetric response in the decision to divorce when the wife has a negative change in predicted permanent income. These variables are explored further in Table 1.5.

Table 1.5: Effect on Divorce Probability: Direction of Changes

	(12)	**(13)**
Pos. Wife's*Husband's$_{t-1}$	-0.0471**	
	(0.0241)	
Neg. Wife's*Husband's$_{t-1}$	-0.0297	
	(0.0229)	
Pos. Wife,Pos. Husband$_{t-1}$		-0.0313
		(0.0398)
Pos. Wife,Neg. Husband$_{t-1}$		-0.0419
		(0.0361)
Neg. Wife,Pos. Husband$_{t-1}$		-0.0168
		(0.0265)
Neg. Wife,Neg. Husband$_{t-1}$		-0.0537*
		(0.0303)
W: Pos. ΔPerm. Inc.$_{t-1}$	0.0031	0.0028
	(0.0022)	(0.0026)
W: Neg. ΔPerm. Inc.$_{t-1}$	-0.0001	-0.0005
	(0.0020)	(0.0021)
H: Pos. ΔPerm. Inc.$_{t-1}$	0.0031	0.0018
	(0.0035)	(0.0042)
H: Neg .ΔPerm. Inc.$_{t-1}$	0.0076***	0.0085***
	(0.0027)	(0.0031)
Year Controls	Y	Y
N (Person-Year)	17,744	17,744
Couples	2,299	2,299
R^2	0.062	0.064

Custom weights constructed for the NLSY79 are used. Standard errors are in parentheses, clustered by person ID. Marginal effects are reported. *,**,*** indicate significance at the 10%, 5%, and 1% level.

Next, we explore the joint directions of the husband and wife's changes in predicted permanent income. The models in Table 1.5 further divide the variable

*Wife's*Husband's*$_{t-1}$ from the baseline regression. When the wife's income shocks times the husband's is positive, it means that their surprises to permanent income are in the **same** direction, and when it is negative, their surprises are in **opposite** directions. First separating this variable into its positive and negative components in Column (12), we see a negative and significant effect on the probability of divorce when both spouses are experiencing a shock in the same direction. Column (13) of Table 1.5 delves deeper to see what happens to the marriage in each of four cases: both spouses face positive income shocks, the wife has a positive shock while the husband has a negative shock, the wife has a negative shock while the husband has a positive one, and both spouses face negative income shocks. Here we observe that the results from (12) are due to periods when both spouses have negative changes in their predicted permanent income. One explanation of this is that it becomes too costly for a couple to divorce if both of them experience a decrease in their expected future incomes.

1.4.3 Robustness Checks and Alternative Samples

Table 1.6 provides a few robustness checks for the results. This paper focuses only on first marriages of the respondents, to avoid issues with higher order marriages which tend to be shorter and more likely to end in divorce (Kreider and Ellis (2011)). Unfortunately, the number of previous marriages of the spouses is

Table 1.6: Effect on Divorce Probability: Alternative Samples

	(14) Spouse Prev. Marr.	(15) No Children	(16) With Children	(17) Unemp. Interact.	(18) Marr. Lgth Interact.
W: Pos. ΔPerm. Inc.$_{t-1}$	0.0000	0.0014	0.0002	0.0004	0.0018
	(0.0022)	(0.0044)	(0.0019)	(0.0013)	(0.0035)
W: Neg. ΔPerm. Inc.$_{t-1}$	-0.0030	-0.0054	-0.0014	-0.0021*	-0.0001
	(0.0019)	(0.0048)	(0.0016)	(0.0012)	(0.0033)
H: Pos. ΔPerm. Inc.$_{t-1}$	-0.0046	-0.0002	-0.0006	0.0007	0.0021
	(0.0029)	(0.0074)	(0.0026)	(0.0020)	(0.0055)
H: Neg .ΔPerm. Inc.$_{t-1}$	0.0039**	0.0039	0.0032*	-0.0001	0.0030
	(0.0017)	(0.0056)	(0.0017)	(0.0016)	(0.0044)
	Interacted with Becoming Unemployed				
W: Neg. ΔPerm. Inc.$_{t-1}$				0.0330***	
				(0.0097)	
H: Neg .ΔPerm. Inc.$_{t-1}$				-0.0085	
				(0.0058)	
	Interacted with Marriage Duration				
W: Pos. ΔPerm. Inc.$_{t-1}$					-0.0002
					(0.0005)
W: Neg. ΔPerm. Inc.$_{t-1}$					-0.0003
					(0.0004)
H: Pos. ΔPerm. Inc.$_{t-1}$					-0.0004
					(0.0006)
H: Neg .ΔPerm. Inc.$_{t-1}$					-0.0001
					(0.0005)
Year Controls	Y	Y	Y	Y	Y
N (Person-Year)	4,390	5,897	11,847	14,452	17,744
Couples	528	1,721	1,804	2,131	2,299
R^2	0.147	0.072	0.075	0.074	0.063

Custom weights constructed for the NLSY79 are used. Standard errors are in parentheses, clustered by person ID. Marginal effects are reported. *,**,*** indicate significance at the 10%, 5%, and 1% level.

only available for the years of 1982 and 1998-2010 in the NLSY79. The analysis in Weiss and Willis (1997) does control for the spouse being previously married and finds a weakly positive effect on the probability of divorce. For a robustness check, the information on the number of previous marriages of the spouse is included, when available.[10] In Column (14), negative changes in predicted permament income of the husband still increase the risk of divorce, though the sample size is much smaller.

In Böheim and Ermisch (2001), the authors choose to only analyze couples who have children, stating that families with children are of the most interest from a policy perspective. In addition, we might expect that the types of couple that have children versus couples that do not have children are different in a substantial way. Finally, the literature often describes children as a type of marriage specific capital. The results in Column (15) and (16) divide the sample into those couples without and with children, respectively. There is no significant difference between the estimated marginal effects of these groups but we only see a significant effect at the 10% level for those with children. The magnitude of the marginal effect for those with children is slightly smaller so perhaps negative income shocks are still bad for marriage, but if the couple has children, the negative effect on the stability of the marriage is dampened.

Unlike the income shocks studied in Charles and Stephens (2004), not all of the negative shocks in this paper are due to unemployment. Instead, many of them are

[10]Or the number of previous marriages is assumed to be zero if the age at marriage 18 or younger for women and 20 or younger for men as this group is very unlikely to have been married before. According to estimates in Kreider and Ellis (2011) the median age at second marriage for men is 35.8 and for women is 33.3 so this seems to be a reasonable assumption. Among the respondents, for those that divorce, less than 10% divorce before the age of 22 and less than 25% before the age of 25.

simply downward revisions of expectations compared to the expectations at the time of marriage. Using employment status, however, we can attempt to identify those negative shocks that are due to a switch into unemployment. Column (17) interacts an indicator for switching into unemployment with the negative changes in predicted permanent income for each spouse. While in general a negative change for the wife did not affect the divorce hazard, the results here suggest that if that negative change is due to unemployment, it does hurt the marriage. Note that this does not include women who are out of the labor force due to pregnancy, caring for children, etc. The negative changes in predicted permanent income are not significant with the interaction terms included in the model.

In the last column of Table 1.6, I interact the duration of the marriage with each of the four variables of interest to test if the effects are different depending on how far along in the marriage the couple is. From this experiment, the direction of the interaction terms suggests that any effect on the divorce hazard decreases the longer a couple has been married, but is not significant for any of the four main variables of interest.

We may also think that the effects of income shocks on divorce may be different for different socioeconomic groups. Table 1.7 divides the sample by education of the husband and family income of the household. For Columns (18) and (19), low education indicates the husband has a high school degree or less completed

Table 1.7: Effect on Divorce Probability: Socioeconomic Status

	(18) H: Low Educ	(19) H: High Educ	(20) Low Fam. Income	(21) High Fam. Income
W: Pos. ΔPerm. Inc.$_{t-1}$	0.0003	0.0008	0.0005	0.0023
	(0.0036)	(0.0018)	(0.0028)	(0.0022)
W: Neg. ΔPerm. Inc.$_{t-1}$	-0.0015	-0.0022	-0.0052	-0.0011
	(0.0025)	(0.0020)	(0.0025)	(0.0020)
H: Pos. ΔPerm. Inc.$_{t-1}$	0.0004	-0.0002	0.0037	-0.0031
	(0.0047)	(0.0034)	(0.0037)	(0.0043)
H: Neg .ΔPerm. Inc.$_{t-1}$	0.0059*	0.0028	0.0039*	0.0035
	(0.0035)	(0.0019)	(0.0024)	(0.0026)
Year Controls	Y	Y	Y	Y
N (Person-Year)	8,039	9,705	8,496	8,496
Couples	1,137	1,286	1,144	1,049
R^2	0.058	0.072	0.094	0.061

Custom weights constructed for the NLSY79 are used. Standard errors are in parentheses, clustered by person ID. Marginal effects are reported. *,**,*** indicate significance at the 10%, 5%, and 1% level.

education and high education indicates he has some college or more education. Columns (20) and (21) in Table 1.7, divide the sample into two groups by age adjusted family income at the time of marriage.[11] This measure of income is divided at the sample median. We see a stronger and significant effect of negative income shocks for the husband among both measures of lower socioeconomic status. One explanation is that the negative income shocks of the husband are putting even more strain on the relationship if the couple already has relatively low income in their household.

[11]Since people marry at different ages, this gives us a standardized measure of income to determine who is high and low income.

1.4.4 Recipients of Surprises

Table 1.8: Couples Facing Income Shocks,
Compared to All Couples

	All Shocks	W: Pos. Shock		H: Pos. Shock		W: Neg. Shock		H: Neg. Shock	
	Mean	Mean	Difference	Mean	Difference	Mean	Difference	Mean	Difference
Div. This Yr	0.032	0.032	0.000	0.031	-0.001	0.031	-0.001	0.035	0.003*
Wife:									
Black	0.087	0.087	0.000	0.098	0.012***	0.083	-0.004	0.053	-0.033***
Hispanic	0.053	0.042	-0.012***	0.057	0.004	0.068	0.015***	0.045	-0.009***
High School	0.394	0.397	0.003	0.428	0.035***	0.377	-0.016***	0.315	-0.078***
Some College	0.367	0.340	-0.026***	0.348	-0.019***	0.399	0.033***	0.427	0.061***
College	0.230	0.254	0.024***	0.218	-0.011**	0.212	-0.018***	0.241	0.011
log(Income)	7.954	9.349	1.394***	7.804	-0.151***	6.004	-1.950***	8.020	0.065
Age at Marr.	23.56	23.57	0.019	23.34	-0.219***	23.30	-0.255***	23.71	0.155***
Age	30.17	30.69	0.513***	30.43	0.260***	30.41	0.231***	30.91	0.739***
Unemployed	0.024	0.017	-0.007	0.021	-0.002	0.033	0.010***	0.024	0.001
Husband:									
Black	0.086	0.086	0.000	0.097	0.012	0.081	-0.005	0.052	-0.034***
Hispanic	0.052	0.048	-0.004	0.056	0.004	0.058	0.005	0.044	-0.009***
High School	0.395	0.411	0.016**	0.422	0.027***	0.374	-0.021***	0.332	-0.063***
Some College	0.294	0.290	-0.004	0.271	-0.024***	0.308	0.014**	0.334	0.040***
College	0.288	0.284	-0.004	0.277	-0.011**	0.292	0.003	0.330	0.042***
log(Income)	10.35	10.33	-0.016	10.53	0.188***	10.40	0.053**	10.00	-0.351***
Age at Marr.	25.04	25.05	0.011	24.67	-0.367***	24.88	-0.160***	25.33	0.285***
Age	31.66	32.19	0.529***	31.72	0.065	31.99	0.331***	32.57	0.907***
Unemployed	0.020	0.017	-0.003*	0.017	-0.003**	0.021	0.001	0.026	0.006**

*,**,*** indicate significance at the 1%,5%, and 10% level.

Who faces these income "surprises"? The empirical results show that there are different effects on divorce for positive and negative surprises so it could be expected that different types of couples experience them. Table 1.8 compares the characteristics of all couples who have faced an unexpected change in predicted permanent income to those in four sub-groups: where the wife has a positive shock, the husband has a positive shock, the wife has a negative shock, and the husband has a negative shock. Each of these groups is compared to all married couples where an income shock for both the husband and the wife is observed. In the second column, we compare couple where the wife has had a positive income shock to all couples. These couples are less likely Hispanic, have less education and the wife is less likely to be unemployed. Couples where the husband has had a positive income shock are more likely to be black or Hispanic and the husband is less likely to be unemployed, as seen in the third column. So it appears that those relatively disadvantaged groups (blacks, Hispanics, low education) are who experience positive surprise to their permanent income. One explanation is that since these groups are not expected to have high earnings capacity, so are more likely to have a positive surprise if they start earning more money.

Different patterns are seen for couples experiencing negative shocks. When the wife faces a negative shock, as in the fourth column, we see these couples are more likely white or Hispanic, have higher education, and the wife is far more likely to be unemployed. Also in the fifth column, couple where the man faces a negative income shock, which was most disruptive to a marriage, the couple is more likely to be white, have higher education, and the husband is more likely unemployed. Given these results, it appear that many of the negative income shocks come through unemployed individuals, as expected. In addition, the groups that experience these shocks are more likely white and highly educated, relatively advantaged groups. So perhaps the opposite is true here compared to those with positive shocks: these are groups that are expected to do well in the labor market so when they do not, it results in a negative revision to their expectations of permanent income.

1.4.5 Testing the Validity of the Empirical Divorce Model

The divorce model used in this paper is different that that used in WW, the most closely related paper in the literature as noted in Equation 1.4 and Equation 1.5. The particular functional form chosen here was based on the natural way of thinking about what might constitute a "surprise" for married couples and how to model these surprises in a way that the couples themselves might think of them. Thus, I chose measure an income shock as the difference between the current year's predicted permanent income minus the predicted permanent income at marriage to obtain a measure of cumulative deviations over the course of the marriage, separately by their direction. This functional form makes an assumption about the relationship between predicted permanent income now and at marriage.

Expanding the regression described in Equation 1.5:

$$
\begin{aligned}
div_{i,t} = {} & \gamma_{1,t} * log(Y^p_{H,t}) * \mathbb{1}(Pos.) - \gamma_{1,t} * log(Y^p_{H,M}) * \mathbb{1}(Pos.) + \gamma_{2,t} * log(Y^p_{H,t}) * \mathbb{1}(Neg.) \\
& - \gamma_{2,t} * log(Y^p_{H,M}) * \mathbb{1}(Neg.) + \gamma_{3,t} * log(Y^p_{W,t}) * \mathbb{1}(Pos.) - \gamma_{3,t} * log(Y^p_{W,M}) * \mathbb{1}(Pos.) \\
& + \gamma_{4,t} * log(Y^p_{W,t}) * \mathbb{1}(Neg.) - \gamma_{4,t} * log(Y^p_{W,M}) * \mathbb{1}(Neg.) \\
& + \alpha'_{1,t} * x_{H,t} + \alpha'_{2,t} * x_{W,t} + u_{i,t}
\end{aligned}
\tag{1.6}
$$

and rearranging

$$
\begin{aligned}
div_{i,t} = {} & \gamma_{1,t} * log(Y^p_{H,t}) * \mathbb{1}(Pos.) + \gamma_{2,t} * log(Y^p_{H,t}) * \mathbb{1}(Neg.) - \big(\gamma_{1,t} + \gamma_{2,t}\big) * log(Y^p_{H,M}) \\
& + \gamma_{3,t} * log(Y^p_{W,t}) * \mathbb{1}(Pos.) + \gamma_{4,t} * log(Y^p_{W,t}) * \mathbb{1}(Neg.) - \big(\gamma_{3,t} + \gamma_{4,t}\big) * log(Y^p_{W,M}) \\
& + \alpha'_{1,t} * x_{H,t} + \alpha'_{2,t} * x_{W,t} + u_{i,t}
\end{aligned}
\tag{1.7}
$$

Now let the coefficients on $log(Y^p_{H,M})$ and $log(Y^p_{W,M})$ be designated as $\beta_{H,t}$ and $\beta_{W,t}$. Therefore, the implicit assumption of the divorce model is that the estimated coefficients are such that $\gamma_{1,t} + \gamma_{2,t} = \beta_{H,t}$ for the husbands' income shocks and $\gamma_{3,t}+\gamma_{4,t} = \beta_{W,t}$ for the wives' income shocks. Using a t-test to test this assumption we have a χ^2 value of 4.02 with a p-value of 0.05 for the husbands and a χ^2 value of 0.02 with a p-value of 0.89 for the wives. So we confirm the assumptions of the model for women, but must reject it for men.

Thus, an alternative to this model is presented here to support the robustness of the findings, rather than measuring an income shock as the difference between the current year's predicted permanent income minus the predicted permanent income at marriage. Instead, we consider that the relevant time horizon for couples is not how different your predicted permanent income is from when you were first married, but what we thought your permanent income would be five years ago. One might think that couples are using a shorter time horizon as their frame of reference rather than the entire length of the marriage. So the new equation for Δ Perm. Inc.$_{i,t}$ is $log(Y^p_{i,t}) - log(Y^p_{i,t-5})$. Using this new measure of income shocks a new regression is run following Equation 1.7 to again test for the validity of this model. Using a t-test to test the above assumptions we have a χ^2 value of 1.14 with a p-value of 0.29 for the husbands and a χ^2 value of 0.44 with a p-value of 0.89 for the wives. So we confirm the assumptions of the model for both men and women.

To confirm the results in Table 1.4 we now run the same set of regressions using instead this change in predicted permanent income over the last five years, as shown in Table 1.9. Again, each subsequent column adds in more control variables. Across all specifications we continue to see strong evidence that negative changes in the husband's predicted permanent income destabilize marriage. The size of the marginal effects using this methodology is over 50% larger. This provides a robustness check since the model assumptions were rejected using the change in predicted permanent income since the beginning of the marriage. In some

Table 1.9: Effect on Divorce Probability: 5 year Time Horizon

Model	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
W: Pos.ΔPerm. Inc.$_{t-1}$	0.0014	0.0001	-0.0009	-0.0014	-0.0006	-0.0006	-0.0015
	(0.0021)	(0.0021)	(0.0020)	(0.0019)	(0.0019)	(0.0019)	(0.0019)
W: Neg.ΔPerm. Inc.$_{t-1}$	-0.0021	-0.0025	-0.0037*	-0.0044**	-0.0035*	-0.0038**	-0.0010
	(0.0018)	(0.0019)	(0.0020)	(0.0019)	(0.0019)	(0.0018)	(0.0018)
H: Pos.ΔPerm. Inc.$_{t-1}$	0.0058*	0.0050	0.0035	0.0029	0.0024	0.0023	0.0019
	(0.0033)	(0.0034)	(0.0033)	(0.0033)	(0.0032)	(0.0031)	(0.0032)
H: Neg.ΔPerm. Inc.$_{t-1}$	0.0087***	0.0087***	0.0056***	0.0055***	0.0051***	0.0049**	0.0047**
	(0.0022)	(0.0022)	(0.0021)	(0.0020)	(0.0019)	(0.0020)	(0.0022)
Wife's*Husband's$_{t-1}$	-	-	-	-	-	-0.0018*	-0.0020*
	-	-	-	-	-	(0.0010)	(0.0011)
Year Controls	N	Y	Y	Y	Y	Y	Y
Demographic Controls	N	N	Y	Y	Y	Y	Y
Duration/Age at Marr.	N	N	N	Y	Y	Y	Y
Fertility Controls	N	N	N	N	Y	Y	Y
Emp. Status	N	N	N	N	N	N	Y
N (Person-Year)	20,310	20,310	16,808	16,808	16,808	16,808	15,482
Couples	3,086	3,086	2,432	2,432	2,432	2,432	2,386
R^2	0.003	0.010	0.046	0.060	0.068	0.069	0.077

Custom weights constructed for the NLSY79 are used. Standard errors are in parentheses, clustered by person ID. Marginal effects are reported. *,**,*** indicate significance at the 10%, 5%, and 1% level.

regressions we see a negative and significant estimate coefficient for the wife's negative income shock, however it is not consistent across specifications. One possible explanation is that when the wife experiences a negative income shock, she is less able to support herself if a divorce were to occur increasing the value of the marriage.

1.5 Theory

From the empirical results of this paper, we see that shocks to permanent income matter for the stability of the marriage. The likely channel that this occurs through is changes to the marital surplus. There are several different types of models of marital formation and dissolution, each offering predictions as to what the effects of changes in marital surplus might be. The goal of this section is to discuss types of models with predictions that are consistent with the results of this paper, and types of models that are not.

Consider models of learning where the agents have some uncertainty about the value of permanent income for themselves and their spouses. Let $Y^p_{H,t}$ and $Y^p_{W,t}$ be the husband's and the wife's predicted permanent income at time t. Since the couple has married, we know that what ever their expectations of permanent income were at the time of marriage, the match was acceptable at that point. Denote these expectations at the time of marriage by $Y^p_{H,M}$ and $Y^p_{W,M}$, where M is the date of marriage. However, if there are changes in these expectations, which change the marital surplus, the match might no longer be acceptable and the couple will divorce.

1.5.1 Efficiency In Divorce

First, consider a simple model where predicted permanent income of the husband and wife affect the marital surplus in a linear way.

$$S_{H,W} = Y^p_{H,t} + Y^p_{W,t} \tag{1.8}$$

Where $S_{H,W}$ is the total value of the marital surplus of husband H and wife W.

In addition to increasing the marital surplus, permanent income also increases and agent's outside options. This could either be through the effect on the marital surplus of potential future matches, or simply through value that is gained being single. For simplicity, assume that it also affects the outside option in a linear (but potentially different) way:

$$O_{H,W} = (1+\alpha)Y^p_{H,t} + (1+\beta)Y^p_{W,t} \tag{1.9}$$

Where $O_{H,W}$ is the total value outside option of husband H and wife W, and α and β are constants.

Suppose that divorce only occurs if it is efficient, that is when the value of the outside option is greater than the marital surplus. If the couple is initially indifferent between being married and not, then it is true that

$$S_{H,W} = Y^p_{H,t} + Y^p_{W,t} = (1+\alpha)Y^p_{H,t} + (1+\beta)Y^p_{W,t} = O_{H,W} \tag{1.10}$$

In this model, if there are changes to predicted permanent income, it will change the value of both the outside options, and the value of the marital surplus. But how it changes these will depend on the parameter values of α and β.

1. $\alpha > 0$, $\beta > 0$

If both α and β are positive, then increases in permanent income for either the husband or the wife will increase the value outside of marriage more than they increase the value inside of the marriage. So for these parameter values positive income shocks would increase the probability of divorce.

2. $\alpha < 0$, $\beta < 0$

   In this case, positive income shocks may still increase the value of outside options (depending on the size of α and β, but it will certainly increase the marital surplus faster.) A model with these parameter values would suggest that positive income shocks should stabilize marriage, as they increase the value inside the marriage by more than the outside options.

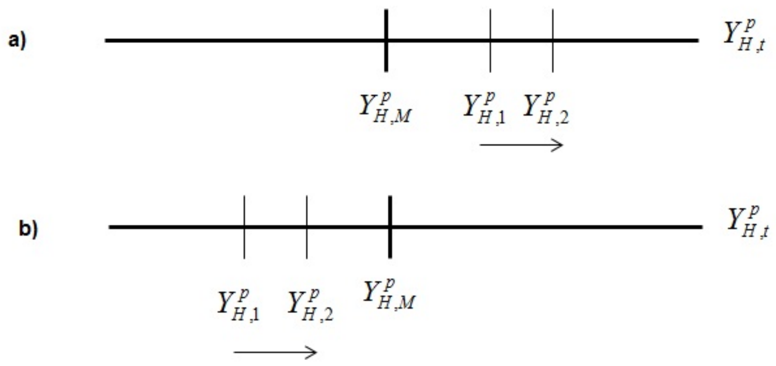
3. $\alpha > 0$, $\beta < 0$

   With these parameter values, the model predicts different effects on the probability of divorce for each spouse. For the husband, positive shocks increase the outside options by more than they increase marital surplus. So positive income shocks for the husband would increase the divorce hazard. But for the wife, positive income shocks would decrease the divorce hazard.

