House Prices and Economic Conditions: Location, Location, Location

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Abstract

This paper shows that local economic conditions are correlated with deviations between house prices and rents in a price-rent model framework, suggesting that the demand for credit and housing is greater when a variety of local economic conditions are more supportive. We consider several different measures of local economic conditions: local unemployment rates, local unemployment rates relative to the natural rate of unemployment, local inflation rates, and measures of local perceptions of the cost of credit. We view this explanation not as *how* or *why* house prices increased, but rather, given the myriad of national factors making home purchase easier and cheaper, *where* house prices increased. In our minds, this approach resolves a bit of a puzzle as to why the housing bubble was so pronounced in some areas (such as cities in the sand states) and not others (such as cities in the rust belt).

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1. Introduction

The financial crisis not only had its roots in, but also had severe effects on housing markets, affecting many households, lenders, investors, and the overall health of the economy. The large declines in house prices eroded many households' housing equity and left many borrowers underwater and at risk of default. The resulting wave of defaults left lenders and investors on the hook for losses that depleted, and sometimes exhausted, funds available to cover those losses. And the resulting collapse of financial markets led to a severe recession in which the unemployment rate increased dramatically. Moreover, much literature has pointed out the adverse effects of mortgage default (e.g., Agarwal et al. (2013), Anenberg et al. (2014), to name a few).

This begs the question: What happened? The Financial Crisis Inquiry Commission report (FCIC 2011), among others, has pointed out a myriad of potential factors, some related, that contributed to the financial crisis. Among them, the report points to large increases in subprime lending activity; large increases in securitization activity; large increases in house prices that were not supported by economic fundamentals; widespread fraud and predatory lending; large increases in mortgage debt and cash-out refinance activity; and large increases in financial firms' trading activities, especially in derivatives and short-term funding markets. In addition, the report found "little meaningful action … to quell [these] threats in a timely manner" and a "failure to stem the flow of toxic mortgages" (p. xvii).

Other papers provide support for some of the report's findings. Mian and Sufi (2009) show that the expansion in mortgage credit (and the resulting mortgage defaults) was disproportionately pronounced in subprime ZIP codes. Securitization was instrumental to this expansion of credit, satisfying an inherent pent-up demand for mortgage credit. Similarly, Keys et al. (2010) show that loans with credit scores of 620, and therefore likely to be securitized, had much higher default rates than loans with credit scores just below 620, and therefore less likely to be securitized. This suggests that securitized loans faced less screening than unsecuritized loans. Nadauld and Sherlund (2013) also show that the increased securitization activity by investment banks, especially in ZIP codes experiencing the largest increases in house prices, reduced lenders' incentives to carefully screen mortgage borrowers.

Demyanyk and Van Hemert (2011) and Mayer et al. (2009) show how underwriting standards eased significantly leading up to the financial crisis. Credit scores and documentation decreased, while the share of mortgages with high loan-to-value ratios and the incidence of second liens increased. In fact, the median subprime purchase mortgage originated during 2005-2007 had a combined loan-to-value ratio of exactly 100 percent. Borrowers, lenders, and investors clearly banked on continued house price appreciation to keep these loans performing (see, among others, Gerardi et al. (2008)). Moreover, investors seem to have put extremely low probabilities on adverse house price scenarios.

Alternative mortgage products and features and the stretching of housing affordability have also been cited as playing a role in the house price bubble. Dokko et al. (2011) show just how much alternative mortgage products could stretch the affordability of high-priced homes in terms of monthly payments. For example, a borrower purchasing a $225,000 home with a $180,000 mortgage at 6 percent interest would have a monthly payment of about $1,080. Based on the same monthly payment, the same borrower would be able to "afford" a home worth $268,750 using an adjustable-rate mortgage, a home worth $303,500 using a 40-year amortization schedule, a home worth over $366,000 using an interest-only ARM, and a home worth over $1,600,000 using a negative amortization ARM. Borrowers likely used these types of mortgages to afford high-priced homes, likely fueling house price appreciation even further.

Taylor (2007) and Gordon (2009) cite the extraordinarily low interest rate policy of the Federal Reserve during the early 2000s as a factor contributing to the large increase in house prices. Dokko et al. (2011), however, find it difficult to point to monetary policy as the basis for the run-up in house prices. House prices also increased rapidly in many other countries, and the deviations of Federal Reserve policy from a commonly accepted “policy rule”, though persistent, were relatively small and well within statistical confidence bands. Moreover, real-time data, which often revises with later data releases, made these deviations smaller still.

