An Honors Thesis on the US Housing Bubble

by

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The Housing Bubble: The Role of Loan to Value Ratio as a Risk Signaler in Subprime Borrowing

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Introduction

The precipitating event in the current mortgage crisis was an extended period of very low interest rates that began after the dot-com bust and September 11, 2001. Low interest rates made the return on US Treasury bills less attractive, and shifted the attention of global investors to collateralized debt obligations, and more specifically to mortgage-backed securities. These were new credit instruments that eliminated much of the risk associated with mortgage loans—they were effectively pooled together with conventional loans, spliced, and sold to investors. Before securitization, lenders held all the risk. They had to thoroughly check the borrower's financials and form relationships of trust to ensure credibility. But with the creation of standardized financial assets like MBS's and CDO's, the risk was lifted from lenders and spread among investors. The risk that any one of these loans in an MBS or CDO should default was mitigated by a small probability of other loans in the pool defaulting, as well.

These seemingly riskless credit instruments induced lenders to push home loans on customers who traditionally did not qualify for them, and in effect created a subprime mortgage market boom. Slackened underwriting standards and lack of regulation allowed for applicants with poor credit scores, low income, and high levels of debt to acquire mortgages that previously existed only in the prime mortgage market. Applicants with these characteristics were more likely to be late on payments and pay higher interest, and were therefore more profitable.

For the borrower, these loans were only a good deal if house prices continued to appreciate, because it enabled them to refinance and tap into constantly increasing home equity. Subprime borrowers, however, did not always fully understand the risk of default, especially if home prices were to fall. The recent downward spiral in home prices has left many of these borrowers financially stranded, as they face rate resets and the inability to extract home equity.

It now seems that some lenders opportunistically used subprime borrowers—borrowers with limited information about the dangers of accepting loans they could not afford—to increase the rate of return on mortgage-backed securities.

The subprime boom was not without its upsides. As Edward Gramlich states in his book *Subprime Mortgages: America's Latest Boom and Bust*, "The good news is that millions of new homeowners, who formerly would have been denied mortgage credit, can now take out mortgage loans, buy homes, live in better neighborhoods, and send their kids to better schools" (9). Although the subprime boom gave millions of previously ineligible Americans the opportunity to become homeowners, the recent housing crash has put many of these new owners at extreme risk. According to Gramlich, "The bad news is that a smaller share of these new homeowners is stretched thin, vulnerable to the least shock, saving very little, with high levels of consumer debt, at the mercy of predatory lenders, being forced to sell their houses early, and often ending up in foreclosure" (9). Gramlich's book, published in 2007, understates the bad news. The "smaller share" of these new homeowners has become a much larger share over the past two years. The problem currently unfolding is that those who borrowed heavily can no longer refinance their mortgages because their house values have fallen and they have little or no home equity to borrow against.

My primary motivation in this paper is to see what types of borrowers were given home loans that retrospectively should never have been made. Traditionally, loan to value ratio (the ratio of mortgage to house price), was used as a signal of borrower risk; a high loan to value (LTV) reflected a borrower's relatively low income, high debt, or some combination of factors that led to a small down payment relative to loan size. According to Epley, et al. in their 1996 paper "Borrower Risk Signaling Using Loan-to-Value Ratio," "The default risk information signaled by a loan-to-value ratio above 80% has been considered historically to be 'high risk' as the borrower has less collateral and, supposedly, less commitment in repaying the loan" (74). Epley, et al. "[…] provide further justification for the continual use of the loan-to-value ratio as an initial tool of borrower creditworthiness" (80).

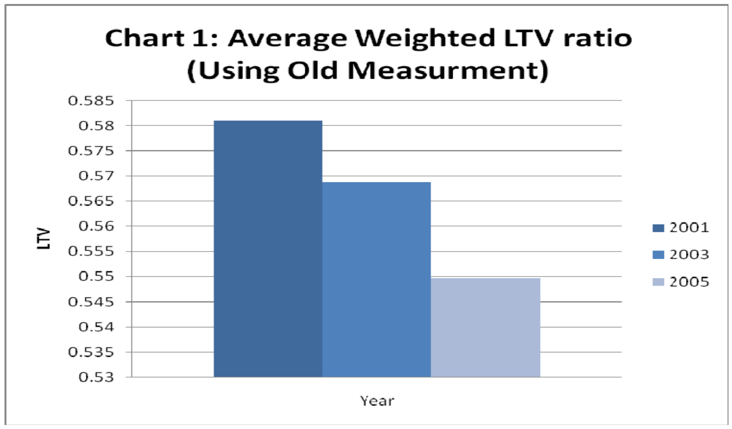
During a bubble, however, when the market is volatile and precarious loans are given out, high LTVs are thought to reflect a wider range of borrowers looking to capitalize on the boom. In other words, high LTVs in the recent boom were thought to reflect extracted home equity by homeowners taking advantage of high levels of house appreciation. In this paper, I look to determine the characteristics of homeowners with high LTVs during the five-year housing boom. I postulate that if these borrowers tended to have average to low levels of risk, then LTV shifted its role as a measure of loan quality and instead reflected the average homeowner taking advantage of exorbitant price appreciation; low or non-existent risk characteristics represent a crowding out of subprime borrowers by conventional mortgage borrowers extracting equity.

To test this hypothesis, I use a data set from the University of Michigan's Panel Study of Income Dynamics (PSID)—one of the University's long-standing survey research projects. The PSID is a longitudinal study over the past 40 years of a representative sample of over 8,000 U.S. families and over 65,000 U.S. individuals. What I find, however, is that these loans were made to borrowers with traditionally risky characteristics, and that LTV appears to have retained its role as a measure of loan quality throughout the boom. I further analyze the amount of debt that risky, subprime borrowers were permitted to assume to show just how precarious a position they were in right before the housing market crash.

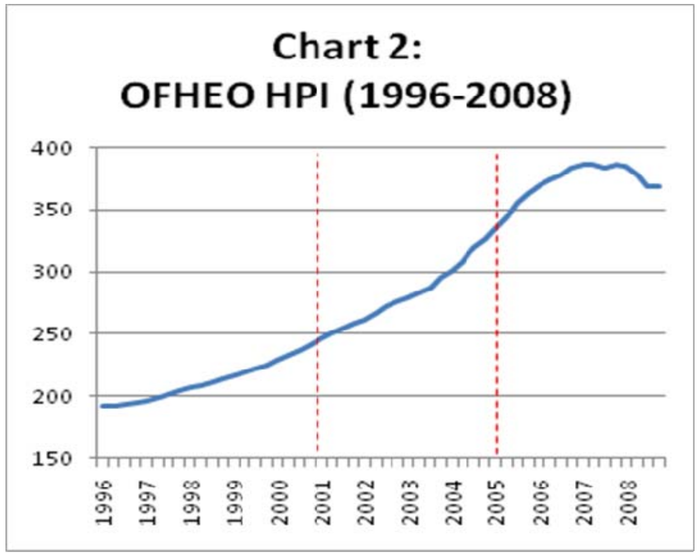
Loan to Value Ratio and Risk Characteristics

Creating an Accurate Measure of Loan to Value Ratio

Loan to value ratio (LTV) is the ratio of mortgage to house price. As there is no LTV variable in the PSID, I had to create it using the available data. To create a mortgage variable, I subtracted home equity from the house value. As there was no home equity variable, I subtracted "WEALTH105 (NO MAIN HOME EQUITY)" from "WEALTH205 (MAIN HOME EQUITY INC)." After subtracting this value from home value to get the outstanding mortgage value, I divided mortgage by home value to get LTV. This initial measure, however, was problematic. Given that the subprime market was constantly expanding and that homeowners extracted increasing amounts of equity between 2001 and 2005, I predicted that average LTVs increased over that time period. However, I discovered that the average LTV actually decreased between 2001 and 2005 (see Chart 1), a trend that directly contradicts an expanding subprime market. I first hypothesized that lenders foresaw a market slowdown or even a market crash and therefore decided to cut back on the number of unsafe loans they made; however, this could not be the case for two reasons. First, the securitization of mortgages allows lenders to sell these mortgages to investors, thereby removing their liability and reducing any precautionary disincentive to give out risky loans (if they can sell them in the first place). Second, even if lenders foresaw such a crash, slowing subprime loans would entail an immediate loss of market share for their company and most likely the loss of their job.



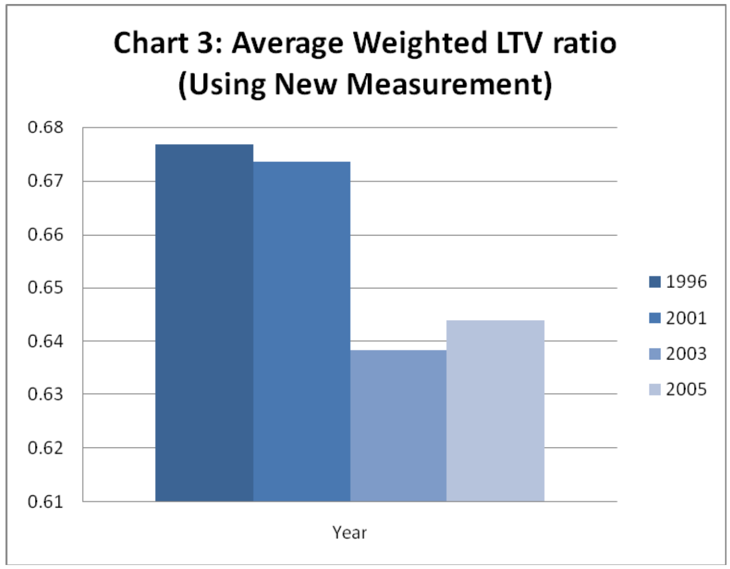
The reason my findings pointed to increasingly safer LTVs over time is because of increasing house values (LTV = mortgage/house value). As evidenced by the Office of Federal Housing Enterprise Oversight's House Price Index (see Chart 2), house values rapidly appreciated from 2001 to 2005. The rate of increase between 2001 and 2005 was more than double and sometimes triple that between 1996 and 2001. Holding mortgage constant, a higher house value necessitates a lower LTV. So my initial LTV was not measuring the *creation* of safe and unsafe LTVs over time (ex ante LTVs), which is what I initially wished to analyze. Instead, this measure of LTV indirectly allows me to measure changing house values from 2001 to 2005.



To correct for appreciating house values, I limit my sample within each year to those who obtained or refinanced their loan within 1 year of the sample year. For example: for the year 2003 I limit my sample to those who obtained or refinanced in either 2002 or 2003. While this is not a perfect measure of ex ante LTV, it eliminates those homeowners whose last refinance was many years before the sample, thus limiting the effect of house appreciation. Whereas in Chart 1 I measured already existing and constantly changing LTVs, this restriction allows me to more closely measure the *creation* of safe and unsafe loans over time.

An additional restriction I make on the LTV variable is to exclude LTVs over 2. Respondents with LTVs higher than 2 are most likely the victims of some sort of house damage, causing their house value to drop far below the remaining mortgage. LTVs of 6 and 7 existed in the sample, but such LTVs are non-representative and are thus excluded.

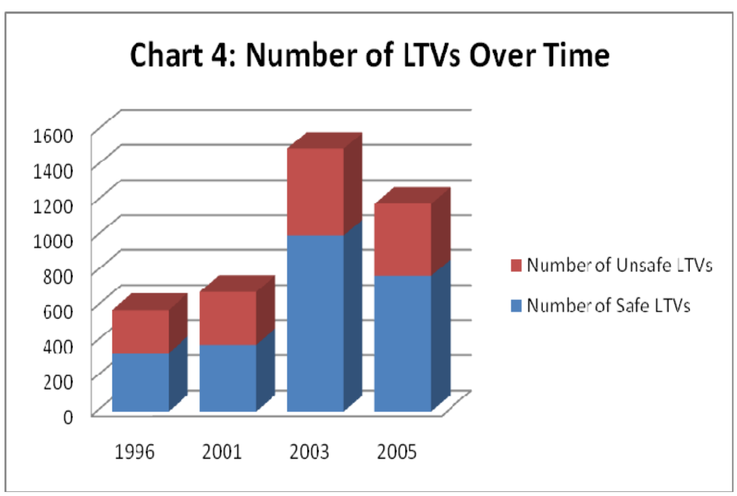
With this new definition of LTV, I predicted that an analysis of average LTVs over time would more closely fit the subprime boom. Chart 3, now including 1996 LTV, shows the average weighted value of LTVs over time. Unfortunately, the results do not perfectly mirror the market trends. The only time period that fits my prediction is 2003 to 2005. During this time, average LTV increased from .638 to .645. One counterintuitive result is a decreasing LTV between 1996 and 2001. I expected average LTV to increase substantially between these time periods. A possible reason for this counterintuitive result is that my definition of LTV is slightly different in 1996 than in the 2000s. In 1996 there is no wealth variable, and thus I am not able to measure home equity by subtracting wealth with home equity from wealth without home equity. With no reliable measure of home equity, I am not able to find the mortgage on the home by subtracting the home equity from the house value. I instead use the remaining principle on the mortgage as the loan value. This difference in measurement of mortgage, and thus LTV, is one possible reason my analysis shows average LTV decreasing between 1996 and 2001.



The second counterintuitive result is a further decrease in LTV between 2001 and 2003. Actual LTV values rose during this period. There are two potential measurement errors here. First, increasing house values may still have an effect. Restricting the sample to only those who obtain or refinance their loan in the sample year or the year before the sample year still leaves room for house appreciation. While the appreciation in 1996 may have been relatively small, it is possible that a house with a refinanced mortgage in 2002 appreciates significantly by 2003. According to the OFHEO, house appreciation between 1995 and 1996 was about 3%, whereas between 2004 and 2005 it was upwards of 14%. Unfortunately, I cannot look solely at respondents who obtain or refinance their loan during the particular sample year because the resulting sample size is too small.

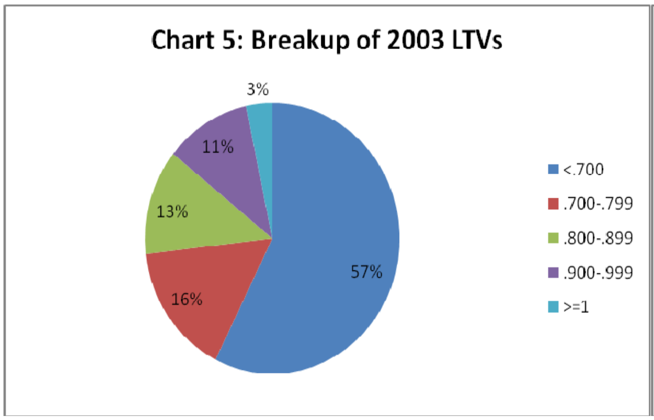
A second factor potentially affecting these results is when in the sample year the respondent is surveyed. Take for example, two respondents each surveyed in 2001 and 2003. Respondent A could have been surveyed in February 2001 and again in December 2003, whereas respondent B might have been surveyed in December 2001 and again in February 2003. The time between surveys for respondent A is almost three years and the time between surveys for respondent B is a little over one year. As evidenced by the OFHEO's House Price Index, a lot was happening in the middle of the boom, and an extra year between respondent A and B's surveys might cause disparities in their recorded house appreciation.

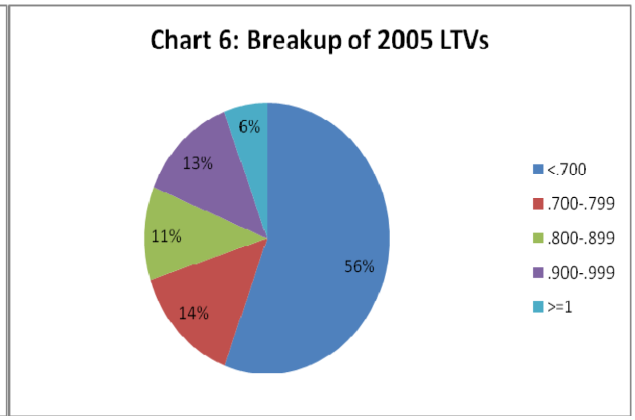
I must also note that the sample sizes in the years exhibiting counterintuitive results are considerably different than in the years that are consistent with my predictions. The sample size of those who obtained or refinanced their loan within 1 year of the sample year is about 600 for both 1996 and 2001, but double that size in 2005



and almost triple that size in 2003 (see Chart 4). While one might postulate that the number of obtained or refinanced loans should increase from 2003 to 2005, it is quite possible that homeowners refinanced to the maximum (or beyond) by 2005. Despite the apparent drop in 2005, the fact that there is a sharp rise in the number of refinances post 2001 makes sense because 2003 and 2005 coincide with the largest expansion in the subprime era.

Given that the only average LTV change in Chart 3 that seems to mirror the subprime boom is the change between 2003 and 2005, I take a more in depth look at the breakup of LTVs





in these years (see Charts 5 & 6). The number of safe LTVs, those below 0.8 (as defined by Epley, et al.), decreased by about 3% between 2003 and 2005. This change explains the majority of the change in average LTV because the percentage—and therefore weight—of prime loans in the housing market far exceeds subprime loans. It is also interesting to note the increase in LTVs above 1. The sample size is about 1,500 for 2003 and 1,200 for 2005. This means that the increase in greater than 1 LTVs from 3% in 2003 to 6% in 2005 represents a 60% increase in the number of respondents with LTVs over 1.

LTV Ratios and Mortgage Rates Over Time

Table 1 below maps weighted mortgage rates against various brackets of LTVs, and shows that mortgage rates and loan to value ratio are positively correlated. This is one finding that may suggest the continued role of LTV as a measure of loan quality. Higher mortgage rates are traditionally given to higher risk homeowners. The combination of a homeowner's problematic financial history and a relatively small down payment on a home has historically led to higher loan rates. However, this is solely a correlation, and could be the result of two factors: (i) the *inability* of the borrower to pay a sizeable down payment leads to a high LTV and high mortgage rates, suggesting LTV and rates reflect the risk characteristics of the borrower, or (ii) the extraction of home equity leads to a high LTV, and the correlation suggests that higher LTVs require higher rates solely as a cost of borrowing more money. Scenario (i) supports LTV as a continued measure of loan quality throughout the boom, and scenario (ii) supports the changed significance of LTV to a mere reflection of increased borrowing.

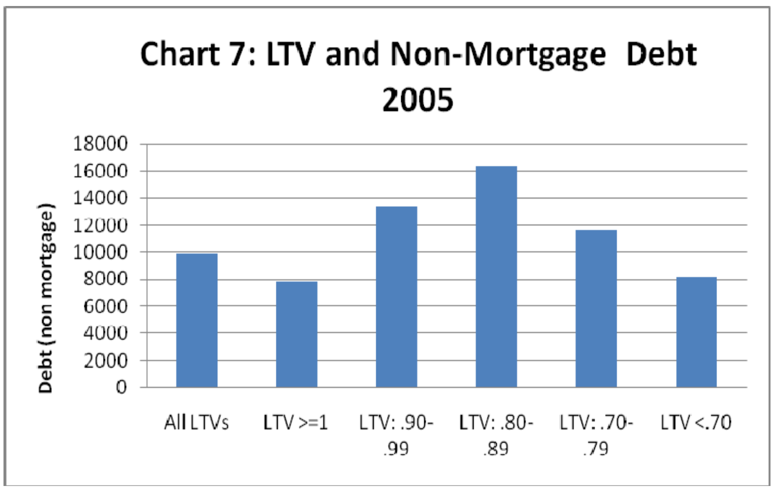
Another observed trend is the change in mortgage rates over time. In 2001 the average loan rate was 7.4, in 2003 it was 6.3, and in 2005 it was 5.7. This decreasing trend is observed in all LTV brackets. Freddie Mac's *Primary Mortgage Market Survey* confirms this trend: the average mortgage rate declined from 6.97 in 2001 to 5.87 in 2005. This statistic, in tandem with the advent of mortgage securitization and low "teaser" rate adjustable mortgages, helps explain the large increases in home loan borrowing during this time period.

Table 1: Mortgage Interest Rates and LTVs over time

	All LTVs	LTV>=1	LTV: .90-.99	LTV: .80-.89	LTV: .70-.79	LTV: <.70
2005 Mortgage Interest Rate	5.6673	6.7743	5.8821	5.9099	5.6330	5.5783
2003 Mortgage Interest Rate	6.2728	7.6756	6.5480	6.3795	6.2264	6.1991
2001 Mortgage Interest Rate	7.3725	8.0070	7.5939	7.4172	7.4024	7.3066

LTV Ratios and Non-Mortgage Debt

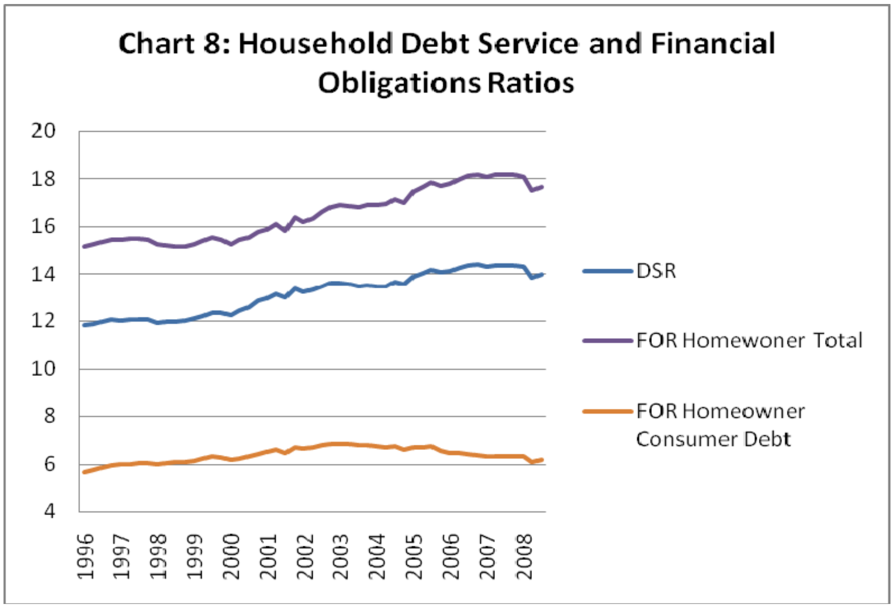
An intriguing trend occurs when comparing LTVs and non-mortgage debt. Chart 7 illustrates that debt appears to be distributed normally over the sample; homeowners with LTVs over 1 and under 0.7 tended to have less debt, and homeowners with LTVs between 1 and 0.7 tended to have more. One possible explanation for low debt among homeowners with very high LTVs is that they did not have the means



to borrow and assume high amounts of non-mortgage debt; subprime borrowers with the highest LTVs tended to have bad credit and low incomes, and may not have been eligible for large loans outside of the housing market. While almost anyone could get a mortgage, credit was not so easily obtained for other spending. This explanation lends credence to the notion that homeowners with the highest LTVs tended to be subprime, and that LTV remained an effective measure of loan quality throughout the bubble. However, another potential explanation is that these were responsible homeowners who decided to extract large amounts of home equity; borrowers with little non-mortgage debt may have had higher LTVs than borrowers with large amounts of debt because they could better afford to take the risk. In the event that the housing market went sour, these homeowners would have only one major source of debt. This explanation suggests that high LTVs were no longer indicative of borrowers with the telltale subprime risk characteristics, and that LTV shifted its role during the bubble.

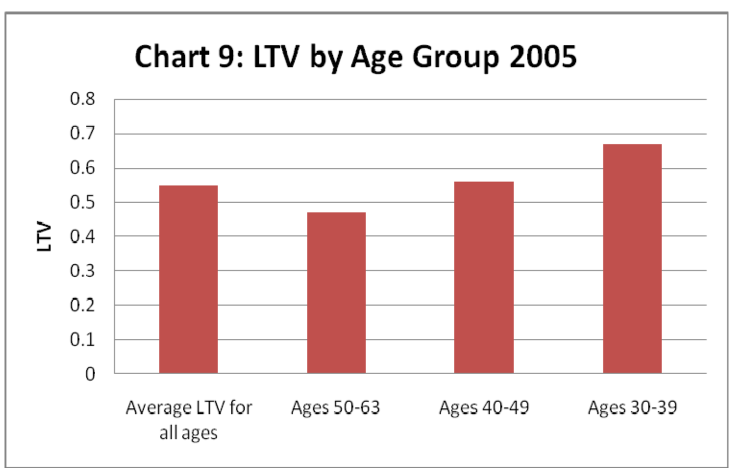
The likely explanation for the other end of the spectrum—homeowners with LTVs of less than 0.7—is that they assumed less debt simply due to sound money management; a low LTV is likely indicative of responsible borrowing. Homeowners on the margin of safe and unsafe LTVs may have had the highest debt because they had relatively higher incomes than those borrowing over 100% of their home value, but were relatively less responsible than homeowners with low LTVs. The sheer magnitude of debt for these homeowners—an average of over $16,000—helps explain the unfolding crisis; those who previously used their ever-increasing home equity as a financial buttress became unable to supply the money for their debts. Take for example a hypothetical homeowner in 2003 with lots of non-mortgage debt and an LTV of 0.8. Aware of the unparalleled levels of house appreciation, this individual might have refinanced to an LTV of 0.95 in order to pay off that non-mortgage debt. Completely confident their house value would continue to appreciate, they decided to increase their non-mortgage debt again. Come 2007, however, as house prices around the country began to fall, this homeowner with an LTV of 0.95 might soon discover they had no home equity at all (and thus no way to pay off their non-mortgage debt).

