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NEGATIVE EQUITY AND ITS EFFECT ON DIVORCE RATES

A study on the effect of debt and distressed housing markets on US divorce rates

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Abstract: Several lifestyle and financial variables have been observed to have an effect on divorce rates, but the possible effect of debt and housing prices remains unknown. Variables that have been used, such as employment, education level and income have been shown to not fully explain variations in divorce rates. In this paper we measure the prevalence of negative equity for American households to see if it has any significant effect on divorce rates, while suggesting that as the share of homeowners with underwater mortgages increases, divorce rates will decrease due to locked-in effects. We exploit the financial shock in 2008 which reduced the overall house price index and decreased asset values for numerous households. By gathering data on both a county and state level, we use aggregate data to measure if distressed housing prices and debt has a significant effect on divorce rates. In contrary to our thesis, although with slight explanatory value, low debt-to-income values in households seem to reduce divorce rates and high debt-to-income values seem to increase divorce rates. Furthermore, our research suggests that the differences in divorce laws between states and counties as well as the decreasing overall marriage rate have had the largest impact on American divorce rates.

Keywords: *business cycle, divorce, marriage, debt, unemployment, housing prices*

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1. INTRODUCTION

Financial factors have been shown to influence household decisions and more specifically to affect the propensity for couples to divorce in earlier studies. By analyzing data between 1960-2005, researchers found a negative correlation of unemployment rates and divorce rates (Amato and Beattie, 2010). Furthermore, previous research has shown that financial challenges could cause hardship in relationships, leading to an increase in divorce rates. Some academic research suggests that economic hardship increases marriage dissolutions (South 1985), whereas other suggest the opposite (Hellerstein and Morrill, 2010).

Less explored is how household debt in combination with decreasing housing prices affect couples´ tendency to divorce. The effects of leverage on household decisions was studied by Jennifer Brown and David A. Matsa in the paper “Locked in by Leverage: Job search during the housing crisis”, which demonstrates that work applicants in distressed housing markets limited their job search to a narrower geographical area (Brown & Matsa, 2017). While household debt might affect employment decisions, it is also imaginable that the locked-in effects could function in a similar way for married homeowners, namely that decreasing housing prices and high levels of debt decreases the propensity to divorce. In a downturn, some homeowners might not be able to sell their house and walk away if their property is underwater.

The ideal way to test our thesis would be to have a large number of married couples that would randomly be assigned a certain level of debt while decreasing the housing prices. We would then test if the different levels of debt had any effect on the respective couples´ probabilities of divorce. Another way of testing the hypothesis would be to have couples with equal amounts of debt assigned a random decrease in the price of their house. Afterward we could test whether this exogenous shock had any effect of these couples’ propensity to divorce. Unfortunately, there does not exist any data on such a disaggregate level and the general lack of US data on divorces has been lamented before. Instead of conducting these experiments, we will use aggregate data on two different levels, state and county, to test whether the differences in debt levels and housing prices have any effect on the crude divorce rate in that specific geographical area.

However, there are problems associated with using aggregate level data to produce inferences for individual units. There might exist relevant variation between individuals in both of the data sets that is lost on an aggregate level. For instance, individuals with higher debt-to-income ratios might be less likely to divorce than individuals with lower ratios in distressed housing markets, but that this effect is lost when comparing averages between states or counties. This problem could be mitigated by using individual, disaggregated data. Unfortunately, this data is not available and we have thus concluded that it is still worthwhile to conduct the analyses with aggregate data while keeping the potential pitfalls of the data in mind.

In 2008 the US housing market experienced a significant price decrease. Since then, the fall in prices has been followed by a recovery in US housing prices (Figure 2). The rapid decrease will serve as the exogenous shock in this experiment and this is one reason for why the empirical analysis takes place in the US. In addition to the large variation in housing prices, there exists plenty of market data and a sufficiently big sample in terms of the number of states and counties to make the results from aggregate data interesting.

Another important reason to why this study was done using US empirical data, is that there exist two very distinct kinds of legal differences between US states. Firstly, in terms of foreclosure laws, the states could be divided into recourse states and non-recourse states. In the recourse states, homeowners who foreclose on their houses will be personally liable for the bank´s losses. On the other hand, in the non-recourse states, homeowners can turn the keys over to the bank and seize to be accountable for the mortgage on the house. It is expected that decreases in housing prices and higher leveraged ratios will have a more pronounced effect on the non-recourse states, since couples in these states will be liable for the bank´s losses.

Secondly, there exists different legal restrictions for how a married couple´s property is separated in the case of divorce. In states that practice community property assets are basically split between the spouses evenly, without considering which spouse has the largest income. In contrary, equitable distribution examines the assets and tries to create a fair distribution based on income and contribution. A worthwhile comparison would be the average divorce rates of states that practice community property law with the average of the states that practice equitable distribution law. One could hypothesize that the findings would suggest an increase in divorce rates in the community property states, mainly due to the increased bargaining power of the spouse with the least assets. On the other hand, it could also mean that community property states have lower divorce states due to incentives created for the partner with the highest assets to keep the marriage together in fear of losing assets.

By using time series data from the period 1999 to 2016 on both a state and county level we can test the influence of leverage ratios and housing prices on divorce rates. The literature on divorce rates is mostly focused on ex-post individual data even though some quantitative studies have been performed on subjects such as divorce laws and unemployment. To the best of our knowledge, there has not been any study conducted on the correlation between negative equity and divorce rates yet. The contribution of this thesis is to show if there is any correlation between these phenomena. To find economic indicators for how a certain geographic area will develop demographically is important to forecast nativity, tax revenue, recipients of welfare programs as well as the labor market behavior for men and women. Ultimately, a misunderstanding of the aggregate welfare effects of a business cycle downturn might contribute to a wrongful measurement of said effect, an idea which has been discussed previously (Schaller, 2013).

After conducting regression analyses on both the state and county level data we can make a few conclusions about how economic factors, leverage in particular, affect divorce rates. Firstly, the lower bound for the debt-to-income ratio has a significant, positive effect on divorce rates. There is little evidence suggesting that the locked-in effect of a high debt to income ratio combined with a distressed housing market has any decreasing effect on divorce rates, the positive effect of the lower bound provide prima facie evidence against this hypothesis. On the other hand, we find that social and legal factors have a quite large effect on divorce rates compared to economic factors, such a housing prices, income or unemployment. The variation in marriage rates provide the highest explanatory value for explaining the variation in divorce rates.

The findings in this research can be related to previous research conducted on the influence of legal, financial and sociological factors on divorce rates. Significant research has been conducted on the effects of no-fault laws, i.e. laws stipulating that a divorce should be granted to any married individual filing for it regardless of reasons (Nakonezny, Shull and Rodgers, 1995). During financial distress, spouses will their bargaining power to protect their interests in a dispute (Olafsson and Thörnqvist 2016). The bargaining power is determined by the spouses expected utilities outside the marriage. The expected utilities are in this case what income the spouses will have on their own, their so called, fall-back incomes. For instance, according to some research papers, as female employment increased, the risk of divorce increased by 22% (Poortman and Kalmijn 2002). However, the amount of quantitative research on divorce rates remains sparse and most of the studies focus on the subjective experiences of the individuals involved.

This paper has been organized in the following manner: Section 2 discusses the motivation for conducting our research in this specific way, Sections 3 describes our data sources, institutional preconditions and method for testing our hypothesis, Section 4 presents the results we arrive at and in Section 5 the conclusions drawn from this study will be summarized. All figures and tables are found in the Appendix.

2. MOTIVATION

The amount of research on the impact of financial factors on divorce rates is quite small. In previous research economic hardship has been suggested to increases marriage dissolutions (South, 1985). However, other research suggest that the mechanics might works the other way around (Hellerstein and Morrill, 2010). In this study we have tested whether an increase in debt-to-income ratios combined with decreasing housing prices leads to higher divorce rates.

The debt-to-income ratios for households vary drastically, both between states or counties and between points in time. The variation of the upper and lower bound for the debt-to-income ratio is illustrated over time in the descriptive statistics in Figure 3. This figure illustrates that there has been a raise in both the lower and the upper bound for the debt to income ratios which peaked coincidentally with the Great Recession and that these ratios have decreased since. Those two measurements, the upper and lower bound for the debt-to-income ratios will serve as a starting point to test whether the locked-in effects that we except to have taken place during the financial crisis are an economic reality.

To gain a better understanding of how these ratios affect the divorce rates in different areas we have run regressions on divorce rates for solely the high and low variables. If there is any explanatory value in the lower and upper bounds of a state´s or county´s debt-to-income ratios this should become apparent after the regressions. However, this method does not fully incorporate the effect of whether the combination of increased leverage ratios and negative prices affects divorce rates. For instance, households might increase their debt in response to a positive growth in housing prices because they know that their property is worth more. Debt-to-income ratios alone does not make for a good proxy of negative equity. To find a better measurement for when the locked-in effect of negative equity will take place we have combined it with a price index.