Each of the aforementioned explanations for large increase in house prices and the resulting financial crisis suffers from one important omission, however: Each is based on a factor which affects the nation as a whole, and therefore does not explain the vast differences observed across cities and states leading up to, and following, the financial crisis. This paper proposes a complementary explanation which we believe works in concert with the work done so far. In particular, we argue that the relative strength of local economies changes the calculus on how attractive investment in housing might be (i.e., the expected returns to housing). In particular, we consider local unemployment rates, local unemployment rates relative to a measure of the natural rate of unemployment, local inflation rates, and measures of the local perceived cost of credit. That is, in areas where economic conditions are really good households tend to leverage up and the demand for housing increases (increasing house pirces); whereas in areas where economic conditions aren’t very good households tend to deleverage and the demand for housing falls (decreasing house prices).

To measure local perceptions of the cost of credit, we borrow from the literature on discretionary monetary policy (more specifically, Taylor Rules). For our purposes, Taylor Rules provide a convenient conversion of economic conditions to interest rates (the cost of credit). And because we can measure local economic conditions at a local level, we can estimate a “shadow” cost of credit at the local level. We argue that this city-specific Taylor Rule measure summarizes the relative strengths of local economies.

In our minds, this approach resolves a bit of a puzzle as to why the housing bubble was so pronounced in some areas (such as cities in the sand states) and not others (such as cities in the rust belt). For a concrete example, consider Phoenix versus Detroit. Detroit's local economy failed to gain hold during the national housing boom, as it suffered from high unemployment rates. So potential borrowers in Detroit might view the potential returns to housing as quite low and therefore perceive the cost of credit as relatively high. Phoenix, however, had very low unemployment rates. So potential borrowers in Phoenix might view the potential returns to housing as quite high and therefore perceive the cost of credit as relatively low. Yet borrowers in both cities faced the same prevailing cost of credit and had similar access to subprime lending, securitization markets, and alternative mortgage products.

Perhaps not so surprising, we find fairly strong evidence to suggest that the relative strength of local economies do indeed explain a meaningful portion of the run up in house prices relative to rents across a range of cities. Local economies that are relatively strong, and therefore perceive the cost of credit as being relatively low, demand more credit and more housing. Local economies that are relatively weak, however, perceive the cost of credit as being relatively high, and therefore demand less credit and less housing. We view this paper as not so much about *why* house prices increased, but rather *where* house prices increased.

The remainder of the paper is organized as follows. Section 2 provides a brief overview of price-to-rent models, while Section 3 describes our measures of local economic conditions. Section 4 describes our data, while Section 5 presents our empirical model. Section 6 presents our empirical results including some robustness analysis, and Section 7 concludes and provides some extensions for future research.

2. Price-to-Rent Models

The price-to-rent models' foundation is based on the concept of rents covering the user cost of housing (Gallin (2008)):

$$R_t = P_t\left[\left(i_t + \tau_t^p\right)\left(1 - \tau_t^y\right) + \delta_t + \lambda_t - E_t G_{t+1}\right],$$

where R_t is the rent, P_t is the price of housing, i_t is the interest rate, τ_t^p is the property tax rate, τ_t^y is the marginal income tax rate, δ_t is the combined maintenance and depreciation rate, λ_t is the risk premium associated with housing, and $E_t G_{t+1}$ is the expected capital gain from holding housing. Letting $C_t = \left(i_t + \tau_t^p\right)\left(1 - \tau_t^y\right) + \delta_t$ denote the direct user cost of housing capital:

$$R_t = P_t[C_t + \lambda_t - E_t G_{t+1}].$$

Taking logs (lowercase letters denote logs):

$$r_t = p_t + \log(C_t + \lambda_t - E_t G_{t+1}).$$

This equation ties house prices to rents—large deviations between house prices and rents should not persist over long periods of time (outside of movements in C_t, λ_t, or $E_t G_{t+1}$). Some studies explicitly control for taxes, depreciation, and allow for and test the effects of disequilibria (house prices too high or too low) on house prices or rents via error correction. Gallin, in particular, finds that house prices typically adjust to disequilibria but rents do not. In other words, when house prices are over or undervalued relative to rents, house prices (not rents) will adjust to move toward the long-run equilibrium relationship between house prices and rents.