The Federal Reserve Board’s household debt service and financial obligation ratios provide good evidence of this increasing financial burden. Chart 8 shows three ratios. First, the bottom time series represents homeowners' consumer (non-mortgage) debt as a percentage of disposable personal income. This category of debt peaks in about 2003 and then sharply declines. This result is probably due to homeowners refinancing and paying off their non-mortgage debt at the height of the boom. Now that refinancing is so difficult it will be interesting to see if this ratio increases in the coming years. Second, the middle series provides an estimate of the remaining non-mortgage and mortgage debt payments as a percentage of personal disposable income. Lastly, the top series adds auto lease payments, homeowner's insurance, and property tax to the non-mortgage and mortgage debt payments. If this data were readily available during this time period, it should have been a red flag for the FED. The increase in total payment obligations, the top series, is an indicator of the extreme levels of debt that were assumed during the bubble and the likely financial stress that homeowners now face.



LTV Ratios and Age

Age has long been used in mortgage lending to determine risk due to its correlation with ability to pay.



Younger homeowners are less likely to have significant funds to put towards their down payments. A smaller down payment necessarily requires a larger mortgage, which might explain why the average LTV for the age group 30-39 is the highest, at close to 0.7 (see Chart 9). In addition, younger homeowners have not had as much time to pay off an initially high mortgage, whereas older individuals have made more payments. A second wealth-related reason for a negative correlation between age and LTV is house value. Older homeowners probably have higher incomes and more net wealth than younger homeowners, thus enabling them to purchase more expensive homes. Holding mortgage constant, a higher house value will drive down LTV.

One might hypothesize, however, that because a higher house value necessitates a larger mortgage, the LTVs of the old and young should be similar. For example, a 60 year old buying a new home may have more wealth to put towards a down payment, but may also be purchasing a more expensive home, requiring a comparatively larger down payment. Younger homeowners may not have as much accumulated wealth, but are likely to be purchasing less expensive homes, making their down payments relatively less costly. If mortgages and house value are proportional for the old and young, their LTVs should be similar. The observed difference in LTVs may thus be attributable to responsibility. Similar to the explanation of the relationship between LTV and non-mortgage debt, it is possible that a low LTV is indicative of financial responsibility; older homeowners probably have more experience in the housing market and better understand the importance of assuming as little debt as possible.

It is very likely that what is really happening with young adults is a combination of the above explanations: lack of accumulated wealth and lack of financial experience. Young adults just entering the housing market are much more likely than older individuals to have outstanding school loans, and much less likely to have accumulated wealth. In addition, they lack the financial experience that might prevent them from assuming too much home debt.

Whether Chart 9 is a reflection of inability to pay, a lack of financial responsibility, or both, for LTV to have shifted its role as a measure of loan quality one would predict a close-to-zero correlation with age. If higher LTVs were solely a representation of extracted equity on the part of everyone in the housing market, age—a risk predictor—and LTV should have no discernable relationship. This leads me to believe that LTV remained a measure of loan quality and did not shift its role during the housing bubble.

Panel Analysis: 2005 LTV regression

The main regression for this project is a panel analysis in which I look for past and present predictors of LTV in 2005. I hope to discover whether LTV retained its role as a measure of loan quality during the housing bubble or if it solely reflected increased activity in home equity extraction. To do this I regress 2005 LTV on borrower characteristics that are likely to determine risk: age, education, number of children, an interaction of low income and high non-mortgage debt (for the years 2003, 2001 and 1996), whether the loan is under the original terms or is refinanced, money problems in 1996, and bankruptcies filed before 1996. If these characteristics are insignificant or are significant with small enough coefficients, it will lead me to conclude that traditional subprime characteristics were not a factor in LTV, and that LTV shifted its role during the housing bubble. If, on the other hand, these risk characteristics are significant with large enough coefficients, it will lead me to conclude that LTV retained its role as a measure of loan quality and that LTV should have been analyzed more closely during the bubble to prevent the crash. The following subsections explain my choice of regressors, how they are restricted, and their effects on 2005 LTV.

Regression 2005 (A): Predictors of 2005 LTV (all regressors)

LTV (2005) = $\beta_0 + \beta_1$ Age (2005) + β_2 Education (2005) + β_3 Children (2005) + β_4 Race (2005) + β_5 Original Loan (2005)+ β_6 Low Income & High Debt (2003) + β_7 Low Income & High Debt (2001) + β_8 Low Income & High Debt (1996) + β_9 Money Problems (1996) + β_{10} Bankruptcies (1996) + u

Observations = 545

R^2 = .2378

Independent Variables	Coefficient	Standard Error	T	P-Value
Age 2005	-.0034371	.0010058	-3.42	0.001
Education 2005	-.0500581	.0193301	-2.59	0.010
Children 2005	.0216792	.0088851	2.44	0.015
Race 2005	-.0583341	.0224468	-2.60	0.010
Original Loan 2005	.0976973	.019248	5.08	0.000
Low Income & High Debt 2003	.0565645	.0194643	2.91	0.004
Low Income & High Debt 2001	.0627981	.0197109	3.19	0.002
Low Income & High Debt 1996	.0516556	.0223035	2.32	0.021
Money Problems 1996	.048255	.0194018	2.49	0.013
Ever Bankrupt 1996	.0580331	.0374057	1.55	0.121
Constant	.7517548	.0594707	12.64	0.000

Legend: (Dependent) LTV 2005: greater than 0, less than 2; (1) Age 2005: values between 21 and 95; (2) Education 2005: 1 if more than 12 years of education, 0 if 12 or less years; (3) Children 2005: values between 0 and 18; (4) Race 2005: 1 if white, 0 if nonwhite; (5) Original Loan 2005: 1 if original loan, 0 if loan has been refinanced; (6) Low Income & High Debt 2003: 1 if income<$50,000 and debt>$5,000, 0 otherwise; (7) Low Income & High Debt 2001: 1 if income<$50,000 and debt>$5,000, 0 otherwise; (8) Low Income & High Debt 1996: 1 if income<$50,000 and non-mortgage debt>$5,000, 0 otherwise; (9) Money Problems 1996: 1 if any money problems, 0 if none; (10) Ever Bankrupt 1996: values between 0 and 3.

(1) Age

The variable I use for age in 2005 is "ER25017: AGE OF HEAD," and I restrict it to above 21 and under 96. My descriptive results in the first section of this project show that age and LTV are negatively correlated. If LTV lost its role as a measure of loan quality during the boom, age is one of the characteristics that should have lost its predictive power for LTV. While the regressor is significant at the 1% level, the estimated effect on LTV does not appear large (-.0034). It must be noted, however, that this effect measures the change in LTV from a one year change in age. A 30 year difference in age highlights the magnitude of the age effect. Holding other factors constant, a 60 year old is expected to have an LTV of roughly 0.1 lower than a 30 year old. The fact that age is a significant predictor of LTV, even when factors such as income and credit worthiness are held constant, might suggest that age was indicative of financial responsibility. What it clearly shows is that age continued to predict LTV levels during the height of the boom, an indication that LTV retained its ability to indicate loan risk.

(2) Education

I first tried using the variable "ER27417: L54 WTR RECD COLLEGE DEGREE-HD," which asks whether or not the respondent received a college degree. I used it as a dummy variable with 1 being a yes and 0 being a no, and predicted that having a college degree has a negative effect on LTV. My reasoning was that financial factors aside, those with less education are less likely to grasp the potentially dire consequences of holding too much debt. While the coefficient was negative, it was not significant.

I then tried a different education variable, "ER28047: COMPLETED ED-HD," which gives an updated measure of total years of education . I made this a dummy variable in which I restrict 12 or less years of education to 0, and more than 12 years to 1. This measure is therefore a little different than my first attempt, as I change the education variable to look at the effect of having at least some college versus no college instead of a college degree versus no degree. With this new measure of education, I find that having more than 12 years of education—i.e. having some college experience—has a negative estimated effect on LTV of -0.05, significant at the 1% level. Since income, debt, and race are held constant, this might suggest that education has an effect on financial responsibility, and that homeowners with college experience assume less debt out of principle. If education is indeed a measure of responsibility, then its ability to predict LTV in 2005 points to the continued role of LTV during the boom as a measure of loan quality.

(3) Children

I use the 2005 variable "ER25020: # CHILDREN IN FU" to measure the effect of number of children on LTV. The regression confirms that having more children results in a higher LTV. The regressor is significant at the 5% level and the coefficient is roughly 0.022. For every additional child, one might expect an increase in LTV by 0.022. This makes sense considering extensive resources are needed to take care of a child and additional children do not provide additional sources of income. Holding income constant, homeowners with more children will have to borrow more against their homes than those with few or no children at all. The fact that number of children was a predictor of LTV during the boom adds weight to the concept that LTV maintained its role as a measure of loan quality.

(4) Race (A Look into Predatory Lending)

While race is certainly not a risk characteristic, I include it in the regression to look for a troubling trend pertinent to the mortgage crisis—predatory lending. Predatory lending is when lenders deceptively convince homeowners to agree to unfair loan terms. A common explanation for observed racial differences in LTV is that nonwhites tend to have worse credit. However, a 2006 article by Ernest Bocian, "Unfair Lending: The Effect of Race and Ethnicity on the Price of Subprime Mortgages," shows that even after controlling for credit history, African Americans and Latinos are about 30% more likely to get a high-priced loan than their white counterparts. One might also attribute the higher LTVs of nonwhites to differences in education or income. In my regression I control for credit history (by looking at nonmortgage debt), education, and income to see if these factors do in fact explain away the notion of discriminatory lending.

The race variable I use is from 2005— "ER27393: L40 RACE OF HEAD-MENTION 1." I make it a dummy variable with 1 being white and 0 being nonwhite. At a 1% level of significance, the estimated effect of race is significant. The coefficient is roughly -0.058, an estimate that being white decreases LTV by 0.058—a fairly large number considering most LTVs fall within 0.4 of each other. Additional factors beyond the scope of my regression may account for the observed racial difference, but having controlled for credit, education, and income, this result lends some credence to the predatory lending hypothesis.

(5) Original or Refinanced Loan

I used this regressor to look at whether the 2005 loan in question was under the original terms or was refinanced. I created a dummy using the variable "ER25041: A23B WTR ORIGINAL

LOAN/REFINANCED #1," in which original is set to 1 and refinanced is set to 0. This regressor is included for two reasons. First, I hypothesize that original loan status is a risk characteristic because the borrower is not a tested homeowner; a refinanced loan is a sign of continued homeownership whereas original loan holders have not proved their ability make payments. Second, it is an indirect measure of another risk characteristic: age. All else equal, a respondent with an original loan is likely to be younger than a respondent with a refinanced loan because they have had less time to make payments. In this respect, loan type is a financial cycle indicator and reflects a sort of economic age effect.

At the 5% level of significance, having a loan under the original terms is significant and has an estimated positive effect of 0.098 on 2005 LTV. Whether it reflects ability to pay, age, or both, the significance and magnitude of the coefficient lends supports to the idea that LTV was still a consistent measure of risk during the housing boom. It must be noted, however, that part of this effect could be attributed to house value. Homeowners that refinanced operated under loan terms with an updated house value, whereas homeowners under original loan terms did not. If a homeowner refinanced a 2003 loan in 2005 without changing the value of the mortgage, the house appreciation over those two years necessarily drove down the LTV. The LTVs of homeowners under original loan terms did not reflect changing house prices and would have appeared relatively high compared to refinanced LTVs. However, if refinances were primarily characterized by extracted equity and increased mortgage values—as they tended to be during the recent bubble—changing home prices were less of a factor.

(6-8) Low Income and High Debt Over Time

For the years 2003, 2001 and 1996 I created interaction dummy variables to represent respondents with low income and high nonmortgage debt, a common characteristic of subprime borrowers. Interestingly, I discovered that the interaction of low income and high debt in all three years has a significant impact on 2005 LTV, suggesting that LTV was an effective measure of loan quality during the boom, and that financial problems were persistent over time. In the following two sections I explain these three interaction variables and their effects on LTV.

(6) Low Income and High Debt in 2003

For 2003 I create two dummy variables: low income and high nonmortgage debt. For low income I use the variable “ER24116: LABOR INCOME OF HEAD LAST YEAR” and restrict values less than $50,000 a year to land values of $50,000 or more to 0. For high nonmortgage debt I use the variable “S607: VDEBT03 (2003$)”—which excludes housing debt—and restrict values of $5,000 and above to 1 and values of less than $5,000 to 0. I then create an interaction dummy variable of the two to capture the effect of respondents with both low income and high nonmortgage debt. The regression shows that the interaction in 2003 does in fact have a significant effect on 2005 LTV. Significant at the 1% level, those with both low income and high debt in 2003 are estimated to have a 2005 LTV 0.057 higher than those with either high income or low debt. The significance and magnitude of the interaction indicate that LTVs during the housing bubble were strongly influenced by poor credit—a common characteristic of the subprime borrower. The ability of LTV to reflect borrower characteristics such as credit is further proof that LTV retained its role as a measure of loan quality throughout the bubble.

(7 & 8) Low Income and High Debt in 2001 and 1996

To get a better idea of the extent to which LTV reflected poor credit during the boom, I look at the same interaction variables in 2001 and 1996. If poor credit standings of a borrower predicted their 2005 LTV five to ten years back, it shows that 2005 LTV was an especially good measure of loan quality. For 2001 I use the variables "ER18561: G13 WAGES/SALARY OF HEAD" to specify low income (less than $50,000) and "S507: VDEBT01 (2001$)" to specify high debt (greater than or equal to $5,000). I use the variable "Wages/Salary of Head" because "Labor Income" is not offered in 2001. Although some of the data for this variable is negative due to negative returns from a respondent's business, I restrict the variable to zero and positive values only. Significant at the 1% level, those with both low wages/salary and high debt in 2001 are estimated to have a 2005 LTV 0.063 higher than those with either high income or low debt in 2001. This is consistent with the interaction variable in 2003 and suggests that respondents with financial trouble 4 years prior to the measured LTV are likely to exhibit higher LTVs.

I restrict for 1996 low income (less than $50,000) using the variable "FAMINC96: TOTAL FAMILY INCOME 1995." For debt in 1996, however, there is not a variable measuring the value of nonmortgage debts. At first I tried using a categorical variable unique to 1996, "ER8855: G119 DEBTS INVOLVED1 1," which specifies the category of debt the respondent has the most trouble with. I made a dummy variable restricting those with no debt and those with primarily mortgage debt to 0 and those with primarily nonmortgage types of debt to 1. Making an interaction variable with these two dummies, however, does not have the same effect as the interaction variables in 2001 and 2003, and the regressor is statistically insignificant. There are two possible reasons for this. First, it could be a problem with the interaction variable. It is not defined in the same manner as the 2001 and 2003 interaction variables because I cannot get a quantitative measure of debt. Second, it may be that those with high debt and low income were able to turn their financial situation around during the nine years between 1996 and 2005.

To see if my measure of debt is causing the problem, I try the 1994 variable "S307: VDEBT94 (1994$)" to measure the value of nonmortgage debt. I assume that 1994 debt is sufficiently close to a would-be measure of 1996 debt, and that the two year difference should not have a large effect. Creating a new interaction variable for low income and high debt, the regressor is significant at the 5% level with a coefficient of roughly 0.052. It appears that respondents with low income and high nonmortgage debt in 1996 tended to have higher LTVs in 2005. This further supports the continued role of LTV as a measure of loan quality during the boom (specifically in 2005).

(9) Money Problems in 1996

One of the variables unique to 1996 is "ER8841: G115 MONEY PROBLEM MNTN1." The survey question asks whether respondents were unable to pay bills on time, unable to obtain a loan to consolidate debts, had a creditor call to demand payment, had wages garnished by a creditor, or had a lien filed on their property. I make this a dummy variable with 1 being a "yes" answer to one of the above money problems and 0 being a "no" answer to all. Those with money problems in 1996 are estimated to have a 2005 LTV about 0.048 higher than those who did not. The fact that money problems variable is a significant predictor of 2005 LTV is not too surprising considering money problems and poor credit go hand in hand. Nevertheless, it is an additional risk representative predictor that is reflected by LTV during the boom era.

(10) Ever Bankrupt Pre-1996

Another variable unique to the 1996 survey is the number of times a respondent filed for bankruptcy: "ER8916: G134 # BANKRUPTCIES." While bankruptcies are not common (at least they were not so common 10 years ago), they are likely to be indicative of poor financial responsibility. I make a dummy variable in which any number of bankruptcies is set to 1 and no bankruptcies is set to 0. I feel it is okay to equate respondents with more than one bankruptcy to those with only one because there are only three respondents in the sample with 2 bankruptcies and one respondent with 3. Although having filed for bankruptcy is a significant predictor of higher LTV in many of the test regressions I ran for this project, it becomes insignificant once I make the correct change in my education variable (as explained above). Running a separate regression, I find that education in 2005 is a significant predictor of previous bankruptcy, partly explaining why bankruptcy becomes insignificant. It is important to note in the main regression above, however, that the p-value for bankruptcy is not very large (0.121), and that the estimated effect is quite large (0.058), suggesting previous bankruptcies may have some predictive power for 2005 LTV. Another reason to believe bankruptcy has an effect is that it is a proxy for financial trouble, and all other measures of financial trouble thus far appear to be good predictors of a high LTV.

Inconsequential and Unusable Predictors

I incorrectly predicted that two additional regressors would have an effect on LTV: house value and number of rooms in the house. Holding income and debt constant, I predicted that house value would have a negative effect on LTV. I hypothesized that homeowners with larger houses are able to purchase those homes because they can better manage their money and are more financially responsible. Regressing LTV on house value, I find that while house value is significant, the estimated effect is extremely small (-9.9*10^-9). This suggests that having an expensive home is not a deterrent to borrowing, and that wealthy and non-wealthy homeowners assume proportionate amounts of debt. I then tried regressing LTV on the number of rooms in the house to verify my findings on house value (under the assumption that the number of rooms is a proxy for house value in that the more expensive a home, the more rooms it will have). Number of rooms has small coefficient and a very large p-value, and therefore is a poor predictor of LTV, as well. I hypothesize that the poor predictive power of these two regressors is due in part to the housing bubble; while house value may have indicated wealth and ability to pay in the past, just about anyone could get a loan for a house outside their means during the boom.

I also predicted that loan rejections and property liens, two variables unique to 1996, would effect 2005 LTV in the same way money problems and bankruptcies do. I am unable to use these regressors, however, because of very small sample sizes. The sample of those in 1996 who had a loan rejected on the same property was 33, and of those 33 none had obtained or refinanced their current loan as recently as 1995 or 1996—a key component of the updated LTV measure. Similarly, previous liens make up a relatively small sample in 1996, and an even smaller sample when restricting to those who obtained or refinanced loans within 1995.

<u>Cross Section Analysis: 1996 LTV regression</u>

I run a similar analysis for LTV in 1996. My motivation here is to see if 2005 LTV regressors have similar predictive power for LTV in 1996. Because LTV is viewed traditionally as a measure of loan quality, I predict the regressors in 1996 will have similar coefficients on LTV. If the effects of the regressors are notably different, it might suggest that the 2005 regressors are unique to the subprime boom, and possibly that 1996 LTV was not an accurate measure of loan quality. In this regression, 1996 LTV is regressed on age, children, race, whether the loan is original or refinanced, an interaction of low income and high non-mortgage debt in 1996, money problems, and bankruptcies pre-1996. I restrict these variables in the same manner as I do for 2005.

I must note that this regression does not exactly mirror the 2005 regression. I exclude the interaction of low income and high debt for 2001 and 2003. They are excluded because the purpose of this regression is to see which past or present characteristics of homeowners predict their present LTV (present being 1996 in this regression).

Regression 1996 (A): Predictors of 1996 LTV (all regressors)

LTV (1996) = $\beta_0 + \beta_1$ Age (1996) + β_2 Education 1996 + β_3 Children (1996) + β_4 Race (1996) + β_5 If Original Loan (1996) + β_6 Low Income & High Debt (1996) + β_7 Money Problems (1996) + β_8 Ever Bankrupt (1996) + u

Observations = 496
R^2 = .1829

Independent Variables	Coefficient	Standard Error	T	P-Value
Age 1996	-.0050173	.0009122	-5.50	0.000
Education 1996	-.0004299	.0194672	-0.02	0.982
Children 1996	-.0025127	.0085048	-0.30	0.768
Race 1996	.0186401	.0539545	0.35	0.730
If Original Loan 1996	.1368335	.0212597	6.44	0.000
Low Income & High Debt 1996	.0114997	.025783	0.45	0.656
Money Problems 1996	.0188855	.0214325	0.88	0.379
Ever Bankrupt 1996	-.0239414	.038777	-0.62	0.537
Constant	.8304633	.0506936	16.38	0.000

Legend: (Dependent) LTV 1996: greater than 0, less than 2; (1) Age 1996: values between 21 and 95; (2) Education 1996: 1 if more than 12 years of education, 0 if 12 or less years (3) Children 1996: values between 0 and 18; (4) Race 1996: 1 if white, 0 if nonwhite; (5) Original Loan 1996: 1 if original loan, 0 if loan has been refinanced; (6) Low Income & High Debt 1996: 1 if income<$50,000 and nonmortgage debt>$5,000, 0 otherwise; (7) Money Problems 1996: 1 if any money problems, 0 if none; (8) Ever Bankrupt 1996: values between 0 and 3.

I compare the 2005 and 1996 regressions [2005(A) and 1996(A)] in the following chart. Also included are 2005 and 1996 regressions excluding loan status. The explanations and analysis follow.

Comparison of LTV Regressors in 2005 and 1996[1]

	Explanatory Variable	2005(a)	2005(b)	1996(a)	1996(b)
Demographics	Age	-.003*** (.001)	-.004*** (.001)	-.005*** (.0009)	-.006*** (.0008)
	Education	-.050*** (.019)	-0.39** (.020)	-.0004 (.019)	.013 (.020)
	Children	.022** (.009)	.017* (.009)	-.003 (.009)	-.003 (.009)
	Race	-.058*** (.022)	-.058** (.023)	.019 (.054)	.086 (.054)
Type of Loan	Original/Refinanced	.098*** (.019)	<>	.137*** (.021)	<>
Financial Problems	Low Income / High Debt 2003	.057*** (.019)	.052** (.020)	--	--
	Low Income / High Debt 2001	.063*** (.019)	.076*** (.021)	--	--
	Low Income / High Debt 1996	.052** (.022)	.065** (.023)	.011 (.026)	.012 (.027)
	Money Problems 1996	.048** (.019)	.051** (.020)	.019 (.021)	.015 (.022)
	Ever Bankrupt pre-1996	.058 (.037)	.081** (.039)	-.024 (.039)	-.006 (.039)
R^2		.23	.19	.18	.12

(All variables have the same definitions and are restricted in the same manner across years, except for race. The US Census question regarding race changed between 1996 and 2005 to allow respondents to select more than one race. Professor Stafford states that this modification was not enough to change the underlying independent variable.) Values shown are the estimated coefficients with the standard errors in parentheses. ***significant at the .01 level; **significant at the .05 level; *significant at the .10 level; -- variable not available for selected year; <> variable dropped in selected regression

[1] See Appendix for individual regressions

A Comparison of Regressions 2005 (A) and 1996 (A)

Inconsistent Predictors

A comparison of regressions 2005 (A) and 1996 (A) with all regressors shows that education, children, race, an interaction of low income and high debt, money problems, and bankruptcies are significant for 2005 LTV but not 1996 LTV.

Education and the number of children are significant in 2005 but not in 1996. I do not have a theory as to why these two regressors are inconsistent. I hypothesized that these two demographic variables are consistent risk characteristics over time and should thus be reflected in 1996 LTV at the least. The more educated a homeowner is the more likely it seems they would understand the importance of financial responsibility. One would also think that holding income constant, increasing the number of children in a family will increase financial distress, irrespective of time period or housing era.

