Default when House Prices are Uncertain*

Morris A. Davis and Erwan Quintin

University of Wisconsin-Madison

Department of Real Estate and Urban Land Economics

June, 2013

Abstract:

During the 2000-2011 housing boom and bust, changes to self-assessed house prices in 20 different metro areas are highly correlated with changes to the Case-Shiller-Weiss (CSW) house price indexes, but do not change percent-for-percent with the CSW indexes during the boom or bust. We argue this evidence is consistent with an environment in which homeowners imperfectly observe the value of their home and update their guess of home value using a Kalman filter. Using data on self-assessed house prices and the CSW indexes, we estimate the parameters of a simple model of imperfectly-observed house prices. In an out-of-sample forecast exercise, we show the model is nearly perfectly able to repliate the sequence of self-assessed house prices from 2006-2011 in many MSAs, from places experiencing a modest boom like Atlanta and Detroit to the "bubble" areas like Miami and Phoenix. We then specify an economic model of the optimal default decisions of homeowners when homeowners imperfectly observe the value of their home. We show that, relative to a standard model of default, homeowners delay their decision to default after a bad house price shock. We argue this phenomenon helps to explain default patterns in the United States during the 2007-2011 housing bust.

*We would like to thank the Lincoln Institute of Land Policy for support and seminar participants at the Homer Hoyt Institute. Email: *mdavis@bus.wisc.edu*

1 Introduction

2 Data

In this paper, we compare changes to Case-Shiller-Weiss (CSW) house price indexes and changes to self-reported house prices for 20 Metropolitan Statistical Areas (MSAs) over the 2000-2011 period. The CSW house price indexes are derived from repeated sales of single-family housing units, which in principle delivers a constant-quality price index.[1] we average the monthly nominal CSW index values in each year and convert the nominal annual index to real by deflating using the personal consumption price index in the National Income and Product Accounts (NIPA), line 2 of NIPA table 1.1.4.

The data on self-assessed home values are from the 5% sample of the 2000 Census and the annual 2005 through 2010 American Community Surveys (ACS).[2] 2005 is the first year that the ACS includes metropolitan-area data and 2010 is the last year of publicly available ACS data. The geographic boundaries defining metropolitan areas in the 2000 Census and the 2005-2010 ACS are consistent with the 2000 definition and are consistent with the MSA boundaries in the CSW data.[3] From the Census and ACS data, we include only nonfarm, single-family detached or attached, owner-occupied housing units. The large majority of these units are detached. We keep any housing unit where the reported house value is specified in a flag variable as "unaltered."[4] The Census and the ACS continually sample

[1]The CSW discards transactions that occur with 6 months; regression weights (used to compute the index) are reduced the longer the time between sales; and, price anomalies are down-weighted. For further discussion, see http://www.macromarkets.com/csi_housing/documents/tech_discussion.pdf

[2]These data are available from the IPUMS web site, see http://usa.ipums.org/usa/. See Ruggles et. al. (2010).

[3]With the exception of New York and Chicago, the CSW indexes cover the full set of counties in each of the 20 metro areas. The Chicago index does not cover properties sold in the Kenosha, WI and the Gary, IN metropolitan divisions. The CSW index for New York samples all 23 counties included as part of the New York Metropolitan Statistical Area and 6 others: Fairfield and New Haven counties in Connecticut, Mercer and Warren counties in New Jersey, and Dutchess and Orange counties in New York. In 200, the excluded divisions in Chicago account for 16 percent of the MSA population and the additional 6 counties in the New York metro area increase the population by 15 percent.

[4]Of all metro areas in all years, there are 150 total instances where $0 is reported as the house value.

throughout the survey year. The total number of housing units in the Census and ACS sample that meet the criteria listed above are reported in Table 1. Unlike other commonly used surveys of self-reported house prices, such as the American Housing Survey and the Survey of Consumer Finances, the sample sizes in these data are large.

The Census and ACS data include information on whether or not the units are detached or attached; the age of the units; and, the number of bedrooms in each unit. We assign every unit in the sample to a bin based on these observable characteristics.[5] Attached housing units account for a small percentage of the overall sample and we bin them together by MSA. For the detached units, the bins are based on bedrooms (1 or 2, 3, or 4 or more) and age of structure: Built before 1940; decade-by-decade from 1940-1949 through 1990-1999; 2000-2004; and 2005-2010. We compute sampling weights for each bin prior to discarding any missing or imputed observations on house prices. The sum of the sampling weights across bins is 1.0 in each metro area in every year.

We calculate the average value of housing as the sampling weight for each bin multiplied by the average of the non-missing house values in that bin. We then adjust for inflation using the NIPA price index described earlier. In the remainder of this section, for transparency We compare changes to the real CSW index to changes in the real average self-reported value of housing. As we explain later, model estimation requires data on the average value of the *log* of self-reported house prices, and we show these data later in the paper.[6]

Table 2 reports the real ($2005) average self-reported value of housing. The table shows there is meaningful variation in the self-reports, and the variation coincides with what we know about level and changes of house prices. For example, the standard deviation of the values reported in the table in 2006 is $151 thousand (bottom row), suggesting meaningful geographic dispersion in self-reported house prices. The median of the MSA-average values

These are treated as missing. In addition, we discard from the sample in the 2005 ACS any house reported as built in 2005. Finally, note that housing values in the Census and ACS data are top-coded. The top code is $1,000,000 in 2000 and 2005-2007 and varies by state after 2008. The bottom row of Table 1 shows the percentage of the sample (after accounting for sampling weights) with a top-coded observation for house value. We do not adjust any top-coded responses.

[5]Bins are chosen such that each bin in every metro area in every year contains at least one house price observation.

[6]We compute the average value of the log of house prices using the analogous procedure.

increases from \$209 to \$345 thousand during the housing boom and then falls to \$246 thousand by 2011. In 14 of the 20 MSAs, the average of the self-reported values peaks at the same time or one year after the CSW index peaks.[7]

However, the CSW indexes and the self-reported data do not move in lock-step throughout the sample, the focus of this paper. Figure 1 compares the CSW index (solid line, "CSW") to the average of the self reports (dashed line, "AVG") for each of the 20 MSAs in the sample. The AVG line is linearly interpolated between 2000 and 2005. In every MSA, the average of the self-reports and the CSW indexes are normalized to 100 in the year in which the CSW peaks. Figure 1 shows that after the peak, in every MSA the CSW price index declines more sharply than the self-reports. In many MSAs, the difference in the percentage decline of the CSW index and the self reports is quite large. Table 3 reports the percentage decline in the average self-report data and the CSW indexes, measured from the MSA-specific peak date of the CSW to 2011. At the median MSA, the CSW declines by 14 percentage points more than the self-reports. In the extreme case of the San Francisco MSA, the CSW index declined by 44 percent whereas the self-reports only declined by 19 percent.