Because the debt-to-income ratio is not an adequate measurement of negative equity alone we have combined it with the prices of local housing prices. This adds a new variable which both incorporates the debt-to-income ratio of the geographical area as well as the growth in housing prices. To construct this variable, we have used two restrictions to conclude whether there is a reasonable risk that a significant proportion of the homeowners in an area will have negative equity.

The first restriction is that there should be a decline in housing prices which means that the housing price index for the area should have decreased compared to the value it had the year before. This ensures that a significant number of homeowners will have bought their property for a higher price than its current value. It should also mean that a larger than average proportion of the homeowners will owe more on their house than what the property is worth. Even though a proportion of the purchase price is sometimes paid by the homeowner as a down payment, as the national housing markets peaked this proportion had become less and less significant. In 1998 the median loan-to-value ratio of the 75 metropolitan areas used in the research paper “Did Credit Market Policies Cause the Housing Bubble” was 84 %, in 2006 the ratio had increased to 88 %. However, one quarter of all home purchases made in 2006 was made by a debt-to-income ratio of 99 % (L.Glaeser et. al). This should reassure us that even a small decrease in prices might have led to a big proportion of homeowners with higher loans than the values of their homes.

The second restriction is that either the lower or higher bound should be in the highest quartile of values. To determine this, we separated all yearly observations for each state or county into quartiles based on the upper and lower bound for their debt-to-income ratios. The observations that were in either the highest quartile in terms of their lower bound level or in the highest quartile in terms of the upper bound level and had seen a negative development in prices for that specific year, were included in a new group which we deem to have a larger prevalence of homeowners with negative equity than in the other geographical areas.

In the state level data set, the number of observations that can be described as having an increased probability of negative equity is 105 compared to 719 observations that are less probable to have negative equity. In the county level data set a total of 1178 observations have higher probability of negative equity compared to 8183 observations that are less probable to have negative equity. Again, a county or state being in the probable group means to have both a top quartile level debt-to-income ratio as well as a negative development of prices in that particular year. However, the average divorce rate is lower for the states and counties that do not have a high probability of negative equity (Table 4). This suggests that states and counties with a combination of high debt-to-income ratios and negative prices do have higher divorce rates in general.

In our regressions we have included all four of these variables, i.e. lower bound for debt-to-income ratios, upper bound for debt-to-income ratios, negative price development in the current year and whether the observation is likely to have a higher prevalence of homeowners with negative equity.

The effect of community property laws has been tested to conclude whether they have any effect on divorce rates in general and in particular whether they have any effect when added to a model which incorporates what debt-to-income ratio different states have. The potential effect of different divorce laws is not clearly articulated in previous literature and could affect the dependent variable in either way, this is further elaborated on in Section 3.1. Another legal variable is the prevalence of non-recourse laws. In states that practice non-recourse laws the negative equity is assumed to have a smaller effect on divorce rates since homeowners can hand over their home to the bank without carrying the responsibilities for the bank´s credit losses. Both variables have been incorporated as dummy variables in the regression models.

Divorce rates have been decreasing since the end of the twentieth century until the end of our data set, 2016. During the decrease, another macroeconomic variable has seen record highs, namely unemployment which is available from the Bureau of Labor Statistics. In late 2009 the national unemployment rate reached a 26-year high at 10%. Previous research has explored the question of whether or not these two phenomena are in some way connected, i.e. if there is a causal connection between a country´s business cycle and its divorce rate. However, there are good economic arguments for why unemployment rates might affect divorce rates in either way. Firstly, layoffs might have a decreasing effect on income and thus also on relationship stability. However, in a recession both spouses should face worse economic prospects outside their marriage since the economies of scale that might exist within a couple may be more appealing in bad economic times than in good. Economic theory does not lead us to any definitive conclusion on this matter (Schaller, 2013).

The effect of income, just as many other financial factors, shows little to no conclusive results in having any direct effect on divorce rates (Schaller, 2013). Half of American families fall in to poverty after having a divorce and a total of 75% of all women who apply for welfare benefits do so because of a divorce or a disrupted relationship (Burgess, Propper and Aassve, 2002). This means that families, and women in particular, will endure a divorce even if it means there is a high probability of living in poverty. This is most likely for a reason that financial factors cannot explain. In contrary to Schaller (2013), Nunley and Seals (2010) argue that negative household income shocks increase the probability of divorce, whereas little evidence were found suggesting that an increased household income lowers divorce rates. Becker et al. (1977) contends that surprises, both positive and negative, increase the probability of divorce, meaning that instead of focusing on the direction of the financial change, it is the change itself that prompts divorces. Their framework argues that the spouses expected outcomes from marriages change from an increased household income volatility, which in turn, increases the risk of divorce. In this paper we wish to test these theories to make a comparison on an aggregate basis by using American state and county level data.

3. DATA

In this section we will describe the empirical preconditions, sample selection for both state and county level data and the methodology of this study.

3.1 Empirical preconditions

This section will describe the explanatory models and previous research used in this paper. Firstly, there are two important legal differences between the states used in our state level data sets. These differences can also be applied on the individual counties since the legal structures of the state they belong to applies within their borders.

In the past and even in the present, changing laws on divorce have had a significant effect on the divorce rates. The clearest example was the introduction of the no-fault law, meaning that no one can be held accountable for the separation of a marriage. According to Nakonezny, Shull and Rodgers (1995), who researched the effect of the no-fault divorce law across the 50 states, a significant correlation between the new law and increased divorce rates were found. Most likely since, no matter what faults one may have committed, bargaining power in court remains the same.

Another important factor is the complexity of divorce laws in the current county or state that the couple resides in and who the laws favor in case of a dissolution. The US applies two types of divorce laws – community property and the equitable distribution law. The first one, community property, basically splits all assets between the spouses creating an equal split without considering which spouse has the largest income. In contrary, equitable distribution, examines the assets and tries to create a fair distribution based on income and contribution. A reasonable assumption would be that divorce rates in states that practice community property laws would be higher than in states with equitable distribution laws, because the bargaining power of the lower earning spouse would be higher. However, the effect might also be that the incentives for the higher earning partner to stay in the marriage are stronger. Which of these effect might be stronger is not obvious.

Another important legal distinction between states is whether they practice non-recourse laws or not. By applying recourse laws, the borrowers are personally liable for the debt and the lenders, in most cases banks, can collect the deficiency in payment if the borrowers fail to pay their debt. In states where non-recourse laws are applied, banks are unable to collect deficiencies from the borrower's personal income and assets. If the borrowers are unable to pay their debts, the lenders simply collect the assets that the loan was used for. A relevant example is the financial crisis in 2008, where banks that distributed mortgages in non-recourse states received thousands of underpriced houses as their owners were unable to pay their mortgages, incurring huge losses. This is an exceptional attribute of the American home mortgage market and according to Ron Harris (2010), during the financial crisis in 2008, at least 558 000 mortgage defaults took place due to strategic walk-away mortgage default, causing nearly 20 % of all foreclosures in the country. Most of these were likely not to happen in a state that enforces recourse laws. According to Ghent and Kudlyak (2010), the threat of deficiency judgment enforced by recourse laws deters potential strategic defaulters, as their empirical analysis of the loans made between 1997 and 2008 shows a 32 % lower probability of default in recourse states than in non-recourse states. This research mandates a comparison of recourse and non-recourse states and how this affects the divorce rates during a financial crisis, since households with non-recourse loans do not suffer any losses to their personal assets whereas household that have recourse loans do.

In the paper,” Bargaining over risk”, Olafsson and Thörnqvist (2016) expand on the idea to threat households as two separate decision-making units rather than one. The rationale for this is quite intuitive, the two adults that make up the household will have differences in preferences other and these differences will impact what decisions they make as a unit. In this setting each individual will have a certain degree of bargaining power which the will use when bargaining about the decisions of the household. The bargaining power for each spouse is determined by that spouse´s expected utility outside the marriage and the expected utility is the income each spouse would be able to make on her own, titled a fall-back income.

The concept of bargaining power is related to our research in the following way. In states that practice community property law the fall-back income for each spouse does at least include half of the property held together. This could significantly increase the bargaining power of the lower earning spouse. However, if this would have a positive or negative impact on divorce rates is not clear. On one hand, as the fall-back income of the lower earning spouse increases it might lead to an increase in that person´s likelihood to file for divorce. However, this should be offset by the potential decrease in the fall-back income of the other spouse.

3.2 Sample selection for the state level data

The state level panel data set used in this study was assembled using multiple sources. The data on debt-to-income ratios was extracted from the Federal Reserve, the data on housing prices was extracted from the Federal Housing Finance Agency, the data on divorce and marriage rates was published by CDC/NCHS and was made available through their National Vital Statistics System, the data on unemployment was published by the Bureau of Labor Statistics and the income data was made available by the Bureau of Economic Analysis.

The data set is relatively balanced and contains observation from 51 states, including the District of Columbia which is not formally a state. Only two variables had missing observations. Firstly, the upper bound variable *high* which is an observation on the upper bound of the debt-to-income ratio in that particular state, the total number of observations is 822. Secondly, the variable for divorce rate, *d_rate,* was only present in 824 individual state years. The full number for a complete set of observation would have been 918, including 51 states and 18 years of observations.