Race may be insignificant for a few reasons. The first is that predatory lending was probably not a very significant factor in 1996. If predatory lending caused the majority of racial disparity in LTV in 2005, it might explain why race is not a significant predictor for LTV in 1996. In other words, controlling for income and debt in 1996, there may not be additional race-specific factors to explain LTV. A second potential reason race is insignificant is the change in the U.S. Census race question after 2000. Respondents are now told to check as many race categories that apply, whereas in 1996 they were only asked to check one. This could potentially increase the number of nonwhite respondents post 2000 and thus affect the significance levels. The third, and most probable reason, is that the race variable for these two years seems to be coded differently in the PSID. In 2005, 0 codes are for “wild codes,” whereas in 1996 0 codes are used if it is not a new head in the family unit. The 2005 race variable does not seem to have this restriction, which might point to the change in significance.

The insignificance of the interaction of low income and high debt in 1996 can be explained in two ways. One possibility is that LTV in 1996 was uninfluenced by financial factors in general; having high income and no debt did not cause one's LTV to be low, and having low income and high debt did not cause one's LTV to be high. This explanation would weaken Epley, Liano and Haney's conclusion that LTV was historically an accurate measure of loan quality, and would thus weaken the underlying assumption of this paper. However, I do not believe this regressor is insignificant because LTV was not a good measure of loan quality in 1996. Instead, a more likely explanation is that those with both low income and high debt were ineligible for home loans in the first place. Banks in the 1990's were not nearly as lenient with credit history as in the 2000's, and it was probably near-impossible to approve an applicant with income under $50,000 and debt over $5,000.

The variables measuring money problems and bankruptcies for 1996 are also insignificant, and likely for the same reason. Unlike in 2005, 1996 credit history requirements were much more stringent. In 1996, having serious money problems such as phone calls from creditors or having previous bankruptcies most likely prevented these respondents from even obtaining a home loan.

I believe that the failure of the interaction variable, money problems, and bankruptcies to predict 1996 LTV helps explain an important facet of the subprime era. While borrowers with these characteristics most likely had high LTVs in 2005, it looks as if the same borrowers ten years earlier would not have been eligible for a home loan in the first place.

Consistent Predictors

Of the seven regressors in the 1996 (A) LTV regression that remain the same from the 2005 (A) LTV regression, only two have consistent effects in 1996: age and whether the loan is original or refinanced. Below is the 1996 LTV regression labeled “1996 (C)” with only these two regressors. The R-squared remains virtually the same in Regressions 1996 (A) and 1996 (C) [0.1829 and 0.1808, respectively], which shows that age and whether the loan was original or refinanced account for nearly all of the explained LTV in Regression 1996 (A).

Regression 1996 (C): Predictors of 1996 LTV (including only significant regressors)

LTV (1996) = $\beta_0 + \beta_1$ Age (1996) + β_2 Original Loan (1996) + u

Observations = 501
R^2 = .1808

Independent Variables	Coefficient	Standard Error	T	P-Value
Age 1996	-.0051062	.0008615	-5.93	0.000
If Original Loan 1996	.137668	.0206777	6.66	0.000
Constant	.8379946	.0417092	20.09	0.000

Legend: (Dependent) LTV 1996: greater than 0, less than 2 (1) Age 1996: values between 21 and 95; (2) Original Loan 1996: 1 if original loan, 0 if refinanced.

Age is a significant predictor of LTV in 1996 probably for the same reason it is significant in 2005; older homeowners have been in the housing market longer and are thus more likely to assume less debt because they understand the importance of financial responsibility. The regressor is significant at the 1% level and the estimated effect on LTV is -0.0051, considerably larger than the 2005 age estimate (-0.0034). This is likely the case because in 2005, the old and young alike had blind faith in ever increasing house values.

The second consistent predictor of LTV is loan status. The estimated effect of having an original loan as opposed to a refinanced loan on 1996 LTV is 0.14 at a 1% level of significance. As I explain in the 2005 regression, I hypothesize that original loan status is a risk characteristic because the borrower is not a tested homeowner and that it is an indirect measure of age. In addition, homeowners that refinance operate under loan terms with an updated house value, whereas homeowners under original loan terms do not. The reason the estimated effect appears larger for 1996 than for 2005 is most likely because I do not control for as many variables in the 1996 regression as in the 2005 regression.

A Discussion of Regressions 2005 (B) and 1996 (B)

For these two regressions I removed the regressor "if original loan." I do this to test my earlier hypothesis that loan status reflects an economic age effect. My belief is that homeowners with original loans tend to be younger than those with refinanced loans because they either have not made enough payments on their initial mortgage to refinance or they have not established worthy enough credit. Removing this regressor increases the effect of age on LTV in both regressions, suggesting this hypothesis is correct. In addition, the significance of age in the 2005 regression increases slightly and stays the same in the 1996 regression.

An Additional Predictor: Previous Lender Experience

A variable unique to 1996, "ER7066 "A27D PREV EXP LENDR 1 M1," is added in Regression 1996 (D). The PSID survey question asks whether the respondent has previous experience with the lender who worked their current home loan, and if so, what type of previous experience. I use it as a dummy variable with 1 being a yes answer to any of the types of previous lender experience and 0 being a no answer to all.

Regression 1996 (D): Predictors of 1996 LTV (now including previous lender experience)

LTV (1996) = $\beta_0 + \beta_1$ Age (1996) + β_2 Original Loan (1996) + β_3 Previous Lender Experience + u

Observations = 501
R^2 = .2313

Independent Variables	Coefficient	Standard Error	T	P-Value
Age 1996	-.0050366	.0008355	-6.03	0.000
Original Loan 1996	.1031294	.0209411	4.92	0.000
Previous Lender Experience 1996	-.110775	.0193825	-5.72	0.000
Constant	.902436	.0419857	21.49	0.000

Legend: (Dependent) LTV 1996: greater than 0, less than 2; (1) Age 1996: values between 21 and 95; (2) Original Loan 1996: 1 if original loan, 0 if refinanced; (3) Previous Lender Experience 1996: 1 if any previous experience with the lender, 0 if no previous experience.

The R-squared increases a considerable amount from the regressions 1996 (A) and (C) (an increase of about 0.05). The regressor is significant at the 1% level and has an estimated effect on 1996 LTV of -0.111. There are three probable reasons previous lender experience has such a large and negative effect on predicted LTV. First, a lender who knows the borrower may be more likely to help work the borrower's finances; a personal relationship increases the chance that the lender will deal the best loan terms. Second, having experience with a lender means the individual has experience borrowing. In addition to spotting fair and abusive loan terms, experienced borrowers will be less likely to assume unnecessary debt, especially in 1996 when there was less incentive to do so. Third, an individual with previous lender experience represents a stable, responsible customer who is able to make payments. The lender will thus be more likely to deal the borrower favorable loan terms.

Cross Section Analysis: 1996 Fixed Rate vs. Variable Rate

The reason I take special interest in fixed versus adjustable rate mortgages is the implications for adjustable rate borrowers post crash. As data collected by David Berson in the 2006 Economic Outlook shows, an increasing number of subprime mortgages were adjustable rate mortgages: subprime ARM percentages rose from 65% in 2003 to 74% in 2004 to 82% in 2005 (Berson 2006 Figure 21, pg 312). The danger of adjustable rate mortgages is that in a time of tightened credit like the markets are experiencing now, refinancing becomes difficult. As Berson puts it, "While payment option ARMs have the lowest payments for the first several years, they also have the potential for the largest ultimate increase in payment—as well as the likelihood of negative amortization" (313). As subprime borrowers begin to hit their two or three year rate resets because of the inability to refinance, they will begin to realize large payment increases. Berson gives an example of the exorbitant rate hikes subprime borrowers are likely to experience: "The large number of two-year ARMs originated in 2003, for example, would have upward rate adjustment this year averaging 232 basis points—bringing the average rate up to 10.03 percent. On a $100,000 mortgage, this would increase the monthly principle and interest payment by about 23 percent—a substantial payment shock to a population perhaps least able to afford such a large increase" (Berson 2006, pg 312). Subprime borrowers were thus taking a large risk in choosing variable over fixed rate mortgages.

In his FED article "The Past, Present, and Future of Subprime Mortgages," Shane Sherlund stresses that these rate resets are only a recent problem, and are likely a contributing factor to the observed defaults and delinquencies. He says, "The generally favorable economic environment during 2004-2006, including above- average house price appreciation, relatively low interest rates, and low unemployment, may have masked potential performance problems associated with less stringent mortgage underwriting and mortgage rate resets. Homeowners having difficulty making mortgage payments or facing higher mortgage payments due to mortgage rate resets could easily refinance or sell their homes. Once house price appreciation slowed considerably (and turned negative in many locations) and underwriting subsequently tightened considerably, homeowners were less able to refinance or sell their homes, leading to increased risks of default." (3)

Unfortunately, the only fixed and adjustable rate mortgage variables found in the PSID are in 1996, before the subprime era. Nevertheless, they can be useful for predicting the characteristics of adjustable rate borrowers. In this 1996 cross sectional analysis I try to model the predictors of fixed and variable (also known as adjustable) rate mortgages in 1996. I use the variable "ER7046: A25A FXD OR VAR INT MOR1" as a dummy variable, setting those with fixed rate mortgages (FRM) to 1 and those with adjustable rate mortgages (ARM) to 0. The PSID does not specify what type of variable rate this is. I do not think these variable rates are the same "teaser" adjustable rates that are common to the subprime era. Teaser rates are characterized by an initial low fixed rate for two to three years followed by 25 or so years of higher adjustable rates. Since this variable is unique to 1996, I believe it is specifying a traditional floating variable rate, one that follows the prime rate. Whether traditional or teaser, I predict that adjustable rate borrowers in 1996 will have characteristics similar to subprime borrowers because ARMs are more risky than FRMs. I believe variable rate holders have a higher propensity to assume risk because they are in effect following an unknown future prime rate. To test this prediction I regress the rate type dummy variable on money problems, high nonmortgage debt, low income, 1996 LTV, and whether or not the respondent has a college degree.

Regression: Predictors of Loan Type in 1996—FRM vs. ARM

Fixed Rate (1996) = $\beta_0 + \beta_1$ Money Problems (1996) + β_2 High Debt (1994) + β_3 Low Income (1996) + β_4 LTV (1996) + β_5 College Degree (1996) + u

Observations = 567
R^2 = .0138

Independent Variables	Coefficient	Standard Error	T	P-Value
Money Problems 1996	-.0194215	.0371142	-0.52	0.601
High Debt 1994	-.043045	.0353946	-1.22	0.224
Low Income 1996	-.0842559	.0346014	-2.44	0.015
LTV 1996	-.0039859	.0696968	-0.06	0.954
College Degree 1996	.0960968	.1556746	0.62	0.537
Constant	.8610645	.0575023	14.97	0.000

Legend: (Dependent) Fixed Rate or Adjustable Rate 1996: 1 if fixed rate, 0 if variable rate; (1) Money Problems 1996: 1 if any money problems, 0 if none; (2) High Debt 1994: 1 if nonmortgage debt>$5,000, 0 otherwise; (3) Low Income 1996: 1 if income<$50,000, 0 otherwise; (4) LTV 1996: values between 0 and 2; (5) College Degree 1996: 1 if received college degree, 0 if no degree.

My regression shows that only one of these five regressors is significant. I postulated that money problems, nonmortgage debt, and LTV would predict rate type because they are indicative of risk taking and variable rate holders are taking a risk. However, these three predictors are insignificant. For the sake of double-checking LTV as a good regressor, I calculate the average weighted LTVs for fixed and variable rate holders in 1996. I find that the average LTV is nearly identical for the two rate types: 0.679 for fixed rates and 0.670 for variable rates. This confirms that there is no apparent relationship between type of rate and LTV in 1996. I also postulated that education would predict type of mortgage because educated respondents are potentially less risky and will thus tend towards fixed rates. This predictor is also insignificant, suggesting that type of mortgage rate is unaffected by level of education.

The only significant predictor in this regression is low income. The coefficient is -0.084, suggesting that respondents with low income are about 10% more likely to have a fixed rate mortgage than those with high income. This result is intuitive; those with more money are more likely to follow and understand the markets, thus increasing their propensity to choose a rate that adjusts to the prime rate. However, I must note that the adjusted R-squared is very small in this regression, suggesting that income does not do a great job explaining fixed versus variable rates.

Conclusions

Before securitization, lenders held all the risk when making loans. They had to know the borrower and had to form relationships of trust to ensure credibility. But with the creation of standardized financial assets like MBS's and CDO's, the risk was lifted from lenders and spread among a multitude of investors. This decreased—and in many cases completely eliminated—risk on the part of lenders in turn decreased their incentive to form relationships. This lack of lender-borrower relations, severely slackened underwriting, and lack of government regulation led to unsafe loan-to-value ratios held by borrowers with risky characteristics.

While the recent housing bubble was certainly characterized by increased levels of borrowing by *all* homeowners, it appears it was the subprime borrowers who fueled the boom and led to its crash. As I discover from my use of the PSID, high loan to value ratios consistently reflected risky, subprime borrower characteristics throughout the bubble. Gramlich says, "While all income groups have participated in this new opening up of the mortgage market and rise in homeownership, low- and moderate-income households and racial and ethnic minorities have been at the center of the boom" (3). If subprime borrowers were the primary fuel for the housing bubble and loan to value ratios reflected this, why was loan to value ratio altogether abandoned? Its ability to measure loan quality is consistent throughout history, and my research shows it retained this ability throughout the boom. The answer points to lender opportunism—with the risk clearly off their shoulders, they had no problem making these loans anymore. Lenders certainly realized these loans held much more risk than in the past, but investors were now burdened with the danger. It appears that lack of regulation in the housing market was a major factor in the recent crash. While the advantages to the housing boom were great, such as homeownership increases across all demographics, the role of loan to value ratio as a measure of loan quality should have been a red flag for the FED in 2001 and 2002 as loan to value ratios began their sharp increase. Loan to value ratio should not be abandoned as a risk signaler in the future if we wish to avoid another housing crash.

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Appendix of Regressions

Regression 2005 (A): Predictors of 2005 LTV (all regressors)

Source	SS	df	MS
Model	7.05851926	10	.705851926
Residual	22.6198532	534	.042359276
Total	29.6783725	544	.054555832

Number of obs	545
F(10, 534)	16.66
Prob > F	0.0000
R-squared	0.2378
Adj R-squared	0.2236
Root MSE	.20581

(D)	LTV_05	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
(1)	Race_05	-.0583341	.0224468	-2.60	0.010	-.1024289	-.0142393
(2)	Age_05	-.0034371	.0010058	-3.42	0.001	-.0054129	-.0014613
(3)	Educ_05	-.0500581	.0193301	-2.59	0.010	-.0880304	-.0120858
(4)	Children_05	.0216792	.0088851	2.44	0.015	.0042253	.0391332
(5)	If_Original_05	.0976973	.019248	5.08	0.000	.0598862	.1355083
(6)	IncDebt_03	.0565645	.0194643	2.91	0.004	.0183284	.0948006
(7)	IncDebt_01	.0627981	.0197109	3.19	0.002	.0240776	.1015185
(8)	IncDebt_96	.0516556	.0223035	2.32	0.021	.0078422	.095469
(9)	MoneyProb_96	.048255	.0194018	2.49	0.013	.0101417	.0863682
(10)	Bankrupt_96	.0580331	.0374057	1.55	0.121	-.0154472	.1315134
	_cons	.7517548	.0594707	12.64	0.000	.6349297	.86858

Regression 2005 (B): Predictors of 2005 LTV (without loan status)

Source	SS	df	MS
Model	6.82438733	9	.758265259
Residual	27.9361109	570	.049010721
Total	34.7604982	579	.060035403

Number of obs	580
F(9, 570)	15.47
Prob > F	0.0000
R-squared	0.1963
Adj R-squared	0.1836
Root MSE	.22138

(D)	LTV_05	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
(1)	Age_05	-.0039955	.0010235	-3.90	0.000	-.0060059	-.0019852
(2)	Educ_05	-.0390934	.0200414	-1.95	0.052	-.0784575	.0002707
(3)	Children_05	.0165084	.0092404	1.79	0.075	-.001641	.0346578
(4)	Race_05	-.05854	.0233313	-2.51	0.012	-.1043658	-.0127141
(5)	IncDebt_03	.0518364	.0202778	2.56	0.011	.012008	.0916648
(6)	IncDebt_01	.0763743	.0205011	3.73	0.000	.0361074	.1166413
(7)	IncDebt_96	.065613	.0233866	2.81	0.005	.0196786	.1115473
(8)	MoneyProb_96	.0510732	.0201486	2.53	0.012	.0114986	.0906478
(9)	Bankrupt_96	.081299	.0387335	2.10	0.036	.0052211	.1573769
	_cons	.7866804	.061085	12.88	0.000	.6667013	.9066595

Regression 1996 (A): Predictors of 1996 LTV (all regressors)

Source	SS	df	MS
Model	4.82550109	8	.603187637
Residual	21.5584453	487	.044267855
Total	26.3839464	495	.053300902

Number of obs	496
F(8, 487)	13.63
Prob > F	0.0000
R-squared	0.1829
Adj R-squared	0.1695
Root MSE	.2104

(D)	LTV_96	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]

(1) Age_96	-.0050173	.0009122	-5.50	0.000	-.0068096	-.0032251
(2) Educ_96	-.0004299	.0194672	-0.02	0.982	-.0386799	.0378201
(3) Children_96	-.0025127	.0085048	-0.30	0.768	-.0192234	.0141979
(4) Race_96	.0186401	.0539545	0.35	0.730	-.0873722	.1246523
(5)IfOriginal_96	.1368335	.0212597	6.44	0.000	.0950615	.1786055
(6) IncDebt_96	.0114997	.025783	0.45	0.656	-.0391599	.0621593
(7) MoneyProb_96	.0188855	.0214325	0.88	0.379	-.023226	.060997
(8) Bankrupt_96	-.0239414	.038777	-0.62	0.537	-.1001322	.0522494
_cons	.8304633	.0506936	16.38	0.000	.7308582	.9300684

Regression 1996 (B): Predictors of 1996 LTV (without loan status)

Source	SS	df	MS		
				Number of obs =	564
				F(7, 556) =	11.13
Model	4.28738578	7	.612483682	Prob > F =	0.0000
Residual	30.5919882	556	.055021561	R-squared =	0.1229
				Adj R-squared =	0.1119
Total	34.8793739	563	.061952707	Root MSE =	.23457

(D) LTV_96	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
(1) Age_96	-.0069866	.0008885	-7.86	0.000	-.0087318	-.0052414
(2) Educ_96	.0125599	.0202123	0.62	0.535	-.0271419	.0522616
(3) Children_96	-.0031498	.0089059	-0.35	0.724	-.020643	.0143434
(4) Race_96	.0860546	.0544395	1.58	0.115	-.0208777	.1929869
(5) IncDebt_96	.0117955	.026624	0.44	0.658	-.0405004	.0640914
(6) MoneyProb_96	.0153919	.0219114	0.70	0.483	-.0276474	.0584311
(7) Bankrup_96	-.006056	.0394375	-0.15	0.878	-.0835208	.0714088
_cons	.9761944	.0449278	21.73	0.000	.8879455	1.064443

Regression 1996 (C): Predictors of 1996 LTV (including only significant regressors)

Source	SS	df	MS		
				Number of obs =	501
				F(2, 498) =	54.95
Model	4.78269825	2	2.39134913	Prob > F =	0.0000
Residual	21.6731201	498	.043520322	R-squared =	0.1808
				Adj R-squared =	0.1775
Total	26.4558184	500	.052911637	Root MSE =	.20862

(D) LTV_96	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
(1) Age_96	-.0051062	.0008615	-5.93	0.000	-.0067989	-.0034135
(2) Original_96	.137668	.0206777	6.66	0.000	.0970417	.1782944
_cons	.8379946	.0417092	20.09	0.000	.756047	.9199423

Regression 1996 (D): Predictors of 1996 LTV (now including previous lender experience)

Source	SS	df	MS		
				Number of obs =	501
				F(3, 497) =	49.85
Model	6.11924336	3	2.03974779	Prob > F =	0.0000
Residual	20.336575	497	.040918662	R-squared =	0.2313
				Adj R-squared =	0.2267
Total	26.4558184	500	.052911637	Root MSE =	.20228

```
      --------------------------------------------------------------------------
(D)          LTV_96 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
      -------------+------------------------------------------------------------
(1)          Age_96 |  -.0050366   .0008355    -6.03   0.000    -.0066781    -.003395
(2)     Original_96 |   .1031294   .0209411     4.92   0.000     .0619854    .1442734
(3)  PrevLendExp_96 |   -.110775   .0193825    -5.72   0.000    -.1488568   -.0726932
              _cons |    .902436   .0419857    21.49   0.000     .8199447    .9849272
      --------------------------------------------------------------------------
```