4. $\alpha < 0$, $\beta > 0$

Finally, the last case is where positive income shocks increase the outside options more than marital surplus for the wife only. The model then predicts that positive shocks for the wife would increase the probability of divorce, while positive shocks for the husband would decrease the probability of divorce.

Figure 1.4: Increases in Predicted Permanent Income



One important aspect of this model to note is that for any of these four possible cases, positive changes in predicted permanent income must have the same effect on the divorce hazard, regardless of what the values are compared to some reference point. For example, consider one reference point of predicted permanent income at the time of marriage. This means that the model predicts that it does not matter if an income shock is increasing predicted permanent income to a point above the reference point, or if it is increasing predicted permanent income from a lower level towards the reference point. Panel a) in Figure 1.4 shows an example where, from period 1 to period 2, the husband's predicted permanent income increases further above the value of predicted permanent income at the time of marriage, $Y^p_{H,M}$. Panel b) instead shows an example where the husband's predicted permanent income is increasing from period 1 to period 2, but remains below the level it was in the year of marriage. A model of this kind would suggest that the effect on divorce must be the same for both of these types of changes.

This figure does not directly relate to the regression results, as this is comparing changes from time $t = 1$ to $t = 2$. Instead, the regressions results would compare $\Delta Y_{H,1} = Y^p_{H,1} - Y^p_{H,M}$ and $\Delta Y_{H,2} = Y^p_{H,2} - Y^p_{H,M}$. In panel a, both of these changes are positive shocks that would stabilize marriage. On the other hand, both $\Delta Y_{H,1}$ and $\Delta Y_{H,2}$ in panel b would appear as negative shocks in the regression results which increase the probability of divorce. But since larger negative shocks have a larger impact on the probability of divorce, $\Delta Y_{H,2}$ would increase the divorce hazard by less than $\Delta Y_{H,1}$.

1.5.2 Assortative Matching

Consider instead a simple model of strict assortative matching. Assume the only factor affecting spouse quality is predicted permanent income, and there are an equal and fixed number of men and women, N. There are distributions of permanent income for each sex of $F_H(.)$ and $F_W(.)$. Over time the values of $Y^p_{H,t}$ and $Y^p_{W,t}$ change. By strict assortative matching, we mean that the man with the largest predicted permanent income matches with the woman with the highest predicted permanent income, $\bar{Y}^p_{H,t}$ and $\bar{Y}^p_{W,t}$. There is costless reshuffling in each period, so as permanent income changes, new matches are immediately formed.

Suppose it is the case that as predicted permanent income changes the overall distribution of permanent income for each sex stays the same. This means that if a married couple does not have a change in $Y^p_{H,t}$ and $Y^p_{W,t}$ from one period to the next, since the distribution stays the same, $F_H(Y^p_{H,t})$ and $F_W(Y^p_{W,t})$ are the same as well. And, if each spouse's position in the distribution for the sex is the same, the couple will stay together. Put another way, if predicted permanent income has not changed, other agents may be shuffling in position around the couple, but the fraction of agents with permanent income higher than each spouse is the same.

On the other hand, this simple model has quite a stark prediction on what will happen if either one of the spouses faces a shock to permanent income. For the husband (wife), a change in either direction of $Y^p_{H,t}$ ($Y^p_{W,t}$) would lead to divorce, given that the distribution of permanent income remains the same. Of course, this is quite a simple example of assortative matching, however similar patterns would be seen in a more complex model with search frictions.

1.5.3 Theoretical Implications

This is, of course, not an exhaustive discussion of the types of models of divorce, and there was no discussion of how the marital surplus is divided within the marriage. However, the results suggest that divorce occurs efficiently in the data, and that positive income shocks raise the marital surplus more than they raise the value outside of marriage. Many arguments could be made as to why this is the case, such as the purchase of public goods in a marriage (washing machines, a house, etc.). The only effect that is consistently observed in the results is an increase in the divorce hazard from negative income shocks of the husband. However, in at least some specifications we observe each of the other type of shock (positive for the wife, positive for the husband, and negative for the wife) increasing the divorce hazard as well. Though this does not strictly fit with either of these simple models it does give some evidence for assortative matching, where shocks in *any* direction change the outside options of the spouse, and if large enough may lead to divorce.

1.6 Concluding Remarks and Future Work

Using data from the NLSY79, a long-lasting panel data set focused on respondents born from 1957 to 1965, predictions of permanent income were constructed using the information known by respondents and their spouses in each year. Knowing the year the respondents were first married, we can then track changes in the predicted permanent income over time, compared to what was expected of the individual at the time of marriage. Compared to the literature, the data used is a longer panel to more accurately obtain a measure of permanent income. The analysis here also goes deeper into potential non-linearities in the effect on the divorce hazard, by direction of the income shock, family structure, and socioeconomic groups. The results show that what hurts a marriage is unexpected negative changes in predicted permanent income for men. Conversely unexpected negative changes in predicted permanent income only matter for women if they are caused by switches into unemployment. In addition, we see it is those from lower income and education groups whose marriages are most detrimentally affected by negative income shocks.

One interpretation is that with lower permanent income of either the husband or the wife, there is a smaller marital surplus. With smaller gains from marriage, one spouse now may take a smaller share of the marital surplus in order to encourage their spouse to want to stay in the marriage. But if the negative shock to income is large enough, the spouse may find it preferable to leave the marriage.

This analysis focused on only a slightly younger cohort than the one in Weiss and Willis (1997), individuals who were aged 45 to 54 at the last year surveyed.

An additional question yet to be answered is if these effects are constant across cohorts. To answer this, another panel study would need to be used with younger respondents. However, for now, the difficulty with focusing on a significantly younger cohort, such as those in the National Longitudinal Survey of Youth of 1997, is that the respondents have yet to enter their peak earnings years. This means that constructing a measure of permanent income would be difficult and perhaps inaccurate.

Examining those couples who experience positive income shocks shows that they are more likely to be non-white and have lower education than the full sample. It appears that those who have positive changes in their expectations are from relatively disadvantaged groups, so perhaps had low expectations for labor market success to start. Conversely, couple who face negative shocks are more likely white and highly educated, groups that one would expect to do well in the labor market. In addition, they are far more likely to be unemployed in the year they experience the negative shock.

In the future, this analysis can potentially be extended to other characteristics that may be important to one's quality as a spouse such as fertility, and health. Specifically, what happens when one of these characteristics change unexpectedly in a marriage? What is the effect on divorce if a couple has more or less children than they expected, etc.? This paper has shown the importance of the initial expectations of an individual upon entering a marriage and that with large divergences from the expectations, the probability of divorce will be affected.

Chapter 2

House Price Shocks and Individual Divorce Risk in the United States

2.1 Introduction

Do economic conditions affect marital stability? This question has seen renewed interest since the recession in 2007 both in the press and academia. Several recent articles in The New York Times have suggested a connection between the recession and the ability of a couple to afford a divorce: Leland (2008), Douthat (2009), and Parker-Pope (2011). These articles speculate that during the housing bust couples wanted to, but could not afford to, divorce. Others state that the recession and economic hardships have deepened couples commitments to each other.

A large portion of the population will experience a divorce in their lifetime: Kreider and Ellis (2011) estimates that 20% of all adults in the U.S. has ever been divorced as of 2011. In addition, divorce is potentially very detrimental for both the spouses and their children. Adults who have divorced have a lower standard of living and less wealth compared to married adults and report higher rates of depression (Amato (2000)). Children whose parents have divorced grow up to have less education, lower earnings, and higher rates of teen pregnancies and high school dropouts (Gruber (2004), McLanahan and Sandefur (1994)). Given the prevalence of divorce and its harmful effects on individuals it is important to understand the determinants of marital stability. This paper will explore the link between changes in the economic opportunities of households and the decision to divorce.

Changing economic conditions affect household wealth and other household characteristics that in turn change the gains to marriage or ease with which a couple can separate. This paper examines one component of household wealth: owner-occupied housing. Specifically, how does a shock to housing prices affect the divorce hazard for married couples? Housing has been the largest component of household wealth for the past several decades, and about 33% of household wealth was held in residential housing as of 2007 (Wolff (2010)). In addition, house price shocks are useful shocks to study as they are likely exogenous to any actions of the individual households, as compared to other types of economic shocks such as job loss.

This paper uses restricted household level data to analyze the effect of house price shocks on the divorce hazard and links this to a quarterly house price index by Metropolitan Statistical Area (MSA). In order to measure unexpected changes in housing prices I take the residuals from a second order autoregressive process of the house price index. The effect on the divorce hazard is identified using variations over time across MSAs, controlling for local economic conditions. I find that positive house price shocks decrease the divorce hazard, however there is no significant effect of negative house price shocks. In particular for the average couple, a one standard deviation increase in the positive house price shock reduces the risk of divorce by about 13 to 18 percent. The results are strongest in the later part of the sample, and for younger cohorts and households with lower income and education. To my knowledge this is the first paper to examine the effect of house price shocks on divorce using micro level data from the U.S.

The economic literature on divorce, beginning with Becker et al. (1977), emphasizes surprises, and in particular economic shocks, as a principal driver of marital instability. In this seminal paper, Becker et. al. posit that it will only be surprises that matter for the decision to divorce as anything known to the couple will have already been considered in the decision to marry in the first place. A few papers have used longitudinal data to attempt to measure changes in expectations of each spouse's income such as Weiss and Willis (1997) and Böheim and Ermisch (2001). The literature generally find that only negative shocks to income increase the divorce hazard, and positive shocks do not have a significant effect.

Also related is the recent literature regarding the link between business cycles and divorce. Hellerstein and Morrill (2011) finds that an increase in the state-level unemployment rate leads to a decrease in the number of divorces per thousand people for the time period 1976-2009. Also using state-level vital statistics, Schaller (2013) confirms these results on divorce and shows marriage rates also decline with higher unemployment rates. Additionally, the author finds that these effects on marriage and divorce rates are permanent, not just changes in timing. Chowdhury (2011) measures the transitory component of income for households and finds that divorce moves pro-cyclically with business cycles. In other words, when income is low in a recession, the cost of divorce is too high so couples that might have otherwise divorced stay together. Low income and minority groups in the Fragile Families and Child Wellbeing Study are found to delay marital dissolution in bad economic times, as measured by state-level mortgage delinquencies and local-level unemployment rates in Harknett and Schneider (2012). Other recent papers have looked for a link between wealth shocks and fertility decisions.[12]

Most closely related to this paper are Rainer and Smith (2010) and Farnham, Schmidt and Sevak (2011), two recent papers that attempt to determine how house price shocks affect partnership dissolution. Contrary to my findings, both papers find that it is only *negative* house price shocks that matter for marital stability, though the results show differing effects. The methodology used in this paper most closely fits with Rainer and Smith (2010) (hereafter RS), which analyzes respondents of the British Household Panel Survey. Using county level housing prices mapped to local authority districts in the UK, the authors calculate unanticipated house price shocks for households. Both legal marriages and cohabitations are studied, and the analysis finds that negative house price shocks increase the risk of partnership dissolution. Farnham et al. (2011) (hereafter FSS) uses Metropolitan Statistical Area level house prices to examine the effect of unanticipated changes on the *stock* of divorced people in the MSA. Using marital status of respondents of the Current Population Survey, the authors find that the fraction of divorced individuals decreases with negative house price shocks. This effect is observed only within groups that are likely to be homeowners (those with higher

[12]Lovenheim and Mumford (2013) use house price data and restricted-use location data from the Panel Study of Income Dynamics (PSID), as in this paper. They find that increases in housing wealth increase fertility rates for homeowners. Dettling and Kearney (2014) also examines the relationship between MSA level housing prices and MSA level fertility rates and also finds an increase in fertility among homeowners.

levels of education). The fraction of the population divorced is a combination of individuals who are getting divorced, those who have not yet remarried, and the net migration of divorced and non-divorced people. Thus the results in FSS have a slightly different interpretation than those for individual households in RS and this paper. To my knowledge, there are no papers that look at house price shocks and divorce in the U.S. using micro level data and this paper attempts to fill this gap.

2.2 Theoretical Discussion

2.2.1 Determinants of Divorce

In economic models of marriage and divorce, a couple will decide to marry if the (expected) value of marriage is higher than the value of staying single. So, the value of the marital surplus also determines whether or not a couple will stay together. If the factors that affect the gains to marriage change, it could lead to a match no longer being acceptable to the couple.

The following two period model of marriage and divorce follows closely to the model presented in Peters (1986). In the first period, the couple must decide whether or not to get married. Suppose that the joint value of marriage in period 1 for the husband, H, and wife, W, is M_1. We assume that this value of marriage is a composite of a variety of factors of both spouses that together determine the value of this couple being married in the following simple relationship: $M_1 = M_{H,1} + M_{W,1}$. Each individual also has an outside option to the marriage: their present value of staying single for the two periods, S_H and S_W, respectively. The couple does not have perfect information about the value of marriage or staying single in the second period. Instead, the true values are not realized until the second period. We assume that both individuals know the expected value of marriage in the second period, $\mathbb{E}(M_2)$, and the expected value of their outside options if they divorce in the second period, $\mathbb{E}(D_H + D_W \text{divorce})$, where D_H is the outside option of the husband and D_W is the outside option of the wife in the second period and $M_2 = M_{H,2} + M_{W,2}$. Also known before the decision to marry is the discount factor, b, and the probability of divorce, p, which is a function of M_2, D_H, and D_W.

The couple must make the decision whether or not to marry in the first period based on their expectations of the value of marriage. Let V be the expected present value of marriage, given the information available in period 1:

$$V = M_1 + b \left[\mathbb{E}(M_2)(1-p) + \mathbb{E}\left(D_H + D_W | \text{divorce}\right) * p \right]$$

where the value of marriage in the second period is the expected joint value of the marriage in period 2 times the probability of staying married, plus the expected joint value of becoming single times the probability of divorcing. Given the information that is available in period 1, the couple decides to marry if the expected value of marriage is at least as large as the sum of their present value of staying single:

$$V \geq S_H + S_W$$

In period 2, the true values of M_2, D_H, and D_W are realized. If any of the various factors that determine the value of marriage or of becoming single change from what was expected, the couple may suddenly find it better to divorce in the second period. For example, if housing prices are unexpectedly high in the second period, this may affect both M_2 and D_i as discussed in the next section. In a model of transferable utility, each spouse can transfer some of his/her value of marriage to the other if it is beneficial. In this case, if that the joint value of marriage in the second period is less than the joint value of being single (the outside option), there is no arrangement they can make between themselves such that they want to continue the marriage:

$$D_H + D_W > M_2$$

$$D_H + D_W > M_{H,2} + M_{W,2}$$

If this is the case, it will be optimal for the couple to divorce. The next section will discuss house price shocks in the context of changing gains to marriage.

Stevenson and Wolfers (2007) provide an excellent overview of what specific factors can lead to divorce, and how these factors have changed over time. The discussion about what influences marital dissolution can be divided into two categories: macrostructural factors (White (1990)) and individual or family characteristics. By macrostructural we mean those factors that affect the cost of divorce for the whole of society such as changes in laws, changes in social norms and stigma surrounding divorce, and gender roles. Next, there are strong links between the underlying forces of divorce and observables such as race/ethnicity, fertility, and socioeconomic status. The data shows that couples who are older when they first marry have a higher chance of reaching any particular length of marriage. This is observed in SIPP data by Kreider and Ellis (2011) and is also true of respondents in the PSID, and Rotz (2011) shows that the increase at the age of marriage explains at least 60% of the decrease in the divorce rate since 1980. Another aspect that may affect divorce has been the rise in cohabitation. Stevenson and Wolfers (2007) report on data from various sources that show very little cohabitation existed before 1970, and then growing at a fairly steady rate thereafter. One rationale for cohabitation is learning about match quality before making the decision to marry. At the micro level there are a number of determinants of divorce. These are changing characteristics that affect either the value of marriage or the outside options of the individuals. For example, marriage or cohabitation takes advantage of economies of scale and if the cost of these shared items changes, the surplus of the marriage changes. To the extent that couples only receive a noisy signal regarding the match quality, a couple may divorce if the realization of the value of marriage is lower than expected. On the other hand, a divorce may occur if the value of the marriage itself changes over time, even if the value of marriage was perfectly observed at the start (Marinescu (2012)). The following section discusses how house price shocks in particular may be a determinant of marital stability.

2.2.2 House Price Shocks and Divorce

The definition of a "house price shock" in this paper is the portion of the change in local housing prices that is unexpected. I chose to use these *unexpected* changes in housing price for several reasons. First, if instead the analysis used just the change in the house price index from one year to the next, this would include both anticipated and unanticipated changes in housing prices. If some portion of the change in housing prices is anticipated, it is unclear when we would expect a household to respond to an anticipated change in wealth. On the other hand, using only the unexpected portion of the change in prices allows us to try to identify a direct response to a change in wealth after it has occurred. The second reason is drawn from the literature on the link between housing prices and consumption/saving decisions of households. In much of the recent literature the focus has changed to housing price shocks, or windfall gains in housing wealth. There has been conflicting empirical and theoretical findings on responses to changes in housing prices, and it has been suggested that this is because some changes in housing prices are anticipated by households. Stemming from the theoretical work of Skinner (1996), the research conducted by Disney et al. (2010), Attanasio et al. (2011), and others demonstrate how a household's consumption decisions might respond to house price shocks. If a household were to experience a rise in housing prices that they had expected, according to the standard life-cycle model of consumption there should be no response since agents are forward looking (ignoring the issue of credit constraints). That is, any expected increase in housing prices has already been incorporated into the consumption/savings path chosen by the households, ignoring any issues of credit constraints. If instead the household faces a shock to housing prices that was unexpected, we might see a change in their behavior.

As discussed in the above model of marriage, a couple will marry (and stay together) so long as the value of staying married is greater than the value of being single. Unexpected changes in housing prices can affect the gains to marriage in several ways and these effects are likely different for owners versus renters. To the extent that housing prices and rent prices are correlated, an increase in housing prices may be a negative wealth effect for renters. If however, they are not strongly linked renters may not have any response to house price changes. Also, positive house price shocks may mean it is more costly for a renter to purchase a home in the future. It is certainly possible that even among homeowners households differ in how they view a shock to housing prices. For some homeowners, an increase in housing prices may be bad news if they intend to purchase a larger home in the future. Or, an increase in prices may be viewed negatively by a retired couple hoping their children will be able to purchase a home in the same area. In this case, even though an increase in housing prices means their own home value increases it also means it will be more expensive to buy new or larger homes. Two main channels through which house price shocks may affect marital stability discussed here: gains of marriage and changes in transaction costs surrounding divorce.

The sociology and psychology literature has extensive research on the positive correlation of a household's financial situation and marital satisfaction as seen in Cutright (1971) and Conger et al. (1990). Increases in income or a better financial position is hypothesized to affect satisfaction in two ways: through the allowed increases in consumption and through the increased "constraints" to marital dissolution. By which we mean that a couple that has increased their income has more to lose in terms of its higher consumption/asset accumulation standing if a divorce were to occur. An increase in housing prices for homeowners is an increase in their wealth which may decrease their financial stress. This decreased stress would increase the value of marriage, which in turn decreases the probability of divorce. In the context of the marriage model, this would lead to an increase in M_2.

One of the gains to marriage in the theoretical literature is that of economies of scale within households. In short, there many consumption goods that must be purchased for each household, including the housing itself, dishwashers, washing machine, etc. These items are those that all members of the household can use, and so living together has its advantages. Renters will save on rent, owners must only purchase one home, and purchasing one dishwasher is better than needing to purchase two. Thus, living together to benefit from these economies of scale provides one reason for cohabiting and/or marrying. For homeowners, an increase in the value of residential housing increases these economies of scale and thus the value to staying married. With higher housing costs, a couple would lose out on these larger economies of scale if they were to divorce and live apart. Put differently, an increase in housing prices would increase the cost of living apart since they couple would become *buyers* in the market. In the case of a shock to housing prices, the couple will not have taken this change into account when making their decision to marry, and thus it may affect their likelihood of staying married. This would be equivalent to a decrease in D_H or D_W. To the extent that increases in housing prices increases rents, this effect may be similar for owners and renters.

Changes in housing prices also affect the equity that homeowners hold in their houses. With a decrease in house prices, there is a decrease in the value of the home, and therefore the equity held in the home. This may not matter to homeowners who have paid off their homes, or who do not intend to sell the home soon. However, during the 2007-2009 recession many homeowners ended up with mortgages that were "under-water", or they owed more on the mortgage than the home was worth. For all homeowners, a decrease in the value of housing means that it must be sold for less money but the amount owed on the home through the mortgage stays constant. Through this channel, an unexpected decrease in housing prices can decrease the divorce hazard since the costs to divorce are higher, or some couples might be "locked" in their homes. This would suggest that negative house price shocks would decrease the divorce hazard.

Another consideration for married couples is their prospects for buying or selling a house. After a divorce occurs and the household's assets must be divided, and often the primary residence must be sold. Since housing is by far the largest asset for most households, there may not be enough wealth in other assets for one spouse to take over sole ownership of the home. In this data, 38% of heads of household switch to renting in the year of divorce. When housing prices are high, and the economy is experiencing a boom, there is an excess demand for housing so it would be relatively easy for a couple to sell their house in the case of a divorce (Case and Shiller (1989) and Genesove and Mayer (1997)). A housing boom would make it easier to sell the home, and leave the couple with a larger amount of money to buy separate residences. This suggests that positive house price shocks would increase the divorce hazard by reducing the transaction costs of divorce. In the context of the model of marriage, this would increase the values of D_H and D_W. Conversely, in a housing bust, there tends to be an excess supply of houses which would make it relatively difficult to sell the house upon divorce, but cheaper to buy a new home.

So, the theoretical predictions suggest that the effect of house price shocks on divorce could go in either direction. Increases in housing prices increase the gains to marriage, which would suggest they decrease the divorce hazard. On the other hand, it is easier to sell your home when prices increase which makes it easier to divorce. Given the theoretical direction of an effect on the probability of divorce is potentially in either direction we explore the question with micro level data on households.

2.3 Data and Methods

Two main data sets are linked in this paper to study the effect of house price shocks on marital stability. The house price index used is the All-Transactions Index for MSAs from the Federal Housing Finance Agency.[13] This index combines transactions from sales as well as appraisals. The All-Transactions Index provides the best-suited house price index for the analysis in this paper as it covers a long period of time and provides information for all currently defined MSAs.[14] As of 2010, there were 374 MSAs defined by the U.S. Office of Management and Budget. In addition, some of the largest of the metropolitan areas have been subdivided into smaller divisions. This gives us a total of 384 MSAs and/or MSA Divisions in the All-Transactions Index. The data contains a price index for some MSAs as far back as 1975, and continues quarterly through the end of 2011. By 1987, the index has data for 80% of the MSAs. The index is deflated using the Consumer

[13] Data obtained through the Office of Policy Analysis and Research in Washington, DC: FHFA (2012)

[14] Other indexes exist, most notably the S&P/Case-Shiller Home Price Indexes, however they do not fit as well with the goals of this paper. The Case-Shiller index only covers 20 Metropolitan Statistical Areas in the U.S., and does not begin until the late 1980s or early 1990s, and so there would be too few observations to use for analysis.

Price Index, CPI, excluding housing. This means that the index used will reflect how housing prices have changed as compared to all other consumer goods.

As previously mentioned, I attempt to measure the unexpected portion of the change in housing prices. To calculate these shocks, I approximate the quarterly house price index with a second order autoregressive process with MSA and quarter fixed effects is used in this paper, as described in Equation 2.11.[15] Quarter fixed effects are included since the index is not seasonally adjusted.

$$HPI_{i,t} = \beta_1 + \beta_2 * HPI_{i,t\text{-}1} + \beta_3 * HPI_{i,t\text{-}2} + \gamma_i + \eta_q + u_{i,t} \tag{2.11}$$

where i is the MSA, t is time, indexed by the year and quarter. HPI is the quarterly house price index, deflated using the CPI, that is regressed on the index for each MSA from the previous two quarters. γ_i is a fixed effect for the the MSA, and η_q is a fixed effect for the quarter. The remaining variation in the residuals from this first stage regression are taken to be the unanticipated change in prices. At each point in time I use the cumulative sum of residuals from Equation 2.11 for the past four years, or past 16 quarters. This methodology ensures that for each MSA in each year we can compare a cumulative sum of residuals that has the same starting date. Thus, using the residuals from the previous regression,

[15]All of the analysis shown in the paper follow this methodology that is used in the rest of the literature. Changing to a longer autoregressive processes does not change the results.

the house price shock, $Shock_{i,t}$ is calculated as:

$$Shock_{i,t} = \hat{u_{i,t}} + u_{i,\hat{t-1}} + ... + u_{i,\hat{t-16}} \tag{2.12}$$

where $\hat{u_{i,t}}$ is the residual from Equation 2.11 for MSA i in time t.[16] By using the residuals of the the AR(2) process, the house price shock variable attempts to measure unexpected changes in local housing prices, rather than changes that are anticipated. As the shock is calculated as the sum of the past four years of residuals, the earliest date for the house price shock is 1979. The average start date for the house price shock in the sample is 1988.[17] Calculating the shock as the sum of the past four years gives us a measure that can be easily compared across locations since each MSA begins collecting housing data at a different time.