This paper proposes using measures of local economic conditions as proxies for the risk premium of housing and/or the expected capital gains from holding housing. Ideally, one might want to use a measure of house price expectations, but these data are unavailable over long periods of time for specific geographic areas. In its simplest form, and conditioning on the results of Gallin (2008), we consider house price models of the form:

$$p_t = \beta_0 + \beta_1 r_t + \beta_2 m_t + \beta_3 X_t + \varepsilon_t.$$

That is, (the log of) house prices are related to (the log of) rents, long-term interest rates or mortgage rates (to proxy for the user cost of housing capital), and measures of local economic conditions (to proxy for the expected returns on housing). In our simplest model, we relate house prices to rents and mortgage rates, then introduce various measures of local economic conditions. We then introduce local unemployment rates. Then local unemployment rate gaps, i.e., local unemployment rates less the natural unemployment rate (NAIRU, to be more precise). Then we add local inflation rates. Then we add our measure of local perceptions of the cost of credit. Then we add a 12-month cumulative version of the local perception of the cost of credit measure. In all, we find evidence that measures of local economic conditions help explain deviations of house prices from rents.

3. Local Economic Conditions

This section explores each measure of local economic conditions, in turn, how each measure might proxy for the expected return on housing, and how each measure might ultimately affect house prices relative to rents.

Local Unemployment Rates

The local unemployment rate might affect the expected return on housing and therefore house prices relative to rents via household incomes. If a lower local unemployment rate is associated with higher incomes, then the demand for owner-occupied housing might increase relative to renting, as owner-occupied housing is typically seen as a normal good. Further, house price-to-income models such as Gallin (2006) suggest a strong relationship between household incomes and average house prices.

Local Inflation Rates

The local inflation rate might also affect the expected return on housing and therefore house prices relative to rents. Although inflation (moderate inflation, at least) is associated with a relatively healthy economy and higher incomes, one might expect inflation to be positively correlated with house prices. But inflation, unaccompanied by equivalent increases in house prices, works against the real expected return to housing. Inflation also reduces the service costs of nominal debt contracts. So local inflation rates could affect house prices given rents in different ways.

Local Perceptions of the Cost of Credit

Our final measure of local economic conditions is the local perception of the cost of credit. Here, we borrow from Taylor (1993, 1999) and Woodford (2001), who proposed models of discretionary monetary policy, to map local economic conditions into an interest rate (cost of credit). This mapping takes the form of the Taylor Rule:

$$i_t^* = 2 + \pi_t + \alpha(\pi_t - \pi^*) + \gamma(y_t - y_t^*),$$

where i_t^* is the "optimal" nominal federal funds rate implied by the underlying economic conditions, π_t is the inflation rate, π^* is the inflation objective (assumed to be 2 percent), and $y_t - y_t^*$ is the output gap as measured by the percent deviation of real GDP from potential GDP. Taylor (1993) suggests setting $\alpha = \gamma = \frac{1}{2}$, while Taylor (1999) suggests setting $\alpha = \frac{1}{2}$ and $\gamma = 1$. In this paper, we assume $\alpha = \gamma = \frac{1}{2}$ as in Taylor (1993).

According to Okun's Law (Abel and Bernanke (2005)), the output gap is related to the unemployment gap, measured as the percent deviation of the unemployment rate from the natural rate of unemployment. Empirically, the factor relating the output gap to the unemployment gap has been estimated at around 2 or 3, i.e., $y_t^* - y_t \approx 2(u_t - u_t^*)$, where u_t is the unemployment rate and u_t^* is the natural rate of unemployment, so that an output gap of one percentage point is typically associated with an unemployment gap of around 2 percentage points. Assuming a factor of 2, we then have:

$$\begin{aligned} i_t^* &= 2 + \pi_t + \frac{1}{2}(\pi_t - 2) - (u_t - u_t^*) \\ &= 1 + \frac{3}{2}\pi_t - (u_t - u_t^*). \end{aligned}$$

The Taylor Rule therefore converts economic conditions, namely the unemployment rate and the inflation rate, into one, easy-to-interpret interest-rate (cost of credit) measure.