Regression: Predictors of Type of Rate in 1996—FRM vs. ARM

```
      Source |       SS       df       MS              Number of obs =     567
-------------+------------------------------           F(  5,   561) =    1.57
       Model |    1.286908     5  .257381599           Prob > F      =  0.1676
    Residual |  92.1557728   561   .16427054           R-squared     =  0.0138
-------------+------------------------------           Adj R-squared =  0.0050
       Total |  93.4426808   566  .165093076           Root MSE      =   .4053

     ------------------------------------------------------------------------------
(D)    FRM_ARM_96 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
     -------------+----------------------------------------------------------------
(1)  MoneyProb96 |  -.0194215   .0371142    -0.52   0.601    -.0923213    .0534782
(2)     NMDebt_94 |   -.043045   .0353946    -1.22   0.224    -.1125671    .0264771
(3)    FAMINC_96 |  -.0842559   .0346014    -2.44   0.015      -.15222   -.0162919
(4)       LTV_96 |  -.0039859   .0696968    -0.06   0.954    -.1408845    .1329126
(5)   College_96 |   .0960968   .1556746     0.62   0.537    -.2096795    .4018731
            _cons |   .8610645   .0575023    14.97   0.000     .7481183    .9740106
     ------------------------------------------------------------------------------
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The Determinants of Consumer Sentiment in the Housing Market

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Duke Schaeffer

Introduction

The motivation for this research was to unearth some of the insights that might be gained from the consumer confidence research data in circulation, specifically regarding the housing market. Given the recent volatility and perceived importance of the housing market, we wanted to examine this confidence data to see what additional insight about market dynamics can be gained from this data set.

We primarily used the University of Michigan's Survey of Consumers to conduct our research. Our immediate purpose was not so much to use this data in order to predict real market trends or assess the accuracy with which consumers assess the market, but rather to unearth the determinants of consumer sentiment. In other words, what factors truly drive how consumers think of the markets, and how many of these factors are real or important, and how many are fictional or unimportant?

Our paper is divided in four sections. Section I introduces the structure of the Survey of Consumers and presents summary statistics of the relevant data. We introduce the basic data sets we use throughout the paper and indicate some of the operations we performed on the data to make it easier to analyze. Our discussion focuses on the general optimism in both buying and selling sentiment throughout the sample period, as this information is critical to understanding the rest of the findings throughout the paper. We postualte driving factors for the observed co-movement of buying and selling sentiment and break down the components of this co-movement. Also, in order to understand periods where summary buying and selling statistics were a little less defined, we look at some determinants for uncertainty in the housing market in order that we might better understand the data ascertained from the periods of relative sentimental certainty throughout the rest of the paper.

Due to similar patterns we found in buying and selling data, in Section II we compared the summary statistics further by looking at the reason response variables for each. These reason were the categorized responses consumers gave when asked why they believed it to be a good or bad time to buy or sell. After some analysis, we isolate interest rates and house prices as the two main determinants of consumer sentiment in the housing market, respectively. With this in mind, our group sought to first create variables that represented the consumer perceptions of these two quantities as they are translated into actual buying and selling sentiment. Once we created these variables, it became a priority to examine what market factors drove these specific perceptions, and specifically how closely they were related to the actual level of house prices and interest rates. When we discovered that this could not be undergone successfully throughout the whole period we studied (1992-2008), we looked for structural breaks in how consumer sentiment related to actual market fundamentals. After finding these important breaks, we generalized findings about how closely consumer sentiment follows market fundamentals and specifically looked into how well consumers account for inflationary effects when evaluating prices and interest rates.

In section III we attempt to explain the structural breakage found in Section II with underlying market factors and create a model that predicts consumer sentiment in the housing market over the entire fifteen-year scope of our data, clearing up all the muddying effects of earlier structural breaks.

In Section IV, we attempt to explain the inevitably of the recent housing crash due to the findings in this paper. Specifically, we focus on the disparity in price estimates people held when asked about buying and selling. When asked about buying, consumers disproportionately answered that prices were low, while when asked about selling, they tended to answer that prices were high (meaning that it was generally a good time to both buy and sell because of prices). We predicted that this unrestrained optimism, largely driven by deceptive mortgage terms, drove the price of housing upward as consumers continued to think that expensive houses were affordable, while sellers, though content with current price levels, upped their ask prices to accommodate the increased demand. This disparity continued at a very consistent level until the crash, when the trend reversed. We also look at the disparities in sentiment between homeowners and nonhomeowners.

I. "The Boom" – Consumer Sentiment Indexes and the Comovement of Buying and Selling Attitudes

The Survey

Buying and Selling Conditions Indexes

The most compelling component of the Survey of Consumers was the buying and selling conditions indexes. Each index was computed based on the response to the following set of questions (insert the appropriate buy/sell wording for the associated index):

(1) Generally speaking, do you think now is a good time or a bad time to buy/sell a house?

(2) Why do you say so? (Are there any other reasons)?

The second question was given in two parts where respondents would first answer the "why" question, and then later have to provide any additional reasons they could think of. Since respondents were allowed to cite multiple underlying reasons to their first response, the percentage of people in each group citing each reason would often add up to over 100%. Based on responses to this second question, the survey divided the reasons into 10 generalized categories or determinants (though an eleventh was added in November 1992).

The final buying and selling indexes are computed based on the response to the first question according to the following formula:

Buying/Selling Condition Index = (% good) – (% bad) + 100.

We focus on these indexes in the first section of this paper. Although this general index gives some insight into consumer sentiment, we were really interested in what drives this number. Thus, our research was considerably more focused on the second question, which is discussed in the second section of this paper.

Non-Response

Keep in mind that the index measure does not include in any way those who were uncertain of buying or selling conditions. Although data is collected on this subgroup, this sort of response is in no way counted toward the buying and selling conditions index. We do analysis on this subgroup later.

Time Scope of Buying and Selling Conditions Indexes

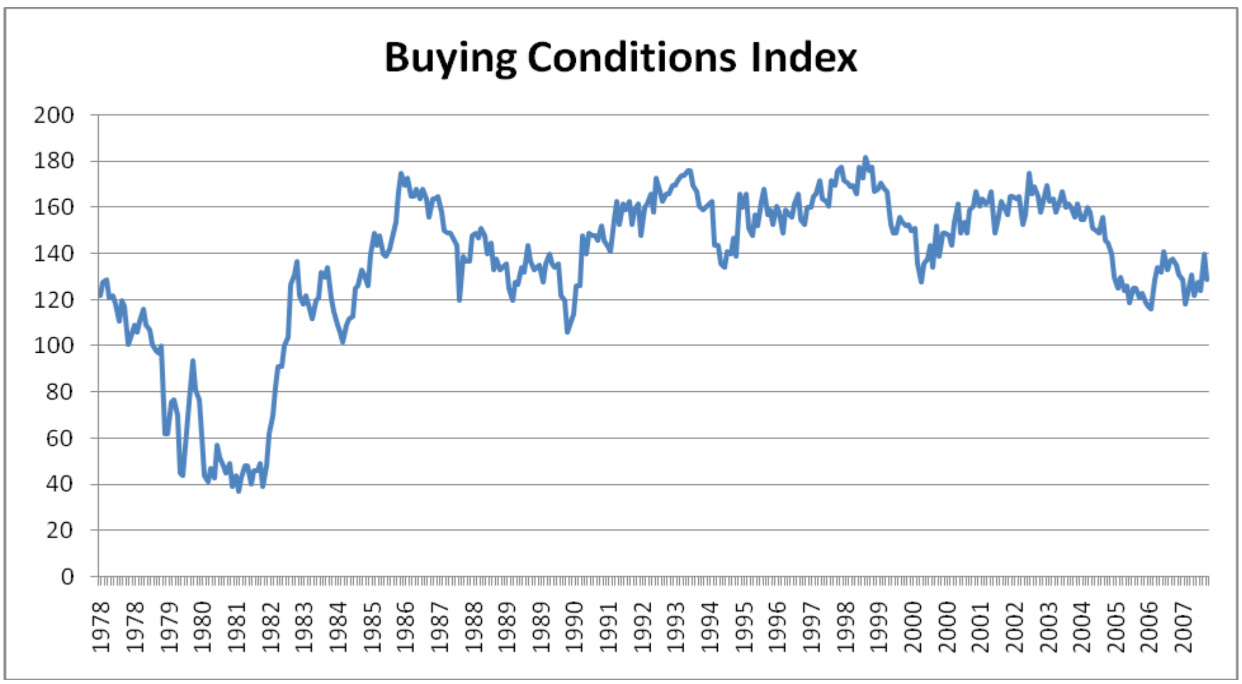
We were able to find this set of questions regarding buying conditions dating all the way back to January 1978, but selling conditions data was only available starting in November 1992. The most recent data available for both of these data sets was March 2008. Therefore, when we look at buying data alone, we use data back to 1978, but when we compare buying and selling data together, we use data going back only to 1992.

Analysis of Summary Statistics: Buying and Selling Sentiment Indexes

Summary of Home Buying Index (1978-2008)

Variable	Observations	Mean	Standard Deviation	Min.	Max
Home Buying Index	362	136.1961	33.53896	37	182

One might expect that when consumers answer the question of whether it's a good or bad time to buy a house, they are comparing current conditions some sort of market average. In this case, we would regularly expect that half of the time, people would respond that it is a relatively "good" time to buy, and the other half of the time, they would say it is a relatively "bad" time to buy. If this were the case, we would expect the mean of the buying index to equal 100, but this is not the case at all. As you can see from the Summary of the Home Buying Index above, the mean index over the thirty-year period is about 136. To test whether our average index value was statistically significantly different from 100, we constructed a 95% confidence interval and saw that it was (132.6, 139.6) (see Appendix Table 1.A for t-test). This finding basically states that, since 1978, the number of people who think it's a good time to buy a house outnumber those who think it's a bad time to buy a house by 36 percentage points on average, as shown below.



For purposes of comparison, we also wanted to include the buying index since 1992. We include it below:

Summary of Home Buying Index 1992-2008 (All Respondents)

Variable	Observations	Mean	Standard Deviation	Min.	Max
Home Buying Index	185	153.9568	15.50169	116	182

Our finding for buying sentiment from 1978-2008 is confirmed for buying sentiment from 1992-2008. The buying index is significantly greater than 100 (see Appendix Table 6.A).

We also took a look at the home selling index to see how it compared to buying sentiment. The data for selling did not go back as far as 1978, so we looked at the years 1992-2008.

Summary of Home Selling Index 1992-2008 (All Respondents)

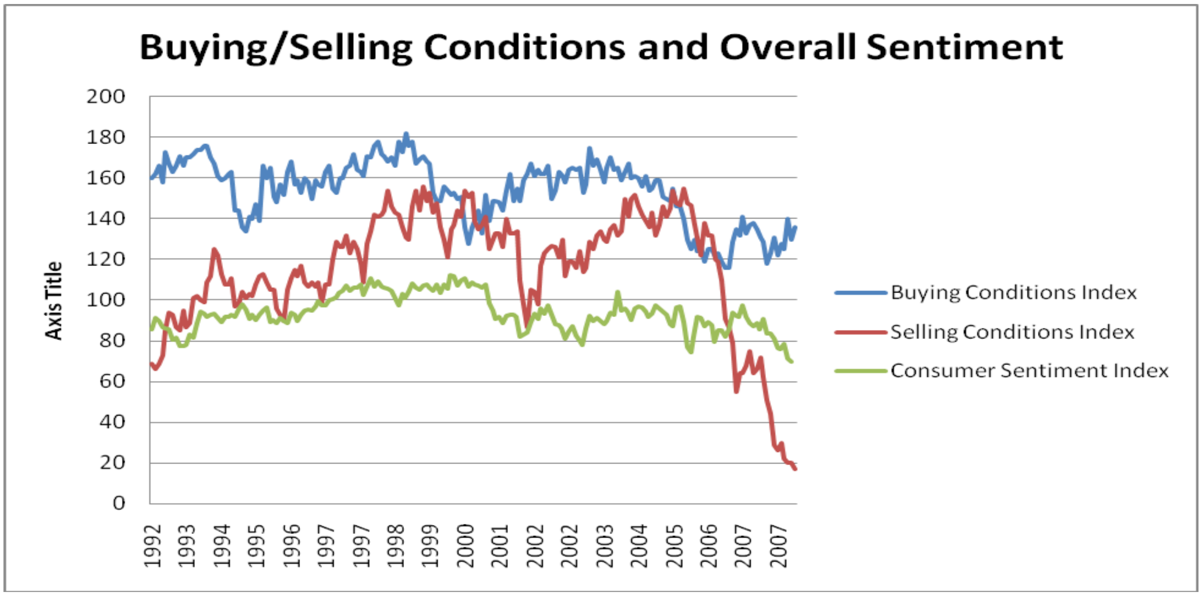
Variable	Observations	Mean	Standard Deviation	Min.	Max
Home Selling Index	185	118.9189	32.22136	14	164

As in the case of our buying statistic, we found a considerable consumer optimism regarding selling conditions over the 15-year span we studied. The mean of the selling conditions index appeared to be considerably higher than 100, so we constructed a 95% confidence interval to assure the statistical significance of this finding and found that it was indeed significant (114.7, 123.8) (see Appendix Table 11.A for t-test).

Co-Movement of Buying and Selling Sentiment

Analysis of Co-Movement

The fact that buying and selling sentiment are both overwhelmingly positive overtime raises an obvious question: why is it that consumers seem to think that it is simultaneously a good time to buy and sell a house? One would think that a certain set of conditions would favor the buyer, while another would favor the seller, so that there would be some perception of a zero-sum game, but this is clearly not the case. The graph below shows the relative levels of the buying and selling conditions index in the housing market.



Correlation Statistics (1992 to present)

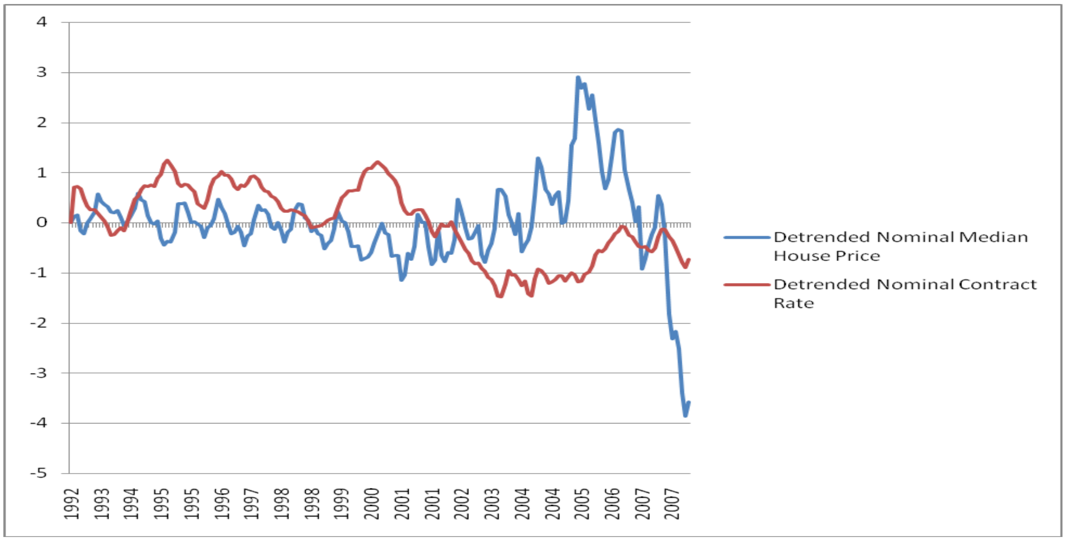
Buying Conditions and Selling Conditions	Buying Conditions and Overall Sentiment	Selling Conditions and Overall Sentiment
0.32300453	0.316826576	0.569059455

Interestingly, selling conditions seem to drive (or be driven by) overall consumer sentiment significantly more than buying conditions. We re-visit this phenomenon later in the paper, but for the moment, we focus primarily on the co-movement of the buying and selling conditions variable.

In line with it being a zero-sum game, our initial prediction was that buying and selling conditions would have a negative correlation, but not necessarily -1. It seems natural to assume a coefficient of slope of -1 when regressing buying and selling conditions because if one additional percent of people thinks it's a good time to buy a house, they would also think it a bad time to sell a house. However, this clearly does not play out in the data, as shown in the table above.

Reasons for Positive Correlation (Prices, Interest Rates, and Inventory/Sales)

One contributing factor to this phenomenon is that some of the reasons given for good buying and selling conditions overlap. For example, "low interest rates" is listed as a reason that it is a good time both to buy and sell a house, as is "good times ahead." Similarly, "high interest rates" and "bad times ahead" are both listed as reasons it is a bad time to both buy and sell a house. If respondents make their assessment of conditions based on a predetermined reason (this assumption is discussed and challenged later), then those who pick one of these overlapping reasons (i.e. "low interest rates" or "bad times ahead") will respond that the market is good (or bad) for both buying and selling. The identical use of interest rates for each sentiment could be explained as follows: lower interest rates make home loans more affordable. This shifts out the demand for housing. An increase in demand necessarily increases the price of houses, which makes it a better time to sell. This hypothesis is confirmed in the graph below, which shows that a decrease in interest rates leads an increase in price and that an increase in interest rates leads a decrease in prices.



The positive correlation may also be explained by business cycles. Over longer periods of time, during booms and recessions, we would expect the two indexes to trend together because they are both indicators of economic well-being (as evidenced by the "good/bad times ahead" response). In the shorter-term, there might still be a negative correlation between the two because a shock in house prices will have opposite ramifications for buying and selling conditions. This disparity between short- and long-term co-movement prompted us to look at buying and selling conditions over shorter periods of time.

When comparing buying and selling data (via scatterplot), we noticed a few structural breaks in the relationship over time. Therefore, we divided our data from 1992-2008 into four periods that had more well-defined relationships between buying and selling sentiment. We display the correlations below:

1992-1997 (55 months)	1997-2002 (60 months)	2002-2006 (41 months)	2006-2008 (28 months)
-0.0975	0.0173	-0.4441	-0.3852

Therefore, although there is a clearly positive long-term trend, the short-term data clearly shows that the relationship tends to be either negative or non-existent, depending on the era.

Another potential explanation for the co-movement of buying and selling sentiment is home inventory to sales ratio[2]. We predicted that when this ratio is high, houses are going unsold, leading to the perception that it is both a bad time to buy and sell. We collected inventory to sales data from the U.S. Census Bureau website to run the two regressions listed below: one of the home buying index on the

[2] Inventory to sales data obtained from the Census Bureau, http://www.census.gov/const/fsalmon.pdf

inventory to sales ratio and one of the home selling index on inventory to sales ratio. Looking at the regressions, the sign on the inventory-sales ratio is negative for both indexes; an increase in the inventory-sales ratio causes a decrease in the corresponding home sentiment index. This was consistent with our prediction. One interesting finding from these regressions is that the portion of selling sentiment explained by inventory to sales is much higher than that for buying sentiment—the r-square value is almost double for selling sentiment. The likely explanation is that the inventory-sales ratio is a direct reflection of ability to sell. A high inventory of homes necessarily means it is a bad time to sell because unsold homes are increasing. This likewise implies that it is a bad time to buy, but less directly: a high inventory for buyers could also represents more homes choices and lower prices, two encouraging factors for buying sentiment.

Regression of the Home Buying Index on the Inventory to Sales Ratio:

Home Buying Index = $\beta0 + \beta_1$ Inventory-Sales Ratio + u

Observations = 185

R^2 = .3605

Independent Variables	Coefficient	Standard Error	T	P-Value
Inventory-Sales Ratio	-6.308444	.6211043	-10.16	0.000
Constant	186.0275	3.287156	56.59	0.000

Regresion of the Home Selling Index on the Inventory to Sales Ratio:

Home Selling Index = $\beta0 + \beta_1$ Inventory-Sales Ratio + u

Observations = 185

R^2 = .6695

Independent Variables	Coefficient	Standard Error	T	P-Value
Inventory-Sales Ratio	-16.30928	.8469956	-19.26	0.000
Constant	198.4534	4.482671	44.27	0.000

Components of Co-Movement

To better understand the dynamics and underlying factors of the co-movement phenomenon, we decided to analyze the co-movement of the individual determinants (i.e. reasons responses) of overall sentiment to see if we could isolate the main drivers of this pattern. To complete this analysis, however, our group had to make a basic assumption:

(1) People enter the survey with a reason for why they think the market is good or bad, and this reason determines their overall sentiment.

We adopt this position over the logical alternative:

(1*) People take the survey with an underlying assumption of the overall goodness/badness of the market and then attempt to conjure up a reason as to why they feel this way.

This assumption allows us to look at the components of the co-movement as sorts of independent factors driving overall co-movement. We are hoping that these co-movements have a logical structure to them (they follow basic economic theory), so that we may isolate one or two intuitive reasons for the overall co-movement present in the data.

It's worth noting that the order of the questions in the survey, in some sense, forces survey-takers into the latter mode of thinking (statement 1*), which may pollute some of the data. We will assume for the time being that had survey-takers been asked the reasons for their sentiments first, that the overall sentiment statistics would remain largely unchanged (this assumes that survey-takers are somewhat decided in how they feel). This assumption will naturally be weaker in the years where the uncertainty statistic (those who answered neither "good" nor "bad") is relatively high.

Test of Independence of Factors

To test the previous assumption, we constructed a correlation matrix to analyze which reason variables tend to move together.

Correlation Matrix of Buying Response Reasons (1992 to 2008):

	Good-Low Prices	Good-Rising Prices	Good - Low Rates	Good-Rising Rates	Good-Good Investment	Good-Good Times	Bad -High Prices	Bad - High Rates	Bad -Can't Afford	Bad-Bad Times	Bad -Will Lose Money

Good- Low Prices	1.00										
Good- Rising Prices	-.43	1.00									
Good- Low Rates	-.07	-.12	1.00								
Good- Rising Rates	-.27	0.60	-.24	1.00							
Good- Good Investment	-.51	0.40	0.06	0.14	1.00						
Good- Good Times	-.30	0.43	0.15	0.19	-.004	1.00					
Bad- High Prices	-.06	-.005	-.7	0.05	0.12	-.41	1.00				
Bad- High Rates	0.18	-.10	-.85	0.18	-.22	-.32	0.71	1.00			
Bad- Can't Afford	0.43	-.32	-.71	-.06	-.20	-.57	0.67	0.80	1.00		
Bad- Bad Times	0.21	-.36	-.28	-.13	-.22	-.62	0.41	0.38	0.53	1.00	
Bad- Will Lose Money	0.36	-.18	-.61	.013	-.20	-.37	0.54	0.67	0.74	0.37	1.00

We looked at this correlation matrix first intending to determine whether the reasons were independent of one another or whether "good" reasons tended to move together even though they were seemingly unrelated. We figured that if our earlier assumption was true, then seemingly independent factors (such as "high prices" and "rising prices") would demonstrate no correlation, while things we know to be negatively correlated (such as "rising prices" and "rising interest rates") would demonstrate negative correlations even though they both indicate a good time to buy.

It turns out that there is always either an insignificant relationship or a significant movement together of "bad" reasons, and never any kind of significant opposite movement (see the bottom right portion of the matrix). We found something similar for the "good" reasons, except in the case of "low prices" which seems to be correlated with an increase in "bad" sentiment. When looking at the time series, this makes perfect sense because the lowest prices occurred at the most recent times, when buying sentiment was lowest.

In addition, we noticed that the strength of relationships between the "good time to buy" variables was far lower than the "bad time to buy" variables. The highest correlation found in the upper left corner of the triangle (good reasons) is 0.60, which is roughly the average correlation found in the bottom right corner (bad reasons).

Unexpectedly weak correlations: There are some variables we expected to have extremely strong correlations, such as "increasing prices" with "good investment" (0.40), and "high prices" with "low prices" (-0.06), that weren't so strong.

Unexpectedly strong correlations: Oddly enough, some of the strongest positive correlations in the matrix came from what we had earlier conjectured to be negatively correlated. Remember earlier that we showed that interest rates and prices tended to be inversely related because of the shift in demand caused by a movement in the interest rate. The "high prices" and "high interest rates" variables (0.71) as well as "high prices and "low interest rates" (-0.70), and "rising prices" and "rising interest rates" (0.60) were very surprising in both strength and sign.

Interesting relationship: "Can't afford" was considerably more strongly correlated with "high rates" (0.80) than it was with "high prices" (0.67). This is finding is not so surprising given what we found earlier in the paper that suggested that consumers consider interest rate to be a better determinant of housing cost than prices.

The above trends also hold true when looking at the data back to 1978, but the sign on the "low prices" correlations are fairly unique to this time period. However, the results of this correlation matrix throw a very difficult twist in our assumption about consumers taking the survey with a pre-conceived reason as to why conditions were good or bad, and then base their sentiment on this underlying reason. Due to the strong positive correlations among "bad" reasons with one another, (and "good" with the exception of "low prices"), even in the presence of supposedly opposite-moving factors (prices and interest rates), we are forced to conclude that consumers likely have a stronger sense of their general housing sentiment, but a weak sense of their reason for believing so.

This phenomenon is strong enough to cause opposite-moving factors (prices and interest rates) to appear to move together in the minds of consumers. In other words, if there is a general move toward good sentiment in buying conditions, there will be an increase in both the number of people who think interest rates and prices are low, even though these two measures will rarely ever move together..

Later we will explore how to measure this "consumer sentiment regarding housing price and interest rate" by creating variables to gauge this. But for the time being, it is worth remembering that consumers are more likely to move from a general sentiment to a specific reason rather than vice versa.

Uncertainty

When describing the summary statistics, we noted that our analysis was based on a small majority of the population that responded conclusively about their sentiment and gave at least one of the reasons listed in the table at the beginning. This small majority was somewhat disconcerting, so we wanted to gain some insight as to what caused consumer uncertainty regarding conditions in the housing market. Here uncertainty is defined as the percentage of people who answered neither “good” nor “bad” when asked about buying/selling conditions. We first decided to create an “agreement” statistic defined as the absolute difference between the percentage respondents responding “good” and “bad” when asked about overall buying/selling conditions in the housing market.

Agreement = Abs[(% Good) – (%Bad)]

The reason we call this “agreement” is because, if everyone agrees that the market is either “good” or “bad”, this measure will be 100, whereas if there is a 50-50 split (total disagreement), this measure is 0. Therefore, we surmised that this statistic is a good measure of market agreement. We were curious as to how much of consumer uncertainty was predicted by what we called a “neutral market”, or a situation where there was very low disparity between good and bad sentiments (i.e. high disagreement).

We predicted that as Agreement increased, then Uncertainty would decrease because it would be very clear to most consumers whether it was a good or bad time to buy a house. Therefore we decided regress the uncertainty statistic on the agreement statistic. Our prediction, therefore, is that we would find a significantly negative correlation between Agreement and Uncertainty.

Regression of Buying Uncertainty on Buying Agreement from 1978 to 2008:

Uncertainty = $\beta_0 + \beta_1$ Agreement + u

Observations = 361

R^2 = .0489

Independent Variables	Coefficient	Standard Error	t	P-Value
Agreement	-.0239088	.0055675	-4.29	0.000
Constant	5.604817	.2741501	20.44	0.000

Regression of Buying Uncertainty on Buying Agreement from 1992 to 2008:

Uncertainty = $\beta_0 + \beta_1$ Agreement + u

Observations = 185

$R^2 = .0315$

Independent Variables	Coefficient	Standard Error	t	P-Value
Agreement	.021229	.0086949	2.44	0.016
Constant	2.811309	.4880269	5.76	0.000

Regression of Selling Uncertainty on Selling Agreement from 1992 to 2008:

Uncertainty = $\beta_0 + \beta_1$ Agreement + u
Observations = 185
$R^2 = .0249$

Independent Variables	Coefficient	Standard Error	t	P-Value
Agreement	-.023158	.0107031	-2.16	0.032
Constant	7.516167	.3552452	21.16	0.000

We find this result to be evident in our buying data dating back to 1978, but not in the buying data dating back to 1992. However, the regression on selling data back to 1992 does yield a negative coefficient on disparity. We are not sure why the 1992 buying data does not confirm our hypothesis on uncertainty. Overall, we found that disagreement in housing market sentiments does a very poor job at explaining the amount of uncertainty we find in the market.

We also regressed buying uncertainty on selling uncertainty to see how much of each statistic was due to some “general uncertainty”.

Regression of Selling Uncertainty on Buying Uncertainty from 1992 to 2008:

Selling Uncertainty = $\beta_0 + \beta_1$ BuyingUncertainty + u
Observations = 185
$R^2 = .4191$

Independent Variables	Coefficient	Standard Error	t	P-Value
Buying Uncertainty	.9054306	.0788013	11.49	0.000
Constant	3.282296	.3441213	9.54	0.000

From this regression we found that about two-fifths of uncertainty in either buying or selling sentiment can be explained by a general sense of uncertainty in the housing market. The other three-fifths is buying- or selling-specific.

II. Consumer Misunderstanding—Determinants of Price and Interest Rate Sentiment

Analysis of Summary Statistics: Buying and Selling Sentiment Reasons

It's worth noting that the data we researched first grouped respondents into the general "good" or "bad" categories, and then evaluated their reasons conditional on which group they were in. It was much more convenient for our research purposes to instead have variables that told us the percentage who replied good or bad combined with the appropriate reason, out of the entire population rather than a particular subgroup. Therefore, we rescaled the data into "Population variables". For example, we created the variable:

```
"buy_pop_good_low prices" = (% good) * (% low prices | good) / 100.
```

The example above shows how, for any given month, we were given the percentage of respondents saying that buying conditions were favorable, as well the percentage of those people who cited low prices as the reason. We wanted to transform this variable so that we could interpret the total percentage of the population who thought it was a good time to buy a house because of low prices, and the formula is shown above.

We performed this rescaling for every variable, and then looked at the summary statistics. The results for the home buying response reasons from 1978 to 2008 are shown below.

Summary of Buying Response Reasons 1978-2008 (All Respondents)

Variable	Observations	Mean	Standard Deviation	Min.	Max
(1) Good- Low Prices	362	13.05616	8.338298	.54	38.64
(2) Good- Rising Prices	362	5.482486	3.619452	.6	22.2
(3) Good- Low Rates	362	29.39196	19.24012.18	.18	68.53

(4) Good- Rising Rates	362	5.035829	3.816781	0	18.2
(5) Good- Good Investment	362	4.348315	1.755616	.45	9.24
(6) Good- Good Times	362	3.251236	2.897664	0	12.18
(7) Bad- High Prices	362	5.172072	5.629905	.28	24.64
(8) Bad- High Rates	362	8.333122	14.54935	.07	65.57
(9) Bad- Can't Afford	362	2.36326	2.292392	.07	13.68
(10) Bad- Bad Times	362	1.075166	1.126029	0	6.84

Population percentages of buying response reasons:
(1) good time to buy: low prices (2) good time to buy: increasing prices (3) good time to buy: low interest rates (4) good time to buy: rising interest rates (5) good time to buy: good investment (6) good time to buy: good times financially (7) bad time to buy: high prices (8) bad time to buy: high interest rate (9) bad time to buy: can't afford (10) bad time to buy: bad times ahead.

Note that the sum of the means here only adds up to 77.5. This basically means that at any point in time, an average of 77.5% of the population had a definitive ("good" or "bad") opinion about the housing market that was based on the 10 reasons that the survey created categorical variables from. It is this 77.5% of the population that we do most of our analysis on.

From the Summary of Buying Response Reasons table above, since 1978, consumer sentiment regarding the favorability of buying conditions in the housing market is based foremost on interest rates, and secondly on prices. We determined this by looking at the relative sizes of the reason variables. To confirm this finding statistically, we ran four separate t-tests (see Appendix Tables 2.A – 5.A). First, we tested that the percentage of people who answered because of interest rates was higher than those who answered because of prices. Then we tested that the prices response was higher than the next highest response. We did this both for the group who responded "good" and the group that responded "bad". Every result was significant at the 1% level.

For comparison, we look at the buying statistics from 1992-2008:

Summary of Buying Response Reasons 1992-2008 (All Respondents)

Variable	Observations	Mean	Standard Deviation	Min.	Max
(1) Good- Low Prices	185	14.19005	7.140878	4.88	38.64
(2) Good- Rising Prices	185	4.816486	1.90458	.64	9.62
(3) Good- Low Rates	185	38.75124	15.43948	4.88	68.53

(4) Good- Rising Rates	185	5.650595	4.206029	0	18.2
(5) Good- Good Investment	185	4.997351	1.622359	1.24	9.12
(6) Good- Good Times	185	4.963027	2.996399	0	12.8
(7) Bad- High Prices	185	2.593784	2.440873	.28	11.7
(8) Bad- High Rates	185	1.927189	1.975157	.07	8.14
(9) Bad- Can't Afford	185	1.534216	1.365094	.07	6.93
(10) Bad- Bad Times	185	.5278378	.3665463	0	2.07
(11) Bad- Lose Money	185	.0953514	.1539657	0	.74

Population percentages of buying response reasons:
(1) good time to buy: low prices (2) good time to buy: increasing prices (3) good time to buy: low interest rates (4) good time to buy: rising interest rates (5) good time to buy: good investment (6) good time to buy: good times financially (7) bad time to buy: high prices (8) bad time to buy: high interest rate (9) bad time to buy: can't afford (10) bad time to buy: bad times ahead.

Our finding is confirmed for this 16 year period: consumer sentiment for buying conditions is based primarily on interest rates and prices (see Appendix Tables 7.A – 10.A for t-test confirmation).

We then look at the response reasons for home selling conditions:

Summary of Selling Response Reasons 1992-2008 (All Respondents)

Variable	Observations	Mean	Standard Deviation	Min.	Max
(1) Good- High Prices	185	9.518541	5.488996	.12	25.74
(2) Good- Falling Prices	185	1.01373	.8243005	0	4.38
(3) Good- Low Rates	185	12.03103	6.195115	.08	24.96
(4) Good- Rising Rates	185	1.150811	1.134632	0	4.5
(5) Good- Good Investment	185	2.289892	1.520742	0	8.14
(6) Good- Good Times	185	9.114108	5.095135	0	19.5
(7) Bad- Low Prices	185	9.544378	10.90258	1.14	55.2
(8) Bad- High Rates	185	2.367189	2.533822	.17	14.62
(9) Bad- Can't Afford	185	4.676973	5.051313	.28	28.16
(10) Bad- Bad Times	185	1.038703	1.109772	0	6.3
(11) Bad- Lose Money	185	1.902108	2.286148	0	13

Population percentages of selling response reasons:
(1) good time to sell: high prices (2) good time to sell: decreasing prices (3) good time to sell: low interest rates (4) good time to sell: rising interest rates (5) good time to sell: good investment (6) good time to sell: good times financially (7) bad time to

sell: low prices (8) bad time to sell: high interest rate (9) bad time to sell: can't afford (10) bad time to sell: bad times ahead (11) bad time to sell: lose money.

Here we found that consumers also base their sentiment of selling conditions primarily on interest rates and prices (see Appendix Tables 12.A – 15.A).

Note that the sum of the means for selling here only adds up to 54.6. This basically means that at any point in time, less than 54.6% of the population had a definitive ("good" or "bad") opinion about the housing selling market that was based on the 11 reasons that the survey created categorical variables from. We say "less than" because respondents were allowed to list multiple reasons, allowing for double-counting among these reasons. Therefore, it is on this 54.6% (or less) of the population that we do most of our selling conditions analysis.

Implications of Summary Buying and Selling Statistics

Once we statistically confirmed that interest rates and then prices are most important in determining consumer sentiment, we sought out a reason as to why consumers would place a sort of importance premium on interest rates over prices for buying conditions sentiment. Certainly both have a strong influence on the ultimate cost or affordability of housing. It seemed to us that consumers would tend to shy away from basing their opinion on the state of the market based a relatively stable measure of cost. It seemed more intuitive that consumers would base their opinions on something in the market that fluctuated considerably with differing economic conditions. Therefore, we hypothesized that the tendency to base sentiments on a certain measure reflected a general sense of perceived volatility of that measure by the consumer. As a result, we concluded that consumers likely consider interest rates to be a more volatile measure of housing cost than the house price itself.

To analyze the validity of this perception, we looked at the standard deviations of the national average contract mortgage rate and median real house price relative to their means. We only looked at data from 1992 to the present, since this is when we had data on both buying and selling sentiments, and these measures together were the basis of our last conclusion. Here is what we found:

Summary of Contract Rate and Real Median House Price 1992-2008

Variable	Observations	Mean	Standard Deviation	Min.	Max	(Std. Dev./ Mean)
Contract Rate	185	6.835351	.7271557	5.36	8.08	.1063816
Real Median	185	126370.1	17853.49	101827.3	167118.6	.1412794

House Price						

When we calculated the standard deviation relative to the mean for each rate, we found that the contract rate had a scaled standard deviation of 0.106 “means” and median house price had a scaled standard deviation of 0.141 “means”. In this sense, we found that, contrary to the suggestion of the relative importance of price and interest rates, house prices tend to be more volatile than interest rates according to this measure. This could be the first instance of consumer misunderstanding regarding the housing market.

Perceived Prices and Interest Rates

It became apparent very quickly that the two main components that influenced buying and selling sentiment in regards to the housing market were house prices and interest rates. It was clear that the perception of these factors was the main driving force in housing market sentiment. In order to compare perceptions against actual levels, however, we needed a variable that represented consumer perception of these two quantities, or at least determined how consumer attitudes indicated their perception of them.

It must be stressed that, although we used names like “Perceived Price” and “Perceived Interest Rate” for our variables, these are both significant misnomers. These variables do not measure how all consumers perceive the price level or interest rate level, but only how consumers are basing their general housing sentiments on prices and interest rates. For example, a consumer may think that prices are high, but that interest rates are so low that she still considers it a good time to buy a house. This person will only be counted in the “low interest rate” category, and not the “high price” category, since “high price” did not determine her overall sentiment. Therefore, there is a considerable lack of information if one chooses to interpret these as the actual perceived price or interest rate level, rather than how prices and interest rates are actually affecting housing sentiment.

We created the variables according to the following formulas:

Perceived interest rate = $[(Hb + Hs) - (Lb + Ls)]/2 + 100$

(1)Lb = % responding that is good time to buy a house because of low interest rates
(2)Hb = % responding that is a bad time to buy a house because of high interest rates
(3)Ls = % responding that is good time to sell a house because of low interest rates
(4)Hs = % responding that is bad time to sell a house because of high interest rates

Perceived Price = [(Hb + Hs) - (Lb + Ls)]/2 + 100

(1)Lb = % responding that is good time to buy a house because of low prices
(2)Hb = % responding that is a bad time to buy a house because of high prices
(3)Ls = % responding that is bad time to sell a house because of low prices
(4)Hs = % responding that is good time to sell a house because of high prices

Naturally, we were only able to construct these variables as such since 1992 because selling information was only available after this time. Like our other index variables, these have a potential range of 0-200 and take into account the level of prices and interest rates people perceive both in buying and selling. Below is a summary of these index variables and their components:

Summary of Perceived Price

Variable	Observations	Mean	Standard Deviation	Min.	Max
Perceived Price	185	94.12459	11.464	54.245	113.09

Summary of Perceived Price Components

Variable	Observations	Mean	Standard Deviation	Min.	Max
Selling- Good-High Prices	185	10.17703	5.729338	.08	26.52
Selling- Bad-Low Prices	185	9.531676	11.18047	.76	54.9
Buying- Good-Low Prices	185	14.72503	7.450776	4.96	39.2
Buying- Bad-High Prices	185	2.328865	2.250377	.24	9.9

(1) Population variable of those who say good time to sell because of high prices (2) Population variable of those who say bad time to sell because of low prices (3) Population variable of those who say good time to buy because of low prices (4) Population variable of those who say bad time to buy because of high prices.

Summary of Perceived Interest Rate

Variable	Observations	Mean	Standard Deviation	Min.	Max
Perceived Rate	185	75.18843	12.55559	54.065	104.44

Summary of Perceived Interest Rate Components

Variable	Observations	Mean	Standard Deviation	Min.	Max
Buying- Good-	185	40.14978	15.93903	4.96	69.3

Low Interest Rates					
Buying- Bad- High Interest Rates	185	1.754757	1.838939	.06	7.48
Selling- Good- Low Interest Rates	185	13.75049	7.088292	.08	29.64
Selling- Bad- High Interest Rates	185	2.382378	2.560822	.17	14.62

(1) Population variable of those who say good time to buy because of low interest rates (2) Population variable of those who say it is a bad time to buy because of high interest rates (3) Population variable of those who say good time to sell because of low interest rates (4) Population variable of those who say it is a bad time to sell because of high interest rates

Though we wanted to include all reason variables to construct our perceived interest rate for a more holistic view, note that the variables representing the percentage of individuals who think it's a good time to buy because of low interest rates and those who think it's a good time to sell because of low rates dominate this index measure (meaning it is almost always less than 100). Therefore, our perceived interest rate will be mostly a reflection of these two variables.

Consumer Compensation: Compounding Interest

We were afforded the option of using either the "contract" rate of interest (that which is visible on the loan itself) or the effective rate of interest in measuring the actual interest rate on housing[3]. The effective rate of interest seems to be an indicator of the final cost of a home because it accounts for compounding effects, but we were curious as to whether consumers based their decisions more on the contract rate because it is more visible. We decided to regress perceived interest rate on both of these measures to see if effective rate became a pretty useless predictor in the presence of contract rate (i.e. consumers pay no attention to compounding effects). We noticed a significant structural break in interest rate trends (more on this later), so we broke up our regression into two smaller pieces where the trends were fairly consistent. The first period is 11/92 to 8/02, and the second is 9/02 to 3/08.

Regression of Perceived Interest Rate on Effective and Contract Rate from November 1992 to August 2002:

Perceived Interest Rate = $\beta_0 + \beta_1$ Effective Rate + β_2 Contract Rate + u

Observations = 118

R^2 = .7403

Independent Variables	Coefficient	Standard Error	T	P-Value
Effective Rate	-30.88293	12.76118	-2.42	0.017
Contract Rate	50.95585	13.47189	3.78	0.000
Constant	-67.68322	8.067558	-8.39	0.000

[3] Contract interest rate data obtained from the Federal Reserve Board and effective interest rate data obtained from the National Association of Realtors.

Regression of Perceived Interest Rate on Effective and Contract Rate from September 2002 to March 2008:

Perceived Interest Rate = $\beta_0 + \beta_1$ Effective Rate + β_2 Contract Rate + u
Observations = 67
R^2 = .7091

Independent Variables	Coefficient	Standard Error	T	P-Value
Effective Rate	-32.46262	37.8363	-0.86	0.394
Contract Rate	68.35785	39.7895	1.76	0.083
Constant	-135.5536	17.34119	-7.82	0.000

We expected a positive coefficient on the contract rate (the rate that homebuyers actually see), and an insignificant coefficient on the effective interest rate (the rate the homebuyers actually pay). This hypothesis was correct for the most recent period, but there was actually a significant negative coefficient on the effective rate before 2002. This leads us to conclude that homebuyers do not compensate for compounding interest in their perceptions of interest rates on housing, and often compensate “backwards” for it.

This finding is important in and of itself, but it was also important in selecting which variable to use in order to maximize explanatory power in later regressions. We decided to use contract rate in each case because it more clearly represented the interest rates consumers are considering when they formulate their housing market sentiments. We were actually interested in seeing how much extra explanatory power the contract rate afforded us, so we decided to regress perceived interest rate on each variable and check how the R-squared statistics compare. In both time periods, contract rate provides a better fit and adds 1-2% explanatory power.

This has quite a few implications for banks, and highly encourages banks to use a simple interest rate so that they can make their contract rate as low as possible while providing the same effective rate as other banks.

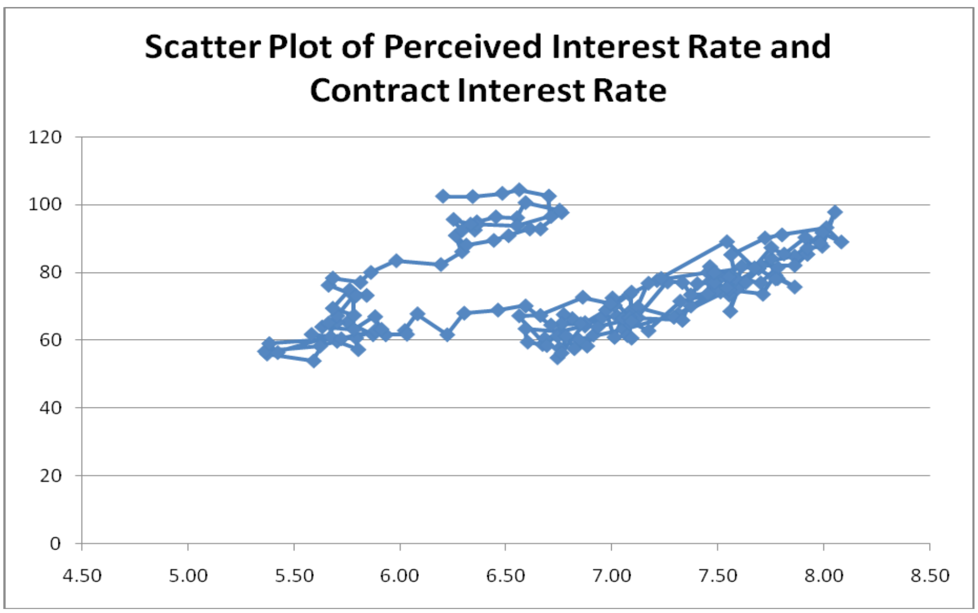
Consumer Compensation: Inflation

In view of our large-scale goal of determining consumer sentiment in the housing market, we discovered that house price and interest rate were the two dominating factors. It was also clear that both of these measures were quite influenced by the rate of inflation, and we wanted to see how good consumers were at discerning (and accounting for) the rate of inflation[4] as it affects these two measures. We therefore embarked on comparing two regressions:

(1) Perceived Interest Rate = $\beta_0 + \beta_1$Contract Rate + u

(2) Perceived Interest Rate = $\beta_0 + \beta_1$ Real Rate + u

"Real rate" is simply the contract rate adjusted for inflation. However, when we ran both regressions over the time period 1992-2008, we disappointingly had a very poor fit ($R^2 = 0.07$). We decided to investigate why this was the case, and found that there was a very clear structural break in the interest rate data, as found below:



We saw a very clear linear trend in the "lower" leg on the very right (when interest rates were 6.5-8.5%), followed by a short horizontal segment, into the "upper leg" (in a time period when interest rates were 5-6.5%). As a result, we decided to split the regression into two separate pieces to account for each of these separate trends. It turns out that this lower leg occurred between November 1992 and August 2002 (118 months). The transition period and upper leg occurred between September 2002 and March 2008 (67 months).

[4] Inflation data obtained from Bureau of Labor Statistics

We then ended up with far more satisfactory R^2 values:

Regression of Perceived Interest Rate on Contract Rate (11/92-8/02):

Perceived Interest Rate = $\beta_0 + \beta_1$Contract Rate + u
Observations = 118
R^2 = .7271

Independent Variables	Coefficient	Standard Error	T	P-Value
Contract Rate	18.448	1.049359	17.58	0.000
Constant	-60.51826	7.660164	-7.90	0.000

Regression of Perceived Interest Rate on Contract Rate (9/02-3/08):

Perceived Interest Rate = $\beta_0 + \beta_1$Contract Rate + u
Observations = 67
R^2 = .7057

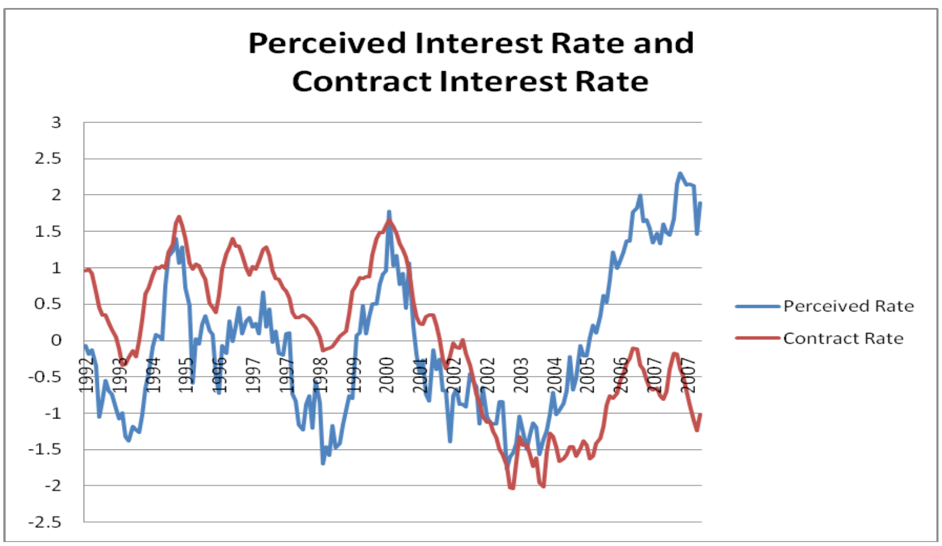
Independent Variables	Coefficient	Standard Error	t	P-Value
Contract Rate	35.16561	2.816543	12.49	0.000
Constant	-132.9647	17.04195	-7.80	0.000

We got a slightly lower R^2 in the second period because it included the horizontal transition period, but because the first regression had such a large number of observations and a very clear trend, we decided to state its R^2 value (slightly under 73%) as a finding: about three-fourths of the movement in the contract interest rate is translated into changing housing market sentiment based on the interest rate.

The second compelling finding from this graph and subsequent regressions was that there was a considerably steeper slope in the "upper leg" of the graph. Not only did an increased number of consumers base their housing sentiments on the presence of a "high interest rate" when the interest was at historically low levels, but they were also more sensitive to changes in the contract rate (as witnessed by a near-doubling of the coefficient from 18.4 to 35.2).

The interpretation here is that a one-percentage-point increase resulted in 18% more of the population basing their housing sentiment on the presence of a high interest rate (as opposed to a low one) in the earlier period, whereas that same change result in 35% more of the population basing their housing sentiment on the presence of a high interest rate in the later period. An easy way to summarize this is that consumers about doubled in sensitivity beginning in 2003 (when we exclude the transition period, our second period essentially begins in 2003).

This finding is illustrated in the chart below, which shows that beginning around 2003, the perceived rate moved at a more drastic slope than the contract rate.



Our search for the effects of inflation on consumer sentiment regarding interest rate certainly produced some interesting findings, but these have yet to address the initial question regarding how consumers take inflation into consideration in determining the interest rate.

Therefore, we decided to perform two new regressions:

(1) $\text{Perceived Interest Rate} = \beta_0 + \beta_1 \text{Contract Rate} + \beta_2 \text{Inflation} + u$ (11/1992-08/2002)
(2) $\text{Perceived Interest Rate} = \beta_0 + \beta_1 \text{Contract Rate} + \beta_2 \text{Inflation} + u$ (09/2002-03/2008)

Our hypothesis was that we would get a negative coefficient on inflation ($\beta_2 < 0$) because, if the inflation rate was higher, consumers would realize that the real interest rate was lower, and so the perceived interest rate would drop (holding contract rate constant, of course). What we found, however, was quite surprising.

In both regressions, $\beta_2 > 0$ at the 10% confidence level (see Appendix Tables 1.C and 2.C). This result was quite surprising, especially considering the cleanness of the trends in each period. It's worth noting that the coefficient on inflation was far more significant ($t = 4.21$) in the second period than it was in the first ($t = 1.92$). Since the coefficient in the first period is significant at the 10% level, but not the 5% level, and because we believe it to be the more representative of the regressions, we are hesitant to go all the way to infer that consumers judge inflation backward. For the time being, we infer only that inflation is not correctly taken into account.

In addition, we found that when we regressed perceived rate on the real contract rate of interest by itself, we found an insignificant coefficient on the real interest rate as well as an $R^2 < 0.01$ in both periods (see Appendix Tables 3.C and 4.C). No matter the technique employed (we even tried accounting for other factors we think affects what consumers think about the interest rate, including house price and indicators of general economic well-being including unemployment and the overall Index of Consumer Confidence, as shown below), we could not obtain a negative coefficient on inflation, and most commonly found a statistically-significant positive coefficient. This spoke volumes regarding consumers' ability to properly account for inflation.

Regression of Perceived Interest rate on Contract Rate, Nominal Median House Price, Inflation, the Index of Consumer Sentiment and Unemployment:

Perceived Interest Rate = $\beta_0 + \beta_1$ Contract Rate + β_2 Nominal Median House Price (in thousands of dollars) + β_3 Inflation + β_4 Index of Consumer Sentiment + β_5 Unemployment + u

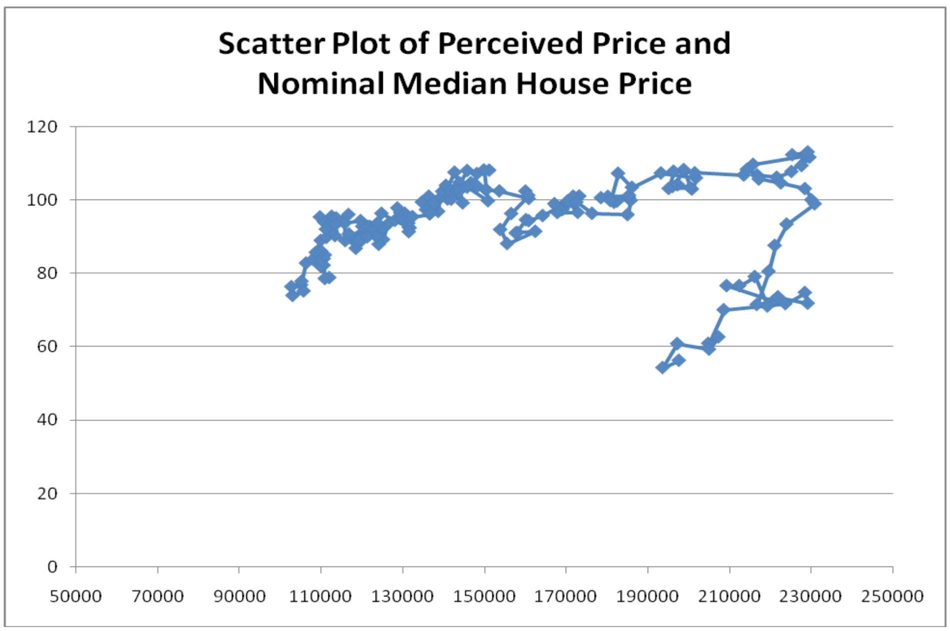
Observations = 185

$R^2 = .7735$

Independent Variables	Coefficient	Standard Error	t	P-Value
Contract Rate	15.51674	1.391789	11.15	0.000
Nominal Median House Price	.2754013	.0300359	9.17	0.000
Inflation	4.188877	.6659337	6.29	0.000
Index of Consumer Sentiment	-.4407659	.0893985	-4.93	0.000