In order to assign the correct house price shock to each household, we exclude those households who have lived in the MSA for less than four years, and so a sum of the shocks from the past four years would not be relevant to them. In comparison, the methodology used in RS gives a measure of the price shocks since

[16]The index is measured quarterly, so adding the residuals from the past 16 quarters to the current quarter gives us the sum for 4 years. House price shocks of other lengths are tested in Section 2.4.

[17]This is somewhat different to the calculation of house price shocks in RS and FSS. Both of those papers use methodology presented in Disney et al. (2010) where the house price shocks are calculated as the cumulative residuals of an AR(2) process of the house price index with county fixed effects. Unlike the U.K. House Price data used by Disney et al. (2010) and Rainer and Smith (2010), the All-Transactions Index starts at different dates for different MSAs. Therefore, simply cumulating the residuals from Equation 2.11, as in RS, is not an ideal strategy since the shock could not be accurately compared across MSAs.

the start of the housing data. For households that have just moved from one MSA to another, the entire past history might not be the relevant house price shock that matters for decision-making.

The second main data set used is the PSID[18], a household panel survey that currently has data available annually from 1968-1997 and bi-annually from 1999-2009. The panel began with a nationally representative sample of 4,802 families, and has followed the initial sample and their children as they split off and formed new households. As of the latest release in 2009, there were 8,690 households being interviewed. The analysis is completed using the original households and their split-offs. In addition, the restricted Geocode Match data from the PSID is used to obtain finer location measures for the households. This data is then used to match households to a house price shock by Metropolitan Statistical Area.

Finally, we link to the county unemployment rate, in order to observe the effect of house price shocks on divorce independent of changes in local business cycles.[19] As expected, the county unemployment rate is negatively correlated with the house price shocks. However, the coefficient of correlation between the two series is relatively low at -0.27. Note that the sample in each model in Section 2.4

[18] Data obtained through the University of Michigan: PSID (2012).

[19] Unemployment data by MSA is only available beginning in 1990, so county unemployment data was used. In many cases the MSA covers one county, however for some larger MSAs there may be several counties included.

begins in 1982, rather than in 1979 at the start of the housing price shocks, due to the availability of the county unemployment rate data.

Table 2.10: Summary Statistics of Married PSID Households, 1975-2009 Means

	Estimation Sample		**All Homeowner Couples**	
	Husband	Wife	Husband	Wife
Demographics:				
< High School	0.155	0.114	0.196	0.151
High School	0.295	0.426	0.320	0.438
Some College	0.211	0.204	0.185	0.191
College	0.338	0.256	0.299	0.221
White	0.875	0.875	0.896	0.894
Black	0.063	0.064	0.056	0.056
Hispanic	0.051	0.053	0.040	0.045
Year of Birth	1943	1945	1941	1944
Number of Children	0.821	0.821	0.882	0.882
Marriage:				
Age First Married	23.62	21.65	23.25	21.32
Year First Married	1967	1967	1965	1965
# of Marriages	1.198	1.183	1.243	1.181
Length of Curr. Marriage	26.42	26.42	24.30	24.30
Frac. Divorcing this Yr	0.011	0.011	0.012	0.012
Employment:				
Employed	0.738	0.576	0.748	0.561
Unemployed	0.015	0.012	0.016	0.013
Labor Income	$57,331	$21,670	$50,815	$18,591
Housing:				
House Value	$210,320	$210,320	$179,555	$179,555
Remaining Principal	$69,448	$69,448	$59,997	$59,997
House Price Shock	0.111	0.111	0.102	0.102
County Unemployment Rate	0.059	0.059	0.062	0.062
Couples	3,893	3,893	9,675	9,675
N (Couple-years)	30,013	30,013	64,190	64,190

NOTE: Monetary variables are in 2009 dollars. The house values are self-reported yearly measures of the value of the current residence for homeowners. Estimation sample begins in 1982 when county unemployment data is available. Sample weights are used.

Table 2.10 explores summary statistics for the two different married homeowner groups in the data: married households who are in the baseline estimation sample in Section 2.4 and have a valid house price shock and all married home-owners, including those who are not in the estimation sample. The 'House Price Shock' variable listed in the table is calculated as mentioned in Equation 2.11. These two groups of couples are compared to see if there are any major differences between the estimation sample and the entire population of married home-owners. The couples who are not in the estimation sample either do not have a measured house price shock, or have missing data for another explanatory variable. There are several reasons why a couple might not have a house price shock matched to them: the couple does not live in an MSA, they do not live in an MSA during the period that the MSA has housing data available, or they do not have a location reported with in the PSID Geocode Match Data. This means that for those couples who do have observations in the Geocode Match data but have no house price shock, they live in towns of less than 50,000 people and/or rural areas, or they live in an MSA with fewer than four years worth of housing data. So differences in the means are mostly explained by the fact that the estimation sample is from urban areas or large towns, whereas the rest of the sample is from more rural areas.

Both men and women in marriages in the estimation sample have more education compared to the whole sample, and are more likely to be white. In addition, both the husbands and the wives earn more income than those in the whole sample. The average current duration for married couples is 26 years for couples in the sample and 19 for couples who are not in the sample. Those couples included in the sample have fewer children and are slight more likely to be divorcing in a given year. The baseline estimation sample is limited to couples who own a home and they live in more expensive homes compare to the entire sample of couples who are homeowners. These couples also have more principal remaining on their mortgages, which is unsurprising since their homes are more valuable. Looking at the number of couples in each category, we see that a significant number of couples are excluded from the sample mostly because there is no housing data for them. Some of these couples are addressed further in Section 2.4.1, using a different house price index.

One potential complication to note is that from the beginning of the PSID data in 1968, until around 1985, there were important changes occurring in the legal environment surrounding divorce. During the 1970s, the majority of states changed these requirements to allow for "no-fault" divorce.[20] Allowing for no-fault, unilateral divorce increases the ease with which a couple can end their marriage (Gruber (2004)). This may lead to differences in the likelihood of divorce by state over time as each state switches to the new divorce law regime. This not much of a concern here since the earliest date of the analysis is 1982, for virtually

[20] Freed (1972), Freed and Henry H. Foster (1979), Jacob (1988), and Marvell (1989) contain information about when each state introduced some legal method for obtaining a divorce through no-fault to either spouse.

every observation in the regressions the state in question has already converted to no-fault terms of divorce. In addition, all of the specifications of the divorce model have year fixed effects to take out any other unobserved year-specific differences in the propensity to divorce.

2.3.1 Description of House Price Shocks

Figure 2.5: Yearly Mean of House Price Shock of Respondents

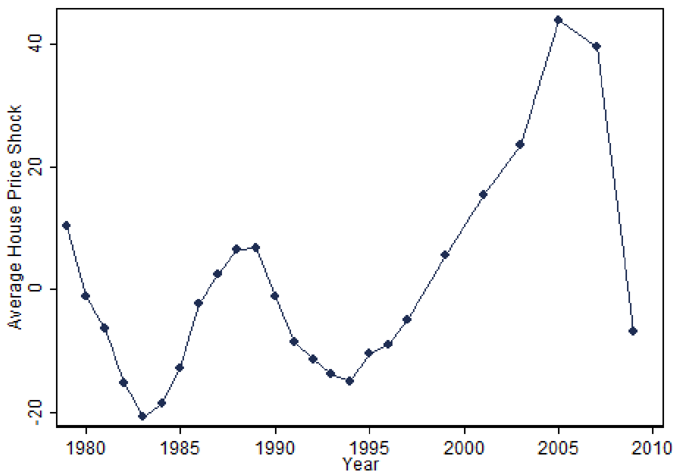


Figure 2.5 presents the yearly means of the house price shocks that the households of the PSID face. This is constructed using the house price shocks calculated in Equation 2.12 and combining them with the data on the PSID households based on the CBSA code of each metropolitan area (or FIPS State/County code for the largest metropolitan areas). The figure illustrates that on average households had positive house price shocks during the late 1990s and early 2000s, and on average

negative house price shocks during 2007-2009. The weighted mean of the shock for all respondents is 2.59, with a standard deviation of 27.95. This is very close to the mean and standard deviation of the estimation sample. The size of the house price shocks range from -109 to 147. It should also be noted that this figure represents averages for all metropolitan areas, so although on average the house price shock variable is positive in the 1990s and 2000s, there was much variation across locations.

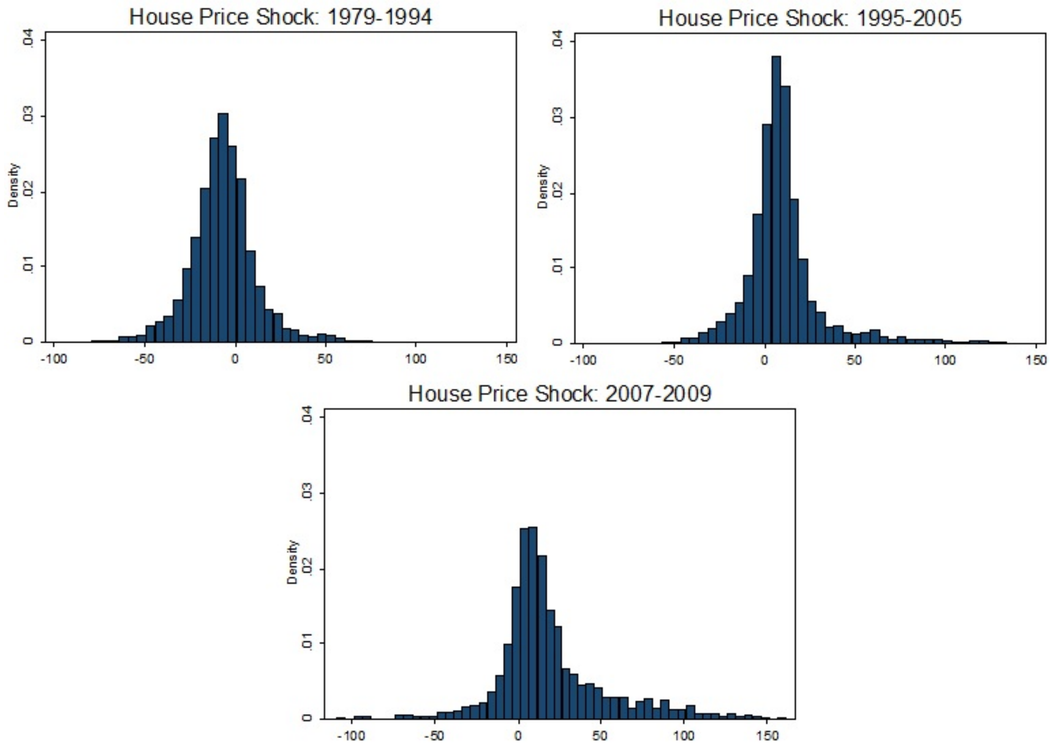
Table 2.11: House Price Shock by State: 1995 and 2005

State	**Shock in 1995**	**Shock in 2005**	**Difference**
Smallest:			
Indiana	6.49	2.17	-4.32
Ohio	7.10	4.29	-2.81
Iowa	7.07	6.72	-0.35
Colorado	12.99	14.17	1.18
Nebraska	7.42	9.62	2.20
Kentucky	5.42	8.29	2.86
Michigan	4.11	7.57	3.46
Largest:			
Massachusetts	-32.42	46.84	79.26
New Hampshire	-37.27	44.83	82.10
Maryland	-16.90	68.18	85.07
Arizona	-1.47	92.96	94.42
Nevada	2.97	100.68	97.71
New Jersey	-26.48	74.19	100.67
Rhode Island	-29.92	73.24	103.16
Florida	-9.61	110.82	120.43
Washington D.C.	-24.51	100.10	124.60
California	-28.31	114.30	142.61

To see this is true, Table 2.11 shows the average value of the house price shock in different states in 1995 (the beginning of the housing boom) and 2005 (the peak of the housing boom). The last column shows the overall change in the house price shock during this time. The table illustrates that there were very large differences across states during this time period of rising house prices. The first few rows show the values for the states with the smallest change in house price shocks from 1995 to 2005. A few states even had prices falling unexpectedly or perhaps not rising as quickly as expected. If we compare these to the states that had the largest change in house price shocks during the housing boom we notice two facts. First, many but not all of the states with the largest shocks had large negative house price shocks at the start of the boom. Second, all of these states had much larger positive house price shocks in 2005, as compared to the small shock states. It is encouraging that the states that have been identified as having large shocks during the housing boom, Arizona, Florida, California, etc., are indeed the places that anecdotally we know had extreme increases in prices.

To further describe the distribution of the house price shocks, the next figure shows how the distribution of the house price shock has changed over time. Figure 2.6 divides the sample into three time periods: pre-housing boom (1979-1994), during the housing boom (1995-2005), and during the housing bust (2007 and 2009). The house price shock is measured in index units, and the width of

Figure 2.6: Histogram of House Price Shock over Time



each bin on the histograms is five index points. The figure shows that compared to the other two time periods, the distribution was much more concentrated during 1995 to 2005. The earliest time period had negative house price shocks on average, and the middle time period had positive house price shocks on average with a relatively large number of observations in the right tail of the distribution. The latest time period does not have a very smooth distribution, likely because it is only for two years and so has far fewer observations included than the other two sample periods. We can see that there were still many positive house price shocks calculated during the recession years of 2007-2009, which is a feature of the large positive shocks observed in the four years prior to these.

The next four figures provide a visualization of the house price shocks for a select few years. The figures show the house price shock data overlaid on a map of MSAs using ArcGIS software.[21] The color gradient shows house price shocks of different sizes from -160 to +160. Thus MSAs that are more red to orange in color experienced negative house price shocks in the given year, and MSAs that are more green to yellow in color experienced positive house price shocks in the given year. Note that the shocks switch from negative between the fourth and fifth color category. As described above, there are only some of the MSAs that were collecting housing data early enough to appear in Figure 2.7. Figure 2.8 shows the house price shocks roughly at the start of the housing boom, where many places had experienced negative shocks. Moving to Figure 2.9, many more MSAs are appearing in yellow-green as many locations were experiencing positive shocks. A few places to note in bright green that had very large shocks are several MSAs in California, Nevada, Arizona, Washington D.C., and Florida as illustrated by

[21]Note that in the analysis some larger population MSAs are divided into subregions for finer location measures. However, the GIS maps of metropolitan areas groups all of these subregions one area, so the house price shocks shown on the maps are the average for the year for the larger areas. The MSAs that are sub-divided in this way in the analysis are Boston, Chicago, Dallas/Ft. Worth, Detroit, Los Angeles, Miami, New York, Philadelphia, San Francisco, Seattle, and Washington, D.C.

Table 2.11. Once we get to 2009, we observe several places begin to experience housing "busts", the locations appearing in red in Figure 2.10.

Figure 2.7: Map of House Price Shocks: 1981

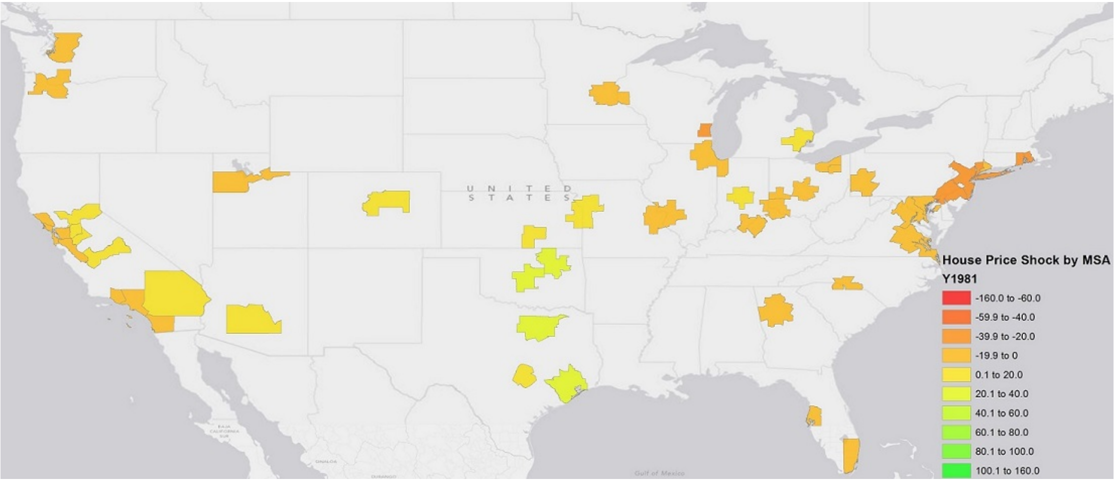


Figure 2.8: Map of House Price Shocks: 1995

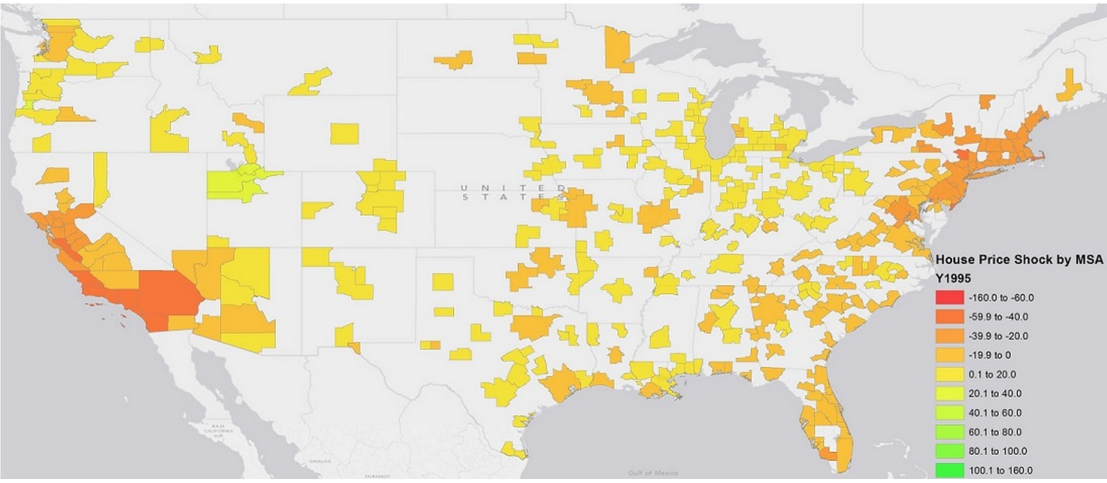


Figure 2.9: Map of House Price Shocks: 2005

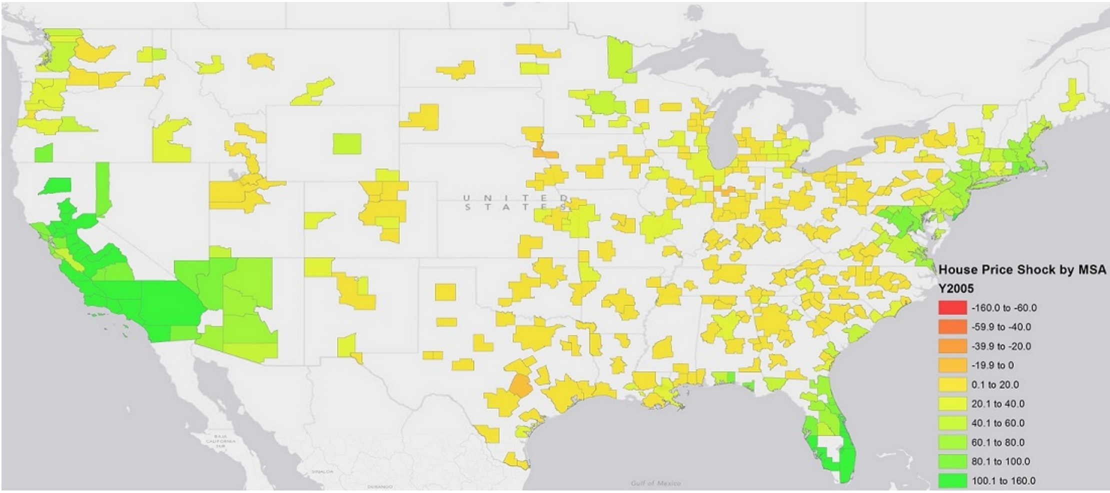
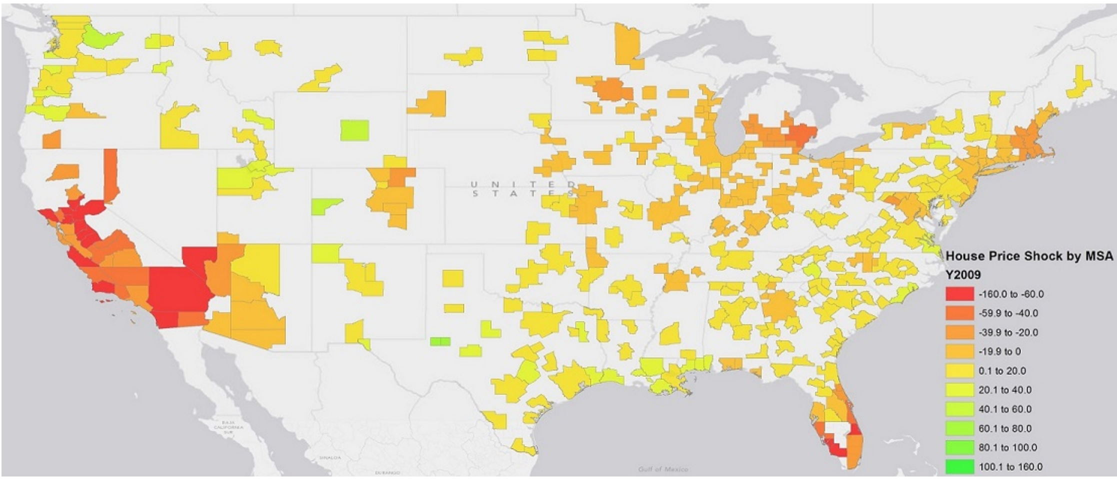


Figure 2.10: Map of House Price Shocks: 2009



2.4 Results

Discrete time duration analysis is used to analyze the effect of house price shocks on the probability of divorce. The interpretation of the results of a duration model would be how house price shocks affect the instantaneous probability of divorce for the couple, conditional on the couple having stayed together for this long. These types of models control for the length of time the couple has survived, as we know that the likelihood of divorce occurring changes with the current length of the marriage. The date of divorce is set as the date of separation. In the PSID, the reported separation date is the date at which the couple stopped living together and so it is a good measure of the end of the relationship. The legal process of divorce can often take a long time and so if the couple does not report a separation date, we use one year prior to the date of divorce as a proxy for the date of separation. This method allows us to most accurately capture the true end date of the relationship. As noted in Kreider and Ellis (2011), using data from the Survey of Income and Program Participation, the median length of time between a separation and divorce is one year. The shock variable is scaled by dividing by the standard deviation of the variable. Therefore, the interpretation of the coefficients in the regressions is for a one standard deviation change in the variable.

The divorce model used in the regressions is similar to the specification in RS, Böheim and Ermisch (2001), and Weiss and Willis (1997). I estimate the effects of house price shocks while controlling for various observable factors about the couples that may affect the divorce hazard. This includes things that would change the gains to marriage, the value of being single, and the direct or indirect costs of divorce. The model includes demographic controls, such as race, education, and age at marriage, as the baseline divorce hazard may vary across these dimensions. Year fixed effects are included in the regression as there may be legal or social factors that affect the divorce hazards differently across the years of the sample. In addition, the PSID was a nationally representative sample of households in 1968, so the respondents come from very different birth cohorts. To address this, each of the regressions include dummy variables for birth cohort groups. Finally, the county unemployment rate for each year is included to isolate the effects of house price shocks on the divorce from local area business cycles.