It is not obvious from Figure 1 and Table 3, but the magnitude of the difference between the CSW and self-reported values is strongly correlated with the change in the CSW index. This is true for the boom period (2000 to CSW peak date) as well as the bust period. The top panel of figure 2 shows results from the boom period. For each MSA, cumulative real growth in the CSW index, the x-axis, is plotted against cumulative real growth in the self-reports. Figure 2 shows that growth in the CSW and self-reports are highly correlated but growth in self-reports does not reflect growth in the CSW index on a percent-for-percent basis. Rather, when cumulative growth in the self-reported data over this period is regressed on cumulative growth in the CSW index, the coefficient is 0.74 with a standard error of 0.04 and the intercept is 15.9 with a standard error of 3.0.[8] The bottom panel of figure 2 shows results from the bust period, the CSW peak date through 2011. As with the boom period, cumulative growth of the two series are highly correlated, but they do not move

[7]In the case of Dallas, we adjust the real peak date of the CSW from 2002 (no comparable self-report data) to 2006. This adjusts the level of the CSW peak down by 1.3 percent.

[8]The $R2$ of the regression is 0.95.

percent-for-percent. A regression of cumulative growth in the self-reported data over this period on cumulative growth in the CSW index yields a coefficient of 0.86 with a standard error of 0.09; an intercept of 9.4 with a standard error of 3.5; and a $R2$ value of 0.85.[9]

In sum, during both the boom period and bust period, although the CSW and self-report data are highly correlated, the averaged self-report data do not increase or decrease percent-for-percent with changes to the CSW indexes. In the next section we present evidence that these results are consistent with a model in which homeowners receive noisy signals (such as the CSW) about the value of their home and optimally smooth through these signals when determining their home's current value.

3 Model

We consider a simple model that has the potential to capture the experience of house prices during the boom-bust period of 2000-2011. We assume the true log price of home i in metro area m at time t, denoted h^*_{imt}, follows a first-order autoregressive process with autoregressive parameter ρ, fixed mean $\bar{h}_{im}/\left(1-\rho\right)$, and shock e_{imt},

$$h^*_{imt} = \bar{h}_{im} + \rho h^*_{imt-1} + e_{imt} \ . \tag{1}$$

h^*_{imt} is not directly observable but owners observe a noisy signal of the true log price, denoted h^o_{imt}

$$h^o_{imt} = h^*_{imt} + \nu_{imt} \ . \tag{2}$$

e_{imt} and υ_{imt} are assumed to be Normally distributed with mean 0 and variances σ_e^2 and σ_ν^2, with $e_{imt} \perp \nu_{imt}$, $e_{imt} \perp e_{imt+s}$ and $\nu_{imt} \perp \nu_{imt+s}$ for all t and s.[10]

Denote homeowner i's self-assessed value of his house as of date $t-1$ as $\hat{h}_{imt-1}$. Given the model structure and assumptions, the homeowner optimally updates the guess of the

[9] The coefficient estimates are sensitive to the ending year of the sample; for example, the slope coefficient falls to 0.74 if the data are restricted to end in 2010. We view this evidence as supportive of the model we estimate, detailed next.

[10] We allow e_{imt} and e_{jmt} to be correlated for homeowners i and j in metro m at time t and allow a similar correlation for the ν terms. I discuss this correlation in section 5.2.

value of his home in period t using a Kalman Filter,

$$\hat{h}_{imt} = (1-\kappa_{imt})\left[\bar{h}_{im} + \rho\hat{h}_{imt-1}\right] + \kappa_{it}h^o_{imt} \ . \tag{3}$$

κ_{imt} is the Kalman gain which is updated each period using the following recursion (Hamilton 1994)

$$\begin{aligned} V^p_{imt} &= \rho^2 V_{imt} + \sigma^2_e \\ \kappa_{imt} &= \frac{V^p_{imt}}{V^p_{imt} + \sigma^2_\nu} \\ V_{imt+1} &= (1.0 - \kappa_{imt})\, V^p_{imt} \end{aligned}$$

For any $0 < \rho < 1$, κ_{imt} converges monotonically to a fixed value κ, with $0 < \kappa < 1$.

Assume κ_{imt} has converged to its steady-state value κ for each homeowner such that equation (3) can be written as[11]

$$\hat{h}_{imt} = (1-\kappa)\left[\bar{h}_{im} + \rho\hat{h}_{imt-1}\right] + \kappa h^o_{imt}. \tag{4}$$

Since (4) holds for any homeowner i, it holds for the average of all homeowners $i = 1, \ldots, N$. Denote the cross-sectional average of a variable in metro m at time t using a capital letter, for example $\hat{H}_{mt} = \left(\sum_{i=1}^{N} \hat{h}_{mit}\right)$. After taking averages and substituting notation, equation (4) can be written as

$$\hat{H}_{mt} = (1-\kappa)\left[\bar{H}_{m} + \rho\hat{H}_{mt-1}\right] + \kappa H^o_{mt}. \tag{5}$$

Equation (5) cannot be taken directly to data since the average signal H^o_{mt} is not observed. Rather, a metro-area house price index is observed. Assume the log of this index, denoted $\mathcal{H}_{mt}$, is an unbiased estimate of H^o_{mt} up to an metro-specific additive scale factor α'_m and error u'_{mt}

$$\mathcal{H}_{mt} = H^o_{mt} - \alpha'_m - u'_{mt} \ . \tag{6}$$

The assumptions embedded into equation (6) are straightforward. Individual homeowners use sales prices in their neighborhood as a signal for the log price of their own home, and

[11] We evaluate the plausibility of this assumption in section 5.2.

the log of the MSA-level CSW index is assumed to be the correct weighted average of those neighborhood signals up to a scale factor and some measurement error.

Inserting (6) into (5) and defining

$$\alpha_m = \kappa\alpha'_m + (1-\kappa)\,\bar{H}_m \tag{7}$$

$$u_{mt} = \kappa u'_{mt} \tag{8}$$

gives

$$\hat{H}_{mt} = \alpha_m + (1-\kappa)\,\rho\hat{H}_{mt-1} + \kappa\mathcal{H}_{mt} + u_{mt}\ . \tag{9}$$

In estimation, we restrict ρ, σ_e^2, σ_ν^2 and κ to be identical across metro areas but allow $\bar{H}_m$ and α'_m to vary.