Unemployment	-3.045603	1.353965	-2.25	0.026
Constant	-27.67659	25.57086	-1.08	0.281

The positive coefficient of inflation in these three regressions leads us to conclude that consumers do not properly account for inflation in their evaluation and subsequent sentimient in the housing market regarding interest rates.

We went through a similar process to see how inflation affected consumer sentiment regarding house prices. We first ran a wholesale regression of the perceived price rate on the median nominal house price for the 1992-2008 era and once more discovered a poor R^2. We looked at the scatterplot for structural breaks and this time found two breaks instead of one, as we had for interest rates. We show the scatterplot below.



We saw three distinct legs in this scatterplot corresponding to three positive-sloping linear trends (as we had expected) with distinctly different slopes and intercepts. The structural breaks resulted in our running three separate regressions over the following time periods:

(1) November 1992 – September 2000 (95 months)

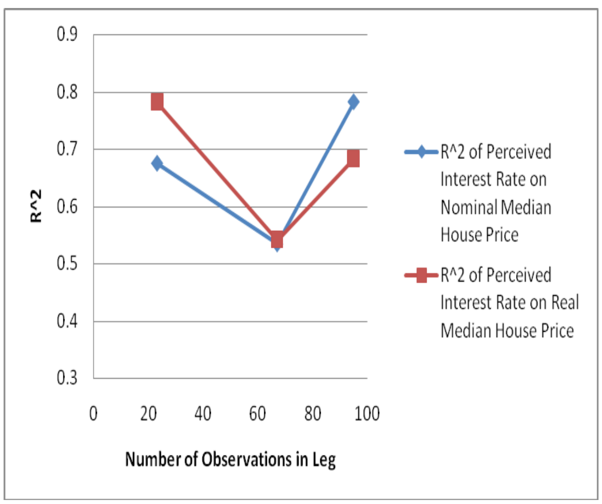
(2) October 2000 – April 2006 (67 months)

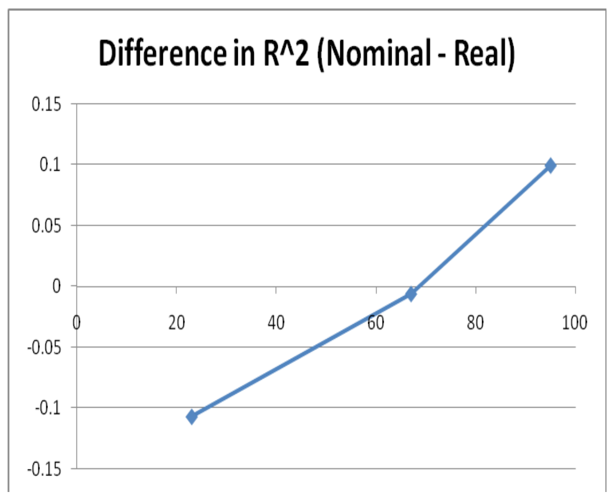
(3) May 2006 – March 2008 (23 months)

We then performed the following regressions on each period:

(1) Perceived Price = $\beta_0 + \beta_1$ Nominal Median House Price
(2) Perceived Price = $\beta_0 + \beta_1$ Real Median House Price

We found that as the length of the time period increased (i.e. the number of data points), then so did the fit of the regression on the nominal house price relative to that on the real price (see Appendix Tables 1.D – 6.D).





The fit for the first and third legs were considerably better than that for the second. Over the first and third legs, we achieved R^2 values around 75%, whereas in the second period, they were about 55%. We expected nominal prices to be the better predictor in the short-run, but for real prices to be the best long-run predictor, but the graph on the right directly contradicts this idea. This seems to indicate that consumers also poorly compensate for inflation when formulating their sentiment on house prices. To confirm this notion further, we ran the following regressions:

(1) Perceived Price = $\beta_0 + \beta_1$ Nominal Median House Price + β_2 Inflation + u (11/1992-09/2000)
(2) Perceived Price = $\beta_0 + \beta_1$ Nominal Median House Price + β_2 Inflation + u (10/2000-04/2006)

(3) Perceived Price = $\beta_0 + \beta_1$ Nominal Median House Price + β_2 Inflation + u (05/2006-03/2008)

In each case, we got an R^2 value around 0.75 (see Appendix 7.D – 9.D). So about three-fourths of the movement in nominal median house price (and inflation) is translated into changing housing market sentiment based on the price of housing. However, just as was the case for interest rates, there was a positive coefficient on inflation ($\beta_2 > 0$ in every regression). Even with nominal prices held constant, consumers tended to look at inflation backwards. This led us to conclude that consumers do not properly accoutn for inflation in their evaluation and subsequent sentiment in the housing makrety regarding house prices.

We also noticed that β_1 (which we have labeled price sensitivity) fluctuated considerably over the three periods (0.51, 0.11, and 1.04 respectively). This led us to our conclude that consumer sensitivity to prices has undergone sever deviations—first hyposensitivity, then hypersensitivity—since 2001.

III. Moving Toward a Unified Model

All of the structural breaks in both price and interest rate sensitivity led our group to believe that there were other factors at play in a very strong sense that were affecting how consumers thought of the current housing market. These structural breaks were beginning to get a bit annoying, so we decided to move toward a more uniform model that could explain consumer sentiment for the entire 15-year period from 1992 to 2008.

To begin the process of variable selection, we decided it was best to start with the reasons that were most listed in the survey as determinants of consumer sentiment. Our general assumption was that the reasons people gave behind their sentiment actually had backing in real economic conditions. Therefore, we sought real economic variables to represent reasons like “high interest rates”, “falling prices”, “can’t afford”, and “bad times ahead”. The table below shows the reasons variables that were collected with the survey as well as our real-world proxy:

Survey Response Reason	**Corresponding Economic Indicator**
Low/High Prices	Nominal House Price, Inflation
Rising/Falling Prices	De-trended House Price
Low/High Interest Rates	Contract Rate, Inflation
Rising Interest Rates	ΔContract Rate

Good Investment	De-trended House Price
Good/Bad Times Ahead	Consumer Expectation Sentiment (ICE), ΔUnemployment
Can't Afford	Current Consumer Sentiment (ICC), Unemployment
Will Lose Money	De-trended House Price

We then created saturated models for buying and selling sentiment with each of these variables and performed a backward elimination model selection process to arrive at the most useful models in the end. We used the Bonferroni correction because of our large models and decided to only select variables with a p-value < 0.01.

Considering the very small R^2 values we got by looking at interest rates and prices alone over this entire period, the fits we got in these holistic models were quite satisfying. It turns out that the vast majority of the structural breakage we saw in our perceived price and interest rate regressions can be explained by these real-world proxy variables.

Regression of Home Buying Index on Contract Interest Rate, Nominal Median House Price in thousands of dollars, De-trended House Price in thousands of dollars, Inflation, Unemployment Level, Quarterly Percentage Change in Contract Interest Rate, Yearly Percentage Change in Unemployment Level, and the Index of Consumer Expectations from 11/1992 to 3/2008:

Home Buying Index = $\beta_0 + \beta_1$ Contract Rate + β_2 NominalHousePrice + β_3 DetrendedHousePrice + β_4 Inflation + β_5Unemployment + β_6 ContractRateChange + β_7UnemploymentChange + β_8ConsumerExpectations + u

Observations = 173
R^2 = 0.8695

Independent Variables	Coefficient	Standard Error	T	P-Value
Contract Rate	-21.75486	1.390742	-15.64	0.000
Nominal House Price	-.5205197	.03083	-16.88	0.000
De-trended House Price	.2834122	.0603047	4.70	0.000
Inflation	-2.658266	.7823252	-3.40	0.001
Unemployment	-3.31794	1.190715	-2.79	0.006
Contract Rate Change	35.71694	13.36007	2.67	0.008
Unemployment Change	20.55295	4.586778	4.48	0.000
Consumer Expectations	.3914198	.0704713	5.55	0.000
Constant	375.5732	21.90125	17.15	0.000

Regression of Home Selling Index on Contract Interest Rate, Nominal Median House Price in thousands of dollars, De-trended House Price in thousands of dollars, Inflation, Unemployment Level, Quarterly Percentage Change in Contract Interest Rate, Yearly Percentage Change in Unemployment Level, and the Index of Consumer Expectations from 11/1992 to 3/2008:

Home Selling Index $= \beta_0 + \beta_1$ Contract Rate + β_2 NominalHousePrice + β_3 DetrendedHousePrice + β_4 Inflation + β_5Unemployment + β_6 ContractRateChange + β_7UnemploymentChange + β_8ConsumerExpectations + u

Observations = 173
$R^2 = 0.8067$

Independent Variables	Coefficient	Standard Error	T	P-Value
Contract Rate	-39.74705	3.129876	-12.70	0.000
Nominal House Price	-.7887699	.0693831	-11.37	0.000
De-trended House Price	2.26503	.1357163	16.69	0.000
Inflation	12.06819	1.760629	6.85	0.000
Unemployment	-20.20593	2.679713	-7.54	0.000
Contract Rate Change	131.4703	30.06694	4.37	0.000
Unemployment Change	72.20845	10.32258	7.00	0.000
Consumer Expectations	1.469863	.1585962	9.27	0.000
Constant	461.3129	49.28893	9.36	0.000

Interestingly enough, even when starting with very large saturated models, we arrived at identical final models. It was quite exciting to explain 87% and 81% of buying and selling sentiment respectively over such a diverse and volatile period. Quite interestingly, every predictor except inflation has the same sign in each regression, showing a fairly similar and consistent formulation of buying and selling sentiment, even though we were expecting opposite signs for the house price variables.

We wondered if these similarities in coefficients were simply because buying and selling sentiment moved together over this period, but when we included the buying statistic in the selling regression and vice versa, we were met with insigifnicant results.

The results of these phenomena are a bit difficult to interpret. It seemed to us that the inflation coefficient should be positive in each regression because higher inflation meant a lower real rate of interest, which would result in people thinking it a good time to buy and sell a house. However, we only found this in the selling data. Also, it is still unclear as to why the house price variables show the same sign on the coefficeint in both the buying and selling data, though it is heartening to see that de-trended house price was fare more meaningful in selling sentiment, because it seems that people with opinions on this matter (most likely homeowners) are clearly informed about prices relative to normal levels, and the sign for this was correctly positive.

IV. Implications: The Recent Housing Crash

Homeowners vs. Non-homeowners

Beginning in 1992, the data on buying and selling sentiment is split into two categories: all respondents and homeowners. We thought it would be interesting to distinguish between the perceptions of homeowners and non-homeowners on the market, because this paper is primarily interested in discovering the determinants of consumer sentiment. Our hypothesis coming in was that we would see significantly more disparities in the selling sentiments between homeowners and non-homeowners than we would for buying because everyone in the market is a potential buyer, but only *homeowners* are potential sellers. For this reason, we predicted that homeowner selling sentiment was considerably more informed and would show a closer relationship to actual market conditions.

Note on the data: Since the data was originally split up into homeowners and all respondents, we had to formulate for ourselves the data on the non-homeowners category. We used the following formula:

All = p_{HOME}*Home+ $p_{NONHOME}$*Nonhome

Where p_{HOME} = the proportion of respondents that are homeowners

And $p_{NONHOME}$ = the proportion of respondents that are not homeowners

(both of these variables were easy to calculate because we were given both the number of homeowners and all respondents for each month)

From this, we solved for and constructed the "Non-home" variable using the "All" and "Home" variables. It's worth noting that the "All" and "Home" variables are all integer-valued, but because of this formula we used, the "Non-home" data is not. We decided to leave it this way rather than round because we felt that it provided us the most accurate information, even if it was inconsistent with the format of the others.

We first compared the indexes of homeowners and non-homeowners for buying data:

Summary of Home Buying Index 1992-2008 (Homeowners)

Variable	Observations	Mean	Standard Deviation	Min.	Max

Home Buying Index	185	159.0757	15.48613	119	185

Summary of Home Buying Index 1992-2008 (Non-Homeowners)

Variable	Observations	Mean	Standard Deviation	Min.	Max
Home Buying Index	185	138.1767	22.2641	65.62963	176.7914

We then compared the homeowner and non-homeowner indexes for selling data:

Summary of Home Selling Index 1992-2008 (Homeowners)

Variable	Observations	Mean	Standard Deviation	Min.	Max
Home Selling Index	185	119.227	31.47657	18	164

Summary of Home Selling Index 1992-2008 (Non-Homeowners)

Variable	Observations	Mean	Standard Deviation	Min.	Max
Home Selling Index	185	106.0596	24.92768	22	161.2857

We found the same law at work in the selling data as we did in the buying data: homeowners are considerably more optimistic than non-homeowners (see Appendix Tables 1.B and 2.B for t-tests). This result was confirmed with paired t-tests comparing the means of each reason for homeowners and non-homeowners (see Appendix Tables 3.B and 4.B for t-tests). All good reason means were significantly higher for homeowners and all bad reason means were significantly higher for non-homeowners.

Also of note is the relative weight each group gives to low interest rates and low prices. For buying data, both rank interest rates as most important and then low prices, but the ratio of the mean response of these variables for homeowners is about 3:1, whereas it is only 2:1 for non-homeowners. This is shown below.

Homeowner Low Price and Low Interest Rate Response Variables

Variable	Observations	Mean	Standard Deviation	Min.	Max
(1) Good- Low Prices	185	14.93984	8.079826	5.04	40.6
(2) Good- Low Rates	185	43.61341	17.05729	10.88	73.08

Non-homeowner Low Price and Low Interest Rate Responses Variables

Variable	Observations	Mean	Standard Deviation	Min.	Max
(1) Good- Low Prices	185	11.42658	6.491393	-1.387778	31.64545
(2) Good- Low Rates	185	24.87025	13.87228	-25.61714	64.18079

Heterogeneity in the Saturated Model

Noticing these differences in sentiment across homeowners and non-homeowners prompted us to examine our saturated model seperately with regard to homeowners and non-homeowners. This yielded four regressions provided below: saturated models determining buying sentiment of homeowners and non-homeowners as well as saturated models determining selling sentiment of homeowners and non-homeowners.

Regression of Homeowner Buying Index on Contract Interest Rate, Nominal Median House Price in thousands of dollars, De-trended House Price in thousands of dollars, Inflation, Unemployment Level, Quarterly Percentage Change in Contract Interest Rate, Yearly Percentage Change in Unemployment Level, and the Index of Consumer Expectations from 11/1992 to 3/2008:

Home Buying Index $= \beta_0 + \beta_1$ Contract Rate + β_2 NominalHousePrice + β_3 DetrendedHousePrice + β_4 Inflation + β_5Unemployment + β_6 ContractRateChange + β_7UnemploymentChange + β_8ConsumerExpectations + u

Observations = 173

$R^2 = .8565$

Independent Variables	Coefficient	Standard Error	T	P-Value
Contract Rate	-23.54465	1.457343	-16.16	0.000
Nominal House Price	-.5316172	.0323064	-16.46	0.000
De-trended House Price	.2790933	.0631927	4.42	0.000
Inflation	-2.594505	.8197897	-3.16	0.002
Unemployment	-3.656629	1.247736	-2.93	0.004
Contract Rate Change	44.38337	13.99986	3.17	0.002
Unemployment Change	20.94994	4.806432	4.36	0.000
Consumer Expectations	.3439705	.0738461	4.66	0.000
Constant	400.3327	22.95007	17.44	0.000

Regression of Non-Homeowner Buying Index on Contract Interest Rate, Nominal Median House Price in thousands of dollars, De-trended House Price in thousands of dollars, Inflation, Unemployment Level, Quarterly Percentage Change in Contract Interest Rate, Yearly Percentage Change in Unemployment Level, and the Index of Consumer Expectations from 11/1992 to 3/2008:

Home Buying Index $= \beta_0 + \beta_1$ Contract Rate + β_2 NominalHousePrice + β_3 DetrendedHousePrice + β_4 Inflation + β_5Unemployment + β_6 ContractRateChange + β_7UnemploymentChange + β_8ConsumerExpectations + u

Observations = 173

$R^2 = .7650$

Independent Variables	Coefficient	Standard Error	T	P-Value

Contract Rate	-18.74585	2.684573	-6.98	0.000
Nominal House Price	-.627704	.0595116	-10.55	0.000
De-trended House Price	.4254496	.1164072	-3.65	0.000
Inflation	-3.01995	1.510135	-2.00	0.047
Unemployment	-3.042572	2.298456	-1.32	0.187
Contract Rate Change	5.460214	25.78916	0.21	0.833
Unemployment Change	21.85534	8.853933	2.47	0.015
Consumer Expectations	.6204988	.1360319	4.56	0.000
Constant	336.0301	42.27635	7.95	0.000

Regression of Homeowner Selling Index on Contract Interest Rate, Nominal Median House Price in thousands of dollars, De-trended House Price in thousands of dollars, Inflation, Unemployment Level, Quarterly Percentage Change in Contract Interest Rate, Yearly Percentage Change in Unemployment Level, and the Index of Consumer Expectations from 11/1992 to 3/2008:

Home Selling Index = $\beta_0 + \beta_1$ Contract Rate + β_2 NominalHousePrice + β_3 DetrendedHousePrice + β_4 Inflation + β_5Unemployment + β_6 ContractRateChange + β_7UnemploymentChange + β_8ConsumerExpectations + u

Observations = 173

R^2 = .8065

Independent Variables	Coefficient	Standard Error	T	P-Value
Contract Rate	-44.1593	3.376404	-13.08	0.000
Nominal House Price	-.8950215	.0748482	-11.96	0.000
De-trended House Price	2.398863	.1464061	16.38	0.000
Inflation	13.10736	1.899307	6.90	0.000
Unemployment	-20.22267	2.890783	-7.00	0.000

Contract Rate Change	146.6437	32.43519	4.52	0.000
Unemployment Change	80.498848	11.13565	7.23	0.000
Consumer Expectations	1.594552	.1710882	9.32	0.000
Constant	498.8439	53.17123	9.38	0.000

Regression of Nonhomeowner Selling Index on Contract Interest Rate, Nominal Median House Price in thousands of dollars, De-trended House Price in thousands of dollars, Inflation, Unemployment Level, Quarterly Percentage Change in Contract Interest Rate, Yearly Percentage Change in Unemployment Level, and the Index of Consumer Expectations from 11/1992 to 3/2008:

Home Selling Index = $\beta_0 + \beta_1$ Contract Rate + β_2 NominalHousePrice + β_3 DetrendedHousePrice + β_4 Inflation + β_5Unemployment + β_6 ContractRateChange + β_7UnemploymentChange + β_8ConsumerExpectations + u

Observations = 173

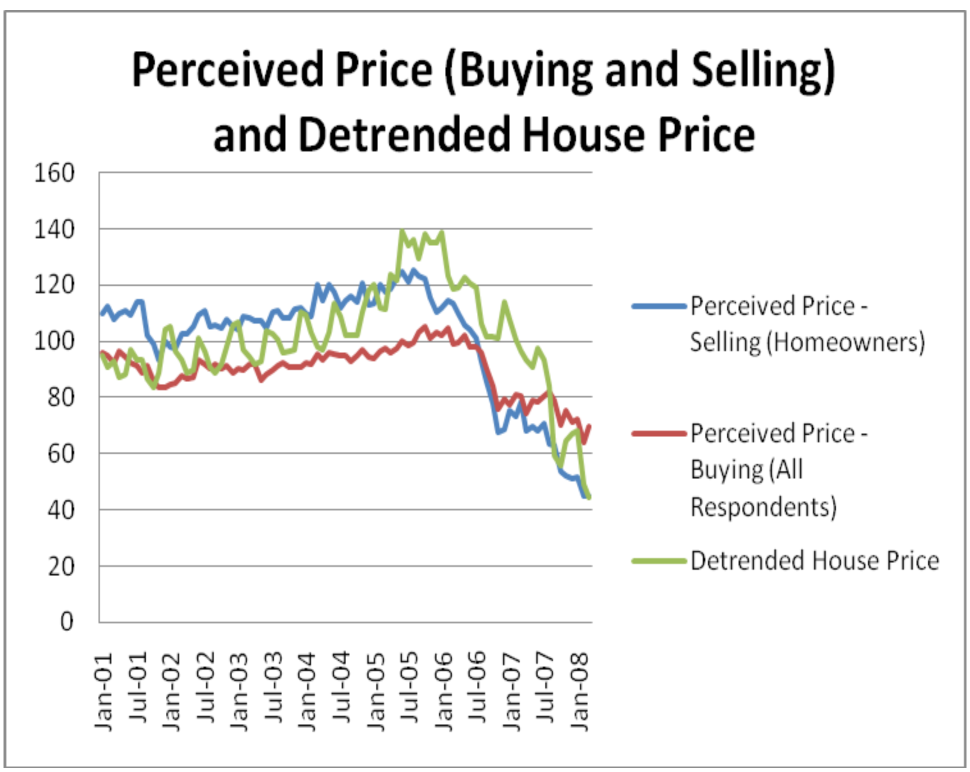
R^2 = .6845

Independent Variables	Coefficient	Standard Error	T	P-Value
Contract Rate	-23.09554	3.301614	-7.00	0.000
Nominal House Price	-.4274387	.0731902	-5.84	0.000
De-trended House Price	1.67112	.1431631	11.67	0.000
Inflation	6.72317	1.857236	3.62	0.000
Unemployment	-19.32654	2.82675	-6.84	0.000
Contract Rate Change	92.63923	31.71673	2.92	0.004
Unemployment Change	36.88916	10.88898	3.39	0.001
Consumer Expectations	.9992224	.1672985	5.97	0.000
Constant	329.905	51.99345	6.35	0.000

Interestingly, both homeowner saturated models have noticeably higher R^2 values than their non-homeowner counterparts. This indicates that more of the variation in homeowners' sentiment can be explained by the real-world macroeconomic variables we have identified as the most influential drivers of consumer sentiment. Furthermore, in both the buying and selling saturated models, nonhomeowners are less sensitive than homeowners to the contract interest rate as well as the quarterly change in contract interest rate. Since the homeowners, who are doing all of the selling, are more informed than the non-homeowners, those we assume to be doing a good part of the buying, changes in the macro-economy that might affect price will favor the sellers. In other words, if there is a disparity in perceived price between sellers and buyers, shifts in actual price will favor the sellers because they best adjust to the new information. So if there is indeed a disparity in sellers' and buyers' perceived price level, prices will tend to rise to the sellers' perceived price as opposed to lowering to the buyers' perceived price.

An Unsustainable Optimism

This disparity in perceived price between homeowners and nonhomeowners is confirmed in the data. More importantly, this disparity continues throughout the 4 year boom period—a reflection of unmitigated optimism on the part all agents in the housing market. When asked about buying, the general optimism tended to dictate a perception of low prices, while that same optimism for selling tended to dictate a perception of high prices. The prolonged disparity is illustrated in the graph below.



We decided to look at data starting in 2001, since it seemed that we never found any structural breaks or exceptional trends before that time. It is very obvious that from January 2001 all the way up to the housing crash in 2006, there was an unsustainable trend in that consumers were largely basing their buying sentiment on the perception of low prices while basing their selling sentiment on the perception of high prices. We hypothesize that this unmitigated optimism led to an unsustainable rate of increase in the price of housing since sellers (homeowners) are more informed regarding macro-economic indicators and thus shifts in price will favor them. In addition, those looking to buy homes continued to think that prices were low, and therefore that it was a good time to buy. This caused demand to shift outward and prices to rise sharply until 2006. At this point there was the realization that prices were far above fundamentals, and prices subsequently dropped.

Conclusion

This paper started as an exploration of the University of Michigan Consumer Sentiment data, specifically the questions about the housing market. As our analysis progressed we were able to report some interesting findings, test some economic theories, and propose a hypothesis on the housing boom and crash.

We notice from our summary statistics that since 1978 both buying sentiment and selling sentiment have been mainly positive. Although this would at first glance seem slightly odd, we propose that the housing market is not, in fact, a zero-sum game. Low interest rates, for one, benefit both the buyer and the seller. We present Inventory-Sales ratio as a way to reinforce that the housing market is not a zero-sum game.

Splitting the data into shorter periods of time, we found that there was a nonexistent or negative relationship between the two indexes. Over the longer 15 year period of time, our final saturated models for buying and selling sentiment are well-explained by the same economic indicators, all with the same signs (except for inflation). The similarity in signs may suggest that consumers base their sentiment of buying and selling conditions more on general economic wellbeing—when rates are low, unemployment is low, and expectations are good—than on any one particular reason specific to buying or selling. This finding helps explain why the buying and selling sentiment during the housing boom were simultaneously optimistic; an optimism that contributed (if not led) to a purely speculative housing bubble.

We also notice from our summary statistics that consumers mainly base their opinions on housing on interest rates and prices. However, as we report in Section II, consumers do not fully understand the main determinants of their own sentiment, exhibiting inflation illusion in prices and interest rates. With this misunderstanding in mind, we measure in Section III how much consumer sentiment is based on actual market fundamentals. We are able to explain about 80% of buying and selling sentiment with real-world variables that correspond to the reasons consumers are giving for their beliefs about the housing market.

In our last section we use the findings in the previous section in order to explain the housing market boom and subsequent crash. We believe that the asymmetry we find in beliefs about prices between homeowners and nonhomeowners created an unsustainable boom in prices. The crash was inevitable as the less-informed potential buyers finally realized that prices were well above fundamentals.

Appendix A—One-Sample t-tests of Conditions Indexes and Paired t-tests to show most influential response reasons

Table 1.A

T-test to show Buying Conditions Index >100 from 1978 to 2008