A probit model is used for analysis, controlling for the current duration of the marriage. Given that a household is observed many times in the data, the interpretation of the marginal effects from a probit regression is the effect on the probability of divorce in the current year, conditional on the marriage having reached the current duration. Jenkins (1995) shows that by including controls for the elapsed duration of the marriage, as well as other controls at time $t-1$, then the maximum likelihood estimation of the parameters from a probit analysis are consistent.[22] Thus, a probit model in this form provides a framework for discrete time duration analysis. To control for the length of the marriage, the log of the current duration of the marriage is included in the divorce regression. This choice of the log of the marriage duration specifies a particular parametric form for the baseline hazard. We see that the baseline probability of divorce in the data is decreasing at a decreasing rate over time, thus the choice of the log of the duration of the marriage.

Since positive and negative shocks to house prices may have different effects on the divorce hazard, the variable $Shock_{i,t-1}$ is divided into its positive and negative components. The variables of interest reported in Table 2.12 are "Positive House Price Shock" and "Negative House Price Shock", which are equal to zero when a shock of the opposite sign occurs. To make the negative shock coefficients easier to interpret, the absolute value of the shock is used. The results in Table 2.12 are for those couples who are homeowners, and allows for respondents who have multiple marriages in the sample. In each probit model, the marginal effects are

[22]Ideally we want the value of each variable at the date of divorce. A divorce occurs between the previous and current interview so the closest date, without going past the divorce, is the date of the previous interview. Thus, the analysis does not include information that occurred AFTER the date of divorce.

reported for the explanatory variables. The divorce regression to be estimated is:

$$div_{i,t} = \alpha_0 + \alpha_1 * \text{Pos. House Price Shock}_{t-1} + \alpha_2 * \text{Neg. House Price Shock}_{t-1} + \beta_1' * X_{i,t-1} + \beta_2' * Z_i + \gamma_t + u_{i,t}$$

where $div_{i,t}$ is 0 while married and 1 at the date of separation; *Pos. House Price Shock*$_{t-1}$ and *Neg. House Price Shock*$_{t-1}$ are the calculated positive and negative house price shocks; $X_{i,t-1}$ are a set of time-varying controls such as education, marriage duration, and the county unemployment rate; Z_i are time-invariant controls such as race, age at marriage, birth cohort, and number of previous marriages; and γ_t are year fixed effects. The shock from Equation 2.12 is quarterly and the household respondents are surveyed annually. Because of this, the quarterly shocks are averaged across each year to obtain the variables of interest in the regressions. Although this takes away some of the variation in the variable, it seems unlikely that a large house price shock that occurs in one quarter only would affect a marriage, instead it is likely persistent shocks that matter.

Each column in Table 2.12 represents a different regression model, sequentially adding in more and more explanatory variables. I find that positive shocks are statistically significant at the 5% in each column of Table 2.12, except for Column

Table 2.12: Probit Model of Divorce Hazard:Homeowners

Variable	(1) Marg. Eff. (S.E.)	(2) Marg. Eff. (S.E.)	(3) Marg. Eff. (S.E.)	(4) Marg. Eff. (S.E.)	(5) Marg. Eff. (S.E.)
Pos. House Price Shock$_{t-1}$	-0.0013	-0.0034***	-0.0014**	-0.0014**	-0.0014**
	(0.0011)	(0.0012)	(0.0007)	(0.0007)	(0.0007)
Neg. House Price Shock$_{t-1}$	-0.0032*	-0.0014	-0.0003	-0.0003	-0.0003
	(0.0019)	(0.0019)	(0.0011)	(0.0011)	(0.0011)
Year Effects	No	Yes	Yes	Yes	Yes
Demographic Ctrls	No	No	Yes	Yes	Yes
Fertility Ctrls	No	No	No	Yes	Yes
Income Ctrls	No	No	No	No	Yes
# of Couples	4,243	4,243	3,894	3,894	3,893
N (couple-years)	32,091	32,091	30,016	30,016	29,960
Pseudo-R^2	0.0018	0.0188	0.1138	0.1152	0.1150

Sample weights are used. Standard errors are clustered by person ID to account for each individual being present multiple times. *,**,*** indicate significance at the 10%, 5%, and 1% level.

(1) which contains only the variables of interest and the county unemployment rate.[23] In each of the models, there is a negative sign on the positive house price shock variable which indicates that larger, positive house price shocks stabilize marriage. The standard errors are clustered by household, however the results are also robust to two-way clustering on household and MSA since the house price shocks only vary at the MSA level. In most models, the sign on the marginal effects suggest that negative house price shock also stabilize marriage but it is only significant at the 10% level with no other controls.

Column (2) shows regression results for a divorce model with only the house price shock variables, county unemployment rate, and year fixed effects. Including

[23]Positive house price shocks also have a significant and negative effect using a logit model or a linear probability model.

demographic control variables such as age, birth cohort, education, and race in Column (3) reduces the size of the marginal effect compared to Column (2) to -0.0014, however it is still significant at the 5% level. Next in Column (4), I add fertility controls for the age of the youngest child and number of children in the household. The specification in Column (4) is used as the baseline specification for later tables, when other regressors are not specified. This baseline estimation sample has 30,016 couple-year observations, for 3,894 couples. This covers 309 divorces experienced by the couples. The average number of times a couple is observed in the estimation sample is eight times, with a maximum of 22 times. Column (5) adds measures of income for the husband and wife. We might think that the county unemployment rate does not sufficiently control for the changes in the economic environment which are correlated with housing price shocks. Controlling for the income of the spouses does not change the estimated marginal effects. Given that income is likely endogenous with the decision to divorce, it is not included in the baseline regressions. The full specification for the probit model is shown in Table B.1 in the Appendix.

I find a marginal effect of -0.0014 in the baseline regression of Column (4) in Table 2.12 which means that for a one S.D. increase in the house price shock, the divorce hazard is decreased by 0.14 percentage points. The average value for the dependent variable, representing the fraction of the sample that is divorcing in a given year, is 0.0105 or 1.05%. This is a 13.3% decrease in the divorce hazard at the means of all variables.[24] In 1995 near the start of the housing price boom the average house price shock was 5.5 and in 2005 near the peak of the housing prices average house price shock was 43.9 for a change in the positive house price shock of about 38.4 index units. The standard deviation of the house price shock variable is 26.6 so this was a 1.44 standard deviation increase in housing prices. This would suggest that the housing boom of the late 1990s and early 2000s decreased the divorce hazard for the average couple by 19.2%.

Table 2.13: Length of House Price Shocks: Probit Models

Variable	(6) Shock Sum of Past 1 Year Marg. Effect (S.E.)	(7) Shock Sum of Past 2 Years Marg. Effect (S.E.)	(8) Shock Sum of Past 3 Years Marg. Effect (S.E.)	(9) Shock Sum of Past 6 Years Marg. Effect (S.E.)
Pos. House Price Shock$_{t-1}$	0.0001	-0.0005	-0.0012	-0.0035***
	(0.0007)	(0.0007)	(0.0007)	(0.0012)
Neg. House Price Shock$_{t-1}$	-0.0005	0.0000	-0.0004	-0.0025
	(0.0010)	(0.0014)	(0.0011)	(0.0020)
Year Effects	Yes	Yes	Yes	Yes
# of couples	4,490	4,354	4,008	3,488
N (couple-years)	36,225	34,578	31,910	27,089
Pseudo-R^2	0.1062	0.1135	0.1160	0.1219

Sample weights are used. Standard errors are clustered by person ID to account for each individual being present multiple times. *,**,*** indicate significance at the 10%, 5%, and 1% level.

[24]This is comparable in magnitude to the effect of a 1 S.D. negative income shock which decreases the divorce hazard by about 15% as estimated from my previous work in Milosch (2012). The effect on the divorce hazard of 13.3% is much larger than what RS found, but smaller than the effect of job loss as studied by Charles and Stephens (2004).

Table 2.13 shows the long-lasting effects of unexpected changes in housing prices by modifying the way house price shocks are calculated compared to the previous table. Recall from Equation 2.12, that the house price shock is the sum of residuals from Equation 2.11 for the past four years. Table 2.13 explores sums of other lengths for the shocks. Looking at the one-year sum and two-year sum in Columns (6) and (7) we see the same sign as the baseline regression, though not significant. In Columns (8) and (9) use measures for the house price shocks by taking the sum of residuals from Equation 2.11 for three and six years respectively. In Column (8) the marginal effect is about the same magnitude as the baseline results, though it's p-value falls just short of significance at 0.107. Column (9) exhibits an even larger and more significant effect than the baseline at -0.0035.[25] As before, in each of these regressions households who have moved into the MSA in the past one, two, three, and six years respectively are excluded from the analysis. This indicates that short-term fluctuations in housing prices, even if they are unexpected, do not affect the divorce hazard. Instead, it is only the longer lasting shocks to housing prices that affect this household decision.

I find that positive house price shocks stabilize marriage. Couples who have positive house price shock essentially experience a positive wealth shock, but also an increased cost to living apart. One interpretation of these results is that an

[25]The results look almost identical if we limit the sample to only the couples that would be included in every one of the four models in Table 2.13.

increase in housing prices increases the gains to marriage. A positive house price shock means that it would be even more costly than before for a couple to maintain separate residences in the event of a divorce. This makes marriage a more attractive option than before. Another possible explanation, as cited by the psychology and sociology literature (i.e. Cutright (1971), Conger et al. (1990)), is that the positive wealth shock decreases the financial stress in the relationship, thus decreasing the risk of divorce. Much of the economic literature finds that only negative financial shocks have a significant effect on divorce hazards. It may be that this paper finds an effect from positive shocks since it covers the time period of the U.S. housing boom where we saw large, positive shocks. Since the data ends in 2009 the results are representative of only that time period, and perhaps not of the years during the housing market crash.

Table 2.14 shows a few additional findings. First, Column (10) does not separate the positive from the negative shocks, and the result from the previous tables still holds: increases in the house price shock decrease the risk of divorce. In Column (11), all couples are included in the analysis, regardless of whether they rent or own. Column (12) looks exclusively at the couples who are renters. The direction of the effect is the same for renters so unsurprisingly the marginal effect for all couples is similar.

Table 2.14: Combined Positive and Negative Shocks, All Couples, Renters

Variable	(10) Owners Marg. Effect (S.E.)	(11) All Couples Marg. Effect (S.E.)	(12) Renters Marg. Effect (S.E.)
House Price Shock$_{t-1}$	-0.0009*		
	(0.0005)		
Pos. House Price Shock$_{t-1}$		-0.0017**	-0.0026
		(0.0007)	(0.0026)
Neg. House Price Shock$_{t-1}$		0.0000	0.0025
		(0.0011)	(0.0039)
Year Effects	Yes	Yes	Yes
# of Couples	3,894	4,620	1,516
N (couple-years)	30,016	35,719	5,703
Pseudo-R^2	0.1146	0.1251	0.1399

Sample weights are used. Standard errors are clustered by person ID to account for each individual being present multiple times. *,**,*** indicate significance at the 10%, 5%, and 1% level.

The result that is consistent across all of these specifications is that positive local area house price shocks reduce the divorce hazard. This is suggestive of the scenario in Section 2.2 where homeowners face a sudden increase in cost of living apart which in turn increases the costs of divorce or that the better financial position of the household decreases stress in the marriage and makes divorce less likely. The only evidence that negative house price shocks stabilize marriage, as found by Farnham et al. (2011) is when year fixed effects are not included in the regressions though the sign of the coefficient in most models is consistent with their findings.

2.4.1 Who is Affected By House Price Shocks?

Table 2.15: Alternative Samples-Probit Models

Variable	(13) Younger Cohort Marg. Eff. (S.E.)	(14) Older Cohort Marg. Eff. (S.E.)	(15) 1982-1994 Marg. Eff. (S.E.)	(16) 1995-2009 Marg. Eff. (S.E.)
Pos. House Price Shock$_{t-1}$	-0.0034*	-0.0006	-0.0013	-0.0017*
	(0.0020)	(0.0005)	(0.0008)	(0.0016)
Neg. House Price Shock$_{t-1}$	0.0006	-0.0004	-0.0008	0.0000
	(0.0036)	(0.0006)	(0.0018)	(0.0010)
Year Effects	Yes	Yes	Yes	Yes
# of Couples	2,456	1,438	3,230	2,352
N (couple-years)	15,069	14,947	14,666	15,350
Pseudo-R^2	0.0629	0.1339	0.1103	0.1404

Sample weights are used. Standard errors are clustered by person ID to account for each individual being present multiple times. *,**,*** indicate significance at the 10%, 5%, and 1% level.

In this section we identify groups/time periods where the respondents are most affected by the house price shocks. Column (13) of Table 2.15 restricts the sample to the younger cohorts of heads of households in the PSID. Included are only households where the head was born in 1949 or later. The sample size is smaller, but as in the previous models positive house price shocks appear to stabilize marriage. There is no significant effect of house price shocks on households from the older birth cohort. Of course, this may not necessarily be indicative of no effect for the older cohort, since there is considerable selection bias among the older married couples. We do not observe the older birth cohort during their riskiest years of marriage and so are only seeing those stable matches that have lasted until now. Next, we examine the beginning and ending periods of the data separately, as there was much greater variation in the house price shocks across MSAs later in the sample and different divorce rates across the country over time. The results from Columns (15) and (16) show that the results are driven by the time period with the greater volatility in house price shocks. In addition, since the housing data used by RS is from 1991-2009, their paper only contains couples in the BHPS during this time. The years in Column (16) are close to the years used in RS, providing a check that there was not just something different about the particular years used in their sample, rather than the full specification in Table 2.12 of 1982-2009.

Table 2.16: By Education and Income Levels

Variable	(17) Husband: HS or less Marg. Eff. (S.E.)	(18) Husband: Some Coll. or more Marg. Eff. (S.E.)	(19) Low: Family Income Marg. Eff. (S.E.)	(20) High: Family Income Marg. Eff. (S.E.)
Pos. House Price Shock$_{t-1}$	-0.0021**	-0.0007	-0.0021**	-0.0007
	(0.0010)	(0.0008)	(0.0009)	(0.0008)
Neg. House Price Shock$_{t-1}$	-0.0010	0.0007	0.0011	-0.0013
	(0.0011)	(0.0016)	(0.0012)	(0.0014)
Year Effects	Yes	Yes	Yes	Yes
# of Couples	1,966	2,025	1,963	1,963
N (couple-years)	14,554	15,462	14,985	14,975
Pseudo-R^2	0.1705	0.0980	0.1669	0.1062

Sample weights are used. Standard errors are clustered by person ID to account for each individual being present multiple times. *,**,*** indicate significance at the 10%, 5%, and 1% level.

Next the sample is divided by the education of the husband and the income level of the family in Table 2.16. The table shows results for respondents with education levels of *high school or less* and for *some college or more.* Comparing these two samples we see that the house price shock appears to only affect those respondents with lower education. A wealth shock like a house price shock might affect couples with different levels of household income differently. The sample is divided at the 50th percentile for age-adjusted family income at the time of marriage. From the marginal effects reported in Columns (19) and (20), we see that it is the lower income families that are affected by house price shocks. It may be the case that a shock to housing wealth has more of an impact on low income families if a greater fraction of their total wealth is held is housing.

Table 2.17 provides results for an attempt to include some respondents who do not live in an MSA. The All-Transactions Index provides a house price index only for those respondents who reside in a Metropolitan Statistical Area, which is defined by the Office of Management and Budget as a geographical area with an urban area of more than 50,000 people. So in the baseline specification households located in areas with a population smaller than 50,000 are excluded. The FHFA provides another quarterly house price index for non-metropolitan areas at the state level beginning in 1995. The procedure from Section 2.3 is repeated for the Non-Metropolitan Index with quarter and state fixed effects. This index is used

Table 2.17: Including State Non-Metro. House Price Shocks: Homeowners

Variable	(21) Shock Sum of Past 4 Years Marg. Eff. (S.E.)	(22) Shock Sum of Past 6 Years Marg. Eff. (S.E.)
Pos. House Price Shock$_{t-1}$	-0.0012*	-0.0013**
	(0.0007)	(0.0007)
Neg. House Price Shock$_{t-1}$	-0.0003	-0.0013
	(0.0011)	(0.0011)
Year Effects	Yes	Yes
# of couples	4,068	3,639
N (couple-years)	30,599	27,584
Log-Psuedolikelihood	-1594.2	-1308.5
Psuedo-R^2	0.1142	0.1200

Sample weights are used. Standard errors are clustered by person ID to account for each individual being present multiple times. *,**,*** indicate significance at the 10%, 5%, and 1% level.

for households who are not located in an MSA but we know the state they live in. Since this only varies at the state level, and house prices can be vastly different across different areas of a state this is a much worse measure of house price shocks that what is measured using the All-Transactions Index. The results of probit models are presented in Column (21) and (22) for two different lengths of the house price shock. The positive house price shocks are significant across all four specifications. The size of the marginal effects is very close to what was found in the baseline sample. This indicates that it is not something specific to couples who live in larger towns and cities, but applies to those in more rural areas as well.

2.4.2 Robustness Checks

A few robustness checks were performed to test the validity of the results presented above. First, an alternative type of duration analysis is performed using the Cox Proportional Hazards Model (Cox (1972)). This second type of model is used to check for consistency in the results found using a probit model. The Proportional Hazards model allows the researcher to use partial likelihood to estimate the coefficients of the model without specifying a particular functional form for the baseline hazard function.[26] As with the probit model, the analysis with the Proportional Hazards model allows for the respondents to have multiple marriage spells within the data. For each marriage at each point in time, the Proportional Hazards model estimates the effect of the explanatory variables on the divorce hazard. The results are presented in Table 2.18. For each of the variables, a hazard ratio greater than one indicates that an increase in the variable increases the divorce hazard, and a hazard ratio less than one indicates that an increase in the variable decreases the divorce hazard. For the same reasons as

[26]Discrete time duration models and continuous time duration models both provide estimates of the effect of the variables on the probability of divorce, but view the explanatory variables in slightly different ways. Jenkins (1995) states that for discrete time duration analysis, if the unit of time is a year, and the time-varying variables are measured at the end of each year, the model makes the assumption that the variables are constant over the year. This seems to be a reasonable assumption since most of the time-varying variables do not change very quickly (education, number of children, etc.). Evidence has shown that in general the time aggregation does not cause significant bias in the estimates for simple parametric approaches (Bergström and Edin (1992)).

noted with the probit models, all of the regressions using the Cox Proportional Hazards Model include the time-varying variables measured at time $t-1$.

Table 2.18: Cox Proportional Hazards Model of Divorce Hazard:Homeowners

Variable	(23) Haz. Ratio (S.E.)	(24) Haz. Ratio (S.E.)	(25) Haz. Ratio (S.E.)	(26) Haz. Ratio (S.E.)	(27) Haz. Ratio (S.E.)
Pos. House Price Shock$_{t-1}$	0.810**	0.779***	0.820*	0.820*	0.821*
	(0.069)	(0.074)	(0.087)	(0.087)	(0.086)
Neg. House Price Shock$_{t-1}$	0.908	0.878	0.922	0.918	0.922
	(0.135)	(0.144)	(0.175)	(0.174)	(0.175)
Year Effects	No	Yes	Yes	Yes	Yes
Demographic Ctrls	No	No	Yes	Yes	Yes
Fertility Ctrls	No	No	No	Yes	Yes
Income Ctrls	No	No	No	No	Yes
# of Couples	4,623	4,623	4,224	4,224	3,899
N (couple-years)	32,531	32,531	30,397	30,397	30,017
Log-psuedolikelihood	-2185.7	-2170.2	-1694.8	-1693.3	-1673.8

Average of sample weights for each marriage are used. Standard errors are clustered by person ID to account for each individual being present multiple times. *,**,*** indicate significance at the 10%, 5%, and 1% level.

The direction of the effect for the positive house price shocks in Table 2.18 is the same as in Table 2.12.[27] The hazard ratio for the positive shocks is less than one in all models, suggesting that larger positive shocks decrease the probability of divorce for the couple. The effect is significant at the 10% level for all specifications. The hazard ratio for the models in Table 2.18 is around 0.821. This would suggest that a one standard deviation larger positive house price shock would

[27]The difference in sample size between these regressions and those in Table 2.12 are partially because of the few households that are only observed once in the sample. A household must be observed at least twice to be included in a Cox Model. The other reason for the difference is the few observations with a zero weight. A Cox Model must have a constant weight for the duration of a marriage, so the average of the weight variable is used, which washes out a zero for one year in the weight variable.

decrease the divorce hazard of the couple by 17.9% (compared to an estimate of 13.3% from the baseline estimation). Again thinking about the housing boom of the late 1990s to early 2000s, which had an average increase in house price shocks of about 38.4 index units. This corresponds to a 1.44 standard deviation increase in the house price shock. The results using the Cox Proportional Hazards model suggest that the housing boom decreased the probability of divorce for married couples by about 25.8% on average over the entire period.

Next, the estimation of the house price index as in Equation 2.11 includes lags from housing prices in the two previous quarters. This was chosen as to follow the methods used in the literature. However, the results hold if a longer lag structure is chosen (i.e. lags from the past three or four quarters). In addition to differences in the propensity to divorce across different years, there also may be regional differences over time. Including region-year interactions, the marginal effect on the positive house price shock is approximately the same at -0.0015 with a standard error of (0.0008) so the effect is significant at the 10% level. I also checked the robustness of the results using other levels of aggregation of the unemployment rate. The county unemployment rate begins in 1982, so a few years of data is cut off from the analysis. The results are unchanged when including the state unemployment rate, which covers the entire 1979-2009 time period of the available house price shock data, though this is clearly a much cruder measure of local business cycles. I also check the results using the unemployment rate at the MSA level, however these are only available from 1990 on. Though the sample size is reduced, the size of the significant marginal effect on the positive house price shock is about the same, though the standard error increases slightly to 0.0008 so it is now significant at the 10% level. The probability of divorce may also be influenced by the employment status of the husband and wife, however these are potentially endogenous variables if individuals change their labor market choices in anticipation of divorce. Including employment status of each spouse in the regressions does not change the results. To ensure that higher order marriages are not driving the results, I restrict the estimation sample to only first marriages of respondents. The marginal effect of the positive house price shock in that regression is slightly smaller (-0.0011) but is still marginally significant at the 10% level.

As an additional check we also examine the effect of a change in the level of the house price index. This would incorporate both the unexpected change in housing prices (as analyzed above) as well as the expected change in housing prices. Given that some portion of this variation may be expected by individuals, it is unclear when households would respond to anticipated changes in housing prices. I estimate regressions using the percent change in the All-Transactions Index, adjusted for seasonality, rather than the house price shock variable. The percent change variables are not significant whether using the change from one year to the next, or the change in prices over the past four years. The results are unchanged if the MSA-specific variation is also removed from the index.

2.5 Concluding Remarks and Future Work

This paper has examined how wealth shocks affect marital stability. In particular, the paper asks how a wealth shock in the form of a house price shock affects the divorce hazard of individual households. Using household level data from the Panel Study of Income Dynamics and a MSA level house price index from the Federal Finance and Housing Administration, a measure of house price shocks are made for each household. Housing prices are approximated by a second order autoregressive process with MSA and quarter fixed effects. The residuals from the AR(2) process are cumulated for the past four years, and this cumulative sum serves at a measure of the house price shock. This calculation of house price shocks is an improvement over those previously used in the literature which did not consider the moving behavior of households. Consistent across different specifications is the result that positive house price shocks stabilize marriage. In addition, this result is robust to different econometric models of duration analysis, including probit models and Cox Proportional Hazard Models. Although the coefficient of negative house price shocks have the same sign as Farnham et al. (2011), the result is not significant in any specification with the house price shocks.

The role of housing shocks is explored further, by the birth cohort of the head of household, education and income levels, and remaining mortgage debt. The findings in this paper show that the couples that are affected are those with the heads of households from the younger cohort in the PSID, though this may be because those couples in the older cohort who were meant to divorce already have by the time they are observed in the data. It is not surprising that the house price shocks affect households with low education and low family income the most, as they would have the most difficulty paying for two homes.