4 Estimation

We start by estimating equation (9) using non-linear least squares (NLS). The NLS estimates are biased because u_{mt} is correlated with $\mathcal{H}_{mt}$ but they serve as a basis for comparison to results from an instrumental-variables approach. For data, we use the balanced panel of 20 MSAs described earlier covering the 2005-2011 period (120 observations). For each metro area and year, we define $\hat{H}_{mt}$ as the average of the log of self-reported house values and $\mathcal{H}_{mt}$ as the log of the reported CSW index. The unrestricted NLS estimates, including a full set of MSA dummy variables (the α_m), are $\kappa = 0.483$, standard error 0.015, and $\rho = 1.06$, standard error 0.03.

As is well known, in a short time-series ρ is difficult to estimate. To get a sense for the sensitivity of κ to the estimate of ρ, we fix $\rho = 0.60, 0.65, \ldots, 0.90, 0.95, 0.99$ and estimate κ at each value of ρ. For convenience, rewrite equation (9) as

$$\left[\hat{H}_{mt} - \rho\hat{H}_{mt-1}\right] = \alpha_m + \kappa\left[\mathcal{H}_{mt} - \rho\hat{H}_{mt-1}\right] + u_{mt} \tag{10}$$

Given a value for ρ, the terms in brackets are data and equation (10) can be estimated with a simple regression. To get a sense of model fit that is free of the influence of predictable shifts in levels across metro areas, we remove MSA-fixed effects from both terms in brackets before estimating (10). Table 4 shows OLS estimates of κ with standard errors and R^2 values. The estimates of κ fall in the narrow range of $[0.49, 0.57]$ and the $R2$ of the regressions are all above 88 percent.

As mentioned, NLS and OLS estimates are biased because u_{mt} is correlated with $\mathcal{H}_{mt}$. Table 5 reports 2SLS estimates of equation (10). We estimate κ for the same set of values of ρ as in table 4. We use two instruments, the first lag of the CSW index and the second lag of the average of log self-reported house values. We remove MSA-level fixed effects from both instruments prior to estimation. The estimates of κ in table 5 vary a bit more than those in table 4, but the results seem quite similar. The results of table 5 suggest a plausible range for the Kalman gain is $[0.43, 0.63]$. At all values of ρ, the predictive power of the instruments is quite high. The first-stage F value is always larger than 57 and the R^2 is always greater than 54 percent.[12]

5 Analysis

5.1 Model Fit

To show model fit in more detail, we pick one ρ and κ from table 5. The criteria we use to choose ρ is to find the pair (ρ, κ) that minimizes the standard deviation of u'_{mt} – the distance between the log of the real CSW index and the (unobserved) aggregate MSA signal. To uncover u'_{mt}, at each of the set of ρ and κ in table 5, we estimate α_m as the average value of

$$\hat{H}_{mt} - (1-\kappa)\,\rho\hat{H}_{mt-1} - \kappa\mathcal{H}_{mt}$$

over the 2006-2011 period in each MSA. Then, given α_m we use equation (9) to determine u_{mt} in each MSA. Finally, we set $u'_{mt} = u_{mt}/\kappa$.

The standard deviations of u'_{mt}, estimated using the entire sample of MSAs over the 2006-2011 period, are reported in the rightmost column of table 5. Although the results

[12] Parameter estimates and standard errors are almost identical when we use the twice-lagged value of the real log CSW index and the twice-lagged value of the real log Federal Home Finance Agency (FHFA) metro-area house price index as instruments, and the first stage F-values are 37 and above. Details are available on request.

are similar at all the listed parameters, and generally speaking the results presented in this section do not depend on the specific (ρ, κ) pair chosen from table 5, the values that minimize $SD\left(u'_{mt}\right)$ are $\rho = 0.80$ and $\kappa = 0.510$. At this set of parameters, a two standard error confidence band around the CSW index for the true but unobserved average signal in any year is approximately $\pm$ 10.8 percent.

To get a practical sense for the size of u'_{mt}, we check how well the model could have predicted the sequence of average self-reports from 2005-2011 given (a) data on self-reports $(\hat{H})$ for *only* the year 2000 and (b) the realized values of the Case-Shiller-Weiss index for the period 2001-2011. Given α_m, a sequence of $\mathcal{H}_{mt}$, and a starting value for $\hat{H}_{mt-1}$ (the year-2000 value, but no other values), I generate a model-predicted sequence of values for $\hat{H}_{mt}$ for the years 2001-2011. To be crystal clear, only data on $\hat{H}_{mt-1}$ from the year 2000 is used to generate predicted values. No other self-report data are used in this exercise.

Figure 3 shows a scatter diagram of the the self-reported data (y-axis) against the predicted self-reported values (x-axis) for all 20 metro areas over the years 2005-2011. We subtract an estimate of $\bar{H}_m/\left(1-\rho\right)$, discussed later, from all variables such that goodness of fit is not overrepresented because of differences in scale in the self-reported values.

The model fits the out-of-sample data remarkably well, a result that is not necessarily due to the starting value: The weight given to the year-2000 jumping off point in 2005, the first year of comparison, is only $0.009 = \left[(1-0.510)\,0.80\right]^5$. The R^2 of the pictured regression line of $\hat{H}_t$ on predicted values is 0.96 and the intercept of the regression is exactly zero. The point estimate of the slope coefficient is 1.066 with a standard error of 0.017, implying that self-reports vary a bit more than the out-of-sample predictions generated by the model.

To get a better sense for how the model predicts the data, we plot actual and predicted values of $\hat{H}_{mt}$ against the appropriately scaled CSW index, $\mathcal{H}_{mt} + \alpha'_m$. To do this requires an estimate of α'_m for each metro area. Equations (1) and (2) imply $(1/T)\sum_t H^o_{mt}$ is a consistent estimator of $\bar{H}_m/\left(1-\rho\right)$ (used earlier to generate figure 3). From equation (7), we estimate α'_m as

$$\alpha'_m = \frac{\alpha_m}{\kappa} - \frac{(1-\kappa)(1-\rho)}{\kappa}\left[\frac{1}{T}\sum_t H^o_{mt}\right] \tag{11}$$

Figure 4 compares the rescaled CSW index to the actual and predicted self-reports for each of the 20 MSAs in the sample. The model appears to predict $\hat{H}_{mt}$ from 2005-2011 (given only CSW data from 2001-2011) remarkably well *everywhere*, with the possible exception of a few years in Dallas, Denver, and Las Vegas. The model captures the timing and magnitude of the rise and fall in self-reported house prices in places that did not experience a great rise in house prices like Cleveland and Detroit as well as "bubble" areas like Miami, Phoenix and Tampa.