```
One-sample t test
------------------------------------------------------------------------------
   Variable |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
(1)homeb~78 |     361    136.0997    1.765013    33.53524    132.6287    139.5708
------------------------------------------------------------------------------
    mean = mean(homebuyingind_78)                                 t =  20.4530
Ho: mean = 100                                   degrees of freedom =      360

   Ha: mean < 100              Ha: mean != 100              Ha: mean > 100
```

```
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

(1)Home Buying Index since 1978

Table 2.A

Paired T-test Comparing Means of Low Interest Rates and Low Prices Responses from 1978 to 2008

```
Paired t test
------------------------------------------------------------------------------
          Variable |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf.
Interval]
---------+--------------------------------------------------------------------
(1)buy_pop_good_LR |     361     29.3105    1.010748    19.20421    27.32279
 31.29821
(2)buy_pop_good_LP |     361    13.01554    .4375751    8.313927    12.15502
 13.87606
---------+--------------------------------------------------------------------
              diff |     361    16.29496    .9132308    17.35139    14.49902
18.0909
------------------------------------------------------------------------------
     mean(diff) = mean(buy_pop_good_LR - buy_pop_good_LP)       t =  17.8432
 Ho: mean(diff) = 0                              degrees of freedom =      360

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

(1) Population percentage of respondents who say good time to buy because of Low Interest Rates

(2) Population percentage of respondents who say good time to buy because of Low Prices

Table 3.A

Paired T-test Comparing Means of Low Prices and Increasing Prices Responses from 1978 to 2008

```
Paired t test
------------------------------------------------------------------------------
          Variable |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf.
Interval]
---------+--------------------------------------------------------------------
(1)buy_pop_good_LP |     361    13.01554    .4375751    8.313927    12.15502
 13.87606
(2)buy_pop_good_PI |     361    5.486039    .1907286    3.623844    5.110957
 5.861121
---------+--------------------------------------------------------------------
              diff |     361    7.529501    .5320258    10.10849    6.483233
8.57577
------------------------------------------------------------------------------
     mean(diff) = mean(buy_pop_g~ces_78 - buy_pop_good_p~8)       t =  14.1525
 Ho: mean(diff) = 0                              degrees of freedom =      360

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

(1) Population percentage of respondents who say good time to buy because of Low Prices

(2) Population percentage of respondents who saygood time to buy because Prices Will Increase

Table 4.A

Paired T-test Comparing Means of High Interest Rates and High Prices Responses from 1978 to 2008

```
Paired t test
------------------------------------------------------------------------------
         Variable |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf.
Interval]
---------+--------------------------------------------------------------------
(1)buy_pop_bad_HR |     361    8.354044    .7665309    14.56409    6.846603
 9.861485
(2)buy_pop_bad_HP |     361    5.184958    .2964405     5.63237    4.601986
 5.767931
---------+--------------------------------------------------------------------
             diff |     361    3.169086    .5117882    9.723976    2.162616
 4.175556
------------------------------------------------------------------------------
     mean(diff) = mean(buy_pop_bad_HR - buy_pop_bad_HP)       t =   6.1922
 Ho: mean(diff) = 0                              degrees of freedom =      360

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

(1) Population percentage of respondents who say bad time to buy because of High Interest Rates

(2) Population percentage of respondents who say bad time to buy because of High Prices

Table 5.A

Paired T-test Comparing Means of High Prices and Can't Afford Responses from 1978 to 2008

```
Paired t test
------------------------------------------------------------------------------
         Variable |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf.
Interval]
---------+--------------------------------------------------------------------
(1)buy_pop_bad_HP |     361    5.184958    .2964405     5.63237    4.601986
 5.767931
(2)buy_pop_bad_CA |     361    2.366925    .1207637    2.294511    2.129434
 2.604416
---------+--------------------------------------------------------------------
             diff |     361    2.818033    .2237361    4.250985    2.378039
 3.258027
------------------------------------------------------------------------------
     mean(diff) = mean(buy_pop_bad_HP - buy_pop_bad_CA)       t =  12.5953
 Ho: mean(diff) = 0                              degrees of freedom =      360

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

(1) Population percentage of respondents who say bad time to buy because of High Prices

(2) Population percentage of respondents who say bad time to buy because they Can't Afford to buy

Table 6.A

T-test to show Buying Conditions Index >100 from 1992 to 2008

```
One-sample t test
------------------------------------------------------------------------------
       Variable |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
(1)buyindex_ALL |     185    153.9568    1.139707    15.50169    151.7082    156.2053
------------------------------------------------------------------------------
    mean = mean(buyindexALL)                                      t =  47.3427
Ho: mean = 100                                   degrees of freedom =      184

   Ha: mean < 100              Ha: mean != 100              Ha: mean > 100
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

(1)Home Buying Index from 1978 to 2008

Table 7.A

Paired T-test Comparing Means of Low Interest Rates and Low Prices Responses for Buying from 1992 to 2008

```
Paired t test
------------------------------------------------------------------------------
             Variable |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf.
Interval]
---------+--------------------------------------------------------------------
(1) buy_popALL_good_LR |     185    38.75124    1.135133    15.43948    36.51169
 40.99079
(2) buy_popALL_good_LP |     185    14.19005    .5250078    7.140878    13.15424
 15.22586
---------+--------------------------------------------------------------------
                  diff |     185    24.56119    1.281314    17.42775    22.03323
 27.08914
------------------------------------------------------------------------------
     mean(diff) = mean(buy_popAL~wrates - buy_popALL_g~ces)       t =  19.1688
 Ho: mean(diff) = 0                              degrees of freedom =      184

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

(1) Population percentage of respondents who say good time to buy because of Low Interest Rates

(2) Population percentage of respondents who say good time to buy because of Low Prices

Table 8.A

Paired T-test Comparing Means of Low Prices and Increasing Prices Responses for Buying from 1992 to 2008

```
Paired t test
------------------------------------------------------------------------------
             Variable |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf.
Interval]
---------+--------------------------------------------------------------------
(1) buy_popALL_good_LP |     185    14.19005    .5250078    7.140878    13.15424
 15.22586
(2) buy_popALL_good_RR |     185    5.650595    .3092334    4.206029    5.040495
 6.260694
---------+--------------------------------------------------------------------
                  diff |     185    8.539459    .6776338    9.216816    7.202528
 9.876391
------------------------------------------------------------------------------
     mean(diff) = mean(buy_popALL_g~ces - buy_popAL~grates)       t =  12.6019
 Ho: mean(diff) = 0                              degrees of freedom =      184

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

(1) Population percentage of respondents who say good time to buy because of Low Prices

(2) Population percentage of respondents who saygood time to buy because Prices Will Increase

<u>Table 9.A</u>

Paired T-test Comparing Means of High Interest Rates and High Prices Responses for Buying from 1992 to 2008

```
Paired t test
------------------------------------------------------------------------------
            Variable |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf.
Interval]
---------+--------------------------------------------------------------------
(1) buy_popALL_bad_HP |     185    2.593784    .1794566    2.440873    2.239727
 2.947841
(2) buy_popALL_bad_HR |     185    1.927189    .1452164    1.975157    1.640686
 2.213693
---------+--------------------------------------------------------------------
                 diff |     185    .6665946    .1267149    1.723509    .4165936
 .9165956
------------------------------------------------------------------------------
     mean(diff) = mean(buy_popALL_b~ces - buy_popALL_b~tes)       t =   5.2606
 Ho: mean(diff) = 0                              degrees of freedom =      184

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

(1) Population percentage of respondents who say bad time to buy because of High Prices

(2) Population percentage of respondents who say bad time to buy because of High Interest Rates

<u>Table 10.A</u>

Paired T-test Comparing Means of High Prices and Can't Afford Responses for Buying from 1978 to 2008

```
Paired t test
------------------------------------------------------------------------------
            Variable |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf.
Interval]
---------+--------------------------------------------------------------------
(1) buy_popALL_bad_HR |     185    1.927189    .1452164    1.975157    1.640686
 2.213693
(2) buy_popALL_bad_CA |     185    1.534216    .1003637    1.365094    1.336205
 1.732228
---------+--------------------------------------------------------------------
                 diff |     185     .392973    .0885435    1.204322    .2182819
 .5676641
------------------------------------------------------------------------------
     mean(diff) = mean(buy_popALL_b~tes - buy_popALL_bad~d)       t =   4.4382
 Ho: mean(diff) = 0                              degrees of freedom =      184

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

(1) Population percentage of respondents who say bad time to buy because of High Prices

(2) Population percentage of respondents who say bad time to buy because they Can't Afford to buy

Table 11.A

T-test to show Selling Conditions Index >100 from 1992 to 2008

```
One-sample t test
------------------------------------------------------------------------------
Variable |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
sellindex_ALL |     185    115.5405    2.162073    29.40737    111.2749    119.8062
------------------------------------------------------------------------------
    mean = mean(sellindex_ALL)                                    t =   7.1878
Ho: mean = 100                                   degrees of freedom =      184

   Ha: mean < 100               Ha: mean != 100               Ha: mean > 100
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

(1)Home Selling Index from 1992 to 2008

Table 12.A

T-Test Comparing Means of Low Interest Rate and High Prices Responses for Selling from 1992 to 2008

```
Paired t test
------------------------------------------------------------------------------
               Variable |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf.
Interval]
---------+--------------------------------------------------------------------
(1) sell_popALL_good_LR |     185    11.51989    .4289455     5.83429    10.67361
 12.36618
(2) sell_popALL_good_HP |     185       9.186    .3875456     5.27119    8.421396
 9.950604
---------+--------------------------------------------------------------------
                   diff |     185    2.333892     .401657    5.463126    1.541447
 3.126337
------------------------------------------------------------------------------
     mean(diff) = mean(sell_popALL_good_LR - sell_popALL_good_HP)       t =   5.8107
 Ho: mean(diff) = 0                              degrees of freedom =      184

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

(1) Population percentage of respondents who say good time to sell because of Low Interest Rates

(2) Population percentage of respondents who say good time to sell because of High Prices

Table 13.A

T-Test Comparing Means of High Prices and Good Times Responses for Selling from 1992 to 2008

```
Paired t test
------------------------------------------------------------------------------
              Variable |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf.
Interval]
---------+--------------------------------------------------------------------
(1) sell_popALL_good_HP |     185       9.186    .3875456     5.27119    8.421396
 9.950604
(2) sell_popALL_good_GT |     185    8.754108    .3574532    4.861889    8.048874
 9.459342
---------+--------------------------------------------------------------------
                  diff |     185    .4318919    .4315319    5.869469    -.419495
 1.283279
------------------------------------------------------------------------------
     mean(diff) = mean(sell_popALL_good_HP - sell_popALL_good_GT)       t =   1.0008
 Ho: mean(diff) = 0                              degrees of freedom =      184

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 0.8409         Pr(|T| > |t|) = 0.3182          Pr(T > t) = 0.1591
```

(1) Population percentage of respondents who say good time to sell because of High Prices

(2) Population percentage of respondents who say good time to sell because of Good Times

Table 14.A

T-Test Comparing Means of Low Prices and Can't Afford for Selling from 1992 to 2008

```
Paired t test
------------------------------------------------------------------------------
             Variable |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf.
Interval]
---------+--------------------------------------------------------------------
(1) sell_popALL_bad_LP |     185    9.612757    .7522009    10.23104    8.128709
11.0968
(2) sell_popALL_bad_CA |     185    4.724649    .3474974    4.726475    4.039057
5.41024
---------+--------------------------------------------------------------------
                 diff |     185    4.888108    .4388787    5.969396    4.022226
5.75399
------------------------------------------------------------------------------
     mean(diff) = mean(sell_popALL_bad_LP - sell_popALL_bad_CA)       t =  11.1377
 Ho: mean(diff) = 0                              degrees of freedom =      184

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

(1) Population percentage of respondents who say bad time to sell because of Low Prices

(2) Population percentage of respondents who say bad time to sell because they Can't Afford to sell

Table 15.A

T-Test Comparing Means of Can't Afford and High Interest Rate Responses for Selling from 1992 to 2008

```
Paired t test
------------------------------------------------------------------------------
              Variable |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf.
Interval]
---------+--------------------------------------------------------------------
(1) sell_popALL_bad_CA |     185    4.724649    .3474974    4.726475    4.039057
5.41024
(2) sell_popALL_bad_HR |     185    2.388378    .1780373     2.42157    2.037121
 2.739635
---------+--------------------------------------------------------------------
                  diff |     185     2.33627    .2146037    2.918926     1.91287
 2.759671
------------------------------------------------------------------------------
     mean(diff) = mean(sell_popALL_bad_CA - sell_popALL_bad_HR)       t =  10.8864
 Ho: mean(diff) = 0                              degrees of freedom =      184

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

(1) Population percentage of respondents who say bad time to sell because they Can't Afford to sell

(2) Population percentage of respondents who say bad time to sell because of High Interest Rates

Appendix B—Paired t-tests of Homeowner vs Non-homeowner indexes and individual response reasons

Table 1.B

Paired T-test Comparing Indexes of Buying Homeowners vs Non-homeowners (1992-2008)

```
Paired t test
------------------------------------------------------------------------------
            Variable |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf.
Interval]
---------+--------------------------------------------------------------------
(1)    buyindex_HOME |     185    159.0757    1.138563    15.48613    156.8294
161.322
(2) buyindex_NONHOME |     185    138.1767    1.636889     22.2641    134.9472
141.4062
---------+--------------------------------------------------------------------
                diff |     185    20.89897    1.027223    13.97174    18.87232
22.92561
------------------------------------------------------------------------------
     mean(diff) = mean(buyindex_HOME - buyindex_NONHOME)          t =  20.3451
 Ho: mean(diff) = 0                              degrees of freedom =      184

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

(1) Index of Buying Conditions for homeowner respondents
(2) Index of Buying Conditions for non-homeowner respondents

Table 2.B

Paired T-test Comparing Indexes of Selling Homeowners vs Non-homeowners (1992-2008)

```
Paired t test
------------------------------------------------------------------------------
             Variable |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf.
Interval]
---------+--------------------------------------------------------------------
(1)    sellindex_HOME |     185     119.227    2.314203    31.47657    114.6612
123.7928
(2) sellindex_NONHOME |     185    106.0596    1.832719    24.92768    102.4438
109.6755
---------+--------------------------------------------------------------------
                 diff |     185    13.16739    1.266442    17.22548    10.66877
15.666
------------------------------------------------------------------------------
     mean(diff) = mean(sellindex_HOME - sellindexNONHOME)         t =  10.3971
 Ho: mean(diff) = 0                              degrees of freedom =      184

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

(1) Index of Selling Conditions for homeowner respondents
(2) Index of Selling Conditions for non-homeowner respondents

Table 3.B

Paired T-tests comparing Response Reasons of Buying Homeowners vs Non-homeowners reasons (1992-2008)

Good: Low Prices

```
Paired t test
------------------------------------------------------------------------------
                 Variable |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf.
Interval]
---------+--------------------------------------------------------------------
(1)    buy_popHOME_good_LP |     185    15.43783     .603907    8.214023    14.24636
  16.6293
(2) buy_popNONHOME_good_LP |     185    12.04183    .4899103    6.663501    11.07527
 13.00839
---------+--------------------------------------------------------------------
                     diff |     185       3.396    .5971061    8.121521    2.217945
 4.574055
------------------------------------------------------------------------------
     mean(diff) = mean(buy_popCOMPHO~lp - buy_popCOMP_N~lp)       t =   5.6874
 Ho: mean(diff) = 0                              degrees of freedom =      184

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

(1) Population percentage of homeowners who say good time to buy because of low prices
(2) Population percentage of non-homeowners who say good time to buy because of low prices

Good: Prices are Rising

```
Paired t test
------------------------------------------------------------------------------
                 Variable |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf.
Interval]
---------+--------------------------------------------------------------------
(1)    buy_popHOME_good_PR |     185     5.32842    .1660135    2.258028    5.000885
 5.655955
(2) buy_popNONHOME_good_PR |     185    4.178047    .1835149    2.496073    3.815983
 4.540111
---------+--------------------------------------------------------------------
                     diff |     185    1.150373    .2124807     2.89005    .7311612
 1.569585
------------------------------------------------------------------------------
     mean(diff) = mean(buy_popCOMPHO~pr - buy_popCOMP_N~pr)       t =   5.4140
 Ho: mean(diff) = 0                              degrees of freedom =      184

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

(1) Population percentage of homeowners who say good time to buy because prices are rising
(2) Population percentage of non-homeowners who say good time to buy because prices are rising

Good: Low interest rates

```
Paired t test
------------------------------------------------------------------------------
                 Variable |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf.
Interval]
---------+--------------------------------------------------------------------
```

```
(1)    buy_popHOME_good_LR |      185    45.27806    1.303749    17.73291    42.70584
 47.85027
(2) buy_popNONHOME_good_LR |      185    26.45324     1.01702    13.83296    24.44672
 28.45976
---------+--------------------------------------------------------------------
                      diff |      185    18.82482    .7162754    9.742398    17.41165
 20.23798
------------------------------------------------------------------------------
     mean(diff) = mean(buy_popCOMPHO~lr - buy_popCOMP_N~lr)       t =  26.2815
 Ho: mean(diff) = 0                              degrees of freedom =      184

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

(1) Population percentage of homeowners who say good time to buy because of low interest rates
(2) Population percentage of non-homeowners who say good time to buy because of low interest rates

Good: Interest rates are rising

```
Paired t test
------------------------------------------------------------------------------
                 Variable |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. 
Interval]
---------+--------------------------------------------------------------------
(1)    buy_popHOME_good_RR |     185    6.398083    .3756619    5.109555    5.656924
 7.139241
(2) buy_popNONHOME_good_RR |     185    4.477023    .2873417     3.90827    3.910115
 5.043932
---------+--------------------------------------------------------------------
                     diff |     185    1.921059    .3206586    4.361429    1.288419
   2.5537
------------------------------------------------------------------------------
     mean(diff) = mean(buy_popCOMPHO~rr - buy_popCOMP_N~rr)        t =   5.9910
 Ho: mean(diff) = 0                              degrees of freedom =      184

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

(1) Population percentage of homeowners who say good time to buy because interest rates are rising
(2) Population percentage of non-homeowners who say good time to buy because interest rates are rising

Good: Good investment

```
Paired t test
------------------------------------------------------------------------------
                  Variable |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. 
             Interval]
---------+--------------------------------------------------------------------
(1)    buy_popHOME_good_GI |     185    5.906185    .1447597    1.968945    5.620582
 6.191787
(2) buy_popNONHOME_good_GI |     185    3.184386    .1943958    2.644068    2.800854
 3.567917
---------+--------------------------------------------------------------------
                     diff |     185    2.721799    .2366262    3.218464     2.25495
 3.188648
------------------------------------------------------------------------------
     mean(diff) = mean(buy_popCOMPHOM~i - buy_popCOMP_NO~i)        t =  11.5025
 Ho: mean(diff) = 0                              degrees of freedom =      184

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

(1) Population percentage of homeowners who say good time to buy because it is a good investment
(2) Population percentage of non-homeowners who say good time to buy because it is a good investment

Good: Good times ahead

```
Paired t test
------------------------------------------------------------------------------
                 Variable |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. 
Interval]
---------+--------------------------------------------------------------------
(1)    buy_popHOME_good_GT |     185    5.409406    .2565105     3.48892    4.903326
 5.915486
(2) buy_popNONHOME_good_GT |     185    4.662629    .2354257    3.202136    4.198148
  5.12711
---------+--------------------------------------------------------------------
```

```
                 diff |     185    .7467774    .2169913    2.951401    .3186664
 1.174888
------------------------------------------------------------------------------
     mean(diff) = mean(buy_popCOMPHO~gt - buy_popCOMP_N~gt)       t =   3.4415
 Ho: mean(diff) = 0                              degrees of freedom =      184

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 0.9996         Pr(|T| > |t|) = 0.0007          Pr(T > t) = 0.0004
```

(1) Population percentage of homeowners who say good time to buy because of good times ahead
(2) Population percentage of non-homeowners who say good time to buy because of good times ahead

Bad: High Prices

```
Paired t test
------------------------------------------------------------------------------
                Variable |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf.
Interval]
---------+--------------------------------------------------------------------
(1)    buy_popHOME_bad_HP |     185    2.233434    .1614186     2.19553    1.914965
 2.551904
(2) buy_popNONHOME_bad_HP |     185    4.284037     .323699    4.402783    3.645398
 4.922676
---------+--------------------------------------------------------------------
                    diff |     185   -2.050602    .2063402     2.80653   -2.457699
-1.643505
------------------------------------------------------------------------------
     mean(diff) = mean(buy_popCOMPHO~hp - buy_popCOMP_N~hp)       t =  -9.9380
 Ho: mean(diff) = 0                              degrees of freedom =      184

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 0.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 1.0000
```

(1) Population percentage of homeowners who say bad time to buy because of high prices
(2) Population percentage of non-homeowners who say bad time to buy because of high prices