As expected, shocks to housing prices have an important effect on the stability of marriage, since such shocks would affect the marital surplus, and the value of the outside options. In this paper, I consider house price shocks faced by individual households as it is likely that such shocks are exogenous to any of the unobserved behaviors of the household. In addition, it is an ideal price shock to study as housing is the largest component of wealth for most households in the United states for the past few decades. Finally, by focusing on shocks to housing prices we are identifying something that was not anticipated by households and therefore is not something they may have already incorporated into their decision regarding whether this marriage was suitable.

The households in the PSID come from a wide range of birth cohorts, and include many older couples that may not be a relevant sample of individuals potentially affected by shocks to housing prices. Thus, this line of research would benefit from examining other data sources with younger birth cohorts. Other questions yet to be investigated are how house price shocks affect other household decisions. There has been some recent research on the effect of house price changes on fertility, notably in Dettling and Kearney (2014) (using MSA level fertility data) and Lovenheim and Mumford (2013) (using self-reported house prices). Further examination of the topic is in order as self-reported housing prices is likely endogenous with a couple's fertility decisions. Another household decision that a house price shock potentially may affect is the labor supply and labor participation choices of households. These questions are to be explored in the next chapter.

Chapter 3

House Price Shocks and Labor Supply Choices

3.1 Introduction

Economists have studied the effects of economic shocks on many different decisions that individuals and households make, including labor supply choices. Given the large changes in the economic environment we have seen since the 2007 recession, it is important for us to understand the broader impacts of these changes on household behavior. In particular the large housing boom and subsequent housing bust have had serious implications for the economic situation faced by households. This paper contributes to the literature on labor supply choices by estimating the effects of unexpected changes in housing prices on employment and hours worked. How do households adjust their labor supply choices in response to positive versus negative house price shocks? How are these responses different across men and women, and different types of households? The answers to these questions will help us further understand the employment patterns and choices observed in the economy as well as provide insight into the consequences of the dramatic changes in the housing market in recent years.

House price shocks are an attractive type of price shock to study since a large fraction of households in the United States own their own home. According to Wolff (2010) housing wealth has been the largest component of household wealth for several decades, and on average a household has 33% of their wealth in owner-occupied housing. In addition, local house price shocks are likely exogenous to many behaviors of individual households.

This paper examines the link between changes in housing prices and labor supply of households. I combine a house price index from the Federal Housing Finance Agency (FHFA) and data on individual households from the Panel Study of Income Dynamics (PSID). Unexpected changes to housing prices are captured using the residuals from a second-order autoregressive process. These residuals are cumulated from the previous three years to generate a measure of long-lasting changes in housing prices. The effects of these house price shocks on labor supply choices are examined at both the extensive and intensive margin for men and women, and separately by marital status. I find that positive house price shocks cause married women to decrease their total labor supply. The effect is significant at the extensive margin, but not the intensive margin for women with positive working hours. I also show that older married males, age 65 and over, increase their total labor supply in response to a negative house price shock. This effect is due to the older males being more likely to remain employed. Finally, I explore particular demographic and economic groups that are most responsive to house price shocks. The results show that it is the high income, high education women with children who decrease their labor supply following a positive house price shock. We see the strongest effect for women with young children, suggesting that women are taking the opportunity of a positive wealth shock to stay home and care for their children. To my knowledge this is the first paper to look at the effects of house price shocks on labor supply for a broad sample of households in the United States.

Several papers have examined the effect of changes in housing prices on the labor supply choices of households, and specifically focused on those individuals who are less attached to the labor force such older households, married women, and the self-employed. Henley (2004) is closely related to the exercise in this paper, and uses household level data from the British Household Panel Survey (BHPS). The author measures changes in average county house prices in the United Kingdom as well as changes in wealth through windfall gains. The paper shows that men increase their labor hours after a decrease in housing prices and women decrease labor hours after an increase in housing prices. Unlike the analysis in this paper, Henley uses changes in local housing prices which is a combination of expected and unexpected changes. Farnham and Sevak (2007) find that households in the U.S. retire earlier when facing positive changes in housing wealth using data from the Health and Retirement Survey. Finally, married women's labor supply choices are studied in Fortin (1995). The author finds that women's labor supply choices are constrained by mortgage obligations and they would decrease labor hours with lower mortgage debt. More recent work in Disney and Gathergood (2013) find evidence across genders that increases in housing prices decrease labor supply with the strongest results among the youngest and oldest respondents using data from the BHPS.

Another group that may be less attached to the labor force are those who are, or would like to become self-employed. The liquidity constraints facing self-employed households is analyzed by Lindh and Ohlsson (1996) studies Swedish Lottery winners and finds they are significantly more likely to become or stay self-employed. Disney and Gathergood (2009) revisit this question by looking at the entry into self-employment of households in the BHPS in response to shocks to housing wealth. They show that house price shocks are a good predictor of starting a small business, however there is no evidence of this affecting the liquidity constraints facing these households. Also using BHPS data, Taylor (2001) looks at the household's response to windfall gains and their role in relaxing these liquidity constraints. He finds that a positive windfall gain increases the rate at which individuals enter into self-employment, but this occurs at a decreasing rate.

Closely related to these studies are those that study labor supply responses to other economic shocks. Households also decrease their labor force participation rate in response to inheritances as found by Holtz-Eakin et al. (1993). Although, Joulfaian and Wilhelm (1994) finds that the labor supply response of households to inheritances is small. Another type of wealth shock comes through unearned income. Imbens et al. (2001) study lottery winners and find that they have decreased labor earnings coming through increased leisure, especially among those closer to retirement age. Benito and Saleheen (2011) find that a deterioration in one's financial situation, compared to what was expected, leads to an increase in labor supply. Using aggregated MSA-level data, Charles et al. (2013) finds that the housing boom of 2000-2007 reduced non-employment among displaced manufacturing workers thus masking the effect of the manufacturing decline during that time period.

There has also been a growing literature on the effects of price or wealth shocks on other household decisions such as fertility or consumption. Using different data sources, both Lovenheim and Mumford (2013) and Dettling and Kearney (2014) find that increases in housing wealth of homeowners increases fertility rates. Other household decisions studied in the literature include marital dissolution, consumption and savings behavior of households, and household equity. Using data from the Dutch Postcode Lottery, Kuhn et al. (2011) shows that lottery winners do not vary their non-durable consumption by much, however they do appear to adjust the timing of durable purchases following the a model of life-cycle consumption smoothing. Browning et al. (2013) examines the link between consumption and unanticipated house price changes using Danish panel data and finds little evidence of housing wealth changes affecting consumption. The link to consumption appears to be almost entirely through its role as collateral.

Similar papers have examined the effects of changes in levels of housing prices on labor supply choices but compared to these closely related papers in the literature, this paper is the first to focus on unexpected changes in housing prices. For reasons explored in Section 3.2, the use of unexpected price shocks is ideal for looking for an effect on households' decisions. Several of these studies have explored the effect on labor supply for select groups (self-employed, retirees). Instead, this paper examines a wide range of household types in the United States. The only other paper using a nationally representative survey of households is Disney and Gathergood (2013) with data from the United Kingdom.

3.2 Theoretical Discussion

Important to the current study is also a large literature on the intertemporal substitution in labor supply with both theoretical and empirical evidence including Heckman and MaCurdy (1980), Heckman (1993), and Altonji (1986). The literature highlights the important distinction between anticipated and unanticipated price changes. Consider a simple life cycle model where each agent only lives for two periods and has utility over leisure and consumption in each period. Then the agent wants to maximize lifetime utility subject to a wealth constraint. For simplicity, I assume that utility is intertemporally separable. Consumption in period one and two is denoted c_1 and c_2 and leisure in period one and two is denoted ℓ_1 and ℓ_2. Let the rate of time preference for the agent equal the market interest rate, r. The agent is endowed with some assets in period one, ω_1 and knows the probability distribution that assets in period two are drawn from. ω_1 and ω_2 are measure of the total value of all assets owned by the agent, including housing prices. Although the agent does not know the true value of ω_2 in period one, he may later adjust his optimal choices upon seeing the realization of ω_2 in period two. Wages are taken to be exogenous at W_1 and W_2 for periods one and two, respectively. The agent has one unit of time in each period to split between leisure and labor. Then the agent's decision problem in period one is

$$\begin{aligned} \max_{c_1,c_2,\ell_1,\ell_2} \quad & U(c_1,\ell_1) + \tfrac{1}{1+r}U(c_2,\ell_2) \\ \text{s.t.} \quad & (1-\ell_1)W_1 + \tfrac{(1-\ell_2)W_2}{1+r} + \omega_1 + \tfrac{\mathbb{E}(\omega_2)}{1+r} = c_1 + \tfrac{c_2}{1+r} \end{aligned} \tag{3.13}$$

Once the agent reaches period two, he observes the realization of the value of assets, ω_2. If the realization of ω_2 is greater than the expected value in period one, it would represent a positive shock to wealth. Likewise, if ω_2 is less than the expected value in period one, the agent would experience a negative wealth shock. In the context of the analysis here, a positive shock to housing prices would correspond with a higher than expected realization of ω_2. After observing ω_2, the agent may find it optimal to adjust his choice of leisure and consumption. If the value of assets have increased we would observe a positive income effect and leisure, ℓ_2, and consumption, c_2, would both increase assuming they are normal goods.

One concept that might lead to important and/or asymmetric responses to house price shocks is the idea of framing by the individual households, or how they view a shock to housing prices. Even for homeowners, it may not be the case that all households view a positive house price shock as a good outcome for their family. Consider a couple that owns a small home but intends to purchase a larger house when they have children. In this case, even though an increase in housing prices means their own home value increases it also means it will be more expensive for them to buy a larger home. These shocks to housing prices could be a direct or indirect effect on the wealth of the household. As an indirect effect, given that housing is typically the largest asset a household has, an increase in prices might just make the household feel wealthier or poorer depending on borrowing constraints and the stage of their life cycle.

On the other hand, if a rise in prices means the household is able to refinance to a lower monthly mortgage payment or if it provides access to credit, the household may feel a direct wealth effect. Households that are borrowing constrained may see an increase in housing prices as an opportunity to obtain/increase a home equity loan and relax those constraints. The question of the uses and benefits of relaxing these borrowing constraints through home equity loans has been thoroughly studied within the finance literature. For example, Klyuev and Mills (2007) find that the amount of home equity withdrawals have been increasing starting in the 1990s and were generally spent to re-balance financial portfolios and replace unsecured debt. Greenspan and Kennedy (2008) find that in addition to restructuring their current debts, homeowners use the funds extracted from home equity loans to finance home improvements and purchase other assets. However, other evidence from a large representative sample of households in Mian and Sufi (2009) shows that for the most part small amounts are used to purchase investment properties or pay down credit card balances, suggesting that the main use for these funds are real outlays. These studies show the potential gains to households from increases in housing prices and the ability to extract equity from their homes. If households choose to reduce their labor supply, the additional funds from a home equity loan may replace the lost wages.

This basic theoretical model of labor supply choices would suggest that an unexpected increase in wealth would cause agents to decrease their labor supply. However, in actuality many agents may face constraints on their labor supply choices. For example, some agents may be able to only vary labor participation, but not hours worked. For this reason the analysis focuses on both the extensive and intensive margins of labor supply, as well as specific groups of workers that may be less attached to the labor force. While many of the respondents of the PSID may not be able to adjust their hours, others might have the ability to. For instance, married women, part time workers, very young or old workers, the self-employed, etc. are groups that may be more likely to have the ability to adjust their labor hours.

The analysis that follows examines the effect of house price shocks on labor supply choices. The change in housing prices from one year to the next contains both anticipated and unanticipated changes in prices. However, it is difficult to determine the correct timing of an individual's response to an *expected* change in prices. In addition, much of the recent consumption/savings literature, including Disney et al. (2010) and Attanasio et al. (2011), has studied unanticipated house price shocks. If a household were to experience a rise in housing prices that they had expected, according to the standard life-cycle model of consumption there should be no response since agents are forward looking, if they are not credit constrained. That is, any expected increase in housing prices has already been incorporated into their labor supply decisions. If instead the household faces a shock to housing prices that was unexpected, we might see a response in their labor supply.

3.3 Data and House Price Shocks

The effect of house price shocks on the labor supply choices of households is studied by combining two main data sets. The Panel Study of Income Dynamics[28] is a longitudinal household survey that began with a national representative sample of 4,802 households in 1968. The panel continued annually from 1968-1997 and bi-annually from 1999-2009. The survey has followed the initial sample and their children as they split off and formed new households. As of 2009, there were 8,690 families being interviewed. Both the original households and their split-

[28] Data obtained through the University of Michigan: PSID (2012).

offs are included in this analysis. The PSID updated its sample several times by adding immigrant and Latino families to attempt to more accurately capture the changing make up of U.S. households. These families are included when available. Also used in this paper is the restricted Geocode Match data from the PSID. This data allows the author to observe the Metropolitan Statistical Area that the household resides in, as well as other location measures such as the county. The finer the location of the house price index, the more accurately it represents what is happening to the individual households' housing prices. The Geocode Match Data is then used to link households to an MSA level house price index.

The analysis utilizes the All-Transactions Index for MSAs from the Federal Housing Finance Agency.[29] This index combines information from all transactions including sales and appraisals in the metropolitan area. The All-Transactions Index is well-suited for this analysis as it covers many years and provides information for all currently defined MSAs. In addition, it is a constant quality measure of house prices over time since it only using homes with repeat sales/appraisals. Thus, the index avoids the problem of the quality of housing changing over time. As of 2010, there were 374 MSAs defined by the U.S. Office of Management and Budget. In addition, some of the largest of the metropolitan areas (New York, Los Angeles, etc.) have been subdivided into smaller areas called Divisions. So the

[29]Data obtained through the Office of Policy Analysis and Research in Washington, DC: FHFA (2012)

All-Transactions Index includes 384 MSAs and/or MSA Divisions. There is price index data for MSAs as early as 1975, and the data continues quarterly through the end of 2011. By 1987, the All-Transactions Index had begun collecting housing data for 80% of the MSAs. The Consumer Price Index (CPI) excluding housing is used to deflate the index. Thus, the housing data will reflect changes in housing prices as compared to all other goods.

Finally, using the Geocode Data, the county unemployment rate from the Bureau of Labor Statistics is combined with these two data sets. The county unemployment rate is available beginning in 1982, and thus is the limiting factor for the starting date of the data used in the analysis. This variable is used to control for local labor market conditions. This way the effect of shocks to housing prices can be isolated from other changes in the local economy.

The following methodology is used to calculate the unexpected portion of changes in housing prices. A second order autoregressive process with MSA and quarter fixed effects is used to approximate the quarterly house price index, as described in Equation 3.14. Quarter fixed effects are included in order to correct for any seasonal variation in housing prices.

$$HPI_{m,t} = \beta_1 + \beta_2 * HPI_{m,t\text{-}1} + \beta_3 * HPI_{m,t\text{-}2} + \gamma_m + \eta_q + u_{m,t} \tag{3.14}$$

where m is the MSA, t is time, indexed by the year and quarter. HPI is the quarterly house price index, deflated using the CPI, that is regressed lagged values of the All-Transactions Index from the past two quarters. γ_i is a fixed effect for the the MSA, and η_q is a fixed effect for the quarter. Thus, the residuals of the regression in Equation 3.14 will be unexplained differences within an MSA over time. At each point in time the house price shock is calculated as the sum of residuals from the past three years. This methodology ensures that for each MSA in each year we can compare a cumulative sum that has the same starting date, and forces there to be data for the past three years in that MSA. Using the residuals from the previous regression, the house price shock, $Shock_{i,t}$ is calculated as:

$$Shock_{m,t} = \hat{u_{m,t}} + \hat{u_{m,t-1}} + ... + \hat{u_{m,t-12}} \tag{3.15}$$

where $\hat{u_{m,t}}$ is the residual from Equation 3.14 for MSA m in time t.[30] This gives us a measure of the portion of the change in housing prices that was unanticipated over the past three years. Note that individuals who have lived in their MSA for less than three years will be dropped, since the shock to housing prices for the past three years is not relevant to them. This is a similar to the methodology presented

[30]The index is measured quarterly, so adding the residuals from the past 12 quarters to the current quarter gives us the sum for three years. House price shocks of other lengths are tested in Section 3.4.

by Disney et al. (2010), Rainer and Smith (2010), and Farnham et al. (2011).[31] The interpretation of the house price shocks is such that a positive value indicates that prices in the MSA were rising faster than expected. Thus, it is possible that individuals in the MSA believed housing prices were going to rise, however they rose by more than what was anticipated.

Table 3.19 shows summary statistics for the linked PSID and FHFA data. It compares males and females in the PSID by marital status. The samples shown start in 1982, which is the beginning of the county unemployment rate data. The samples contain a little less than 12,000 married households, about 10,000 unmarried males, and about 11,000 unmarried females. The number of observations for the unmarried households is much smaller however, since many people spend a relatively short amount of single in the data, before transitioning into a married household.

Unmarried men and women are more likely to be black and have lower education. Married women are younger than their married male counterparts, however unmarried women are significantly older. This is likely due to the number of widowed/divorced women in this group. Among the unmarried respondents, males are much more likely to have never been married. Married respondents have on

[31] One difference in our methodologies is after obtaining the residuals of Equation 3.14, these authors' shocks are calculated as the sum of residual from the beginning of the housing data. However, unlike the U.K. House Price data used by Disney et al. (2010), the All-Transactions Index starts at different dates for different MSAs. Therefore, simply cumulating the residuals from Equation 3.14 would mean that the shock is not comparable across metropolitan areas.

Table 3.19: Summary Statistics for PSID Households: 1982-2009

	Married Males		Unmarr. Males		Married Fem.		Unmarr. Fem.	
Variable	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**
Demographics:								
Birth Year	1946	16.9	1955	18.1	1948	16.2	1943	21.8
Black	0.069	0.254	0.161	0.367	0.068	0.251	0.224	0.417
Hispanic	0.063	0.243	0.065	0.246	0.069	0.253	0.053	0.224
White	0.856	0.351	0.760	0.427	0.853	0.354	0.722	0.448
< High School	0.192	0.394	0.204	0.403	0.159	0.365	0.271	0.445
High School	0.322	0.467	0.321	0.467	0.405	0.491	0.347	0.476
Some College	0.197	0.398	0.236	0.425	0.211	0.408	0.204	0.403
College	0.289	0.453	0.239	0.426	0.225	0.418	0.178	0.382
Family:								
Never Married	-	-	0.511	0.500	-	-	0.309	0.462
Divorced	-	-	0.393	0.488	-	-	0.363	0.481
# of Children	0.904	1.150	0.211	0.646	0.904	1.150	0.474	0.951
Labor Market:								
Labor Hours	34.51	23.29	33.75	22.85	22.62	20.51	22.21	22.28
Labor Income	$47,433	$ 80,526	$ 32,822	$68,609	$ 19,594	$ 29,817	$18,454	$25,101
Hourly Wage	$21.34	$ 21.19	$ 16.34	$ 16.88	$ 12.05	$ 15.03	$10.47	$13.53
Employed	0.742	0.438	0.708	0.455	0.568	0.495	0.526	0.499
Unemployed	0.024	0.153	0.074	0.262	0.018	0.134	0.053	0.224
Unemp. Rate	6.143	2.866	6.112	2.670	6.143	2.866	6.227	2.737
Housing:								
Homeowner	0.835	0.371	0.397	0.489	0.835	0.371	0.487	0.500
House Value	$150,602	$146,497	$51,759	$103,066	$150,602	$146,497	$56,605	$99,286
House Price Shock	-0.112	24.997	0.530	26.091	-0.112	24.997	-0.103	23.840
Households	11,972		10,278		11,948		11,197	
N	91,796		31,298		91,447		52,608	

average one child, and unmarried respondents are less likely to have a child. For the labor market variables, we see that men earn more than women across all categories of marital status. Men are more likely to be employed compared to women. In addition, married respondents earn more than unmarried respondents, looking both at their overall labor earnings and hourly wage. Married respondents are also more likely to be employed, and less likely to be unemployed. The vast majority of the homeowners in the PSID sample are married, with only 40% and 49% of unmarried males and females owning their home, respectively. We can see that there is not much difference across types of households with regards to the house price shocks in their area.

3.3.1 Endogeneity

Two potential problems of endogeneity must be addressed in the regressions in Section 3.4. The first is the issue of homeownership status. As addressed in Section 3.2, there may be different responses to house price shocks for renters versus owners. However, the respondent's homeownership status may be endogenous as those with higher or less volatile labor hours may be more likely to become homeowners. To address this issue, we use multivariate matching on various demographic controls to predict whether or not the respondent is a homeowner. The variables used in multivariate matching are age and birth cohort, race and education, family poverty status, state of residence, and marital status. The results are presented controlling for the actual reported homeownership status, as well as predicted homeownership status.[32]

[32]Henley (2004) includes both renters and owners in regressions and an interaction between ownership status and housing prices. However, as shown in Table C.1 in the Appendix, owners and renters in this sample have significantly different regression coefficients. This fact along with the extremely small sample of renters makes renters a poor comparison group for owners.

The second issue of endogeneity is that of wages, which should be controlled for in some way in the labor supply regression. However, clearly using the respondent's actual wages is endogenous with respect to labor supply. Two different methods are used to proxy for actual wages. Following the methodology used in Henley (2004), we generate fitted wages for each individual. Fitted wages are created using a two stage process. In the first stage, the respondent's log wage is regressed on a set of controls with person fixed effects.[33] Then the predicted log wage from this regression is used to instrument for actual wages in the labor supply regressions. Fitted wages are generated separately for men and women. Given that a fixed effect regression is used for the first stage, only time-varying predictors of wages are used and these may not have much predictive power for wages. The variables that are included in the first stage regression that will be excluded in the labor supply regressions are: the square of the county unemployment rate, whether the respondent lives in an MSA, and whether the respondent lives in a large MSA.

Since the fitted wages may not be a valid instrument and the variables used to instrument for wages (square of unemployment, residence in MSA, residence in large MSA) also may affect labor hours, a second method is also utilized. As an

[33]The the controls used in the first stage are the unemployment rate and its square, whether the respondent lives in an MSA, whether the respondent lives in a large MSA, region of residence, marital status, number of children, the presence of young children, age and education interactions, and year dummies.

alternative strategy to instrument for wages, we use a combination of data from the Census/American Community Survey[34] and the Current Population Survey[35] to estimate average wages for the respondents based on group membership. Groups are determined by 320 bins of age-sex-education-race-marital status. The Census and ACS data covers the years 1980, 1990, and 2000-2009. CPS data is used to fill in for the years 1989-1999. Since there is no data for the years 1981-1988, the 1980 averages are used. While this may be more exogenous than the fitted wages, it is also a much more noisy estimate of wages. And note that the averages used for the time period of 1980-1989 and 1990-1999 are not varying since there is only wage information from the years of 1980 and 1990.

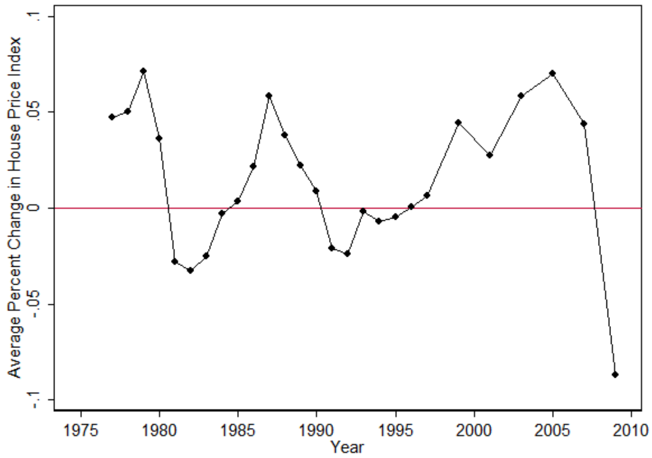
Given the potential issues with either of these methods for controlling for endogenous wages in the labor supply regressions the main results will be presented mostly without these wage instruments. However, Section C.3 in the Appendix shows the results of the fixed effect regressions for our two primary analysis groups (married women and older married males) using both of the above methods..

3.3.2 Exploring the Variation in House Price Shocks

Figure 3.11 shows the average percent change from one year to the next of the All-Transactions Index. We can see from this figure that there is considerable

[34]Census and ACS data is obtained from Ruggles et al. (2010)
[35]CPS data is obtained from King et al. (2010)

Figure 3.11: Average Yearly Percent Change in House Price Index



volatility in the house price index over time. Since the figure shows the percent change in housing prices, when the line is above zero, prices are rising. The figure also shows housing prices slowly increasing from the mid 1990s until 2005, during the years of the housing boom in the United States. After that boom period, we see the sharp decline in housing prices during the housing bust.