So how does a local economy perceive the cost of credit given its local economic conditions? If the local economic environment is supportive of interest rates of i_t^*, and interest rates are i_t, then $i_t^* - i_t$ measures the local economy's perception of interest rates. When $i_t^* - i_t > 0$, the cost of credit is perceived to be low relative to local economic conditions, increasing the demand for credit and, because the expected return to housing is perceived to be relatively high, housing. But when $i_t^* - i_t < 0$, the cost of credit is perceived to be high relative to local economic conditions, thereby decreasing the demand for credit and, because the expected return to housing is perceived to be lower, housing.

4. Data

The data we use come from various sources. Our rent data comes from the Bureau of Labor Statistics' (BLS) Rent of Primary Residence. These data are available at a monthly frequency for 12 of the 25 MSAs covered as well as for the nation as a whole, but only semi-annually for the remaining 13 MSAs.[1] The rent indices are re-indexed to be 100 in January 1990. While we focus mostly on the cities for which we have complete rents data, we do provide some robustness analysis of the cities measured only semiannually. Our house price data comes from CoreLogic's repeat-sales house price index (excluding distressed sales). These data are available at a monthly frequency for all 25 MSAs. The house price indices are also re-indexed to be 100 in January 1990. Figure 1 shows house price and rent indices for the nation and each of the 12 MSAs for which we observe monthly data in our data set. The shaded areas highlight 2004-2007, when house prices grew the fastest. Figure 2 shows price-rent ratios for the same set of cities. Note that price-rent ratios increased dramatically for a number of cities, and peaked at different times. In particular, price-rent ratios peaked as early as 2005 in Cleveland and Detroit, 2006 in Los Angeles and Miami, and as late as 2007 in Dallas and Houston.

Our unemployment rate data come from the BLS' Local Area Unemployment Statistics data. These data are available at a monthly frequency for all 25 MSAs in our data from 1990 onward. Further, we obtain estimates of the natural rate of unemployment (NAIRU, more precisely) from the Federal Reserve Bank of St. Louis' FRED database. Figure 3 shows local unemployment rates relative to NAIRU for our core set of cities as well as for the nation, where the shaded region again highlights the 2004-2007 period. Unemployment rates reached generally low levels during the housing boom, but increased quickly in many different cities during the financial crisis.

Our inflation rate data come from BLS' Consumer Price Index (excluding food and energy). These data have a similar frequency structure to our rents data. Figure 4 shows inflation rates for our core set

[1] MSAs for which rents are measured monthly include Boston, Chicago, Cleveland, Dallas, Detroit, Houston, Los Angeles, Miami, New York City, Philadelphia, San Francisco, and Washington DC. Cities measured only semiannually include Atlanta (through 1997), Cincinnati, Denver, Kansas City, Milwaukee, Minneapolis, Phoenix, Pittsburgh (after 1997), Portland, San Diego, Seattle (through 1997), St. Louis (after 1997), and Tampa. We exclude Anchorage and Honolulu, which also have semiannual frequencies.

of cities as well as for the nation. What is surprising and reassuring for the analysis to come is that inflation rates do vary somewhat across our set of cities.

We augment these data with mortgage rate data from Freddie Mac's Primary Mortgage Market Survey and the target federal funds rate from the Federal Reserve Board. These data are shown in Figure 5. While mortgage rates generally declined over our sample period, the target for the federal funds rate shows several cycles of monetary policy easing and tightening. Some papers, such as Taylor (2007) and the FCIC report (2011) have pointed to the low federal funds rate during the early 2000s as the cause of the housing bubble. But other papers, such as Dokko et al. (2011) and the dissenting views contained within the FCIC report (2011) disagree.

We then compute our measure of local perceptions of the cost of credit as

$$1+\frac{3}{2}\pi_t-(u_t-u_t^*)-i_t,$$

which measures the difference between what the cost of credit might be given local economic conditions (the locally measured Taylor Rule) and what the cost of credit actually is (the target federal funds rate), literally the Taylor-Rule residual measured at the city level. Figure 6 shows how our measure of local perceptions of the cost of credit vary across our core set of cities as well as for the nation as a whole, where the shaded region again highlights the 2004-2007 period. It is worth noting that many of the "hottest" cities experienced long episodes leading up to and including the 2004-2007 period in which our measure of local perceptions of the cost of credit were positive, suggesting that credit was perceived as being cheap. This mechanism might have allowed borrowers to leverage up on housing, thereby increasing the demand for housing and pushing house prices upward.