5.2 Other Parameters

Further assumptions on the nature of the correlation of shocks across households are required in order to estimate the variance parameters σ_ν^2 and σ_e^2. A natural starting point is to assume identical shocks for homeowners in each metro area: That is, $e_{imt} = e_{jmt}$ and $\nu_{imt} = \nu_{jmt}$ for all homeowners i and j in metro area m in period t. We view this assumption as a good starting point because it implies homeowners cannot improve the guess of their house value by talking to neighbors about their signal. In this case,

$$\text{var}\left[H_{mt}^o - \rho H_{mt-1}^o - \bar{H}_m\right] \;=\; \sigma_e^2 + \left(1+\rho^2\right)\sigma_\nu^2 \, . \tag{12}$$

It is possible to show that once the Kalman gain converges to its steady-state value, it satisfies

$$\left[\sigma_\nu^2 \rho^2\right]\kappa^2 + \left[\sigma_e^2 + \sigma_\nu^2\left(1-\rho^2\right)\right]\kappa - \sigma_e^2 \;=\; 0 \, . \tag{13}$$

Although equation (13) is quadratic in κ, it is linear in σ_ν^2 and σ_e^2. Given estimates of ρ, κ, and $\text{var}\left(H_{mt}^o - \rho H_{mt-1}^o - \bar{H}_m\right)$, equations (12) and (13) uniquely determine σ_ν^2 and σ_e^2, with the closed-form expression for σ_ν^2 as

$$\sigma_\nu^2 \;=\; \frac{\text{var}\left[H_{mt}^o - \rho H_{mt-1}^o - \bar{H}_m\right](1-\kappa)}{1+\rho^2\left(1-\kappa\right)^2} \tag{14}$$

and the expression for σ_e^2 naturally following from (12) and (13).

We estimate $\text{var}\left[H_{mt}^o - \rho H_{mt-1}^o - \bar{H}_m\right]$ using data across all metro areas and years (2007-2011) to be 0.010. At $\rho = 0.80$ and $\kappa = 0.510$, and given the computed values of H_o and $\bar{H}$ in each period and metro area, I find $\sigma_\nu = 0.065$ and $\sigma_e = 0.055$. The literal interpretation is that the standard deviation of shocks to home prices is 5.5 percent per year and homeowners understand the standard deviation of the gap between the signal they receive on the value of their home and the true value of their home is 6-1/2 percent.

As a final step, given estimates of σ_ν^2 and σ_e^2, we compute the sequence of optimal Kalman gains for a homeowner starting the year he knows his true log house price with *certainty*.[13] In year 1, the Kalman gain is 41.6 percent; year 2 it is 49.5 percent; year 3 it is 50.7 percent; in year 4 it is 50.9 percent; and so forth. The convergence of the Kalman gain to near its steady state value by year 2 supports the assumption that the Kalman gain has converged for the homeowners in the sample.

6 Default Model when House Prices are Uncertain

7 Conclusion

References

[1] Karl E. Case & John M. Quigley & Robert J. Shiller, 2011. "Wealth Effects Revisited 1978-2009," NBER Working Papers 16848, National Bureau of Economic Research, Inc.

[2] Morris A. Davis & Jonas D. M. Fisher & Marcelo Veracierto, 2010. "The role of housing in labor reallocation," Working Paper Series WP-2010-18, Federal Reserve Bank of Chicago.

[3] Gabriel Ehrlich, 2013, "Price and Time to Sale Dynamics in the Housing Market: the Role of Incomplete Information," Working Paper, Congressional Budget Office.

[4] Jeff Fisher & David Geltner, 2000, "Quarterly Unsmoothing of the NCREIF Index WIthout Assuming an Efficent Market: A Transactions-Based Version of the NCREIF Index," Paper prepared for presentation at the Annual Meeting of the AREUEA, Boston, January 7-9, 2000.

[5] James R. Follain Jr. and Stephen Malpezzi, 1981, "Are Occupants Accurate Appraisers?" Review of Public Data Use, Vol. 9, 47-55.

[6] James R. Follain, 2012, "A Search for the Underlying Structure Driving House Prices in a Distressed Environment," Working Paper, Lincoln Institute of Land Policy.

[7] David Geltner, 1991, "Smoothing in Appraisal-Based Returns," Journal of Real Estate Finance and Economics, Vol. 4, No. 3, pp. 327-345

[13]For convenience, think of this as the year that he bought his home.

[8] Kristopher Gerardi & Adam Hale Shapiro & Paul S. Willen, 2009, "Decomposing the foreclosure crisis: House price depreciation versus bad underwriting," Working Paper 2009-25, Federal Reserve Bank of Atlanta.

[9] John L. Goodman Jr. & John B. Ittner, 1992, "The accuracy of home owners' estimates of home value," Journal of Housing Economics volume 2 issue 4, december, 339-367.

[10] Lu Han & William C. Strange, 2012, "What is the Role of the Asking Price for a House?" Working Paper, University of Toronto.

[11] Allen Head & Huw Lloyd-Ellis & Hongfei Sun, 2012. "Search, Liquidity and the Dynamics of House Prices and Construction," Working Papers 1276, Queen's University, Department of Economics.

[12] Erik Hembre, 2013, "HAMP and the Dynamic Default Decision," Working Paper, University of Wisconsin.

[13] Katherine A. Kiel and Jeffrey E. Zabel, 1999, "The accuracy of owner-provided house values: The 1978-1991 American Housing Survey," Real Estate Economics volume 27 issue 2, june, 263-298.

[14] Benjamin Lester & Ludo Visschers & Ronald Wolthoff, 2013, "Competing with Asking Prices," Working Paper 13-7, Federal Reserve Bank of Philadelphia

[15] Makoto Nakajima & Irina A. Telyukova, 2012, "Home Equity in Retirement," Working Paper, University of California - San Diego.

[16] Daniel C. Quan and John M. Quigley, 1991, "Price Formation and the Appraisal Function in Real Estate Markets," The Journal of Real Estate Finance and Economics, volume 4 number 2, 127-147.

[17] Steven Ruggles, J. Trent Alexander, Katie Genadek, Ronald Goeken, Matthew B. Schroeder, and Matthew Sobek. Integrated Public Use Microdata Series: Version 5.0 [Machine-readable database]. Minneapolis: University of Minnesota, 2010.