In contrast to Figure 3.11, Figure 3.12 shows the yearly average house price shock from the All-Transactions Index. The series is considerably smoother than the yearly percent change, though many of the same events are illustrated here. In both figures we observe a decline in prices in the early 1980s and an increase in prices in the late 1980s/early 1990s. The major difference in the two is that in Figure 3.11 we can see the yearly percent change in housing prices slowly increasing through the 1990s and 2000s and then quickly falling after 2005, but in

Figure 3.12: Average House Price Shock

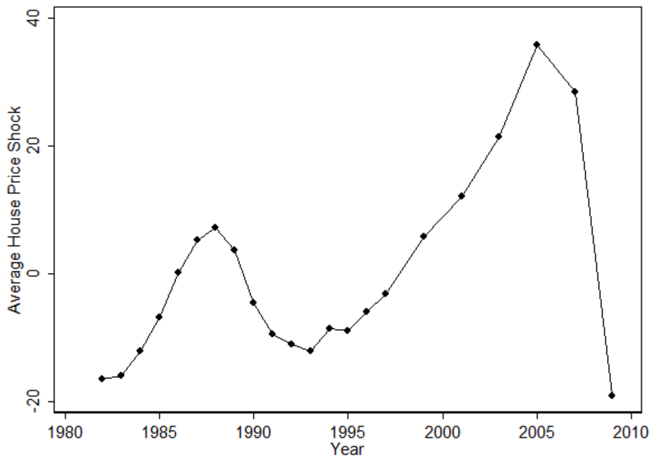


Figure 3.12 the increase during the housing boom is much more dramatic. This suggests although prices were rising throughout that time period, they were rising by faster than expected. In addition, there is much variation in the house price shock across MSAs.

Table 3.20 illustrates this point, and shows the average value of the house price shock in select states in 1995 (the beginning of the housing boom) and 2005 (the peak of the housing boom). The last column shows the overall difference in the house price shock during this time. We can see that during the housing boom year, different places in the country had very different experiences in terms of their local house price shocks. The first few rows show the values for the states with the smallest change in house price shocks from 1995 to 2005. A few states even had prices falling unexpectedly or perhaps not rising as quickly as expected.

Table 3.20: House Price Shock by State: 1995 and 2005

State	**Shock in 1995**	**Shock in 2005**	**Difference (2005-1995)**
Smallest:			
Utah	23.19	9.36	-13.83
Colorado	10.67	9.12	-1.55
Indiana	3.21	3.98	0.77
Nebraska	6.53	7.91	1.38
Ohio	5.66	7.75	2.09
South Dakota	5.63	8.70	3.07
Arkansas	4.76	8.99	4.23
Largest:			
New York	-22.23	49.92	72.15
Arizona	-3.07	71.07	74.14
New Jersey	-19.69	55.46	75.15
Massachusetts	-24.34	52.28	76.62
Maryland	-16.30	66.06	82.37
Rhode Island	-22.35	69.29	91.64
Nevada	-3.02	88.77	91.79
Florida	-9.11	85.53	94.64
Washington D.C.	-20.52	79.04	99.57
California	-33.95	98.27	132.21

If we compare these to the states that had the largest change in house price shocks during the housing boom we notice two facts. First, many but not all of the states with the largest shocks had large negative house price shocks at the start of the boom. Second, all of these states had much larger positive house price shocks in 2005, as compared to the small shock states. So not only did these states make up for their negative shocks at the beginning of the time period, but prices increased dramatically beyond what was expected.

3.4 Results

The analysis is performed separately for married women, unmarried women, married men, and unmarried men as each of these groups may have very different patterns in their labor supply choices. A fixed effects model is used, to remove any person-specific effects with regards to labor supply choices. The dependent variable in each regression is either the log of usual weekly labor hours or a dummy variable for the respondent being employed. The house price shock variable is divided into its positive and negative component, as there may be different effects for each on labor supply. Each are equal to zero when a shock of the opposite sign occurs. For ease of interpretation, the absolute value of the negative house price shocks are used. For the full set of control variables see Table C.2 in the Appendix. As previously mentioned, the county unemployment rate is included in the regressions in order to separate local business cycles from house price shocks. The regressions to be estimated are:

$$\log(N_{i,t}) = \alpha_0 + \alpha_1 * \text{Pos. House Price Shock}_{t-1} + \alpha_2 * \text{Neg. House Price Shock}_{t-1} + \beta_1' * X_{i,t} + \nu_i + \gamma_t + u_{i,t}$$

$$\begin{aligned}\text{Emp.}_{i,t} = {} & \alpha_0 + \alpha_1 * \text{Pos. House Price Shock}_{t-1} + \alpha_2 * \text{Neg. House Price Shock}_{t-1} \\ & + \beta_1' * X_{i,t} + \nu_i + \gamma_t + u_{i,t}\end{aligned}$$

where $N_{i,t}$ is weekly work hours, $\text{Emp.}_{i,t}$ is an indicator equal to one if currently employed, $X_{i,t}$ are various individual and location controls[36], and ν_i and γ_t are person and year fixed effects.

Many of the variables from the PSID apply to what has happened to the respondent since the last interview or are current information, and the interviews tend to be sometime mid-year. However, the house price data and unemployment data is collected on a yearly basis. So to get as close to the timing of the labor supply variables, without going past the date of the interview, the housing and unemployment data is lagged by one year (or two for the post-1997 time period). Also, since the size of the house price shock variable is in some cases quite large, it is scaled down by the standard deviation of the variable, which is about 22 index points. So the results should be interpreted as the effect to a one S.D. change in the house price shock. Each regression included year dummy variables, to control for any changes in overall labor hours across the whole country over time.

[36]Such as fitted or estimated average wage, education, number of children, age of youngest child, indicator for pregnancy, region, county unemployment rate, etc. However, some of these may not actually vary over time for every respondent and would be covered by person fixed effects.

The regressions shown are for groups that we expect to be marginal workers and have less attachment to the labor force. Additional tables are shown in Section C.3 in the Appendix for other groups of individuals that we do not expect to be as responsive to price shocks such as unmarried women, and married and unmarried males.

Table 3.21: Fixed Effects Model: Log of Labor Hours, Married Females, Owners

	Actual Ownership Status					Predict Ownership	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
log(Fitted Wage)	-	-	-	-	3.435***	-	3.412***
	-	-	-	-	(0.358)	-	(0.342)
Pos. House Price Shock$_{t-1}$	-0.109***	-0.054**	-0.060***	-0.043**	-0.038*	-0.042**	-0.035*
	(0.020)	(0.022)	(0.023)	(0.021)	(0.021)	(0.020)	(0.020)
Neg. House Price Shock$_{t-1}$	-0.0019	-0.011	0.009	0.015	0.004	0.011	0.008
	(0.030)	(0.033)	(0.035)	(0.033)	(0.033)	(0.031)	(0.031)
Cnty Unemp. Rate$_{t-1}$	-	-	-0.026**	-0.022**	-0.018*	-0.024***	-0.019**
	-	-	(0.010)	(0.009)	(0.010)	(0.009)	(0.009)
Year Controls	N	Y	Y	Y	Y	Y	Y
Location/Lbr Mkt Ctrls	N	N	Y	Y	Y	Y	Y
Demographic Controls	N	N	N	Y	Y	Y	Y
Fitted Wage Control	N	N	N	N	Y	N	Y
N (Person-Year)	36,930	36,930	34,539	34,191	33,335	39,030	38,006
Groups	4,822	4,822	4,717	4,621	4,566	5,204	5,133
R^2 (within)	0.004	0.009	0.011	0.101	0.112	0.0924	0.1045

Sample weights are used. Standard errors are clustered by person ID to account for each individual being present multiple times. *,**,*** indicate significance at the 10%, 5%, and 1% level.

The results for the intensive margin of labor supply for married females are presented first. The regressions in Table 3.21 include both employed and non-employed women. In this first set of regressions, each subsequent column adds more control variables. The first five specifications are for married female homeowners using the actual homeownership status of the household. The last two columns use the predicted homeownership status using the process described in Section 3.3.1. The county unemployment rate is included in the fixed effect regressions to separate the effect of housing prices from the local labor market. As expected, the sign of the county unemployment rate is negative suggesting that work hours are less the higher the unemployment rate is. Across all specifications the results show that positive house price shocks decrease the number of labor hours that married women work. Here in Column (1), there are no control variables other than the house price shock variables and we see a reduction of labor hours of 10.9% due to a one standard deviation increase of the positive house price shock. In each column more explanatory variables are added: year fixed effects, location controls and the county unemployment rate, demographic variables, and finally the fitted wage.[37] Compared to the regression with no controls, adding these additional variables in columns (2)-(5) decreases the size of the estimated coefficient of the postive house price shock variable, but it remains significant. Finally, in Columns (6) and (7) I instead use the predicted homeowership status, which also does not appear to have much effect on the estimated coefficients. The coefficients range from -0.035 to -0.109, and in the baseline regression a one S.D. increase in the positive house price shock leads married women to reduce their hours of work by 4.3%. Since married females work an average of 25.5 hours per

[37]A set of four regresions using combinations of wage proxies and actual and predicted ownership status is shown in the Appendix in Section C.3

week, this corresponds to about a one hour decrease in their work hours. Note that these regressions do not control for unearned income of the wife (i.e. her husband's earnings) however including the fitted wage of the husband does not change the results.

Table 3.22: Fixed Effects Model: Married Females, Owners

Dependent Variable	**Log(Labor Hrs)**	**Log(Labor Hrs) Employed Only**	**Employment Status**
Pos. House Price Shock$_{t-1}$	-0.043**	-0.008	-0.013**
	(0.021)	(0.010)	(0.006)
Neg. House Price Shock$_{t-1}$	0.0151	-0.008	0.002
	(0.033)	(0.013)	(0.010)
Cnty Unemp. Rate$_{t-1}$	-0.022**	-0.003	-0.005*
	(0.009)	(0.004)	(0.003)
Year Controls	Y	Y	Y
N (Person-Year)	34,191	23,697	34,189
Groups	4,621	3,890	4,621
R^2 (within)	0.101	0.059	0.087

Sample weights are used. Standard errors are clustered by person ID to account for each individual being present multiple times. *,**,*** indicate significance at the 10%, 5%, and 1% level.

The baseline regression (4) from Table 3.21 is shown in the first column of Table 3.22. The second column in Table 3.22 looks only at those married women who are employed (log labor hours greater than zero). We examine this subset of women to see if the observed responses from the baseline regression in Table 3.21 are at the intensive margin, however the coefficients on house price shocks are not significant. Next we examine the effect of house price shocks on the extensive margin of labor supply. The dependent variable in the third column is an indicator variable equal to one if the wife is employed, and equal to zero if she is not. A value of zero would include both unemployed women and those out of the labor force. We observe that positive house price shocks make a married women less likely to be employed. So it appears that the main result from Table 3.21 is driven entirely from married women choosing to exit the labor force.

We focus on married women as they may be more likely to adjust their work hours or labor market status. In particular we know that in the majority of the homeowner households, the husband is employed thus potentially giving the wife the ability to work in the home or only work part time in the market. In particular we see that 82% of married homeowner males are employed and 75% work at least 35 hours in the labor market.

One might be concerned that the effect on labor supply is not driven by housing prices, but instead that labor market conditions are not adequately controlled for using the county unemployment rate. However, if the observed results were due to a boom in local business cycles, we would expect the effect on labor supply to be in the opposite direction as individuals can more easily find work. Thus, if anything not controlling properly for business cycle would attenuate these results. However, other methods of controlling for labor market conditions are explored in Section 3.4.3.

3.4.1 Male Respondents

Section 3.4.1 explores the relationship between house price shocks and labor supply choices for some of the male respondents in the sample. Married males are employed at a very high rate and are not likely to exhibit much flexibility in their labor supply decisions. I show the results for all married male respondents in Table C.8 in the Appendix. Instead in this section, the analysis focuses on a group of males that may have more flexible labor supply choices: those nearing retirement.

Table 3.23: Fixed Effects Model: Log of Hours, Married Men ≥65 Yrs, Owners

	Actual Ownership Status					Predict. Ownership	
	(8)	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**
Fitted Wage	-	-	-	-	-0.316	-	-0.060
	-	-	-	-	(1.256)	-	(1.181)
Pos. House Price Shock$_{t-1}$	-0.116**	0.006	0.024	0.021	0.014	-0.015	-0.023
	(0.045)	(0.051)	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)
Neg. House Price Shock$_{t-1}$	0.0980	0.115*	0.162**	0.154**	0.151**	0.119*	0.116*
	(0.063)	(0.065)	(0.068)	(0.068)	(0.069)	(0.063)	(0.065)
Cnty Unemp. Rate$_{t-1}$	-	-	-0.009	-0.007	-0.010	-0.013	-0.014
	-	-	(0.015)	(0.015)	(0.015)	(0.014)	(0.014)
Year Controls	N	Y	Y	Y	Y	Y	Y
Location/Lbr Mkt Ctrls	N	N	Y	Y	Y	Y	Y
Demographic Controls	N	N	N	Y	Y	Y	Y
Fitted Wage Control	N	N	N	N	Y	N	Y
N (Person-Year)	4,131	4,131	3,929	3,907	3,829	4,425	4,323
Groups	858	858	833	825	818	928	917
R^2 (within)	0.007	0.088	0.085	0.092	0.090	0.093	0.0911

Sample weights are used. Standard errors are clustered by person ID to account for each individual being present multiple times. *,**,*** indicate significance at the 10%, 5%, and 1% level.

Another group of particular interest is older males that are nearing retirement. This group of males may be more likely to have the ability to adjust their labor supply through switching to part time work or adjusting their retirement date. Table 3.23 examines married homeowner males ages 65 and over and sequentially adds in control variables. Looking at this group, we see interesting asymmetries in the response to house price shocks compared to married women, who only responded to positive house price shocks. In contrast, these data strongly suggest that older males increase their work hours in response to a negative house price shock. In particular, a one standard deviation larger negative house price shock increases labor hours by 11.5-16.2%. Given the coefficient in the baseline regression of 0.154 and since older married males work an average of about 10 hours per week, this represents a increase of about 1.5 hours.

Table 3.24: Fixed Effects Model: Married Men ≥65 Yrs Old, Owners

Dependent Variable	**Log of Labor Hours**	**Log(Labor Hrs) Employed Only**	**Employment Status**
Pos. House Price Shock$_{t-1}$	0.021	-0.005	0.008
	(0.052)	(0.080)	(0.014)
Neg. House Price Shock$_{t-1}$	0.1545**	-0.026	0.077***
	(0.068)	(0.084)	(0.021)
Cnty Unemp. Rate$_{t-1}$	-0.007	0.015	-0.005
	(0.015)	(0.027)	(0.005)
Year Controls	Y	Y	Y
N (Person-Year)	3,907	1,143	3,906
Groups	825	393	825
R^2 (within)	0.092	0.105	0.074

Sample weights are used. Standard errors are clustered by person ID to account for each individual being present multiple times. *,**,*** indicate significance at the 10%, 5%, and 1% level.

As with the married women, we examine the responses of older married males across three different specifications and dependent variables. Limiting the sample of older married males in Table 3.24 to only those who are employed in the second column, I find that there is no significant effect of house price shocks. Instead, the using employment status as the dependent variable we see that the results observed on the intensive margin are due to movements in and out of employment, perhaps as individuals delay their retirement. Given the estimated coefficient of 0.77, married males increase their probability of being employed by 7.7 percent in response to a one standard deviation larger negative house price shock. One potential explanation is that homeowners often have significant mortgage obligations and a negative house price shock represents a decrease in wealth which causes a need to extend their working years. As with the results for married women, the direction of the effect of negative house price shocks is such that if it was simply picking up the effect of local business cycles we would observe the opposite sign. So, if the county unemployment rate is not sufficiently controlling for local labor market conditions, the true effect on labor supply would be even larger than the observed effect.

One additional analysis for the respondents is to not look at them as individuals, but rather as an entire household unit. If we think about unitary models of households where they make joint decisions, then it is perhaps appropriate to think about house price shocks as affecting the labor supply choices of both spouses simultaneously. Considering the couple as a whole may also help provide

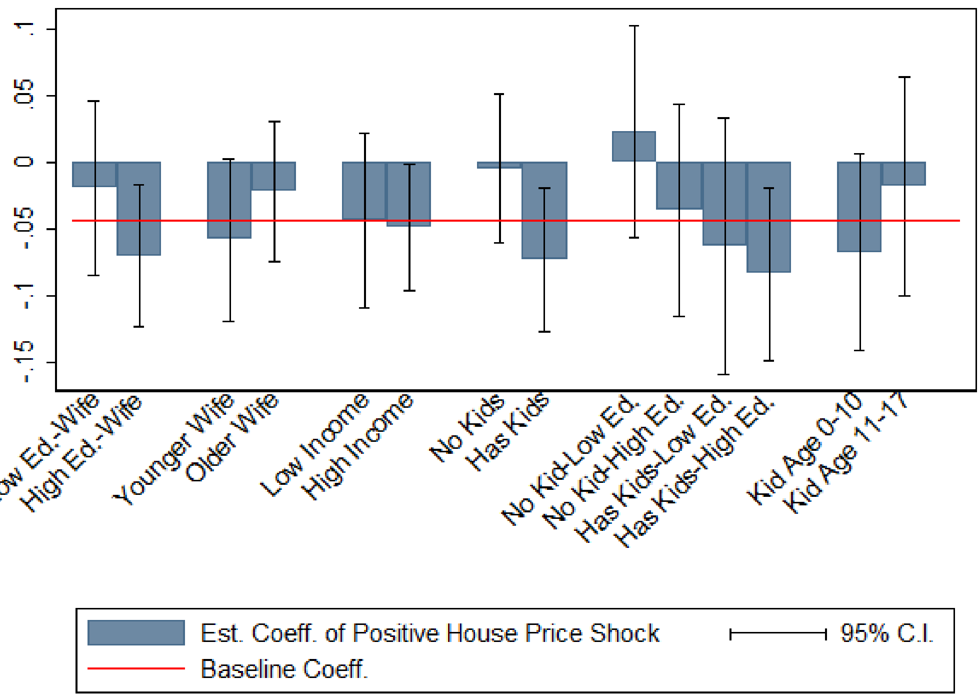
Table 3.25: Fixed Effects Model: Household Level Analysis

Dependent Variable	**Total Labor Hours**	**Diff. in Hours: H-W**	**Both Employed**
Pos. Change in HPI_{t-1}	0.002	0.815**	-0.006
	(0.016)	(0.322)	(0.006)
Neg. Change in HPI_{t-1}	0.0049	0.311	0.002
	(0.027)	(0.518)	(0.010)
Cnty Unemp. Rate_{t-1}	0.003	0.275	-0.005
	(0.007)	(0.141)	(0.003)
Year Controls	Y	Y	Y
N (Person-Year)	34,110	34,110	34,106
Groups	4,490	4,490	4,490
R^2 (within)	0.273	0.187	0.105

evidence of specialization in household roles. I consider a few specifications of the couple as a whole in Table 3.25. In each case a fixed effects model is used at the level of the couple and demographic control variables (age, education) are included for both the husband and wife. The first regression uses the total labor hours of the household as the dependent variable. I find no significant effect of house price shocks suggesting the the overall amount of time spent working in the labor market for the couple does not change. The dependent variable in the next column is the difference in labor hours between the husband and the wife. Here there is a positive and significant effect of positive shocks to housing prices. The average difference between the husband's and the wife's hours is about 19 hours. So, the results show that unexpected increases in local housing prices lead to an increase in this gap of 0.82 hours. While this does not tell us who is adjusting their hours, it does provide some evidence of increased specialization in the household, given the previous results from Table 3.21. Finally, I look at how the house price shocks affect the probability that both spouses and I do not see any significant results.

3.4.2 Demographics Analysis

Figure 3.13: Fixed Effect Models: Log of Labor Hours, Married Females, Owners



The following section delves deeper into the question of what groups are driving the results that positive house price shocks decrease the labor supply provided by married women. The total sample of married women is divided into sub-samples based on various economic and demographic groups such as education, income, race, and family structure. We know that not all married women may have the same abilities to adjust their labor hours or participation and thus this exercise may also shed some light on that question as well if certain groups do not respond to changes in wealth. In particular, it may be the case that those families with higher income have the flexibility to allow the wife to stay out of the labor force. Also, we might expect that the couples that it is beneficial for the wife to work less are those with children to care for. In each model in this section, the regression model used corresponds to that of column (4) in Table 3.21. To present the results in a succinct way, each bar in Figure 3.13 represents the estimated coefficient for the positive house price shock variable in a different regression model. The red line across the figure shows the estimated coefficient from the baseline regression model of column (4) in Table 3.21. The black line over each bar show the 95% confidence interval for the coefficient so if the top or bottom of the black line falls within the bar, the coefficient is significantly different from zero at the 5% level.

The first exercise in this section explores the difference across education groups for the married woman in the baseline sample. The first two bars in Figure 3.13 divide the sample based on the final completed education of the wife where 'Low' education indicates she has a high school degree or less and 'High' education indicates she has some college or more education. We see that it is the higher educated women who respond to positive house price shocks, and that the estimated coefficients are slightly larger than that of the whole sample. We may think that the wives with higher education have more flexible careers and are more likely to choose to work part time or work in the home. Next in Figure 3.13 we compare younger and older married women, with the sample split at the median which is 43 years old. Though only significant at the 10% level, the results do show that younger women respond to positive house price shocks and older women do not. Next I examine how house price shocks affect households with low versus high income. Since the households are at different point in the lifetime wage profile depending on their age, I use an age adjusted measure of the husband's income at the beginning of the sample. The results show that it is among the higher income families that the wives decrease the labor hours in response to positive house price shocks. One possible explanation is that it is only the households with higher income that can afford to have the woman reduce her hours. Though the results are not significant for the lower income households, there is not a significant difference between the estimated coefficients so it could be that the coefficients are just imprecisely measured.

In the last several columns of Figure 3.13 we explore differences in responses to positive house price shocks by the family structure of the household. First, comparing household with and without children under the age of 18 in the home, we observe that married women with children are reducing their work hours due to positive house price shocks, whereas those without children at home are not. Women with children are perhaps choosing to stay at home and spend more time caring for their children during good times, whereas they may not has as much incentive to reduce work hours without children. Continuing as before, I investigate to see if this effect of house price shocks on married women with children is coming at the extensive or intensive margin of labor supply. I find no significant effect of house price shocks on employed wives with children in the home. In addition, I find that positive house price shocks decrease the probability of employment for women with children in the home by 1.9%.[38] This effect is slightly larger than the effect for all married women. We might think that when the household experiences an increase in wealth it gives the wife the opportunity to stop working and stay home with the kids. Looking at households with children ages 0-10 and children ages 11-17, the estimated coefficient is significant at only the 10% level for households with younger children with no significant effect for household with older children. This complements the previous hypothesis since younger children likely require more care than older children, especially for those not yet enrolled in school. Finally, these households are further divided by family structure as well as low and high final completed education. The only significant result of house price shocks on labor hours appears for household with children

[38]Tables available on request.

where the wife has higher education. In addition, the estimated coefficient is larger than the baseline estimations at -0.084 which corresponds to a 8.4% reduction in labor hours. One explanation of this is the differences in child-rearing by social class which has been studied in depth in the sociology literature (Hays (1996), Vincent and Ball (2007), Lareau (2002)). Among the higher educated women, perhaps there is a stronger preference or opportunity to care for children yourself and engage in what is termed "intensive mothering" in the literature. This model of child-rearing suggests a very direct, time-intensive involvement in the child's development.