Figure 7 shows our measure of local perceptions of the cost of credit against house price growth across our set of cities. While there are certainly exceptions, periods of robust increases in house prices tend to be associated with periods in which our measure of local perceptions of the cost of credit is positive, both in the cross section as well as in the time series. Again, we argue that when the cost of credit is perceived to be cheap, borrowers are incented to leverage up, which might increase the demand for assets such as housing and push house prices higher as the expected returns to holding housing has increased. Table 1 presents the data means for our core cities during the 1990-2014 period. We next turn to testing the importance of including local economic conditions in standard price-rent models and the role they play in explaining some of the deviations of house prices from rents.

5. Empirical Model

Our empirical setup is a natural extension of the price-to-rent model, but ultimately includes our various measures of local economic conditions. We start with the simplest model (mortgage rate model) as a baseline:

$$p_t = \beta_0 + \beta_1 r_t + \beta_2 m_t + \varepsilon_t,$$

where p_t is (the log of) house prices, r_t is (the log of) rents, and m_t is the mortgage rate (to proxy for the user cost of housing capital). We then add in local unemployment rates (unemployment rate model):

$$p_t = \beta_0 + \beta_1 r_t + \beta_2 m_t + \beta_3 u_t + \varepsilon_t,$$

where u_t is the local unemployment rate. If owner-occupied housing is a normal good, then higher unemployment rates should be associated with lower house prices so that $\beta_3 < 0$. We also consider local unemployment rates relative to the natural rate of unemployment (enhanced unemployment rate model):

$$p_t = \beta_0 + \beta_1 r_t + \beta_2 m_t + \beta_3 (u_t - u_t^*) + \varepsilon_t,$$

where u_t^* is the natural rate of unemployment. Here, we also expect $\beta_3 < 0$. We then add in local inflation rates (inflation rate model):

$$p_t = \beta_0 + \beta_1 r_t + \beta_2 m_t + \beta_3(u_t - u_t^*) + \beta_4(\pi_t - \pi_t^*) + \varepsilon_t,$$

where π_t is the local inflation rate and π_t^* is the (national) inflation objective—assumed to be 2 percent. Considering only the effect of inflation on the expected nominal return to housing, we expect $\beta_4 < 0$. Finally, we add our measure of local perceptions of the cost of credit to the regression (perceived cost of credit model):

$$p_t = \beta_0 + \beta_1 r_t + \beta_2 m_t + \beta_3(u_t - u_t^*) + \beta_4(\pi_t - \pi_t^*) + \beta_5(i_{t-1}^* - i_{t-1}) + \varepsilon_t,$$

where i_t^* is the implied local cost of credit and i_t is the actual cost of credit as measured by the target federal funds rate. The local perception of the cost of credit, $i_t^* - i_t$, will tend to be positive for relatively stronger local economies, which would stimulate the use of credit and increase the demand for housing via the use of credit as well as through a higher perceived rate of return for housing. Thus, we expect $\beta_5 > 0$. As one final perturbation on our baseline analysis, we consider regression which allow local perceptions of the cost of credit to accumulate over the course of a year (enhanced perceived cost of credit model):

$$p_t = \beta_0 + \beta_1 r_t + \beta_2 m_t + \beta_3(u_t - u_t^*) + \beta_4(\pi_t - \pi_t^*) + \beta_5 \frac{1}{12} \sum_{s=t-12}^{t} (i_{s-1}^* - i_{s-1}) + \varepsilon_t.$$

Here again, we expect $\beta_5 > 0$, as credit will be perceived as inexpensive when $\sum(i_{s-1}^* - i_{s-1}) > 0$, thereby stimulating the use of credit to purchase relatively high rate-of-return housing.

We implement the panel cointegration framework of Pedroni (2000). Our panel data are pooled and we estimate the cointegrating regressions via fully modified ordinary least squares. We allow for heterogeneous first-stage coefficients and report heteroskedaticity- and autocorrelation-consistent

(HAC) Newey-West standard errors. Note that the panel setup allows us to exploit not only the time series variation present in the data, but also the cross-sectional variation. As we note below, this has an important effect on the sharpness of our estimation results.

6. Empirical Results

Table 2 shows our estimates for the mortgage rate model for various geographic areas: all 12 core cities in our sample, the 12 cities split into their respective four Census regions, the cities split into sand states and rust-belt states, and the nation as a whole based on national aggregates. The all-cities and national results are interesting, as the latter only considers time-series variation, while the former also accounts for the cross-sectional variation present in our panel data. House prices are positively correlated with rent and mortgage rates consistently across these results.