Table 1: Sample Sizes for Self-Reported House Values, 1-Family Owner-Occupied Units
2000 5% Census, 2005-2011 American Community Survey

MSA	5% Census 2000	American Community Survey 2005	2006	2007	2008	2009	2010	2011
Atlanta	34,865	10,986	11,180	11,462	11,130	11,398	10,579	8,637
Boston	30,588	7,952	7,875	7,873	7,546	7,706	7,596	7,572
Charlotte	13,125	4,147	4,268	4,501	4,479	4,486	4,357	3,870
Chicago	66,584	16,969	16,875	17,108	16,406	16,665	15,843	14,636
Cleveland	24,888	6,021	6,051	6,028	5,774	5,825	5,778	5,910
Dallas	42,525	12,850	12,908	13,306	13,258	13,315	12,975	12,158
Denver	20,847	5,958	5,957	6,060	5,851	5,856	5,813	5,688
Detroit	39,689	9,937	9,817	9,742	9,093	9,176	8,707	8,742
Las Vegas	11,319	3,767	3,880	3,951	3,853	3,832	3,680	3,417
Los Angeles	82,064	20,354	20,040	20,218	18,989	19,247	19,095	20,048
Miami	14,148	3,475	3,590	3,637	3,409	3,379	3,409	3,410
Minneapolis	24,213	5,883	5,943	5,895	5,806	5,730	5,489	5,161
New York	100,842	24,307	23,735	23,826	23,184	23,231	23,013	23,371
Phoenix	29,324	8,987	8,958	8,958	8,551	8,503	8,093	7,761
Portland	16,173	4,407	4,460	4,546	4,427	4,412	4,379	4,360
San Diego	20,526	5,603	5,529	5,387	5,159	5,194	5,065	5,143
San Francisco	38,864	9,583	9,411	9,371	8,780	9,052	8,870	8,774
Seattle	20,524	5,498	5,462	5,661	5,510	5,569	5,599	5,567
Tampa	24,491	7,219	7,189	7,283	6,860	6,828	6,735	7,066
Washington, DC	46,335	12,175	12,131	12,369	11,894	12,052	11,985	11,505
top-code percent	1.2	4.3	5.3	5.6	0.6	0.6	1.0	1.0

Table 2: Average of Real Self Assessed House Values
2000 5% Census, 2005-2011 American Community Survey

	Thousands of $2005 Dollars								Peak Date		
MSA	2000	2005	2006	2007	2008	2009	2010	2011	AVG	CSW	AVG-CSW
Atlanta	193	238	245	249	248	230	207	189	2007	2006	1
Boston	310	480	475	464	455	432	423	401	2005	2005	0
Charlotte	175	205	211	217	232	219	211	204	2008	2007	1
Chicago	224	301	314	315	312	289	270	250	2007	2006	1
Cleveland	162	183	181	180	174	160	158	147	2005	2005	0
Dallas	152	178	183	187	190	188	184	178	2008	2002	6
Denver	242	308	306	304	309	299	283	277	2008	2006	2
Detroit	183	217	213	206	190	159	142	132	2005	2005	0
Las Vegas	184	355	374	369	317	236	198	176	2006	2006	0
Los Angeles	328	585	626	618	637	560	539	513	2008	2006	2
Miami	184	338	378	381	377	306	272	241	2007	2006	1
Minneapolis	189	299	297	297	285	263	242	226	2005	2006	-1
New York	296	486	508	502	510	483	457	437	2008	2006	2
Phoenix	184	292	349	341	321	261	233	200	2006	2006	0
Portland	232	293	330	348	341	316	288	274	2007	2007	0
San Diego	314	610	615	590	572	500	472	454	2006	2005	1
San Francisco	434	663	682	663	716	618	593	556	2008	2006	2
Seattle	305	398	438	466	474	438	410	373	2008	2007	1
Tampa	137	233	275	265	251	210	196	173	2006	2006	0
Washington, DC	258	471	507	500	480	439	418	399	2006	2006	0
Median	209	305	340	345	319	294	271	246	2007	2006	1
Standard Dev	76	147	151	146	154	137	134	130	1	1	1

Table 3: Real Percent change in CSW and Average Self Reports, CSW peak date to 2011

MSA	Percent Chg. AVG	Percent Chg. CSW	Difference
Atlanta	-22.7	-29.7	7.0
Boston	-16.5	-25.1	8.6
Charlotte	-6.1	-22.9	16.8
Chicago	-20.4	-37.5	17.1
Cleveland	-19.5	-27.7	8.3
Dallas	-2.6	-15.9	13.4
Denver	-9.7	-18.5	8.8
Detroit	-39.2	-51.4	12.2
Las Vegas	-52.8	-63.1	10.2
Los Angeles	-18.0	-43.9	25.9
Miami	-36.3	-54.7	18.5
Minneapolis	-23.8	-40.7	16.8
New York	-14.1	-30.3	16.2
Phoenix	-42.7	-60.0	17.4
Portland	-21.4	-32.9	11.5
San Diego	-25.6	-44.5	18.9
San Francisco	-18.5	-44.2	25.7
Seattle	-20.0	-33.6	13.6
Tampa	-37.0	-51.2	14.1
Washington, DC	-21.3	-34.0	12.7
Median			13.9