3.4.3 Robustness Checks

One potential concern is that the lag of the county unemployment rate is not sufficiently controlling for local labor market conditions in the regression models. To address this, Table 3.26 provides results for several other methods of labor market controls for married females in the PSID. The baseline results from Column (4) in Table 3.21 are shown as well for comparison. In Column (A), I include MSA fixed effects to broadly control for any unobserved characteristics the MSA, and although this does decrease the size of the coefficient the positive house price shocks are still significant at the 10% level. Next in Column (B), the MSA unemployment rate is included rather than the county unemployment rate, as in some

Table 3.26: Other Labor Market Controls: Log of Hours, Married Females, Owners

	Baseline	**(A)**	**(B)**	**(C)**	**(D)**
Pos. House Price Shock$_{t-1}$	-0.043**	-0.039*	-0.058**	-0.044**	-0.040*
	(0.021)	(0.021)	(0.024)	(0.021)	(0.022)
Neg. House Price Shock$_{t-1}$	0.015	0.006	0.060	0.030	0.009
	(0.033)	(0.033)	(0.048)	(0.034)	(0.036)
MSA Unemp. Rate$_{t-1}$	-	-	-0.042**	-	-
	-	-	(0.017)	-	-
Cnty Unemp. Rate$_{t-1}$	-0.022**	-0.018*	-	-0.020**	-0.021**
	(0.009)	(0.010)	-	(0.009)	(0.011)
Cnty Unemp. Rate$_{t-2}$	-	-	-	-0.009	-
	-	-	-	(0.008)	-
Chg. Med. Family Inc.$_{t-1}$	-	-	-	-	-0.391
	-	-	-	-	(0.457)
MSA Controls	N	Y	N	N	N
Year Controls	Y	Y	Y	Y	Y
N (Person-Year)	34,191	34,197	21,893	32,494	30,043
Groups	4,621	4,621	3,827	4,533	4,147
R^2 (within)	0.101	0.129	0.091	0.097	0.104

Sample weights are used. Standard errors are clustered by person ID to account for each individual being present multiple times. *,**,*** indicate significance at the 10%, 5%, and 1% level.

cases the county boundaries will go beyond the borders of the MSA. However, this reduces the sample size as the MSA unemployment is only available beginning in 1990. Next I allow for a more flexible lag structure on the county unemployment rate. Finally in Column (D), another measure of local business cycles is included, the change in the median family income in the metropolitan area. Including this control does not change the coefficient, but increases the standard errors slightly.

As with the previous tables, Table 3.27 shows the same specification as Column (4) in Table 3.21 to show the effects of house price shocks on married female renters. The channel through which shocks to housing prices could affect renters

Table 3.27: Fixed Effect Model: Married Females, Renters

Dependent Variable	**Log of Labor Hours**	**Log(Labor Hrs) Employed Only**	**Employment Status**
Pos. House Price Shock$_{t-1}$	-0.026	0.015	-0.016
	(0.059)	(0.023)	(0.016)
Neg. House Price Shock$_{t-1}$	0.0061	0.041	-0.018
	(0.100)	(0.035)	(0.028)
Cnty Unemp. Rate$_{t-1}$	-0.037	-0.021*	-0.006
	(0.025)	(0.011)	(0.008)
Year Controls	Y	Y	Y
N (Person-Year)	7,612	4,814	7,612
Groups	2,132	1,669	2,132
R^2 (within)	0.079	0.051	0.069

Sample weights are used. Standard errors are clustered by person ID to account for each individual being present multiple times. *,**,*** indicate significance at the 10%, 5%, and 1% level.

is two-fold. First, to the extent that there is a strong correlation between housing prices and rental prices, this may represent a decrease in available wealth/income to the household. On the other hand, if rents do not rise when housing prices do, rents may seem relatively cheaper. Second, if the renter couple is planning to buy a home in the next few years, this increase in housing prices represents a decrease in their lifetime wealth as they will have to pay more to purchase a home in the future. However, the link between wealth and house price shocks is clearly not as strong for renters as for owners. The three specifications shown are for the effect on the log of labor hours, log of labor hours for women that are employed, and employment status. Across all three specifications, we see no significant effect of house price shocks for married renters.

Table 3.28: Log of Hours: Other Shock Lengths, Married Females, Owners

Shock Length	1 year	2 year	**3 year**	4 year	6 year
Pos. House Price Shock$_{t-1}$	-0.036**	-0.045**	-0.043**	-0.038*	-0.032
	(0.014)	(0.018)	(0.021)	(0.022)	(0.023)
Neg. House Price Shock$_{t-1}$	-0.0002	0.022	0.015	0.023	0.011
	(0.028)	(0.033)	(0.033)	(0.032)	(0.035)
Cnty Unemp. Rate$_{t-1}$	-0.022**	-0.024***	-0.022**	-0.024**	-0.022**
	(0.008)	(0.009)	(0.009)	(0.010)	(0.010)
Year Controls	Y	Y	Y	Y	Y
N (Person-Year)	39,886	37,574	34,191	32,105	28,924
Groups	5,638	5,409	4,621	4,475	4,050
R^2 (within)	0.104	0.103	0.101	0.100	0.097

Sample weights are used. Standard errors are clustered by person ID to account for each individual being present multiple times. *,**,*** indicate significance at the 10%, 5%, and 1% level.

Recall that the house price shock variable in the baseline regressions was calculated as the sum of residuals for the past three years from Equation 3.14. Any households that have not lived in the MSA for at least three years are excluded as the shocks from the past three years are not what they have experienced. The results presented in Table 3.28 show the effect of house price shocks of differing lengths on the log of labor hours for married female homeowners. In bold is the column that contains the baseline specification with the 3 year shock length variable. Also shown are the results measuring the house price shock as the sum of residuals from Equation 3.14 for the past one, two, four, and six years. As with the baseline specification, in each case any respondents who have not lived in the MSA for the relevant length of time are excluded. I scale each shock variable by the standard deviation for ease of interpretation. Across all specifications, we see consistent evidence that married women reduce their labor hours in response to a positive house price shock.[39] The size of the effect is very similar in all cases, with a one standard deviation increase in the positive house price shock decreasing the wife's labor hours by 3.2 to 4.5%.

Table 3.29: Three Year Percent Change in HPI, Married Females, Owners

Dependent Variable	**Log of Labor Hours**	**Log(Labor Hrs) Employed Only**	**Employment Status**
Pos. Change in HPI_{t-1}	-0.049	-0.021	-0.035
	(0.080)	(0.032)	(0.024)
Neg. Change in HPI_{t-1}	-0.0092	-0.006	-0.013
	(0.171)	(0.065)	(0.053)
Cnty Unemp. $Rate_{t-1}$	-0.017**	-0.003	-0.003
	(0.008)	(0.003)	(0.002)
Year Controls	Y	Y	Y
N (Person-Year)	40,996	28,407	40,994
Groups	5,870	4,882	5,870
R^2 (within)	0.103	0.062	0.087

Sample weights are used. Standard errors are clustered by person ID to account for each individual being present multiple times. *,**,*** indicate significance at the 10%, 5%, and 1% level.

The final table in this section shows us the effect of the total change in housing prices, combining expected and unexpected changes. In Table 3.29 we use the percent change in the House Price Index over the past three years to be consistent with the measure of house price shocks used previously in the paper. As before, those who have not lived in the MSA for the past three years are excluded. We see across all specifications that there is no significant effect of the percent change in

[39]Similar results are shown in Table C.3 in the Appendix with a constant sample across specifications with different shock lengths.

housing prices over the past three years.[40] This suggests that it is the fact that the change in prices is *unexpected* that leads these married women to alter their labor supply. The table shows the results for the log of labor hours for married female owners, log of labor hours for employed females, and the employment status of married female owners.

3.5 Concluding Remarks

This paper explored the relationship between shocks to household wealth and individual labor supply decisions. In particular, we observed how homeowners responded to positive or negative shocks to housing prices, comparing married and unmarried males and females. The analysis utilized restricted household level panel data from the PSID linked with MSA level house price index from the Federal Housing Finance Agency and county level unemployment rates from the BLS. Housing prices are approximated by a second order autoregressive process with MSA and quarter fixed effects. The residuals from this first stage regression are cumulated for the past three years, and this sum provides a measure of the unexpected change in housing prices. Any households that have moved into the MSA in the past three years are excluded from the analysis as the house price shock from the past three years is not relevant to their experiences.

[40] Results for the percent change in the HPI over the past year are shown in Table C.4 the Appendix.

The analysis on labor supply choices is conducted on homeowners since they have a direct wealth effect from a change in housing prices. Regressions on renters show no significant effect of house price shocks. Fixed effect regressions are used with the dependent variables being either the log of labor hours or a dummy variable for employment status, controlling for various other observables including a measure of wages and the county unemployment rate. I use several methods to deal with the potential endogeneity problems with the homeownership and hourly wage variables. The analysis is performed separately by gender and by marital status as these groups are likely to have very different responses in their labor supply to the control variables. Two groups that are of particular interest are married women and older respondents who are nearing retirement since they are likely to have more flexibility than other groups in their labor supply choices. I find that married women decrease their labor supply when they experience positive house price shocks, and provide evidence that this effect occurs along the extensive margin. On the other hand, married males ages 65 and over are more likely employed in response to a negative house price shock.

In addition, I focus in on particular demographic and economic groups to determine what groups are responding to changes in house price shocks. Interesting patterns emerge in this analysis showing that it is the high income, high education women with children that are most affected by positive house price shocks. We see the strongest effect for women with children ages 0-10 in the home, suggesting that women are taking the opportunity of the positive wealth shock to stay home and care for their children rather than work in the labor market, at least when the children are young. One reason why we see a strong response among the high income/high education wives is that they actually may have the ability to do so, whereas it may not be possible for the lower income wives to exit the labor market.

There has been considerable interest in how the changing economic conditions affect households, especially since the recent recession. Housing prices are a particularly interesting economic factor to analyze since housing contributes such a large fraction of household wealth. This means that changes in housing prices have potentially very large wealth effects for homeowners. In addition, a rise in housing prices may be good for some homeowners but a detriment to a household looking to move from renting to owning. These results provide specific responses of households to such events as the housing boom of the 1990s-2000s and the housing market crash of 2007. The asymmetric results for positive versus negative shocks to housing prices additionally shed light on what groups we might expect to respond in the case of unexpected increases or unexpected decreases in housing prices.

Conclusion

In this dissertation we explored the broad effects of economic shocks on several types of household decisions. The unifying theme in this work is that changes in the financial situation of households have important implications for their behavior and often these responses are asymmetric to gains versus losses. In addition, we see asymmetric effects on household behavior for men and women. So if a household responds in one direction to a positive economic shock, it may not have the opposite reaction to an equal negative economic shock.

In Chapter 1 we saw a decrease in marital stability when the husband experienced a decrease in his predicted permanent income. Data from the National Longitudinal Survey of Youth of 1979 gave us observations of a particular birth cohort for much of their lives from a time before most of their marriages through the end of many of them. Just as the respondents are likely to have done themselves, we made a prediction of the spouses' permanent income in each year of their marriage using only the information available up until that year. The change in the predicted permanent income in the current year compared to the year of marriage is taken to be a shock to income. Although we see that the couple is more likely to divorce if the husband has a negative income shock, we only observe this for the wife if she loses her job.

Next in Chapter 2 the effect of a different type of economic shock on marital stability is studied: shocks to local housing prices. Local house price shocks provide an exogenous change in wealth for households in the Panel Study of Income Dynamics. The probability of divorce decreases with an increase in positive house price shocks, particularly for low income and low education families. This result fits in with a large literature in sociology and psychology showing that with an increase in wealth couples face fewer financial stressors and are less likely to dissolve their marriage. Another possibility is that the higher cost of housing in the area increases the amount the couple with have to pay for housing if they were to divorce and live in separate residences.

Finally Chapter 3 examines the effect of local house price shocks on the labor supply choices of homeowner households in the Panel Study of Income Dynamics. For married women, a positive house price shock induces them to exit the labor force, likely to care for children. The chapter then explores interesting response patterns by education and family structure of the household. We also see that older married males are more likely to be employed in response to a negative house price shock. As expected we do not see responsiveness in labor supply for married males and other groups that are unlikely to adjust their work hours.

Some next steps for this research include extending the first two chapters to other panel data sets. For example, using data from younger birth cohorts in the first chapter would allow us to see if the observed effects are cohort specific or differ in size/direction across cohorts. The second and third chapters can also benefit from the addition of data from the National Longitudinal Survey of Youth as the number of respondents in a given birth cohort are too small to be separately analyzed in the Panel Study of Income Dynamics. Further work remains to examine how changes in a household's economic opportunities affect other types of behavior, such as fertility.

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Appendices

Appendix A

Appendix to Chapter 1

A.1 Survival Probabilities

We can see that in general the respondents who married at older ages were less likely to have divorced by any particular time. For instance, the probability of a marriage lasting 5 years in this sample is 72% if the individual married at age 20, but is 84% if the individual married at age 30. [1] To be as consistent as possible with WW, I determined the end date of a marriage as when the couple was separated or divorced, whichever occured at the earliest date.

A.2 Constructing Predicted Permanent Income for Spouses

Since the previous year's prediction of permanent income is included in the current year's regression, the equations below are slightly different than those used for the respondents. Since the spouse will not be observed in the data until the time of marriage,

[1]Table A.1 contains the probability only for those married between the ages of 18 and 36. The complete data set has individuals marrying from 14 to 48 years old and displays similar trends. The other ages are not included in the table due to the small number of observations. The complete table is available on request.

Table A.1: Survival Probability of Marriage by Age

Age Married	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
Duration																			
0	0.99	0.99	0.99	0.99	1.00	0.99	1.00	0.99	0.99	0.99	1.00	1.00	0.97	1.00	0.99	0.99	0.99	0.99	1.00
1	0.93	0.95	0.96	0.95	0.96	0.97	0.97	0.96	0.97	0.96	0.98	0.97	0.96	0.97	0.99	0.99	0.97	0.96	0.95
2	0.87	0.90	0.89	0.90	0.92	0.92	0.93	0.93	0.94	0.92	0.95	0.94	0.92	0.92	0.96	0.95	0.95	0.91	0.92
3	0.80	0.83	0.82	0.86	0.87	0.88	0.89	0.89	0.90	0.90	0.92	0.90	0.89	0.89	0.90	0.93	0.90	0.86	0.90
4	0.73	0.76	0.76	0.81	0.83	0.84	0.86	0.85	0.87	0.87	0.89	0.87	0.87	0.86	0.86	0.92	0.87	0.79	0.86
5	0.66	0.70	0.72	0.77	0.79	0.82	0.83	0.81	0.83	0.85	0.85	0.84	0.84	0.83	0.82	0.91	0.81	0.79	0.82
6	0.62	0.66	0.68	0.75	0.74	0.78	0.80	0.78	0.81	0.82	0.81	0.81	0.81	0.80	0.81	0.91	0.75	0.79	0.76
7	0.59	0.64	0.64	0.72	0.72	0.75	0.77	0.76	0.79	0.79	0.79	0.79	0.76	0.79	0.79	0.87	0.74	0.76	0.73
8	0.56	0.60	0.62	0.69	0.70	0.73	0.76	0.74	0.77	0.77	0.75	0.78	0.74	0.76	0.77	0.83	0.71	0.74	0.73
9	0.52	0.59	0.61	0.67	0.68	0.71	0.74	0.72	0.74	0.74	0.70	0.75	0.71	0.75	0.74	0.80	0.71	0.73	0.72
10	0.50	0.56	0.59	0.65	0.66	0.69	0.73	0.71	0.72	0.73	0.68	0.74	0.69	0.73	0.70	0.76	0.69	0.70	0.72
11	0.48	0.54	0.56	0.64	0.65	0.67	0.71	0.70	0.69	0.71	0.66	0.72	0.67	0.71	0.69	0.74	0.66	0.69	0.72
12	0.46	0.52	0.55	0.62	0.63	0.67	0.70	0.68	0.68	0.69	0.65	0.71	0.65	0.70	0.64	0.72	0.65	0.68	0.72
13	0.45	0.51	0.53	0.61	0.62	0.65	0.68	0.67	0.66	0.68	0.64	0.69	0.65	0.69	0.64	0.69	0.64	0.68	0.72
14	0.44	0.50	0.52	0.60	0.61	0.64	0.67	0.66	0.64	0.65	0.62	0.69	0.63	0.67	0.61	0.68	0.64		
15	0.43	0.49	0.51	0.59	0.59	0.63	0.66	0.64	0.63	0.64	0.61	0.68	0.61	0.67	0.61	0.67	0.64		
16	0.43	0.48	0.50	0.58	0.59	0.61	0.65	0.63	0.61	0.63	0.60	0.68	0.59	0.66	0.61	0.67			
17	0.42	0.47	0.49	0.56	0.58	0.60	0.64	0.62	0.61	0.62	0.60	0.67	0.59	0.66	0.61				
18	0.41	0.46	0.48	0.56	0.57	0.60	0.63	0.61	0.60	0.61	0.60	0.66	0.57	0.66					
19	0.41	0.45	0.47	0.55	0.56	0.59	0.62	0.60	0.60	0.60	0.58	0.65	0.56						
20	0.39	0.44	0.46	0.55	0.55	0.58	0.61	0.59	0.59	0.59	0.58	0.65							
21	0.38	0.44	0.46	0.54	0.54	0.57	0.60	0.58	0.59	0.58	0.58								
22	0.38	0.43	0.45	0.53	0.53	0.56	0.60	0.57	0.59	0.58									
23	0.37	0.43	0.45	0.52	0.53	0.56	0.60	0.57	0.59										
24	0.36	0.42	0.45	0.52	0.53	0.56	0.59	0.57											
25	0.35	0.42	0.44	0.52	0.52	0.55	0.59												
Observations	713	940	903	930	906	775	696	501	441	363	312	246	195	189	140	127	105	80	79

I take the year of marriage as the first year to generate predictions. Since the first year of marriage could potentially be any time during the sample, dummy variables for the year are included. Let M be the year of first marriage.

For Male Respondents:

$$
\begin{aligned}
log(Y_i^{perm}) = \alpha_{20} * z_i + \beta_{20}' * x_{i,20} + \delta_{1,20} * log(Y_{i,20}) * (1 - d_{i,20}) \\
+ \delta_{2,20} * d_{i,02} + v_{i,20} + u_i^{perm}
\end{aligned}
\tag{A.1}
$$

First the preceding regression is run, similar to Equation 1.1. z_i are characteristics that do not change over time. $x_{i,20}$ are time-varying characteristics at their values at age 20. The variable d is an indicator function for an individual who reports zero earnings at age 20. Finally in the error term is $v_{i,20}$, the portion of permanent income not explained by the information at age 20, and u_i^{perm}, the unexplained variation in permanent income.

Now we find predicted permanent income at age 20:

$$log(Y_{i,20}^p) = \hat{\alpha}_{20} * z_i + \hat{\beta}'_{20} * x_{i,20} + \hat{\delta}_{1,20} * log(Y_{i,20}) * (1 - d_{i,20}) + \hat{\delta}_{2,20} * d_{i,20} \quad \text{(A.2)}$$

Since we are not able to construct similar models for the male spouses of female respondents, we save the estimated coefficients, $\hat{\alpha}_{20}$, $\hat{\beta}_{20}$, $\hat{\delta}_{1,20}$, and $\hat{\delta}_{2,20}$, from equation A.2 for later.

Next, using the predicted permanent income for the male respondents from age 20 as an additional explanatory variable, we estimate coefficients using the new information available at age 21. This is repeated for each year until age 40.

$$\begin{aligned} log(Y_i^{perm}) = \gamma_t * log(Y_{i,t-1}^p) + \beta'_t * x_{i,t} + \delta_{1,t} * log(Y_{i,t}) * (1 - d_{i,t}) \\ + \delta_{2,t} * d_{i,t} + v_{i,t} + u_i^{perm} \end{aligned} \quad \text{(A.3)}$$

for t=21,...,40.

After each regression the estimated coefficients are stored and after completing this process for all years, we have with coefficients from each year after a couple was married: $\hat{\alpha}_{20}, \hat{\beta}_{20}, \hat{\delta}_{1,M}, \hat{\delta}_{2,20}, ..., \hat{\gamma}_{40}, \hat{\beta}_{40}, \hat{\delta}_{1,40}, \hat{\delta}_{2,40}$

Finally, the predicted permanent income is constructed for each year for the male spouses of female respondents using the estimated coefficients collected. Let $xSp_{i,20}$ be a vector of time-varying characteristics for the first spouse of respondent

i at the age of first marriage M. Likewise define $zSp_{i,M}$, $YSp_{i,M}$, and $dSp_{i,M}$ to be time-invariant spouse characteristics, spouse income, and a dummy variable for zero income for the spouse of i. Then to find each male spouse's predicted permanent income in the year of first marriage:

$$\begin{aligned} log(YSp^p_{i,M}) = \hat{\gamma}_t * log(YSp^p_{i,M-1}) + \hat{\alpha}_M * zSp_{i,M} + \hat{\beta}_M * xSp_{i,M} \\ + \hat{\delta}_{1,M} * YSp_{i,M} * (1 - dSp_{i,M}) + \hat{\delta}_{2,M} * dSp_{i,M} \end{aligned} \tag{A.4}$$

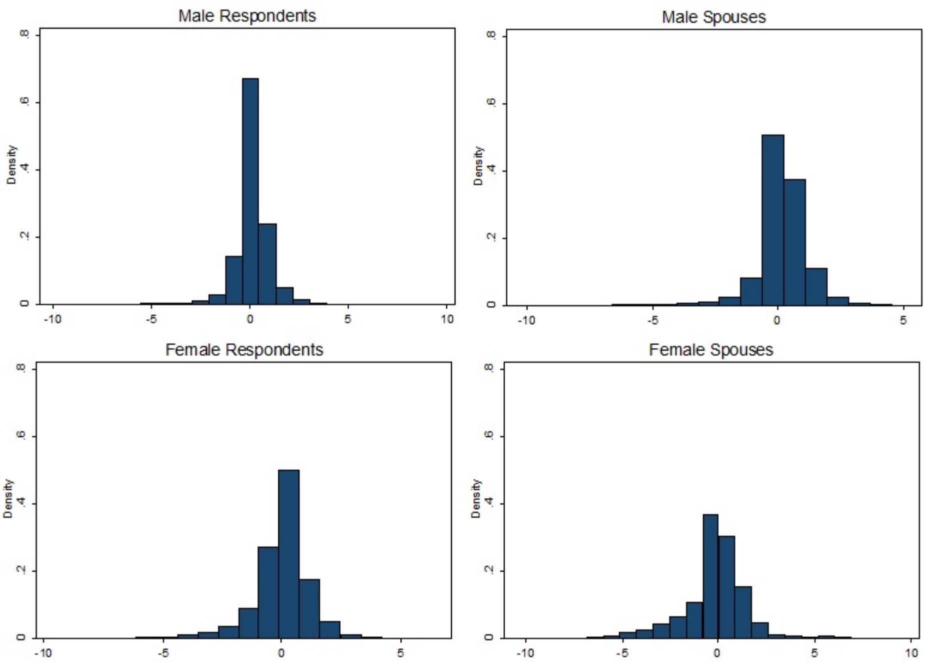
Recall that for the first year of marriage the previous year's prediction was constructed using multivariate matching to represent the unobserved past history. The remaining years are constructed similarly using the relevant coefficients.

$$log(YSp^p_{i,t}) = \hat{\gamma}_t * log(YSp^p_{i,t-1}) + \hat{\beta}_t * xSp_{i,t} + \hat{\delta}_{1,t} * YSp_{i,t} * (1 - dSp_{i,t}) + \hat{\delta}_{2,t} * dSp_{i,t} \tag{A.5}$$

A.3 Comparing Respondent and Spouse Populations

In each histogram in Figure A.1 the size of a bar is constant. This shows further information about the distribution of estimated income shocks for the respondents and spouses. We see very similar distributions among the male respondents and male spouses, and the female respondents and female spouses. In both cases, the distribution of shocks for the spouses are slightly more dispersed. However, we note that overall males have tighter distributions and females have a wider distribution.