The data set does also include three dummy variables, out of which two were programmed using additional data. The first one is a dummy variable representing the presence of community property laws in that particular state. The states which practice community property law are the following: Arizona, California, Idaho, Lousiana, Nevada, New Mexiko, Texas, Washington and Wisconsin. The second dummy variable is named *non_recourse* and represents that the state does practice non-recourse laws as described in the section 3.1. The states which practice non-recourse laws are the following: Alaska, Arizona, California, Connecticut, Idaho, Minnesota, North Carolina, North Dakota, Oregon, Texas, Utah and Washington.

When any of the variables has been reported in a higher than yearly frequency the data for the first quarter has been used. If the data was only available as one data point for each year the yearly average is used, as is the case for state level unemployment data. The data for each state and year has been matched firstly according to the year it concerns and secondly according to the FIPS code of that particular state. This ensures that all data is correctly matched.

3.3 Sample selection for the county level data

The process of arriving at the complete county level data set proved to be more tedious. The data sources for all the variables were nearly the same, except for marriage and divorce rates. These two variables were extracted from the individual reports published by the states, often in their respective Vital Statistics reports. US county level data is sparse and the challenge of finding this data could be separated into two quite different problems.

Firstly, since there is no central agency to collect the county level data on divorce rates the format they are presented in differs, some states present their data in terms of rates, some as a number of divorces per county and others present both. The data set that only includes an absolute number of divorces have been matched together with additional population data to calculate a crude divorce rate. This data originates from the Census Bureau.

Secondly, a number of states do not publish any data on divorces on a county level basis and a large part of the states that do publish data on county level divorce rates have only started to do so in recent years. This causes the data to become unbalanced since some states lack complete data on divorce rates. The second problem was mitigated by using state and time fixed effect. This means that a number of dummy variables, one for each combination of year and state, has been created when running the regressions. These dummy variables incorporate the unobserved heterogeneity found in unbalanced data sets.

The original data set contains 56 303 observations of individual counties and years. This amounts to observations for around 3100 counties the years between 1999 and 2016. The set of counties was restricted to the ones that has published divorce rate statistics on a county level basis during any period in the last 18 years, which amounts to only 9 363 observations or an average of 520 individual counties per year. The number of observations per year differs greatly, from 87 observations in 1999 to 912 observations in 2010, the distribution of the observations can be found in Table 4.

3.4 Methodology

We analyze the data for divorce rates on both a state and county level to find out whether decreasing housing prices and increasing leveraged ratios has a decreasing effect on divorce rates. The rapid decrease in housing prices after 2007 serves as a shock to housing prices, which we exploit to arrive at the results presented in section 4.

To increase the quality of our results, we collect both state and county level data to ensure a large enough data set to be able to capture the true effect of the independent variables in the population. The county level data was restricted to the counties which provided information on county level divorce rates. Fixed effects for both time and state have been incorporated into the model. Fixed effects is a way of mitigating the problem of unobserved heterogeneity and takes into account the effects of variables that affect our dependent but is not incorporated into the model. This means that for each year and state an individual dummy variable has been created which assumes a value of 1 if the observation is made in that particular year or state and 0 otherwise.

There exists unobserved heterogeneity in the county level data set which is caused by the difference in which state the counties are situated. These could for instance be economic preconditions that are limited to the state in which the county is situated. To mitigate the problem with unobserved heterogeneity we have clustered the standard errors on a state level for the county level regressions, this has also been specified in the explanatory text of each table that contains regression results.

4. RESULTS

This section is separated into multiple parts. Firstly, a part which presents the descriptive statistics and the regression results from the use of state level data. Secondly, a section presenting the descriptive statistics and regression results using county level data. Lastly the results from both of our data sets will be discussed.

4.1 Descriptive statistics for state level data

The descriptive statistics show a decreasing trend for divorce rates over time. Figure 1 shows a consistent negative trend for average US crude divorce rates from 1999 to 2016. To mitigate the problem with unobserved heterogeneity between points in time, time fixed effect dummies have been incorporated into the data set, a process which was described at length in Section 3.4.

A general overview of the data used in the state level regressions can be found in Table 2. Figure 2 illustrates the price shock of US housing prices which proves that there exists variation in this variable. In the years following 2007 housing prices decreased until 2012 when they started to recover. Figure 3 clearly shows how the debt-to-income ratio for households increased until the peak of 2010 and has been decreasing since. Table 5 illustrates the decrease in divorces by comparing individual state level divorce rates of 1999 and 2016. The divorce rate has decreased in all states but Connecticut, Montana, Rhode Island and Texas.

4.2 Results for state level regressions

In this section we will present the results from the statistical inference for each variable separately. Furthermore, we will discuss how the regression results fit into the broader theoretical framework laid out in earlier sections.

The variable *low* has a significant positive effect on divorce rates in the regression models which do not take fixed effects into consideration (Table 6). As time fixed effects are added to the regressions the variable has an even more significant positive effect on divorce rates (Table 7 and 9). However, the individual explanatory value is relatively high when combined with fixed effects. The model which incorporates fixed effects has an R2 of 0.9036 (Table 9) but the variable is not significant. This indicates that the vast part of the explanatory value comes from the fixed effects and not from the independent variable. When excluding fixed effects, the R2 is a mere 0.0337 but the variable is significant on a 1 % level (Table 6). After conducting a winsorization of the data with 2.5 % tails the significance rises but the variable is still not significant in the simple regression model. The lower bound for a state´s debt-to-income ratio has a significantly positive effect on divorce rates while still providing a low explanatory value, when we control for state and time fixed effects the variable does not have a significant impact. This could be seen as evidence for the economic hardship explanation of divorce rates, even though the results are ambiguous. However, the statistical analysis of the lower bound for state level debt-to-income ratios do not provide evidence for the locked-in by leverage hypothesis.

The variable *high* does have a negative effect on divorce rates in the regression models presented in Table 6. As time and state fixed effects are added to the regressions the sign shifts between positive and negative. Another effect of the introduction of fixed effects into the models is that *high* ceases to have a significant impact in any of the regression models (Table 9). The winsorization does marginally increase the significance of *high* in some of the regression models, namely model 2,3,4 and 5 (Table 16). The individual explanatory value is low without fixed effect, the R2 value shifts changes from 0.0337 to 0.0287 as the variable is introduced into the the model. This decrease in explanatory value is caused by the increase in the sample size due to a lack of observations for the *high* variable. Table 9 illustrate the effect of incorporating fixed effects into the model does not change the individual explanatory value of *high* very much, the explanatory value changes from 0.9036 to 0.8990 which means that the effect is still negative due to a decreased sample size. The shift between positive and negative signs for this variable and the low significance does not provide evidence in accordance with our hypothesis.

The variable *p_index* has a significantly positive effect in the regression models that incorporate both state and time fixed effects (Table 9). However, the effect becomes negative as the *income* variable is introduced, this happens because there is a rather high positive correlation between the two variables (Table 18). The effect is also significantly positive on an individual level (Table 14) even tough the incremental increase in explanatory value between model 2 and 3 is quite small, R2 increases by 0.0175 when incorporating fixed effects (Table 9). The positive effect from the price index is suggestive evidence for the locked-in by leverage thesis. Areas that have experienced a dramatic increase in the value of the homes in that area will tend to have higher divorce rates. However, this measurement is not connected to debt in any way and there might be other causes to this positive correlation. We do not deem this to be sufficient evidence for out thesis.

A negative price pattern in the housing market and greater predicted prevalence of negative equity for households do not appear to have any significant effect in the state level regressions. The insignificance of the results remains in both the regressions that do and do not incorporate fixed effect into the regression models (Table 6 & 9). The individual regression results illustrated in Table 15 prove that neither of these dummy variable have a significant effect on divorce rates. Although some significance can be found in Table 8, a state level regression without time fixed effects, the lack of significance in remaining regressions are too vast. Not even after the data has been winsorized are the effects from these two variables significant. As these dummy-variables seem to have no effect on divorce rates, our thesis in regard to being locked-in by leverage is not supported.

The variables *p_index* and *income* appear to be highly positively correlated (Table 18). This causes a negative effect on the *p_index* coefficient as *income* is dropped. In the models that include *income* and incorporate fixed effects the income variable has a consistent significantly positive effect on divorce rates, in the same way as *p_index* did. However, in the individual regressions the effect from *income* is negative but not significant. This leads us to the conclusion that *income* does not have any clear effect on divorce rates.

The unemployment variable *unemp* is not significant in hardly any of the regressions. In the regressions that incorporate both time and state fixed effects *unemp* has a negative effect on divorce rates (Table 9). The simple regression for *unemp* does also suggest that unemployment has a negative effect on divorce rates even though this result is not statistically significant either (Table 14). Unemployment does not have a significant effect on divorce rates in any of the models as the data is winsorized (Table 16). Our conclusion is that unemployment does not have an impact on divorce rates in this data set. This is coherent with the view put forward by previous literature, namely that there are sound economic arguments for why unemployment might affect divorce rates in either way and that empirical research has not been able to support solely one of the theories (Section 2).