Bad: High interest rates

```
Paired t test
------------------------------------------------------------------------------
                Variable |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf.
Interval]
---------+--------------------------------------------------------------------
(1)    buy_popHOME_bad_HR |     185    1.775624    .1419319    1.930483    1.495601
 2.055647
(2) buy_popNONHOME_bad_HR |     185    2.862606    .2452878    3.336275    2.378668
 3.346545
---------+--------------------------------------------------------------------
                    diff |     185   -1.086982    .1702322    2.315409    -1.42284
-.7511242
------------------------------------------------------------------------------
     mean(diff) = mean(buy_popCOMPHO~hr - buy_popCOMP_N~hr)       t =  -6.3853
 Ho: mean(diff) = 0                              degrees of freedom =      184

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 0.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 1.0000
```

(1) Population percentage of homeowners who say bad time to buy because of high prices
(2) Population percentage of non-homeowners who say bad time to buy because of high prices

Bad: Can't afford

```
Paired t test
------------------------------------------------------------------------------
                Variable |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf.
Interval]
---------+--------------------------------------------------------------------
(1)    buy_popHOME_bad_CA |     185    1.204315    .0825706    1.123082    1.041408
 1.367222
(2) buy_popNONHOME_bad_CA |     185    2.876531    .2259878    3.073766     2.43067
 3.322391
---------+--------------------------------------------------------------------
```

```
                    diff |     185   -1.672216    .1774465    2.413534   -2.022307
-1.322124
------------------------------------------------------------------------------
     mean(diff) = mean(buy_popCOMPHOM~a - buy_popCOMP_NO~a)       t =  -9.4238
 Ho: mean(diff) = 0                              degrees of freedom =      184

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 0.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 1.0000
```

(1) Population percentage of homeowners who say bad time to buy because they cannot afford it
(2) Population percentage of non-homeowners who say bad time to buy because they cannot afford it

Bad: Bad times ahead

```
Paired t test
------------------------------------------------------------------------------
                 Variable |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf.
Interval]
---------+--------------------------------------------------------------------
(1)    buy_popHOME_bad_BT |     185    .4491571    .0248845    .3384654    .4000615
 .4982527
(2) buy_popNONHOME_bad_BT |     185    .8790815     .057711    .7849551    .7652211
  .992942
---------+--------------------------------------------------------------------
                     diff |     185   -.4299244    .0510178    .6939173   -.5305795
-.3292693
------------------------------------------------------------------------------
     mean(diff) = mean(buy_popCOMPHO~bt - buy_popCOMP_N~bt)       t =  -8.4269
 Ho: mean(diff) = 0                              degrees of freedom =      184

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 0.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 1.0000
```

(1) Population percentage of homeowners who say bad time to buy because of bad times ahead
(2) Population percentage of non-homeowners who say bad time to buy because of bad times ahead

Bad: Will lose money

```
Paired t test
------------------------------------------------------------------------------
                 Variable |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf.
Interval]
---------+--------------------------------------------------------------------
(1)    buy_popHOME_bad_LM |     185    .0814076    .0111766    .1520176    .0593569
 .1034582
(2) buy_popNONHOME_bad_LM |     185    .1804622    .0262815    .3574668    .1286104
  .232314
---------+--------------------------------------------------------------------
                     diff |     185   -.0990546    .0250609    .3408651   -.1484983
 -.049611
------------------------------------------------------------------------------
     mean(diff) = mean(buy_popCOMPHOM~m - buy_popCOMP_NO~m)       t =  -3.9526
 Ho: mean(diff) = 0                              degrees of freedom =      184

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 0.0001         Pr(|T| > |t|) = 0.0001          Pr(T > t) = 0.9999
```

(1) Population percentage of homeowners who say bad time to buy because will lose money
(2) Population percentage of non-homeowners who say bad time to buy because will lose money

Table 4.B

Paired T-tests comparing Response Reasons of Selling Homeowners vs Non-homeowners reasons (1992-2008)

Good Reason: High Prices

```
Paired t test
------------------------------------------------------------------------------
                   Variable |     Obs        Mean    Std. Err.   Std. Dev.   [95%
Conf. Interval]
```

```
---------+--------------------------------------------------------------------
(1)    sell_popHOME_good_HP |     185    10.89183    .4478071    6.090834    10.00833
   11.77533
(2) sell_popNONHOME_good_HP |     185    7.056278    .3625116    4.930691    6.341064
   7.771492
---------+--------------------------------------------------------------------
                       diff |     185    3.835552    .3040548    4.135593     3.23567
   4.435434
------------------------------------------------------------------------------
     mean(diff) = mean(sell_popCOMPH~hp - sell_popCOMP_~hp)       t =  12.6147
 Ho: mean(diff) = 0                              degrees of freedom =      184

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

(1) Population percentage of homeowners who say good time to sell because of high prices
(2) Population percentage of non-homeowners who say good time to sell because of high prices

Good reason: Prices will fall

```
Paired t test
------------------------------------------------------------------------------
                              Variable |     Obs        Mean    Std. Err.   Std. Dev.
  [95% Conf. Interval]
---------+--------------------------------------------------------------------
(1)    sell_popHOME_good_PF |     185    1.002667    .0658188    .8952318    .8728109
   1.132524
(2) sell_popNONHOME_good_PF |     185    1.299947    .0980455    1.333563    1.106509
   1.493385
---------+--------------------------------------------------------------------
                       diff |     185   -.2972796     .094078    1.279599   -.4828898
  -.1116694
------------------------------------------------------------------------------
     mean(diff) = mean(sell_popCOMPHO~f - sell_popCOMP_N~f)       t =  -3.1599
 Ho: mean(diff) = 0                              degrees of freedom =      184

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 0.0009         Pr(|T| > |t|) = 0.0018          Pr(T > t) = 0.9991
```

(1) Population percentage of homeowners who say good time to sell because prices are falling
(2) Population percentage of non-homeowners who say good time to sell because prices are falling

Good reason: low interest rates

```
Paired t test
------------------------------------------------------------------------------
                             Variable |     Obs        Mean    Std. Err.   Std. Dev.
  [95% Conf. Interval]
---------+--------------------------------------------------------------------
(1)    sell_popHOME_good_lr |     185    14.76484    .5615569    7.637999    13.65692
   15.87276
(2) sell_popNONHOME_good_lr |     185    5.805896    .2838069    3.860192    5.245961
    6.36583
---------+--------------------------------------------------------------------
                       diff |     185    8.958947    .4777815    6.498531    8.016313
   9.901582
------------------------------------------------------------------------------
     mean(diff) = mean(sell_popCOMPHO~w - sell_popCOMP_~lr)       t =  18.7511
 Ho: mean(diff) = 0                              degrees of freedom =      184

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

(1) Population percentage of homeowners who say good time to sell because of low interest rates
(2) Population percentage of non-homeowners who say good time to sell because of low interest rates

Good reason: rising interest rates

```
Paired t test
------------------------------------------------------------------------------
                              Variable |     Obs        Mean    Std. Err.   Std. Dev.
  [95% Conf. Interval]
---------+--------------------------------------------------------------------
(1)    sell_popHOME_good_RR |     185    1.333532    .1009134    1.372571    1.134436
   1.532629
(2) sell_popNONHOME_good_RR |     185     .910681    .0886023    1.205121    .7358739
   1.085488
---------+--------------------------------------------------------------------
```

```
                  diff |     185    .4228515      .10788    1.467327    .2100106
   .6356924
------------------------------------------------------------------------------
     mean(diff) = mean(sell_popCOMPH~rr - sell_popCOMP_~rr)       t =   3.9196
 Ho: mean(diff) = 0                              degrees of freedom =      184

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 0.9999         Pr(|T| > |t|) = 0.0001          Pr(T > t) = 0.0001
```

(1) Population percentage of homeowners who say good time to sell because interest rates are rising
(2) Population percentage of non-homeowners who say good time to sell because interest rates are rising

Good reason: good investment

```
Paired t test
------------------------------------------------------------------------------
                             Variable |     Obs        Mean    Std. Err.   Std. Dev.
  [95% Conf. Interval]
---------+--------------------------------------------------------------------
(1)    sell_popHOME_good_GI |     185    2.525895    .1292546    1.758053    2.270883
   2.780906
(2) sell_popNONHOME_good_GI |     185     2.09399    .1401307    1.905984     1.81752
   2.370459
---------+--------------------------------------------------------------------
                      diff |     185    .4319047    .1504242     2.04599    .1351268
   .7286827
------------------------------------------------------------------------------
     mean(diff) = mean(sell_popCOMPHO~i - sell_popCOMP_N~i)       t =   2.8712
 Ho: mean(diff) = 0                             degrees of freedom =      184

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 0.9977         Pr(|T| > |t|) = 0.0046          Pr(T > t) = 0.0023
```

(1) Population percentage of homeowners who say good time to sell because it is a good investment
(2) Population percentage of non-homeowners who say good time to sell because it is a good investment

Good reason: Good times ahead

```
Paired t test
------------------------------------------------------------------------------
                             Variable |     Obs        Mean    Std. Err.   Std. Dev.
  [95% Conf. Interval]
---------+--------------------------------------------------------------------
(1)    sell_popHOME_good_GT |     185    10.04145    .4349232    5.915595    9.183371
   10.89953
(2) sell_popNONHOME_good_GT |     185     8.01166    .3635357     4.94462    7.294426
   8.728895
---------+--------------------------------------------------------------------
                      diff |     185    2.029789    .3203567    4.357322    1.397744
   2.661833
------------------------------------------------------------------------------
     mean(diff) = mean(sell_popCOMPH~gt - sell_popCOMP_~gt)       t =   6.3360
 Ho: mean(diff) = 0                             degrees of freedom =      184

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

(1) Population percentage of homeowners who say good time to sell because of good times ahead
(2) Population percentage of non-homeowners who say good time to sell because of good times aheads

Bad reason: low prices

```
Paired t test
------------------------------------------------------------------------------
                            Variable |     Obs        Mean    Std. Err.   Std. Dev.
[95% Conf. Interval]
---------+--------------------------------------------------------------------
(1)    sell_popHOME_bad_LP |     185    10.01011    .8416066    11.44709    8.349666
 11.67055
(2) sell_popNONHOME_bad_LP |     185     9.87879    .5738432    7.805112    8.746632
 11.01095
---------+--------------------------------------------------------------------
```

```
                    diff |     185    .1313158    .5319501    7.235303   -.9181901
 1.180822
------------------------------------------------------------------------------
    mean(diff) = mean(sell_popCOMPH~lp - sell_popCOMP_~lp)       t =   0.2469
 Ho: mean(diff) = 0                              degrees of freedom =      184

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 0.5974         Pr(|T| > |t|) = 0.8053          Pr(T > t) = 0.4026
```

(1) Population percentage of homeowners who say bad time to sell because of low prices
(2) Population percentage of non-homeowners who say bad time to sell because of low prices

Bad reason: high interest rates

```
Paired t test
------------------------------------------------------------------------------
                             Variable |     Obs        Mean    Std. Err.   Std. Dev.
[95% Conf. Interval]
---------+--------------------------------------------------------------------
(1)    sell_popHOME_bad_HR |     185    2.507225     .193081    2.626186    2.126288
 2.888163
(2) sell_popNONHOME_bad_HR |     185    2.551759    .1869222    2.542417    2.182972
 2.920545
---------+--------------------------------------------------------------------
                      diff |     185   -.0445335    .1507901    2.050967   -.3420334
 .2529664
------------------------------------------------------------------------------
     mean(diff) = mean(sell_popCOMPH~hr - sell_popCOMP_~hr)       t =  -0.2953
 Ho: mean(diff) = 0                              degrees of freedom =      184

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 0.3840         Pr(|T| > |t|) = 0.7681          Pr(T > t) = 0.6160
```

(1) Population percentage of homeowners who say bad time to sell because of high interest rates
(2) Population percentage of non-homeowners who say bad time to sell because of high interest rates

Bad reason: can't afford

```
Paired t test
------------------------------------------------------------------------------
                             Variable |     Obs        Mean    Std. Err.   Std. Dev.
[95% Conf. Interval]
---------+--------------------------------------------------------------------
(1)    sell_popHOME_bad_CA |     185    4.403516    .3491984    4.749612    3.714569
 5.092464
(2) sell_popNONHOME_bad_CA |     185     6.65544    .4221124    5.741349    5.822637
 7.488243
---------+--------------------------------------------------------------------
                      diff |     185   -2.251924    .2077048     2.82509   -2.661713
-1.842135
------------------------------------------------------------------------------
     mean(diff) = mean(sell_popCOMPHO~a - sell_popCOMP_N~a)       t = -10.8419
 Ho: mean(diff) = 0                              degrees of freedom =      184

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 0.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 1.0000
```

(1) Population percentage of homeowners who say bad time to sell because they cannot afford it
(2) Population percentage of non-homeowners who say bad time to sell because they cannot afford it

Bad reason: bad times ahead

```
Paired t test
------------------------------------------------------------------------------
                             Variable |     Obs        Mean    Std. Err.   Std. Dev.
[95% Conf. Interval]
---------+--------------------------------------------------------------------
(1)    sell_popHOME_bad_BT |     185    1.078584    .0898121    1.221576    .9013897
 1.255777
(2) sell_popNONHOME_bad_BT |     185    1.358144    .1114083    1.515317    1.138342
 1.577946
```

```
---------+--------------------------------------------------------------------
                     diff |     185   -.2795607     .099146    1.348531   -.4751698
-.0839515
------------------------------------------------------------------------------
     mean(diff) = mean(sell_popCOMPH~bt - sell_popCOMP_~bt)       t =  -2.8197
 Ho: mean(diff) = 0                              degrees of freedom =      184

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 0.0027         Pr(|T| > |t|) = 0.0053          Pr(T > t) = 0.9973
```

(1) Population percentage of homeowners who say bad time to sell because of bad times ahead
(2) Population percentage of non-homeowners who say bad time to sell because of bad times ahead

Bad reason: will lose money

```
Paired t test
------------------------------------------------------------------------------
                             Variable |     Obs        Mean    Std. Err.   Std. Dev.
[95% Conf. Interval]
---------+--------------------------------------------------------------------
(1)    sell_popHOME_bad_LM |     185    1.915929    .1734031    2.358537    1.573815
 2.258043
(2) sell_popNONHOME_bad_LM |     185    2.607739    .2368595    3.221637    2.140429
 3.075049
---------+--------------------------------------------------------------------
                     diff |     185   -.6918097    .1363641    1.854753    -.960848
-.4227714
------------------------------------------------------------------------------
     mean(diff) = mean(sell_popCOMPHO~m - sell_popCOMP_N~m)       t =  -5.0733
 Ho: mean(diff) = 0                              degrees of freedom =      184

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 0.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 1.0000
```

(1) Population percentage of homeowners who say bad time to sell because will lose money
(2) Population percentage of non-homeowners who say bad time to sell because will lose money

Appendix C- Perceived Interest Rate Regressions

<u>Table 1.C</u>

Regression of Perceived Interest Rate on Contract Rate and Inflation from November 1992 to Septtember 2002

Source	SS	df	MS
Model	4684.94647	2	2342.47323
Residual	3186.48364	64	49.7888069
Total	7871.43011	66	119.264093

Number of obs =	67
F(2, 64) =	47.05
Prob > F =	0.0000
R-squared =	0.5952
Adj R-squared =	0.5825
Root MSE =	7.0561

perceivedrate	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
(1) contractrate	20.60848	2.334684	8.83	0.000	15.94441	25.27255
(2) inflationrate	1.86387	1.079963	1.73	0.089	-.2936046	4.021345
_cons	-38.25033	13.69628	-2.79	0.007	-65.6118	-10.88886

(1) Contract Interest rate
(2) Inflation rate

<u>Table 2.C</u>

Regression of Perceived Interest Rate on Contract Rate and Inflation from October 2002 to March 2008

Source	SS	df	MS
Model	13111.4928	2	6555.74638
Residual	3926.38974	64	61.3498397
Total	17037.8825	66	258.149735

Number of obs =	67
F(2, 64) =	106.86
Prob > F =	0.0000
R-squared =	0.7695
Adj R-squared =	0.7623
Root MSE =	7.8326

perceivedrate	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
(1) contractrate	32.4801	2.591606	12.53	0.000	27.30277	37.65742
(2) inflationrate	5.046976	1.198809	4.21	0.000	2.652081	7.441872
_cons	-131.3245	15.2035	-8.64	0.000	-161.697	-100.952

(1) Contract Interest rate
(2) Inflation rate

<u>Table 3.C</u>

Regression of Perceived Interest Rate on the Real Contract Rate from November 1992 to September 2002

Source	SS	df	MS
Model	36.6221204	1	36.6221204
Residual	9743.49196	116	83.9956203

Number of obs =	118
F(1, 116) =	0.44
Prob > F =	0.5104
R-squared =	0.0037
Adj R-squared =	-0.0048

```
      Total |  9780.11408   117  83.5907186           Root MSE      =  9.1649

------------------------------------------------------------------------------
      perceivedrate |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
(1) realcontractrate |  -1.049039   1.588723    -0.66   0.510    -4.195704    2.097627
              _cons |   78.90218   7.584083    10.40   0.000     63.88094    93.92341
------------------------------------------------------------------------------
```

(1) Real Contract Interest rate (nominal contract rate – inflation)

Table 4.C

Regression of Perceived Interest Rate on the Real Contract Rate from October 2002 to March 2008

```
      Source |       SS       df       MS              Number of obs =      67
-------------+------------------------------           F(  1,    65) =    0.26
       Model |  68.6343942     1  68.6343942           Prob > F      =  0.6099
    Residual |  16969.2481    65  261.065356           R-squared     =  0.0040
-------------+------------------------------           Adj R-squared = -0.0113
       Total |  17037.8825    66  258.149735           Root MSE      =  16.158

------------------------------------------------------------------------------
       perceivedrate |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
(1)  realcontractrate |  -1.237506    2.41352    -0.51   0.610    -6.057637    3.582626
               _cons |   83.28705   7.855715    10.60   0.000     67.59811      98.976
------------------------------------------------------------------------------
```

(1) Real Contract Interest rate (nominal contract rate – inflation)

.

Appendix D—Perceived House Price Regressions

Table 1.D

Regression of Perceived Housing Price on Nominal Median House Price from November 1992 to September 2000

Source	SS	df	MS
Model	4094.10256	1	4094.10256
Residual	1142.44004	93	12.2843015
Total	5236.54259	94	55.7078999

Number of obs	95
F(1, 93)	333.28
Prob > F	0.0000
R-squared	0.7818
Adj R-squared	0.7795
Root MSE	3.5049

perceivedprice	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
(1) nom med price	.5056586	.0276983	18.26	0.000	.4506552	.5606619
_cons	29.60798	3.477664	8.51	0.000	22.70202	36.51393

(1) Nominal Median House Price

Table 2.D

Regression of Perceived Housing Price on Real Median House Price from November 1992 to September 2000

Source	SS	df	MS
Model	3573.2824	1	3573.2824
Residual	1663.26019	93	17.8845182
Total	5236.54259	94	55.7078999

Number of obs	95
F(1, 93)	199.80
Prob > F	0.0000
R-squared	0.6824
Adj R-squared	0.6790
Root MSE	4.229

perceivedprice	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
(1) real med price	1.079861	.0763964	14.13	0.000	.9281527	1.231569
_cons	-28.38215	8.581054	-3.31	0.001	-45.42242	-11.34187

(1) Real Median House Price

Table 3.D

Regression of Perceived Housing Price on Nominal Median House Price from October 2000 to April 2006

Source	SS	df	MS
Model	1063.52859	1	1063.52859
Residual	924.036077	65	14.2159396
Total	1987.56467	66	30.1146162

Number of obs	67
F(1, 65)	74.81
Prob > F	0.0000
R-squared	0.5351
Adj R-squared	0.5279
Root MSE	3.7704

perceivedprice	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
(1) nom med price	.1601463	.0185153	8.65	0.000	.1231687	.1971238

```
          _cons |   72.17809   3.409604    21.17   0.000     65.36864    78.98754
------------------------------------------------------------------------------
```

(1) Nominal Median House Price

<u>Table 4.D</u>
Regression of Perceived Housing Price on Real Median House Price from October 2000 to April 2006

```
      Source |       SS       df       MS              Number of obs =      67
-------------+------------------------------           F(  1,    65) =   76.63
       Model |  1075.39752     1  1075.39752           Prob > F      =  0.0000
    Residual |  912.167146    65  14.0333407           R-squared     =  0.5411
-------------+------------------------------           Adj R-squared =  0.5340
       Total |  1987.56467    66  30.1146162           Root MSE      =  3.7461

------------------------------------------------------------------------------
    perceivedprice |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
(1)  real med price |   .2920141    .033358     8.75   0.000     .2253936    .3586346
            _cons |   60.85217   4.654367    13.07   0.000     51.55676    70.14758
------------------------------------------------------------------------------
```

(1) Real Median House Price

<u>Table 5.D</u>
Regression of Perceived Housing Price on Nominal Median House Price from May 2006 to March 2008

```
      Source |       SS       df       MS              Number of obs =      23
-------------+------------------------------           F(  1,    21) =   43.64
       Model |  2613.98001     1  2613.98001           Prob > F      =  0.0000
    Residual |  1257.98974    21  59.9042733           R-squared     =  0.6751
-------------+------------------------------           Adj R-squared =  0.6596
       Total |  3871.96975    22  175.998625           Root MSE      =  7.7398

------------------------------------------------------------------------------
   perceivedprice |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
(1)  nom med price |   .9718743   .1471255     6.61   0.000     .6659102    1.277839
           _cons |  -132.3591   31.80919    -4.16   0.000      -198.51   -66.20827
------------------------------------------------------------------------------
```

(1) Nominal Median House Price

<u>Table 6.D</u>
Regression of Perceived Housing Price on Real Median House Price from May 2006 to March 2008

```
      Source |       SS       df       MS              Number of obs =      23
-------------+------------------------------           F(  1,    21) =   75.30
       Model |  3027.59836     1  3027.59836           Prob > F      =  0.0000
    Residual |  844.371393    21  40.2081616           R-squared     =  0.7819
-------------+------------------------------           Adj R-squared =  0.7715
       Total |  3871.96975    22  175.998625           Root MSE      =   6.341

------------------------------------------------------------------------------
    perceivedprice |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
(1)  real med price |   1.226626    .141358     8.68   0.000     .9326565    1.520596
            _cons |  -104.8145   21.05101    -4.98   0.000    -148.5924   -61.03649
------------------------------------------------------------------------------
```

(1) Real Median House Price

Table 7.D

Regression of Perceived Housing Price on Nominal Median House Price and Inflation using data from 11/1992 -- 9/2000

Source	SS	df	MS
Model	4101.32873	2	2050.66437
Residual	1135.21386	92	12.3392811
Total	5236.54259	94	55.7078999

Number of obs	95
F(2, 92)	166.19
Prob > F	0.0000
R-squared	0.7832
Adj R-squared	0.7785
Root MSE	3.5127

perceivedprice	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
(1) nom med price	.5118096	.0289004	17.71	0.000	.4544108	.5692084
(2) inflationrate	.4964046	.6486739	0.77	0.446	-.7919178	1.784727
_cons	27.55983	4.394472	6.27	0.000	18.83203	36.28763

(1) Nominal Median House Price
(2) Inflation Rate

Table 8.D

Regression of Perceived Housing Price on Nominal Median House Price and Inflation using data from 10/2000 -- 4/2006

Source	SS	df	MS
Model	1506.29237	2	753.146186
Residual	481.272295	64	7.5198796
Total	1987.56467	66	30.1146162

Number of obs	67
F(2, 64)	100.15
Prob > F	0.0000
R-squared	0.7579
Adj R-squared	0.7503
Root MSE	2.7422

perceivedprice	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
(1) nom med price	.1118528	.0148644	7.52	0.000	.0821577	.141548
(2) inflationrate	3.422835	.4460724	7.67	0.000	2.531703	4.313967
_cons	71.90144	2.48009	28.99	0.000	66.94689	76.85599

(1) Nominal Median House Price
(2) Inflation Rate

Table 9.D

Regression of Perceived Housing Price on Nominal Median House Price and Inflation using data from 5/2006 -- 3/2008

Source	SS	df	MS
Model	2782.83497	2	1391.41749
Residual	1089.13478	20	54.4567391
Total	3871.96975	22	175.998625

Number of obs	23
F(2, 20)	25.55
Prob > F	0.0000
R-squared	0.7187
Adj R-squared	0.6906
Root MSE	7.3795

perceivedprice	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
(1) nom med price	1.042123	.145839	7.15	0.000	.7379081	1.346338

```
(2) inflationrate |   2.998402   1.702781     1.76   0.094    -.5535367    6.550341
            _cons |  -156.7575   33.34357    -4.70   0.000    -226.3109     -87.204
------------------------------------------------------------------------------
```

(1) Nominal Median House Price
(2) Inflation Rate