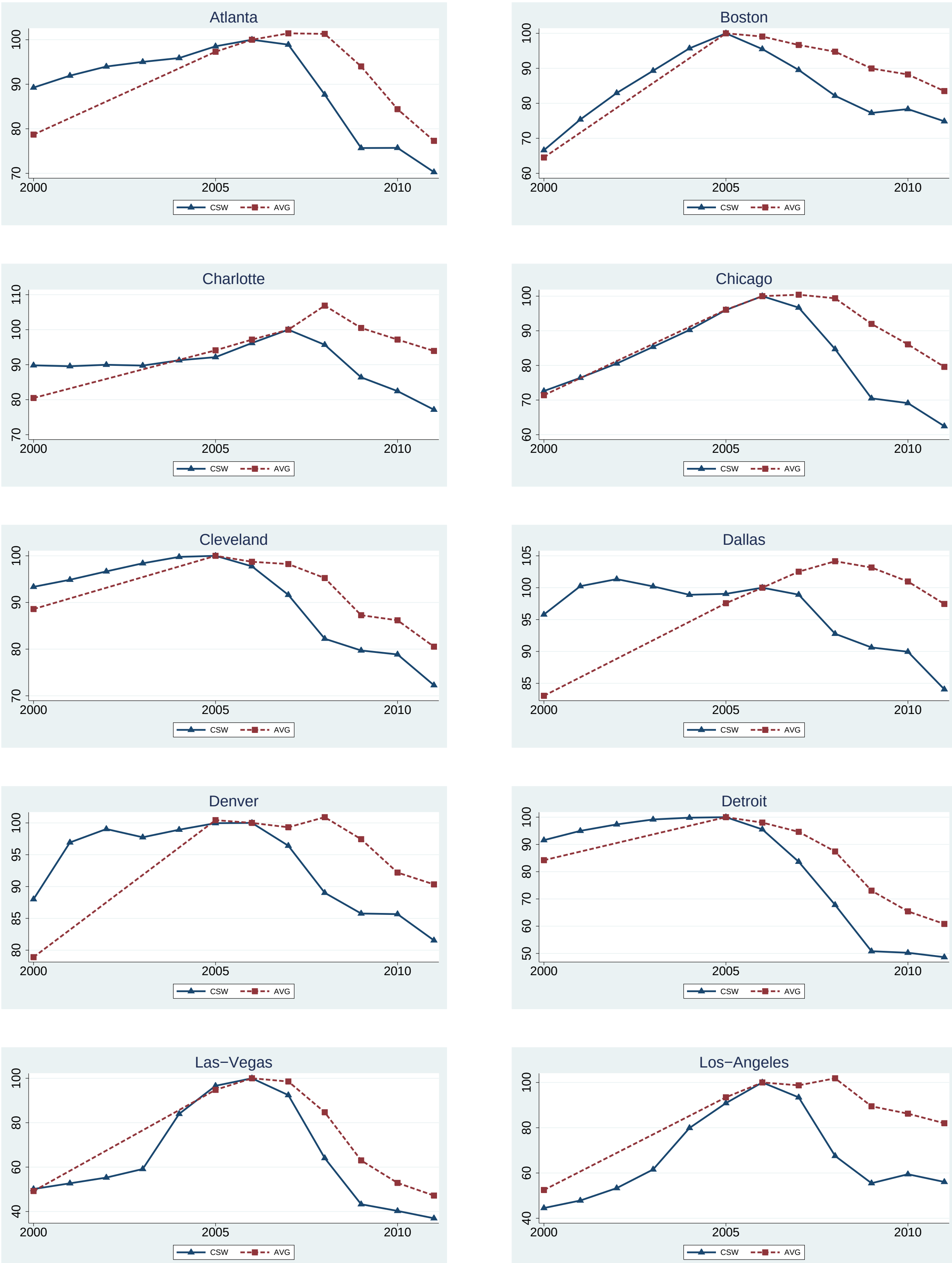
Table 4: OLS Estimates of κ at different values of ρ
Annual panel data, 20 MSAs from 2006-2011

ρ	κ	SE	R^2
0.60	0.566	0.019	0.88
0.65	0.553	0.019	0.88
0.70	0.540	0.018	0.89
0.75	0.528	0.017	0.89
0.80	0.517	0.016	0.90
0.85	0.508	0.015	0.90
0.90	0.499	0.015	0.91
0.95	0.492	0.014	0.91
0.99	0.488	0.014	0.91

Table 5: 2SLS Estimates of κ at different values of ρ
Annual panel data, 20 MSAs from 2007-2011

				1st stage		
ρ	κ	SE	R^2	F	R^2	$SD\,(u'_{mt})$
0.60	0.632	0.037	0.78	87.5	0.64	0.0587
0.65	0.602	0.037	0.78	81.2	0.63	0.0571
0.70	0.571	0.035	0.78	75.7	0.61	0.0557
0.75	0.540	0.034	0.79	70.8	0.59	0.0547
0.80	0.510	0.032	0.80	66.7	0.58	0.0543
0.85	0.482	0.030	0.81	63.3	0.57	0.0545
0.90	0.457	0.029	0.82	60.6	0.56	0.0552
0.95	0.438	0.027	0.83	58.6	0.55	0.0563
0.99	0.427	0.026	0.84	57.6	0.54	0.0569

Figure 1: Comparison of CSW to Average of Self Reports (AVG)
All Indexes = 100 at CSW peak