The dummy variable representing the community property states, *comprop*, shows a highly negative and significant effect in the regression models which both include and exclude state and time fixed effect (Table 6 & 9). The individual explanatory value for this variable is quite low as the R2 value does neither increase nor decrease when including the variable into the models that incorporate both time and state fixed effects. In the simple regressions for only the *comprop* variable the negative effect is also significant. The negative significance is most likely due to balanced fall-back incomes in case of a divorce, evening out bargaining power between each spouse.

Non_recourse seems to have a positive significance in all the regressions that both incorporate and exclude fixed effects (Table 6,7,8 & 9). However, the explanatory value for the model does not increase when the variable is added (Table 9). For the individual regressions the effect is significantly negative and the positive effect is only present when the variable is combined in a model with a greater number of variables. The reason for this is perhaps, although a bit far fetched, due to the reduced locked-in effect, created by being able to preserve your personal assets in case of default. This theory, if true, supports our thesis. However, it is more likely that this significant effect is due to some kind of unobserved heterogeneity in the sample set, meaning that states with non-recourse loan differ from the rest of the states in some way that is not taken into account by our variables.

For marriage rates we can observe a positive significant effect on divorce rates throughout all the regressions, except for the winsorized regression, found in Table 16. The outcome on Table 16 is due to the outliers carrying most of the cause for the significance. In Table 6 we can observe a big jump in explanatory value when the *m_rate* variable is included in the models that does not incorporate fixed effect. The R2 value increases from 0.1177 to 0.3519 which is the single biggest effect from any variable in the Table 6 regressions. The high R2 value and the consistently strong significance outcomes through the regressions, suggest that an increasing marriage rate causes an increasing divorce rate and vice versa. Table 1 one shows a decreasing divorce rate in relation to a decreasing marriage rate. As the variable with the strongest effect on the divorce rate and a direct correlation, one may ask the cause for the decreasing marriage rates. A positive correlation between the decrease of marriage rates and the increase of cohabiting rate can be found, suggesting that marriage rates are not only affected by divorce rates (Bumpass, Sweet, and Cherlin 1991). This suggests that we find societies evolving and start shifting their living arrangements towards a secular approach, which in turn reduces marriage rates and therefore also divorce rates.

4.3 Descriptive statistics for county level data

The descriptive statistics for the variables used in the county level data can be found in Table 3. The variation for the variable *d_rate* is significantly higher compared to the mean for the observations. The range for the observations is quite wide, especially for the observations for divorce and marriage rates, this might lead one to question the quality of the data used in the county level regressions. To mitigate the problem of extreme values we have used winsorizations for some regression (Table 17). Even though this changes the original data it might make the conclusions which can be made from the county level data clearer.

The county level data has an upward bias due to a few outliers. When conducting a winsorization with 2.5 % tails on *d_rate* the mean decreases significantly and so does the standard deviation. With regards to the mean and standard variation the winsorized county level data resembles the state level data, since the standard deviation is proportionately as big in both of the descriptive statistics (Table 2 & 3).

4.4 Results for the county level regressions

The regression tables for the county level data have seemingly less significance and explanatory value in comparison to the state level regressions.

Table 10 shows the regressions without fixed effects and Table 11 shows the regressions with time but without state fixed effects – none of the variables have any significance and the explanatory value for each model is low. In contrary, Table 12, showing the outcome for state fixed effects, has a high significance for both *comprop* and *non_recourse*. The explanatory values remain unchanged throughout the regressions. The significance value for *comprop* is negative and positive for *non_recourse*, matching the results for the state regressions.

Table 12, showing the regression outcomes on a county level with combined state and year fixed effects, finds strong significance for *non_recourse* although the explanatory value remains at 0. The individual regression outcomes for each variable on Table 15 finds strong significance for both *non_recourse* and *comprop*, although as we have seen continuously throughout the county level regressions, with a low explanatory value.

What's obvious about the county level data in comparison to the state level data, is the observation of consistently lower explanatory values for all the variables, not to mention the only two significant variables being *non_recourse* and *comprop*. This is mainly due to the extreme variation found in the county data in comparison to the state level data. The county data has a vast number of outliers that creates extreme values causing high standard deviation outcomes. When the county data is winsorized, the data resembles the state values and become more reasonable. Although this is the case, one can neither ignore or exclude these values since they reflect the true nature of the aggregate data.

4.5 Discussion on the results

The regression analysis on economic factors such as unemployment, income and the debt related variables do not appear to have a particularly large effect on divorce rates in the US. In some respect this is what could have been expected with regards to the previous literature on economic factors and divorce rates. The result for the unemployment rate on divorce rates did not have a significant effect in either of the data sets. However, when comparing this to previous literature it fits into the pre-existing framework. Some previous studies have shown that increases in the unemployment rate have a positive effect on divorce rates, while others proclaim that it has a negative effect. The economic arguments for both positions were outlined in Section 2. Income does not seem to have a distinctive effect on divorce rates in our data sets. This can be explained by the disregard for the economic effects a divorce might have on a spouse which was also detailed at the end of Section 2. On the other hand, various social and legal factors seem to have a quite high explanatory value, including the effect of marriage rates and community property law. Both results seem to indicate that the explanatory value for economic variables on divorce rates is generally low on an aggregate level.

A problem with using debt-to-income ratios is that these might not be adequate for constructing a measurement of how prevalent negative equity might be in a particular geographical area. It would have been ideal to use a debt-to-value measurement of the degree of negative equity instead of debt-to-income, but unfortunately the time series data for that specific ratio is not available. This could be a source of bias in our study since housing markets with generally high debt-to-income might compensate by having a larger part of their debt as secured, in the sense that the debt is tied to an asset and thus less risky. In that case the debt-to-income ratio would actually indicate a higher prevalence of negative equity than in states with high debt-to-value ratios, which should be the actual indicator of negative equity. Although the reasoning for this opposite relationship between debt-to-income ratios and debt-to-value ratios might be a bit extreme, it serves as an example of how a bias could appear from using a less than perfect proxy for debt levels.

The effect of marriage rates deserves a separate discussion on how its impact on our results should be understood. Marriage rate was the variable with the highest effect on divorce rates and it had a significantly positive effect in all the regressions. The decrease in marriage rates in the US can partly be explained by an increase in cohabitation rates (Bumpass, Sweet, and Cherlin 1991). It might be that when researchers try to formulate which factors lead to a decrease in couples' propensity to stay together on an aggregate level they formulate it in questions about marriage and divorce rates. However, not all couples that live together are married and the same goes for couples who own houses together. This does not mean that they are not under the same locked-in effects as the married couples who own property together. Furthermore, couples that cohabitate could theoretically enjoy the same economies of scale as couples that are married, which would affect much of the research conducted on how the general business cycle affect divorce rates. To conduct better research on the subject in the future it will become increasingly important for official agencies to provide data on cohabitation, given that the trend of secularization in marriage remains.

However, this analysis might suffer from a degree of reverse causality, the decrease in divorce rates might not be caused by an increasingly secularist approach towards marriage but it could also be the other way around. It would not be unreasonable to suggest that the decrease in divorce rates might lead to a decrease in marriage rates, since fewer divorces might lead to more permanent relationships thus decreasing the number of marriages an individual has over her lifetime. This hypothesis would be worthy of further analysis.

5. CONCLUSIONS

This paper explores the question of whether or not high debt-to-income ratios in combination with decreasing housing prices have any effects on divorce rates in American states and counties. The statistical analysis is conducted on a state and a county level for each variable. Since few other studies have been conducted on the subject we use the framework from other areas of research to explain our findings.

The lower bound of the debt-to-income ratios seems to have a positive effect on divorce rates. These findings contradict the thesis about how locked-in effects would work and present more evidence supporting the relationship hardship thesis. We hypothesize that a significant reason to why debt-to-income ratios increase is due to economic hardships, which have been shown in a number of studies to decrease marriage stability (Schaller 2013). However, the explanatory value of this variable is quite low and we can not exclude the possibility that this significant result might be caused by some other factor linked to both debt-to-income ratios and divorce rates.

When we combine the factors that are correlated with higher probability of negative equity, having a high debt-to-income ratio and owning a house in a distressed housing market, we do not find any evidence for this to have any significant effect on divorce rates. These finding does not support the locked-in theory of leverage on divorce rates.

The unemployment factor did not have a significant effect in either of our data sets. This is in line with previous research about how the effects of unemployment rates on marriage and divorce rates are not clearly explained in empirical studies. Furthermore, the mechanics for how the business cycle affects divorce rates is not easily predicted using economic theory.

The most important factor for explaining the decrease in divorce rates appear to be social and legal factors. In previous research a number of social factors have been shown to have a significant impact on divorce rates, including the raise of cohabitation (Stevenson & Wolfers, 2007). In our research marriage rate is the factor which appears to have the highest explanatory value for explaining variation in divorce rates.

REFERENCES

Adelino, Schoar, and Severino (2015): “House prices, collateral, and self-employment,” Journal of Financial Economics, 117, 288 – 306.