Figure A.1: Histograms of Change in Predicted Permanent Income



A.4 Full Probit Specification

Table A.2: Full Probit Model of Effects on Divorce Probability

W: Pos. ΔPerm. Inc.$_{t-1}$	0.0009	**Age Difference, Husband-Wife:**	
	(0.0019)		
W: Neg. ΔPerm. Inc.$_{t-1}$	-0.0021	-3 to 0 years	-0.0087*
	(0.0016)		(0.0048)
H: Pos. ΔPerm. Inc.$_{t-1}$	-0.0004	1 to 3 years	-0.0027
	(0.0029)		(0.0053)
H: Neg .ΔPerm. Inc.$_{t-1}$	0.0036**	4 to 7 years	0.0015
	(0.0018)		(0.0062)
High School$_{t-1}$	-0.0063	$>$ 7 years	0.0012
	(0.0069)		(0.0092)
Some College$_{t-1}$	-0.0121*	**H: Age Married, Duration**	
	(0.0062)		
College$_{t-1}$	-0.0200***	$<$21, 1-2 years	0.0128
	(0.0048)		(0.0227)
W: Same Educ$_{t-1}$	0.0050	$<$21, 3-5 years	0.0381
	(0.0047)		(0.0339)
W: More Educ.$_{t-1}$	-0.0031	$<$21, 6-12 years	0.0103
	(0.0073)		(0.0192)
1-3 children$_{t-1}$	-0.0063	$<$21, 13-38 years	-0.0161*
	(0.0039)		(0.0074)
4 or more children$_{t-1}$	0.0037	21-23, 1-2 years	0.0110
	(0.0091)		(0.0174)
Children $\leq$ 5 yrs$_{t-1}$	-0.0075**	21-23, 3-5 years	0.0023
	(0.0030)		(0.0138)
Same Religion	-0.0117***	21-23, 6-12 years	0.0011
	(0.0025)		(0.0123)
Resp. From Intact Home	-0.0019	21-23, 13-32 years	-0.0091
	(0.0032)		(0.0086)
H: Hispanic	0.0017	24-30, 1-2 years	-0.0071
	(0.0040)		(0.0098)
H: Black	0.0067*	24-30, 3-5 years	0.0035
	(0.0041)		(0.0128)
Same Race	0.0049	24-30, 6-12 years	-0.0061
	(0.0040)		(0.0098)
West$_{t-1}$	0.0074*	24-30, 13-29 years	-0.0156*
	(0.0049)		(0.0054)
Central$_{t-1}$	0.0030	$>$30, 1-2 years	-0.0066
	(0.0038)		(0.0093)
South$_{t-1}$	0.0129***	$>$30, 3-5 years	-0.0108
	(0.0042)		(0.0077)
Own Home	-0.0138***		
	(0.0032)		
At Marriage:			
W: Same Educ.	-0.0034		
	(0.0050)		
W: More Educ.	-0.0062		
	(0.0058)		
Own Home	0.0063		
	(0.0045)		
Have Children	0.0027		
	(0.0045)		
Year Controls	Y		
N (Person-Year)	17,744		
Couples	2,299		
R^2	0.063		

Appendix B

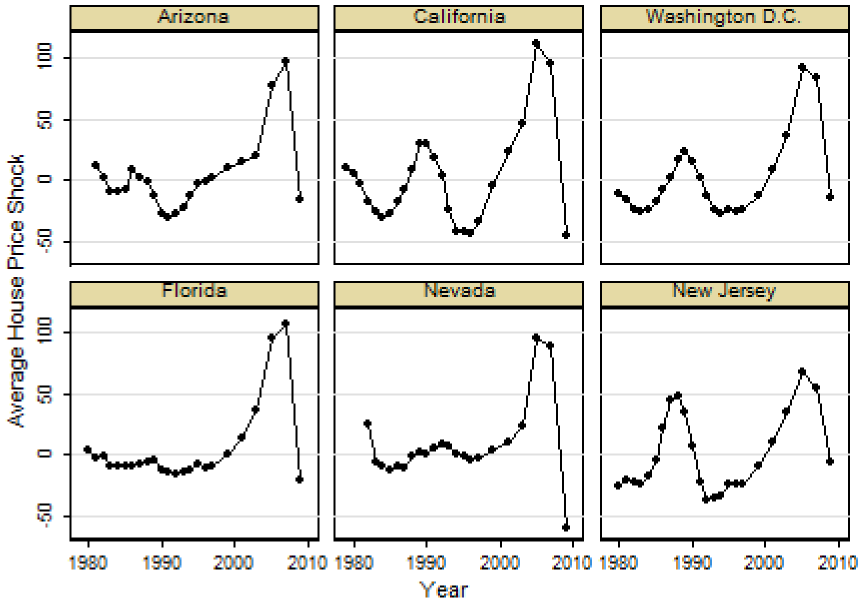
Appendix to Chapter 2

B.1 Further Description of House Price Shocks

The following two figures further explore the differences in the house price shock across locations discussed in the end of Section 2.3.1. Figure B.1 shows panels for six selected states that were among those most affected during the housing boom. The figures show the average house price shock for each of the six states by year from 1979-2009. Even between these states we see there are differences in their experiences of house price shocks over the time period, especially in the earlier years. However, all of these states exhibit the same general pattern as observed in Figure 2.5 in the time period of 1995 to 2005.

Next Figure B.2 shows panels for four selected states that faced the smallest changes in the house price shock over the period 1995 to 2005. Again, the figure shows the average yearly house price shock for each of these four states in order to compare them to the states with large changes in the house price shock. All of these states have a relatively flat series for the house price shock over the time period, in stark contrast to what was experienced in California, Arizona, Florida,

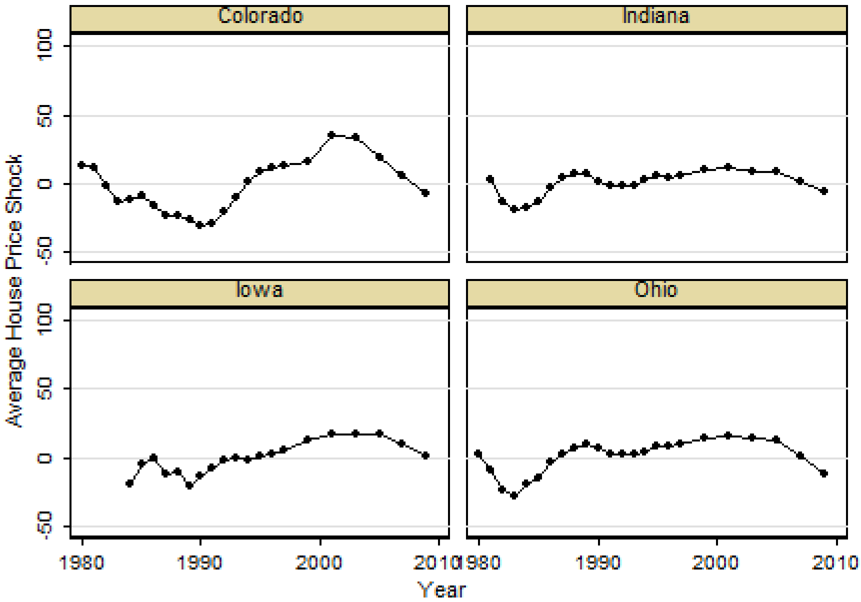
Figure B.1: Large Shock States over Time



etc. Only Colorado has any semblance of the spike in the house price shock we see for the states in Figure B.1. However, even this is dwarfed by the size of the house price shocks in the other states.

These two figures together make it clear that although prices were rising throughout the 1990s and early 2000s, the experiences across different locations were not equal. Thus, the persistent increase observed in Figure 2.5 are due to the fact that some locations had very large increases in the variable during the housing boom years and some locations had no change in the variable during those years. So there is a substantial amount of variation across states and MSAs with which to identity an effect of the house price shock on the decision to divorce.

Figure B.2: Small Shock States over Time



B.2 Additional Tables

Table B.1: Full Probit Model of Divorce Hazard:Homeowners

Variable	Marg. Eff.	Std. Err.	Marg. Eff.	Std. Err.	Marg. Eff.	Std. Err.
Pos. House Price Shock$_{t-1}$	-0.0014**	(0.0007)	-0.0014**	(0.0007)	-0.0014**	(0.0007)
Neg. House Price Shock$_{t-1}$	-0.0003	(0.0011)	-0.0003	(0.0011)	-0.0003	(0.0011)
County Unemp. Rate$_{t-1}$	-0.0074	(0.0202)	-0.0071	(0.0203)	-0.0068	(0.0204)
Age at Marriage-Husb.	-0.0004	(0.0005)	-0.0004	(0.0005)	-0.0004	(0.0005)
Age Diff.(H-W): -5 to -1	0.0030*	(0.0021)	0.0030*	(0.0021)	0.0030***	(0.0021)
Age Diff.(H-W): 0 to 4	0.0044***	(0.0014)	0.0044***	(0.0014)	0.0044***	(0.0014)
Age Diff.(H-W): 5 to 10	0.0084***	(0.0030)	0.0085***	(0.0030)	0.0085***	(0.0030)
Age Diff.(H-W): > 10	0.0290***	(0.0140)	0.0298***	(0.0143)	0.0298***	(0.0143)
Log(Duration)$_{t-1}$	-0.0027***	(0.0006)	-0.0025***	(0.0006)	-0.0025***	(0.0006)
# Prior Marriages-Husb.$_{t-1}$	0.0011	(0.0010)	0.0011	(0.0010)	0.0011	(0.0010)
# Prior Marriages-Wife$_{t-1}$	0.0006	(0.0009)	0.0006	(0.0009)	0.0006	(0.0009)
High School-Husb.$_{t-1}$	0.0013	(0.0015)	0.0013	(0.0015)	0.0013	(0.0015)
Some College-Husb.$_{t-1}$	-0.0001	(0.0015)	0.0000	(0.0015)	-0.0001	(0.0015)
College-Husb.$_{t-1}$	-0.0003	(0.0016)	-0.0003	(0.0016)	-0.0003	(0.0016)
High School-Wife$_{t-1}$	-0.0015	(0.0014)	-0.0016	(0.0014)	-0.0016	(0.0014)
Some College-Wife$_{t-1}$	-0.0009	(0.0015)	-0.0009	(0.0015)	-0.0010	(0.0015)
College-Wife$_{t-1}$	-0.0025	(0.0014)	-0.0025	(0.0014)	-0.0026	(0.0014)
Black-Husb.	0.0027	(0.0020)	0.0029*	(0.0020)	0.0029*	(0.0020)
Hispanic-Husb.	-0.0022	(0.0012)	-0.0020	(0.0013)	-0.0020	(0.0013)
Wife Same Race	-0.0002	(0.0017)	-0.0001	(0.0017)	-0.0001	(0.0017)
# of Children$_{t-1}$			-0.0008*	(0.0004)	-0.0008*	(0.0004)
Young Children$_{t-1}$			0.0012	(0.0012)	0.0013	(0.0012)
Log(Income)-Husb.$_{t-1}$					0.0001	(0.0002)
Log(Income)-Wife$_{t-1}$					0.0001	(0.0002)
Year Effects	Yes		Yes		Yes	
# of Couples	3,893		3,893		3,893	
N (couple-years)	30,016		30,016		29,960	
Pseudo-R^2	0.1138		0.1152		0.1151	

Sample weights are used. Standard errors are clustered by person ID to account for each individual being present multiple times. *,**,*** indicate significance at the 10%,5%, and 1% level.

Appendix C

Appendix to Chapter 3

C.1 Comparing Married Renters and Owners

Table C.1 compares the regression coefficients from fixed effects regressions for married females owners and renters. This shows that it may be inappropriate to include both renters and owners in a regression together as there are a number of control variables that have very effects on labor supply across the groups. Including both owners and renters in the regression would force the coefficients of any variables without interaction terms to have an equal effect on labor supply. In particular, those variables that have a significant difference in the estimated coefficients are dealing with age, the presence of young children, and location. Finally the year fixed effects which are almost all significantly different across the groups.

Table C.1: Log of Labor Hours,
Regression Coefficients of Married Females

	Owner	**Renter**	**Difference**
Fitted Wage	3.435	3.357	0.078
Pos. House Price Shock$_{t-1}$	-0.038	-0.020	-0.019
Neg. House Price Shock$_{t-1}$	0.004	0.059	-0.055
Cnty Unemp. Rate$_{t-1}$	-0.018	-0.035	0.017
1-2 Children	0.159	0.159	0.000
3 or More Children	0.146	0.239	-0.094
Children under 5 yrs	-0.807	-0.520	-0.288*
Children 6 to 10 yrs	-0.427	-0.348	-0.078
Children 11 to 15 yrs	-0.150	-0.136	-0.014
Pregnant	-0.073	0.054	-0.128
High School	-0.346	0.195	-0.541**
Some College	-0.331	0.141	-0.471
College	-1.024	-0.189	-0.834
Age: 24 to 30	-0.119	0.271	-0.390
Age: 31 to 40	-0.085	0.469	-0.554*
Age: 41 to 65	-0.083	0.490	-0.574
Age: 66 to 75	-0.322	0.157	-0.480
West$_{t-1}$	0.352	1.311	-0.959
South$_{t-1}$	0.212	0.900	-0.688
Central$_{t-1}$	0.218	-0.222	0.440
Year: 1983	-0.039	0.176	-0.214*
Year: 1984	-0.059	0.421	-0.479***
Year: 1985	0.157	0.649	-0.492***
Year: 1986	-0.092	0.303	-0.395***
Year: 1987	-0.162	0.324	-0.486***
Year: 1988	-0.350	0.230	-0.580***
Year: 1989	-0.300	0.292	-0.593***
Year: 1990	-0.311	0.267	-0.578***
Year: 1991	-0.308	0.219	-0.527**
Year: 1992	-0.319	0.294	-0.612***
Year: 1993	-0.660	-0.061	-0.598**
Year: 1994	-0.588	0.168	-0.757***
Year: 1995	-0.362	0.490	-0.853***
Year: 1996	-0.454	0.277	-0.731***
Year: 1997	-0.498	0.056	-0.554
Year: 1999	-0.700	-0.288	-0.412
Year: 2001	-1.018	-0.767	-0.251
Year: 2003	-1.175	-0.755	-0.420
Year: 2005	-1.290	-0.905	-0.385
Year: 2007	-1.510	-1.136	-0.374
Year: 2009	-1.558	-1.238	-0.320
Constant	-5.751	-6.972	1.221
N (Person-Year)	33,335	7,319	
Groups (Person)	4,566	2,066	

C.2 Additional Tables

Table C.2 shows the full specification of the fixed effect model where the dependent variable is the log of labor hours and the sample is for married female

Table C.2: Full Specification: Log of Hours, Married Females, Owners

Dependent Variable	**Log(Labor Hrs)**
Pos. House Price Shock$_{t-1}$	-0.043
	(0.021)
Neg. House Price Shock$_{t-1}$	0.015
	(0.033)
Cnty Unemp. Rate$_{t-1}$	0.010
	(0.039)
# of Children	-0.244
	(0.072)
Children under 5 yrs	-1.054
	(0.073)
Children ages 6 to 10 yrs	-0.563
	(0.060)
Children ages 11 to 15 yrs	-0.232
	(0.043)
Pregnant	-0.095
	(0.046)
High School	-0.264
	(0.169)
Some College	-0.010
	(0.217)
College	-0.267
	(0.264)
Age: 24 to 30	0.216
	(0.268)
Age: 31 to 40	0.608
	(0.275)
Age: 41 to 65	0.889
	(0.281)
Age: 66 to 75	0.311
	(0.296)
West$_{t-1}$	0.306
	(0.327)
South$_{t-1}$	0.045
	(0.223)
Central$_{t-1}$	0.245
	(0.284)
Constant	2.481
	(0.382)
N (Person-Year)	34,191
Groups	4,621
R^2 (within)	0.101

homeowners. This corresponds to the model used in the baseline regression of Table 3.21.

In Table C.3, I use a constant sample of households across all specifications of the different lengths of the house price shock, compared to Table 3.28. The

Table C.3: Fixed Effects Model: Log of Labor Hours, Other Shock Lengths

Shock Length	1 year	2 year	**3 year**	4 year	6 year
Pos. House Price Shock$_{t-1}$	-0.040**	-0.039*	-0.038*	-0.032	-0.032
	(0.016)	(0.020)	(0.023)	(0.024)	(0.023)
Neg. House Price Shock$_{t-1}$	-0.0345	-0.010	0.001	0.025	0.011
	(0.034)	(0.037)	(0.036)	(0.034)	(0.035)
Cnty Unemp. Rate$_{t-1}$	-0.019*	-0.021**	-0.021**	-0.025**	-0.022**
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Year Controls	Y	Y	Y	Y	Y
N (Person-Year)	28,924	28,924	28,924	28,751	28,924
Groups	4,050	4,050	4,050	4,034	4,050
R^2 (within)	0.097	0.097	0.097	0.097	0.097

Sample weights are used. Standard errors are clustered by person ID to account for each individual being present multiple times. *,**,*** indicate significance at the 10%,5%, and 1% level.

estimated coefficients do not change by much, though the standard errors increase. However, this is likely due mostly to the significant decrease in sample size.

Table C.4: One Year Percent Change in HPI,
Married Females, Owners

Dependent Variable	**Log of Labor Hours**	**Log(Labor Hrs) Employed Only**	**Employment Status**
Pos. Change in HPI$_{t-1}$	-0.140	0.012	-0.084
	(0.220)	(0.083)	(0.067)
Neg. Change in HPI$_{t-1}$	0.0528	-0.003	-0.048
	(0.323)	(0.130)	(0.097)
Cnty Unemp. Rate$_{t-1}$	-0.019**	-0.003	-0.003
	(0.008)	(0.003)	(0.002)
Year Controls	Y	Y	Y
N (Person-Year)	42,404	29,249	42,402
Groups	5,968	4,954	5,968
R^2 (within)	0.104	0.062	0.088

Sample weights are used. Standard errors are clustered by person ID to account for each individual being present multiple times. *,**,*** indicate significance at the 10%, 5%, and 1% level.

C.3 Wage Controls and Other Household Types

The first two tables in this section shows a set of four regressions using combinations of wage proxies and actual and predicted ownership status to deal with the potential endogeneity problems described in Section 3.3.1. Results are shown for the two main groups of interest in this paper, married women and older married males. The first two columns use the actual homeownership status of the respondents and the last two columns use the predicted homeownership status. Next, we vary the proxy for wages from the fitted wage generated for each respondent to the estimated average wage of a similar demographic group from census data.

Table C.5: Fixed Effects Model: Log of Labor Hours,
Married Females, Owners

	Actual Ownership Status		**Predicted Ownership Status**	
Fitted Wage	3.435***	-	3.412***	-
	(0.358)	-	(0.342)	-
Estimated Avg. Wage	-	0.083	-	0.072
	-	(0.095)	-	(0.090)
Pos. House Price Shock$_{t-1}$	-0.038*	-0.044**	-0.035*	-0.042**
	(0.021)	(0.021)	(0.020)	(0.020)
Neg. House Price Shock$_{t-1}$	0.004	0.015	0.008	0.011
	(0.033)	(0.033)	(0.031)	(0.031)
Cnty Unemp. Rate$_{t-1}$	-0.018*	-0.023**	-0.019**	-0.024***
	(0.010)	(0.010)	(0.009)	(0.009)
Year Controls	Y	Y	Y	Y
N (Person-Year)	33,335	33,916	38,006	38,726
Groups	4,566	4,484	5,133	5,052
R^2 (within)	0.112	0.101	0.105	0.093

Sample weights are used. Standard errors are clustered by person ID to account for each individual being present multiple times. *,**,*** indicate significance at the 10%,5%, and 1% level.

Table C.6: Fixed Effects Model: Log of Hours,
Married Men ≥65 Yrs, Owners

	Actual Ownership Status		**Predicted Ownership Status**	
Fitted Wage	-0.316	-	-0.060	-
	(1.256)	-	(1.181)	-
Estimated Avg. Wage	-	0.183**	-	0.175**
	-	(0.083)	-	(0.081)
Pos. House Price Shock$_{t-1}$	0.014	0.024	-0.023	-0.012
	(0.052)	(0.052)	(0.052)	(0.052)
Neg. House Price Shock$_{t-1}$	0.151**	0.154**	0.116*	0.117*
	(0.069)	(0.068)	(0.065)	(0.063)
Cnty Unemp. Rate$_{t-1}$	-0.010	-0.008	-0.014	-0.013
	(0.015)	(0.015)	(0.014)	(0.014)
Year Controls	Y	Y	Y	Y
N (Person-Year)	3,829	3,897	4,323	4,418
Groups	818	822	917	927
R^2 (within)	0.090	0.093	0.091	0.094

Sample weights are used. Standard errors are clustered by person ID to account for each individual being present multiple times. *,**,*** indicate significance at the 10%,5%, and 1% level.

The next table examines the effect of house price shocks on the labor supply on unmarried women. I perform the analysis separately for young single women and older single women as they are likely to be from two very different demographic groups: younger single women homeowners are more likely never married or divorced, and older single women are more likely widowed and nearing retirement. These two groups have potentially very different labor supply choices and very different responses to wealth shocks from each other. First focusing on younger single female homeowners[1], Table C.7 show the results at the intensive and extensive margin of labor supply for each group. If we compare the group of younger unmarried females to the older unmarried females, we see that the younger women are more educated and are more likely to be black. The younger women also have

[1]Note that given the wide range of birth cohorts in the PSID, the "younger" female homeowners in this sample are ages 53 and younger.

Table C.7: Fixed Effects Model: Single Females, Owners

	Younger Single Females		Older Single Females	
Dependent Variable	**Log of Labor Hours**	**Employment Status**	**Log of Labor Hours**	**Employment Status**
Pos. House Price Shock$_{t-1}$	-0.073	-0.010	-0.090	-0.011
	(0.056)	(0.013)	(0.068)	(0.019)
Neg. House Price Shock$_{t-1}$	-0.1006	-0.002	-0.1470	-0.053*
	(0.066)	(0.019)	(0.110)	(0.031)
Cnty Unemp. Rate$_{t-1}$	-0.003	-0.005	-0.016	-0.005
	(0.019)	(0.005)	(0.026)	(0.009)
Year Controls	Y	Y	Y	Y
N (Person-Year)	4,146	4,146	3,823	3,824
Groups	1,035	1,035	728	729
R^2 (within)	0.338	0.025	0.239	0.195

Sample weights are used. Standard errors are clustered by person ID to account for each individual being present multiple times. *,**,*** indicate significance at the 10%,5%, and 1% level.

considerably higher incomes, however the sample of older women includes many retirees. We see no consistent evidence that these groups of women are affected by house price shocks, though the sample sizes are extremely small.

Table C.8 and Table C.9 show the three different specifications for the sample of married and unmarried male homeowners, respectively. The sample of unmarried males are on average younger and less educated than the married males, as well as more likely to be non-white. As has been observed in the empirical literature, unmarried males also have lower income on average than married males, even when controlling for age. The results are not consistently significant across specifications for either group, as expected since these are not groups we would anticipate would vary their labor supply much. There is some evidence that married and single males respond to house price shocks in terms of their employment status, however the coefficients are in the same direction as they might respond to general business

Table C.8: Fixed Effects Model: Married Males, Owners

Dependent Variable	**Log of Labor Hours**	**Log(Labor Hrs) Employed Only**	**Employment Status**
Pos. House Price Shock$_{t-1}$	0.026	-0.006	0.012**
	(0.018)	(0.007)	(0.005)
Neg. House Price Shock$_{t-1}$	0.0422	-0.007	0.010
	(0.029)	(0.010)	(0.008)
Cnty Unemp. Rate$_{t-1}$	0.000	0.001	0.000
	(0.007)	(0.003)	(0.002)
Year Controls	Y	Y	Y
N (Person-Year)	34,448	27,697	34,446
Groups	4,557	4,207	4,557
R^2 (within)	0.355	0.167	0.217

Sample weights are used. Standard errors are clustered by person ID to account for each individual being present multiple times. *,**,*** indicate significance at the 10%,5%, and 1% level.

cycles so we cannot rule out that the regressions just have not controlled for labor market conditions well enough.

Table C.9: Fixed Effects Model: Single Males, Owners

Dependent Variable	**Log of Labor Hours**	**Log(Labor Hrs) Employed Only**	**Employment Status**
Pos. House Price Shock$_{t-1}$	0.085*	-0.003	0.019
	(0.050)	(0.017)	(0.018)
Neg. House Price Shock$_{t-1}$	0.1215	-0.011	0.051**
	(0.088)	(0.028)	(0.023)
Cnty Unemp. Rate$_{t-1}$	0.010	-0.003	0.000
	(0.025)	(0.010)	(0.007)
Year Controls	Y	Y	Y
N (Person-Year)	4,433	3,375	4,433
Groups	1,319	1,120	1,319
R^2 (within)	0.227	0.146	0.116

Sample weights are used. Standard errors are clustered by person ID to account for each individual being present multiple times. *,**,*** indicate significance at the 10%,5%, and 1% level.