Comparison of CSW to Average of Self Reports (AVG)
All Indexes = 100 at CSW peak

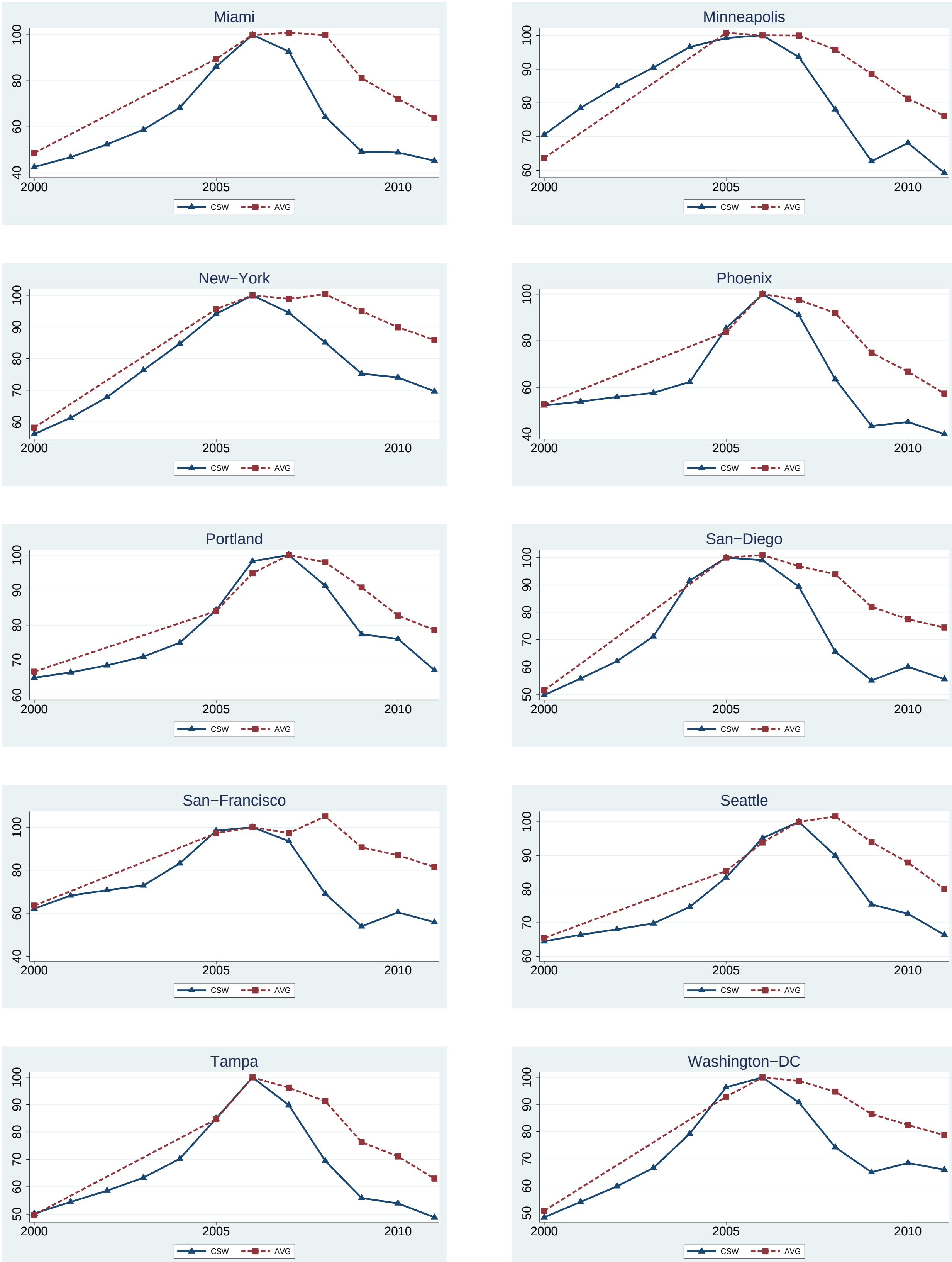
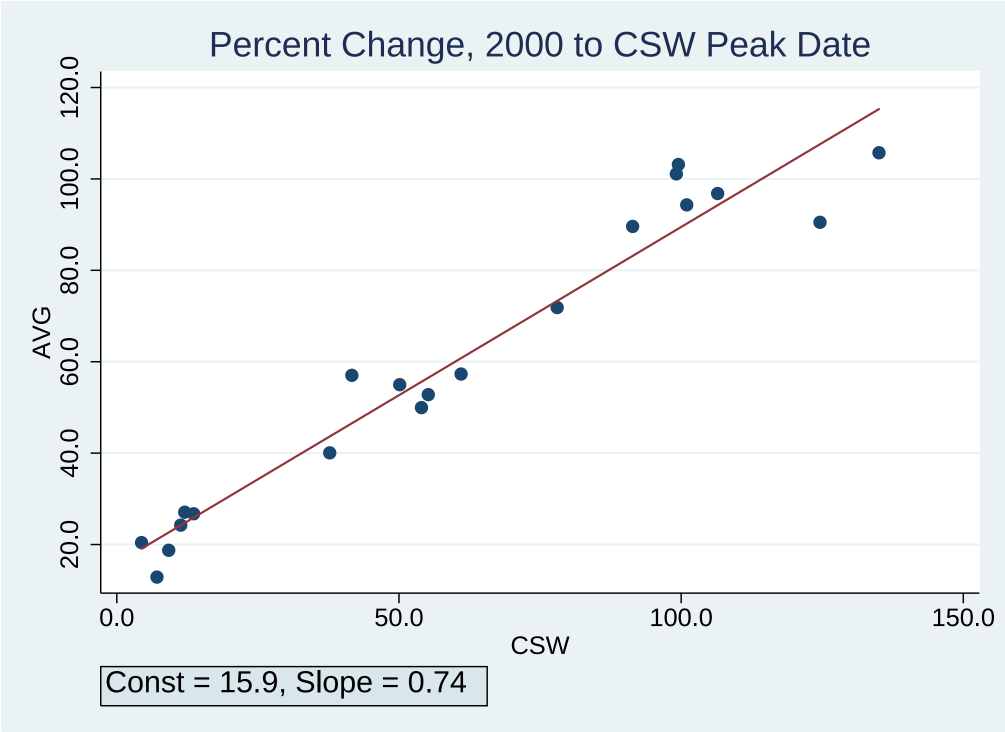


Figure 2: Comparison of Real Growth, CSW and Average of Self Reports (AVG)