Amato and Beattie (2011): ‘’Does the unemployment rate affect the divorce rate? An analysis of state data 1960–2005’’, Social Science Research, Volume 40, 705 – 715.

Becker et al. (1977): ‘’An Economic Analysis of Marital Instability’’, Vol. 85, No. 6, 1141-1187, The Journal of Political Economy

Brown and Matsa (2017): Locked in by Leverage: ‘’Job Search during the Housing Crisis’’, Working Paper

Burgess, Propper and Aassve (2002): ‘’The Role of Income in Marriage and Divorce Transitions among Young American’’, Max Planck Institute for Demographic Research, Working Paper

Ghent and Kudlyak (2010): ‘’Recourse and Residential Mortgage Default: Theory and Evidence from U.S. States’’, Federal Reserve Bank of Richmond Working Paper, No.09-10R

Glaeser, Gottlieb, and Gyourko (2010): ‘’Did Credit Market Policies Cause the Housing Bubble?’’, Rappaport Institute, Taubman Center

Harris (2010): ‘’Recourse and Non-Recourse Mortgages: Foreclosure, Bankruptcy, Policy’’, Tel Aviv University - Buchmann Faculty of Law

Hellerstein, J.K. and M.S. Morrill. (2011): “Booms, Busts, and Divorce,” The B.E. Journal of Economic Analysis & Policy 117

Nakonezny, Shull and Rodgers (1995): ‘’The Effect of No-Fault Divorce Law on the Divorce Rate Across the 50 States and Its Relation to Income, Education and Religiosity’’, Journal of Marriage and the Family 57, 477-488

Nunley and Seals (2010): ‘’The Effects of Household Income Volatility on Divorce’’, Vol. 69, 983-1010, The American Journal of Economics and Sociology

Olafsson and Thörnqvist (2016): ‘’Bargaining over Risk - The Impact of Decision Power on Household Portfolios’’, Working Paper

Poortman and Kalmijn (2002): ‘’Women's Labour Market Position and Divorce in the Netherlands: Evaluating Economic Interpretations of the Work Effect’’, Volume 18, Issue 2, 175–202, European Journal of Population

Schaller (2013): ‘’For richer, if not for poorer? Marriage and divorce over the business cycle’’, Volume 26, Issue 3, 1007–1033, Journal of Population Economics

South (1985): “Economic Conditions and the Divorce Rate: A Time Series Analysis of the Postwar United States.” Journal of Marriage and Family 47(1): 31- 41

Stevenson and Wolfers (2007): ‘’Marriage and Divorce: Changes and their Driving Forces’’, University of Pennsylvania, Working Paper

APPENDIX

FIGURE 1. Average divorce and marriage rate for all US states
The figure illustrates a decline in the average crude divorce rate and the average crude marriage rate for all US states during the last 18 year. US divorce and marriage rates demonstrate a clear downward trend. To mitigate this problem we have used time fixed effects in both of our data sets.

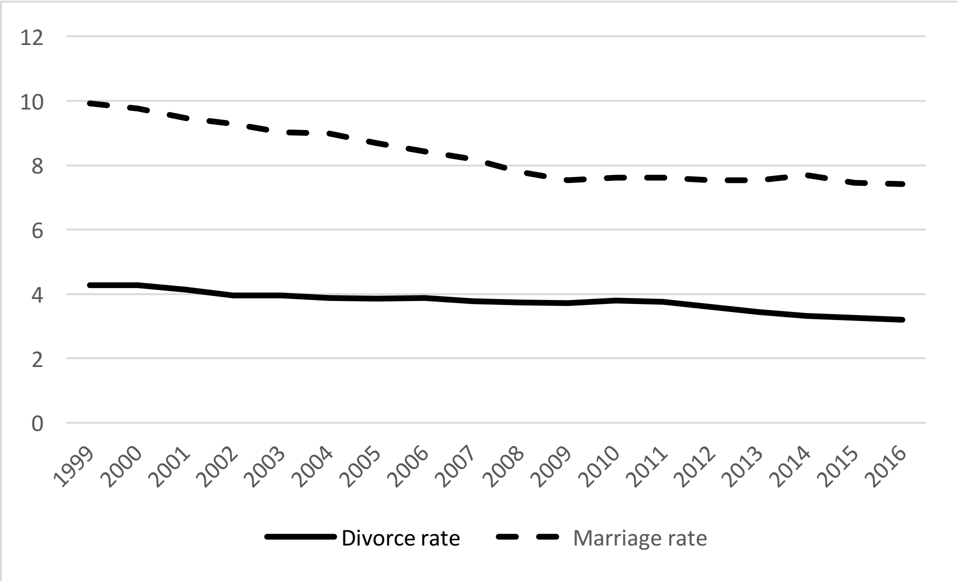

FIGURE 2. Average HPI for all US states
The figure illustrates the fall in US housing prices after 2007 and the price recovery. There is variation in housing prices over time.

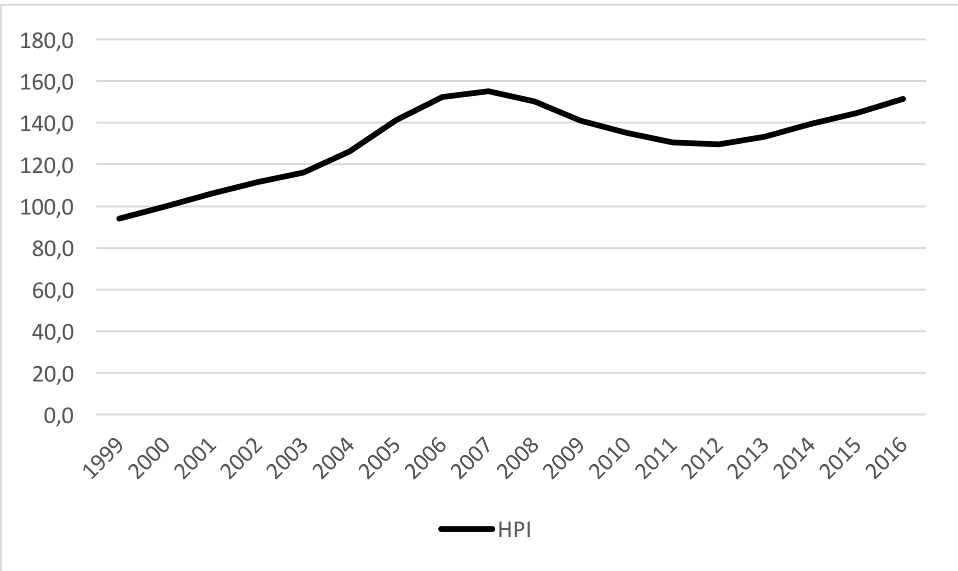

FIGURE 3. Average upper and lower bound for debt to income ratios
The figure illustrates the variation of the values for the average upper and lower bound of the debt to income ratios for households in US states between 1999 and 2016. I might seem strange that the lower bound crosses the upper bound during the peak years in 2009 and 2010. This is due to missing values in the data for the upper bound.

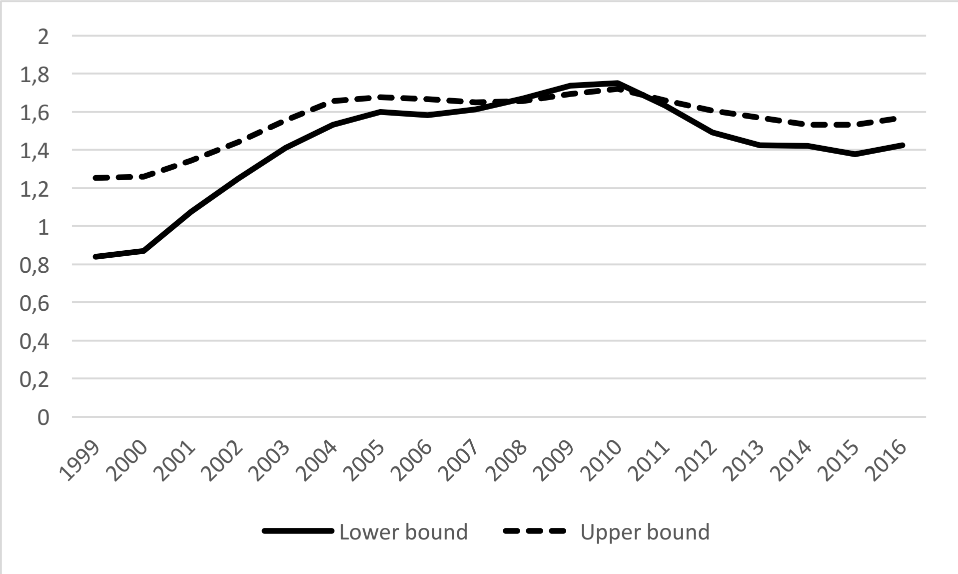

FIGURE 4. Number of observations per year in the county level data set
The figure illustrates the number of observations made per year. This graph illustrates the imbalance of the county level data set, a problem that is mitigated through the use of fixed effects.

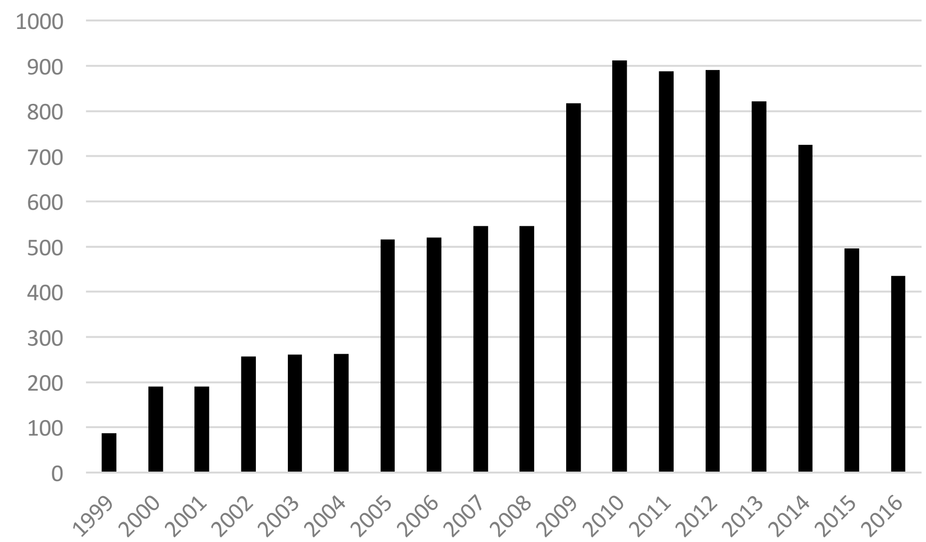

TABLE 1. Definitions of the variables

Variable	Definition
state_fips	The identification code for the county or state. For states this is a number ranging from 1 to 56. For counties the fips code is constructed by combinding the state code and the a county specific code, eg. 01001 is the county of Autauga (001) in Alabama (01).
low	The lower bound for the debt to household income ratio in the geographical county or state.
high	The upper bound for the debt to household income ratio in the geographical county or state.
d_rate	The crude divorce rate is calculated as the number of divorces approved in the county or state divided by its population in thousands.
p_index	A price index which assumes the value of 100 for the state or county in the year of 2000.
m_rate	The crude marriage rate is calculated as the number of divorces approved in a county or state divided by its population in thousands.
unemp	The unemployment rate in the county or state.
income	The gross income per capita in the area.
comprop	A dummy variable which assumes the value of 1 if the county or state practices community property and 0 if it does not.
non_recourse	A dummy variable which assumes the value of 1 if the county or state practices non-recourse mortages and 0 if it does not.
neg_prices	A dummy variable which assumes the value of 1 if the price change was negative in that particular year and 0 if it was not.
neg_equity	A dummy variable which assumes the value of 1 if the price change was negative in that particular year and i the area was part of the highest leveraged quartile in the same year, i.e. it had either a lower or upper debt to income ratio in the highest quartile.

TABLE 2. Descriptive statistics for all variabels on a state level

This table shows a summarization for all the variables used in the state level regressions. As discussed in the main text the state level data set is complete except for the variable *high* and *d_rate*. The difference between the winsorized *d_rate* and the unwinsorized *d_rate* is not particularly large.

Variable	Obs	Mean	Std. Dev.	Min	Max
low	918	1.4276	.4729	0.39	2.13
high	822	1.5469	.3152	1.09	2.13
d_rate	824	3.7750	.9526	1.2	9.9
p_index	918	131.0545	27.8169	87.98	287.45
m_rate	911	8.3276	6.6821	4	82.3
unemp	918	5.7251	1.9791	2.3	13.7
income	918	38167.95	9082.94	20563	75756
comprop	918	.1765	.3814	0	1
non_recourse	918	.2353	.4244	0	1
neg_prices	918	.2614	.4397	0	1
neg_equity	918	.1340	.3408	0	1
d_rate (winsorized)	824	3.7495	.8170	2.5	5.3

TABLE 3. Descriptive statistics for all variabels on a county level

This table shows a summarization for all the variables used in the county level regressions. The variation in this data set is larger for certain variables, including *d_rate* and *m_rate.* There is also a substantial difference between the winsorized *d_rate* and the unwinsorized *d_rate* in terms of mean and standard deviation. The values for the winsorized *d_rate* more closely resembles the data found in the state level data set.

Variable	Obs	Mean	Std. Dev.	Min	Max
low	9361	1.8114	.8929	0	3.46
high	8150	1.9466	.8177	.78	3.46
d_rate	9361	4.9960	19.0907	0	392.9
p_index	8357	132.3476	22.3765	87.05	287.3
m_rate	9361	6.6628	21.1005	0	995
unemp	9361	7.0593	2.6295	1.3	26.3
income	9339	33496.49	9416.88	14993	199813
comprop	9361	.3052	.4605	0	1
non_recourse	9361	.2695	.4437	0	1
neg_prices	9361	.3893	.4876	0	1
neg_equity	9361	.1258	.3317	0	1
d_rate (winsorized)	9361	3.7867	1.1657	1.9	6.2

TABLE 4. Descriptive statistics for *neg_equity* and *d_rate*

The table illustrates that states and counties predicted to have a higher proportion of households with negative equity have higher divorce rates on average. This fact does not support the thesis that higher leverage and decreasing housing prices causes divorce rates to decrease.

State level data			
neg_equity	Mean	Std. dev.	Frequency
0	3.759249	.97414772	719
1	3.8828571	.78488818	105
Total	3.775	.95259765	824
County level data			
neg_equity	Mean	Std. dev.	Frequency
0	4.8455775	17.575242	8,183
1	6.041088	27.382141	1,178
Total	4.996022	19.090695	9,361

TABLE 5. Divorce rates for each US in alfabethical order
This table illustrates the differences between the divorce rate of different states as well as how the average divorce rate for each state has changed over time.

Alabama	5,7	3,8
Alaska	5,0	3,9
Arizona	4,6	3,4
Arkansas	6,2	3,9
California	---	---
Colorado	4,8	3,6
Connecticut	3,0	3,2
Delaware	4,5	3,1
District of Columbia	3,6	2,7
Florida	5,1	3,9
Georgia	4,1	---
Hawaii	3,8	---
Idaho	5,4	4,0
Illinois	3,3	2,0
Indiana	---	---
Iowa	3,3	1,3
Kansas	3,4	2,7
Kentucky	5,5	3,8
Louisiana	---	2,0
Maine	5,1	3,4
Maryland	3,2	2,7
Massachusetts	2,5	2,3
Michigan	3,8	2,9
Minnesota	3,2	---
Mississippi	5,0	3,2
Missouri	4,4	3,3
Montana	2,8	3,1
Nebraska	3,7	3,1
Nevada	7,8	4,3
New Hampshire	5,1	3,4
New Jersey	3,0	2,7
New Mexico	4,6	---
New York	3,3	2,7
North Carolina	4,6	3,2
North Dakota	4,4	2,6
Ohio	3,9	3,0
Oklahoma	---	4,4
Oregon	4,6	3,4
Pennsylvania	3,1	2,6
Rhode Island	2,7	2,8
South Carolina	3,8	2,5
South Dakota	3,7	2,8
Tennessee	5,8	3,8

Texas	3,8	4,2
Utah	4,0	3,6
Vermont	4,4	3,1
Virginia	4,4	3,4
Washington	5,0	3,5
West Virginia	4,9	3,8
Wisconsin	3,2	2,6
Wyoming	5,7	4,2

TABLE 6. Regression outcomes on a state level without any fixed effects

The table illustrates which factors have a significant impact on divorce rates. Marriage rates have the biggest single contribution to explaining divorce rates. The effect from both the lower and the upper bound have a significant effect, the lower bound has a positive effect and the higher bound a negative. *, ** and *** represents 10, 5 and 1 percent significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*
low	.3709008***	.5842878***	.3153128*	.3965861**	.3870453**	.5017572***	.4858711***	.5336342***	.5273326***	.4992183***
high		-.3429074	.2198177	-.0846268	-.0085051	-.4233161**	-.3897121*	-.4870861**	-.4911422**	-.4315438**
p_index			-.0113742***	-.009076***	-.009151***	.004925***	.0049774***	.0054242***	.0054373***	.005399***
m_rate				.0724745***	.0713578***	.0670708***	.0688795***	.0709589***	.071228***	.0711508***
unemp					-.0396698**	.0093005	.0104316	.0143991	.0068242	.0075949
income						-.0000528***	-.0000535***	-.0000547***	-.0000549***	-.000055***
comprop							-.1376146*	-.2147789***	-.2125733***	-.2144378***
non_recourse								.206807***	.214493***	.212928***
neg_prices									.0640535	.0899962
neg_equity										-.0974632
constant	3.252354***	3.492344***	4.448194***	3.924636***	4.059489***	4.506123***	4.491479***	4.494914***	4.541157***	4.4931***
Obs	824	751	751	751	751	751	751	751	751	751
R2	0.0337	0.0287	0.1177	0.3519	0.3572	0.4856	0.4879	0.4948	0.4953	0.4957
Adjusted R2	0.0325	0.0261	0.1142	0.3484	0.3528	0.4815	0.4831	0.4893	0.4891	0.4888