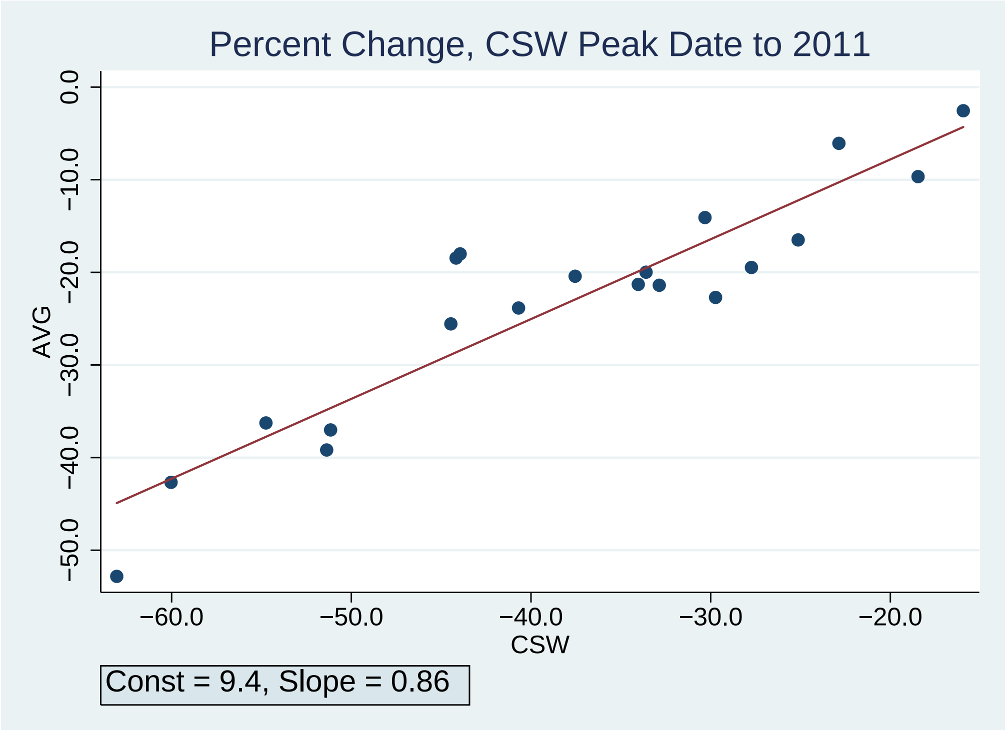
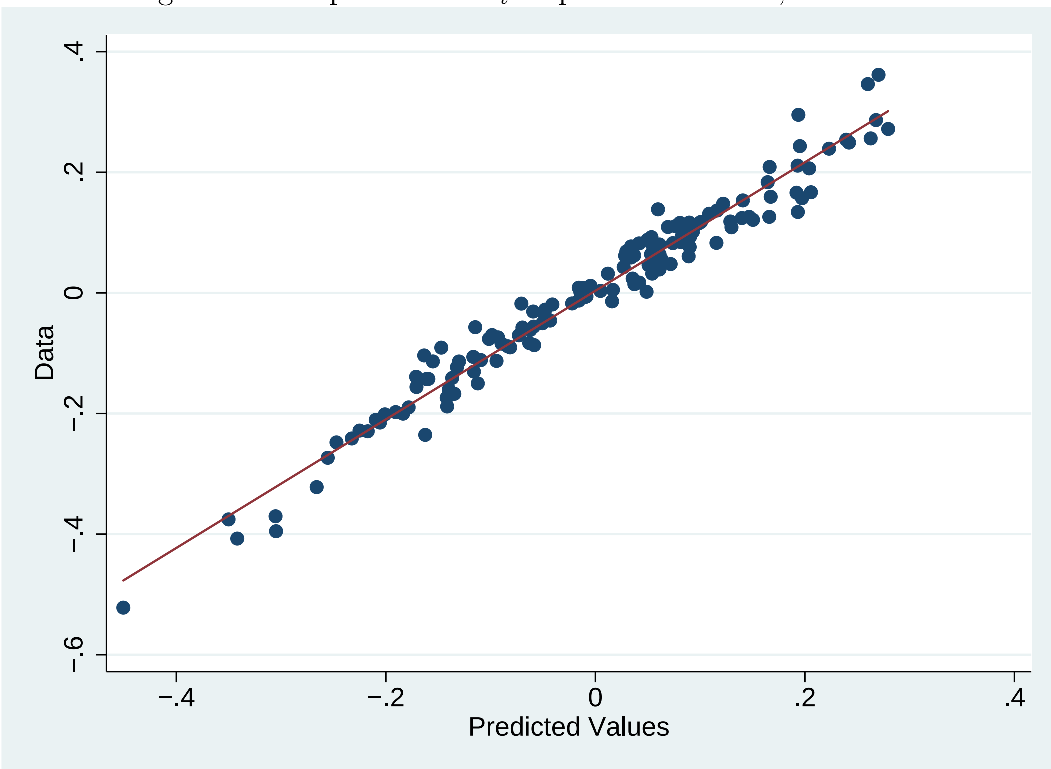
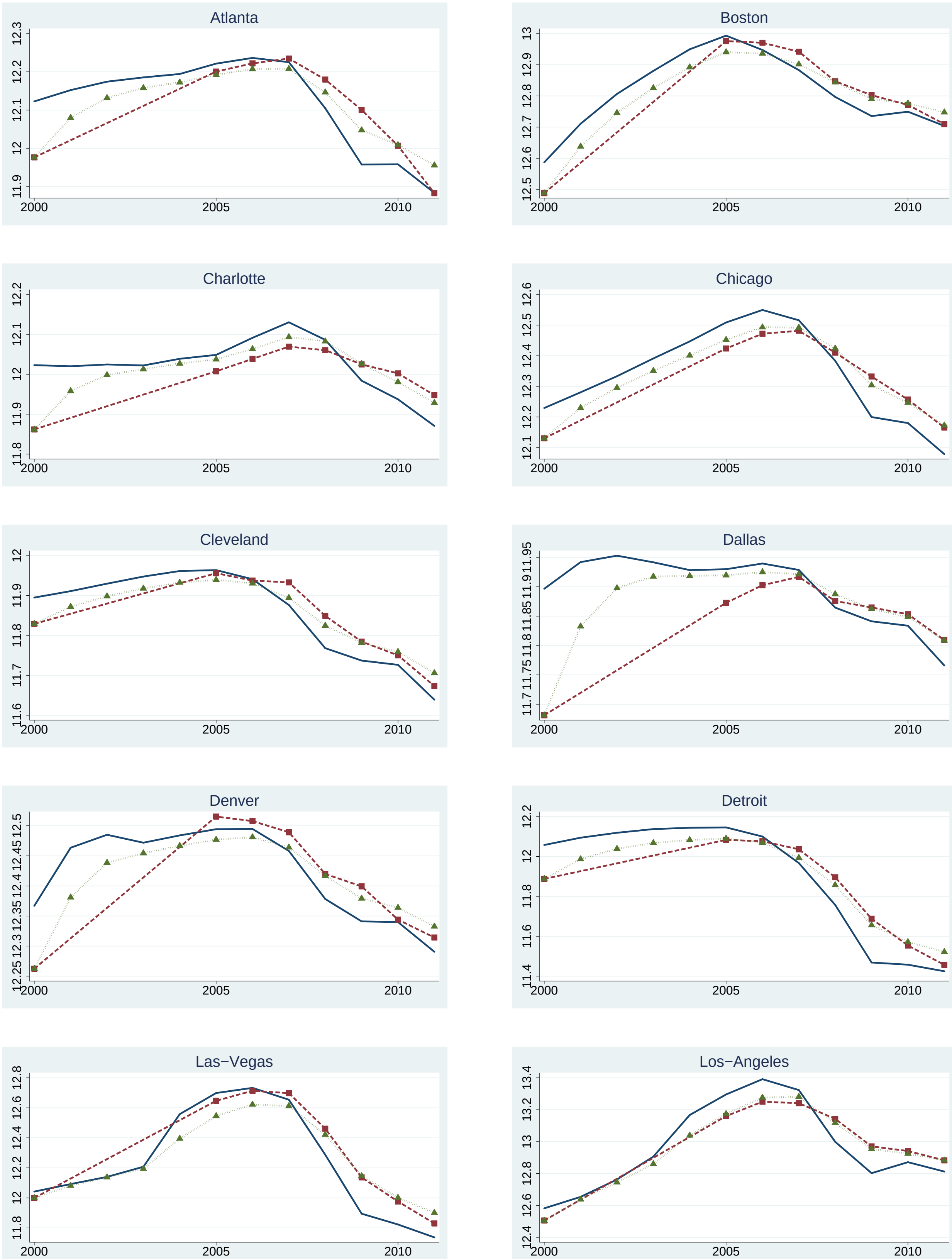


Figure 3: Comparison of $\hat{H}_t$ to predicted values, 2005-2011



$$\hat{H}_t = \underset{(0.003)}{0.003} + \underset{(0.017)}{1.066} * \text{Predicted}$$

Figure 4: Data on $\hat{H}_t$ (square), model-predicted $\hat{H}$ (triangle) and rescaled CSW (line)



Data on $\hat{H}_t$ (square), model-predicted $\hat{H}$ (triangle) and rescaled CSW (line)