TABLE 7. Regression outcomes on a state level with time but without state fixed effects

The table illustrates what factors do have a significant impact on divorce rates. Marriage rates do have the biggest single contribution to explaining divorce rates. In all of the regressions is the variable *low* significantly positive. The signs of the *low* and *high* variables differ and the dummy variable *neg_prices* is not significant, neither is *neg_equity*. *, ** and *** represents 10, 5 and 1 percent significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*
low	.7649046***	1.100155***	1.045968***	.9123458***	.9076044***	.8218662***	.7982066***	.824591***	.840657***	.8097571***
high		-.4664398*	-.4030266	-.5395698**	-.5319587**	-.695873***	-.6550812***	-.735503***	-.729307***	-.6547113***
p_index			-.0012177	-.002221	-.0022679	.0097088***	.0098073***	.0100999***	.0098679***	.00987***
m_rate				.0672514***	.0672498***	.0646796***	.066476***	.0687753***	.0683792***	.068217***
unemp					-.0034183	.0035772	.005201	.0065092	.0131768	.0155319
income						-.0000572***	-.0000585***	-.0000604***	-.0000597***	-.0000597***
comprop							-.1367265*	-.215421***	-.2119953***	-.2141951***
non_recourse								.2050412***	.1873735***	.1849083***
neg_prices									-.1983285	-.1611431
neg_equity										-.1303069
constant	3.622009***	3.921017***	4.002136***	3.700632***	3.713637***	4.451956***	4.443499***	4.484384***	4.44999***	4.377355***
Obs	751	751	751	751	751	751	751	751	751	751
R2	0.2074	0.2183	0.2188	0.4111	0.4111	0.5115	0.5137	0.5203	0.5221	0.5228
Adjusted R2	0.1897	0.1980	0.1974	0.3942	0.3934	0.4960	0.4976	0.5038	0.5049	0.5050

TABLE 8. Regression outcomes on a state level with state but without time fixed effects

The table illustrates which factors have a significant effect on divorce rates with state fixed effect incorporated into the model. *Neg_prices* do have a significantly positive effect on divorce rates while the *neg_equity* variable is still not statistically significant. *, ** and *** represents 10, 5 and 1 percent significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*
low	-.4990958***	-.3075767***	-.2470517**	-.2495659***	-.2337148***	-.0738358	-.0738358	-.0738358	-.079034	-.0946096
high		-.3805068**	.0078026	.2286685*	.3879078***	-.0492675	-.0492675	-.0492675	-.1248217	-.0916292
p_index			-.0079959***	-.0077843***	-.0085613***	.0006688	.0006688	.0006688	.0007257	.000695
m_rate				.0833761***	.080563***	.0705345***	.0705345***	.0705345***	.0694117***	.0694153***
unemp					-.0361755***	.0074897	.0074897	.0074897	-.0153593	-.0150131
income						-.0000357***	-.0000357***	-.0000357***	-.0000358***	-.0000359***
comprop							-1.256364***	-1.256364***	-1.299872***	-1.303675***
non_recourse								1.347883***	1.440445***	1.440874***
neg_prices									.1726523***	.1863365***
neg_equity										-.0526196
constant	5.317291***	5.63729***	5.879708***	4.77706***	4.845074***	5.151366***	5.151366***	5.151366***	5.378781***	5.354834***
Obs	824	751	751	751	751	751	751	751	751	751
R2	0.8096	0.7984	0.8159	0.8659	0.8682	0.8930	0.8930	0.8930	0.8958	0.8959
Adjusted R2	0.7976	0.7840	0.8064	0.8559	0.8582	0.8847	0.8847	0.8847	0.8875	0.8875

TABLE 9. Regression outcomes on a state level with both time and state fixed effects

The table illustrates the regression results with both time and state fixed effects incorporated into the models. The variable *low* is the only significant variable out of all the leverage variables. *, ** and *** represents 10, 5 and 1 percent significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*
low	.1116687	.1809985**	.3037869***	.1725961**	.1656537**	.1730395**	.1730395**	.1730395**	.1784714**	.163512**
high		-.1880511	-.2515871**	-.1152809	-.073588	.0345802	.0345802	.0345802	.0413763	.0939173
p_index			.004716***	.0022583**	.0019895**	-.0023344**	-.0023344**	-.0023344**	-.0022779**	-.002275**
m_rate				.0542525***	.0536371***	.0470117***	.0470117***	.0470117***	.0469926***	.0469257***
unemp					-.0161783	-.0023072	-.0023072	-.0023072	-.001226	.0004844
income						.0000489***	.0000489***	.0000489***	.0000485***	.0000487***
comprop							-1.716712***	-1.716712***	-1.708543***	-1.711488***
non_recourse								.7983025***	.787347***	.7758534***
neg_prices									-.0384785	-.017916
neg_equity										-.0753884
constant	5.041125***	5.202277***	4.786961***	4.370208***	4.42984***	3.629394***	3.629394***	3.629394***	3.616331***	3.557216***
Obs	824	751	751	751	751	751	751	751	751	751
R2	0.9036	0.8990	0.9012	0.9185	0.9187	0.9244	0.9244	0.9244	0.9245	0.9247
Adjusted R2	0.8952	0.8880	0.8913	0.9102	0.9103	0.9165	0.9165	0.9165	0.9164	0.9165

TABLE 10. Regression outcomes on a county level without fixed effects

The table illustrates the regression results from the regressions using county level data. None of the variables in the regressions are significant. The standard errors have been clustered on a state level. *, ** and *** represents 10, 5 and 1 percent significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*
low	.5633061	-.3198499	-1.035058	-1.052267	-1.01866	-1.017287	-.8023084	-.9061199	-.9027012	-.5205838
high		1.007028	1.775214	1.803988	1.791016	1.797889	1.645914	1.65438	1.654451	1.20557
p_index			-.0391384	-.0384451	-.038886	-.043614	-.0433722	-.0531458	-.0530642	-.0528529
m_rate				.0227094	.022611	.0226854	.0236709	.0241077	.0241075	.023996
unemp					-.0243342	-.0170488	-.0199757	-.0734284	-.0635126	-.063831
income						.0000269	.0000261	.0000329	.0000335	.0000329
comprop							.636391	-.2800193	-.2745862	-.2809027
non_recourse								1.993477	1.976506	1.993767
neg_prices									-.1074838	-.2717871
neg_equity										1.054927
constant	3.97563***	3.471243***	8.414854**	8.141096**	8.340724***	7.983981***	7.74546***	9.064354***	9.001604***	9.258888***
Obs	9361	8150	7289	7289	7289	7267	7267	7267	7267	7267
R2	0.0007	0.0011	0.0033	0.0039	0.0039	0.0041	0.0043	0.0058	0.0058	0.0059

TABLE 11. Regression outcomes on a county level with time but without state fixed effects

The table illustrates the result from the regressions which have incorporated time fixed effects but not state fixed effects. The results from these regressions are not significant. Standard errors have been clustered on a state level. *, ** and *** represents 10, 5 and 1 percent significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*
low	.6457598	-.1675205	-1.008791	-.9877279	-1.145215	-1.122815	-.9618571	-1.144027	-1.186374	-.7925787
high		.9785083	1.780476	1.782432	1.843595	1.816073	1.702215	1.774804	1.787581	1.323346
p_index			-.0353744	-.033362	-.0302644	-.0365484	-.0376161	-.0504058	-.0497615	-.0494215
m_rate				.0237967	.0240551	.0239074	.0247894	.0247941	.0248402	.0247654
unemp					.1391658	.2005985	.1957246	.1188607	.1056807	.1066118
income						.0000545	.0000524	.0000573	.0000567	.0000556
comprop							.6492862	-.1662859	-.181946	-.1853716
non_recourse								1.852982	1.902017	1.918242
neg_prices									.5135535	.3587357
neg_equity										1.095109
constant	7.914058***	7.731446***	10.95618**	10.61797**	9.687426***	8.824135***	8.711955***	9.957269***	9.913778***	10.15634***
Obs	9361	8150	7289	7289	7289	7267	7267	7267	7267	7267
R2	0.0022	0.0034	0.0046	0.0053	0.0055	0.0060	0.0062	0.0074	0.0075	0.0076

TABLE 12. Regression outcomes on a county level with state but without time fixed effects

The table illustrates the result from the regressions which have incorporated state fixed effects but not time fixed effects. The variables *comprop* and *non_recourse* are the only significant variable. Standard errors have been clustered on a state level. *, ** and *** represents 10, 5 and 1 percent significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*
low	.3608986	-1.220725	-1.916594	-1.930344	-1.912838	-1.914293	-1.959097	-1.959097	-1.979045	-1.610445
high		1.572664	2.274403	2.295563	2.28723	2.283746	2.319686	2.319686	2.320804	1.886203
p_index			-.0509337	-.0512653	-.0516168	-.0550556	-.0568561	-.0568561	-.057035	-.0568344
m_rate				.032112	.0320634	.0321203	.03208	.03208	.0321729	.0320608
unemp					-.0167845	-.007839	-.0107873	-.0107873	-.0515772	-.0543701
income						.0000229	.0000226	.0000226	.0000202	.0000196
comprop							-4.24329**	-4.24329**	-4.104813**	-4.130687**
non_recourse								12.55345***	12.50491***	12.55545***
neg_prices									.4012749	.2487841
neg_equity										1.005859
constant	3.744856***	3.277943***	9.620668**	9.354671**	9.520338***	9.218854***	9.482669***	9.482669***	9.752574**	10.02621**
Obs	9361	8150	7289	7289	7289	7267	7267	7267	7267	7267
R2	0,0176	0,0162	0,0191	0,0204	0,0204	0,0205	0,0206	0,0206	0,0207	0,0208

TABLE 13. Regression outcomes on a county level with combined and individual state and time fixed effects

The table illustrates the results from the regressions on county level data while incorporating all fixed effects into the model. The only variable with a significant impact is *non_recourse.* Standard errors have been clustered on a state level. *, ** and *** represents 10, 5 and 1 percent significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*
low	.3746198	-1.314518	-2.66857	-2.693713	-2.682976	-2.685663	-2.746759	-2.746759	-2.765372	-2.368741
high		1.666226	2.820154	2.849677	2.843118	2.841727	2.892701	2.892701	2.893411	2.424474
p_index			-.0888183	-.0886526	-.0890609	-.0919526	-.0952863	-.0952863	-.093519	-.0929937
m_rate				.0373816	.0373716	.0372467	.0371715	.0371715	.0371644	.0370372
unemp					-.0192198	.0088216	.0200563	.0200563	.0114245	.0098319
income						.0000192	.0000195	.0000195	.0000188	.0000176
comprop							-5.947105	-5.947105	-5.946702	-6.013841
non_recourse								23.37025***	23.33832***	23.46511***
neg_prices									.5368938	.3951617
neg_equity										1.093943
constant	4.184994***	3.71818***	14.36098	13.97503	14.11217*	13.81326*	14.14378*	14.14378*	14.01448*	14.26967*
Obs	9361	8150	7289	7289	7289	7267	7267	7267	7267	7267
R2	0.0187	0.0225	0.0264	0.0279	0.0279	0.0280	0.0282	0.0282	0.0282	0.0284

TABLE 14. Regression outcomes on a state level for individual variables with both state and time fixed effects

To better understand the individual impact of each of the variables on *d_rate* the following simple regressions have been conducted. However, none of the variables relating to debt are significant. *, ** and *** represents 10, 5 and 1 percent significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*
low	.1116687									
high		-.0694922								
p_index			.0034993***							
m_rate				.0535501***						
unemp					-.0493258***					
income						.0000529***				
comprop							-1.638889***			
non_recourse								-.4722222***		
neg_prices									-.0776479	
neg_equity										-.1092771
constant	5.041125***	5.218382***	4.855771***	4.574886***	5.367807***	4.034881***	5.138819***	5.138819***	5.141336***	5.138325***
Obs	824	751	824	824	824	824	824	824	824	824
R2	0.9036	0.8973	0.9055	0.9214	0.9054	0.9147	0.9033	0.9033	0.9035	0.9040
Adjusted R2	0.8952	0.8874	0.8972	0.9146	0.8972	0.9073	0.8950	0.8950	0.8951	0.8956

TABLE 15. Regression outcomes on a county level for individual variables with fixed effects

The table illustrates the regression results for the simple regressions that have been conducted on the county level data. Only the variables relating to the legal factors are statistically significant. The standard errors have been clustered on a state level. *, ** and *** represents 10, 5 and 1 percent significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*
low	.3746198									
high		.6349916								
p_index			-.0868505							
m_rate				.0319941						
unemp					-.0612818					
income						-0,00000756				
comprop							-1.940423***			
non_recourse								11.82118***		
neg_prices									.8299182	
neg_equity										1.611254
constant	.5421236	-.8896402	5.923181	.8713416**	1.567304	2.653009***	1.149092***	1.149092***	.6876181	1.074203***
Obs	9361	8150	8357	9361	9361	9339	9361	9361	9361	9361
R2	0.0187	0.0223	0.0216	0.0195	0.0184	0.0184	0.0184	0.0184	0.0187	0.0190

TABLE 16. Regression outcomes on a state level with state and year fixed effects, winsorized

The table illustrates the regression results after a 5 % winsorization has been conducted. Even though the results are more significant than in the unwinsorized data the difference is quite small. *, ** and *** represents 10, 5 and 1 percent significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*
low	.0742049	.1408986**	.2020485***	.2117728***	.2044091***	.2122654***	.2122654***	.2122654***	.2168298***	.2027067***
high		-.1843719*	-.2160135**	-.226117**	-.1818941*	-.0668366	-.0668366	-.0668366	-.0611256	-.0115218
p_index			.0023486***	.0025308***	.0022456***	-.0023536**	-.0023536**	-.0023536**	-.0023061**	-.0023034**
m_rate				-.0040214	-.0046742	-.0117216***	-.0117216***	-.0117216***	-.0117376***	-.0118008***
unemp					-.01716	-.0024054	-.0024054	-.0024054	-.0014969	.0001179
income						.000052***	.000052***	.000052***	.0000517***	.0000519***
comprop							-1.872628***	-1.872628***	-1.865764***	-1.868544***
non_recourse								.8639728***	.8547666***	.8439156***
neg_prices									-.0323343	-.0129213
neg_equity										-.071174
constant	4.944723***	5.10567***	4.898838***	4.92973***	4.99298***	4.141554***	4.141554***	4.141554***	4.130576***	4.074765***
Obs	824	751	751	751	751	751	751	751	751	751
R2	0.9177	0.9145	0.9156	0.9157	0.9160	0.9247	0.9247	0.9247	0.9248	0.9250
Adjusted R2	0.9105	0.9061	0.9072	0.9072	0.9073	0.9169	0.9169	0.9169	0.9168	0.9170

TABLE 17. Regression outcomes on a county level with fixed effects, winsorized

This table illustrates the regression results after a 5 % winsorization has been conducted. The sinificance of the variable low and high are higher than in the unwinsorized data but still quite low. The standard errors have been clustered on a state level. *, ** and *** represents 10, 5 and 1 percent significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*	*d_rate*
low	-.0148576	.1478596	.2129368**	.2124804**	.1967449	.1930148	.1744904	.1744904	.1765306	.207828
high		-.0985177	-.1450675**	-.1445316**	-.1349201	-.1307756	-.1153204	-.1153204	-.1153983	-.1524012
p_index			.00377	.003773	.0043714	.0044477	.0034369	.0034369	.0032432	.003284
m_rate				.0006785	.0006932	.0007074	.0006847	.0006847	.0006854	.0006754
unemp					.028166	.0251939	.0286003	.0286003	.0295465	.0294208
income						-0,00000149	-0,00000141	-0,00000141	-0,00000133	-0,00000142
comprop							-1.803175***	-1.803175***	-1.80322***	-1.808517***
non_recourse								.4362517**	.4199696**	.4252513**
neg_prices									-.0588475	-.0700313
neg_equity										.086321
constant	5.433837***	5.352036***	5.294267***	5.288011***	5.068921***	5.018821***	5.063444***	5.063444***	5.097924***	5.117259***
Obs	9361	8150	7289	7289	7289	7267	7267	7267	7267	7267
R2	0.3524	0.3765	0.4031	0.4032	0.4044	0.4051	0.4100	0.4100	0.4103	0.4105

TABLE 18. Correlation coefficients for state level data

This table illustrates the correlation between the variables used in our regressions. The single highest correlation is the correlation between the upper and lower bound for the debt-to-income ratios, *low* and *high.* The correlation between *income* and *p_index* is also significant.

	low	*high*	*d_rate*	*p_index*	*m_rate*	*unemp*	*income*	*comprop*	*non_recourse*	*neg_prices*	*neg_equity*
low	1.0000										
high	0.9102	1.0000									
d_rate	0.1629	0.1288	1.0000								
p_index	0.1511	0.2402	-0.2725	1.0000							
m_rate	0.0923	0.1061	0.5266	-0.0904	1.0000						
unemp	0.2324	0.2637	-0.0813	0.0532	-0.0673	1.0000					
income	0.0086	0.0462	-0.5035	0.6980	-0.1515	0.1741	1.0000				
comprop	0.0930	0.1283	0.1397	-0.0479	0.2668	0.0309	-0.1267	1.0000			
non_recourse	0.0610	0.1149	0.0203	0.0029	-0.0603	-0.0093	0.0249	0.2861	1.0000		
neg_prices	0.2541	0.2591	-0.0822	0.1075	-0.0989	0.5823	0.1795	-0.0591	-0.1156	1.0000	
neg_equity	0.3078	0.4167	-0.0258	0.0978	-0.0282	0.3843	0.0640	-0.0051	-0.0258	0.5284	1.0000