Table 3 shows our estimates for the unemployment rate model for the same geographic areas. Here, local unemployment rates have consistently negative effects on house prices given rents, while rents and mortgage rates retain their positive relationships with house prices. Table 4 shows our estimates for the enhanced unemployment rate model. Again, local unemployment rates have consistently negative effects on house prices given rents, while rents and mortgage rates remain positively correlated with house prices. These results suggest that cities experiencing relatively high unemployment rates tend to experience lower house prices, while cities experiencing relatively low unemployment rates tend to experience higher house prices.

Table 5 shows our estimates for the inflation rate model for various geographies. The coefficient estimates on local inflation rates tend to have mixed signs, depending on the particular geography. This could be because of the opposite effects of inflation on the cost of servicing nominal debt contracts (positive effect) versus the expected nominal return on housing (negative effect). Note that the negative coefficient estimates tend to be located in cities from the Midwest Census region and the rust-belt states.

Table 6 shows our estimates for the perceived cost of credit model for the same geographic areas. Local perceptions of the cost of credit have consistently positive effects on house prices given rents, while local unemployment rates remain negatively correlated with house prices. Table 7 shows our estimates for the enhanced perceived cost of credit model, in which we accumulate year-long local perceptions of the cost of credit. These accumulated local perceptions of the cost of credit also have consistently positive effects on house prices given rents. These results support our hypothesis that when borrowers perceive the cost of credit to be relatively low, they tend to leverage up to take advantage of the perceived higher return to housing, increasing their demand for housing, and pushing house prices higher relative to rents. Of particular note is how the national perception of the cost of credit is statistically insignificant, probably because that particular regression only utilizes time-series variation. But in the panel regressions, which also exploit the cross-sectional variation present in the data, local perceptions of the cost of credit do indeed help explain deviation of house prices from rents.

Robustness

Because of the nature of the CPI and rents data available from BLS, we have thus far considered only 12 of the 25 cities (excluding Anchorage and Honolulu) covered in their surveys. We excluded Atlanta and Seattle, as their CPI and rents data were measured semi-annually prior to 1998. Similarly, we excluded Pittsburgh and St. Louis, as their CPI and rents data were measured semi-annually starting in 1998. In contrast, Cincinnati, Denver, Kansas City, Milwaukee, Minneapolis, Phoenix, Portland, San Diego, and Tampa were all measured semi-annually for the entire 1990-2014 period. In the results to follow, we explore the sensitivity of our results to the inclusion of these cities.

To include these cities, we use statistical procedures to quadratically interpolate the semi-annual data to a monthly frequency. This interpolation occurs on four partial series and nine complete series, as noted above. We expect this interpolation to push our estimated effects downward, as the implicit smoothing coming out of the interpolation procedure necessarily reduces the cross-sectional and time-series variation important for identification. Table 8 shows regression results for the enhanced perceived cost of credit model when we include the four partial series (for a total of 16 cities) and then the nine complete series (for a total of 25 cities). The accumulated local perceptions of the cost of credit continue to have consistently positive effects on house prices given rents, and local unemployment rates continue to have consistently negative effects on house prices given rents. These results support our hypothesis that when borrowers perceive the cost of credit to be relatively low, they tend to leverage up to take advantage of the perceived higher return to housing, increasing their demand for housing, and pushing house prices higher relative to rents.

7. Conclusions

In this paper, we show that local economic conditions help explain some large, systematic deviations of house prices from rents in a price-rent model framework. We consider several different measures of local economic conditions: local unemployment rates, local unemployment rates relative to the natural rate of unemployment, local inflation rates, and measures of local perceptions of the cost of credit. With relatively strong local economic conditions, the expected returns to housing are greater and the perceived cost of credit is lower. As a result, the use of credit is likely higher and the demand for housing greater, pushing house prices upward relative to rents. In contrast, with relatively weak local economic conditions, the expected return to housing is lower and the perceived cost of credit is higher. As a result, the use of credit is likely lower and the demand for housing less, pushing house prices lower relative to rents. In building our measure of local perceptions of the cost of credit, we borrow from the literature on discretionary monetary policy (Taylor Rules). We view this explanation not as *why* house prices increased, but rather, given the myriad of factors making home purchase easier, *where* house prices increased. In our minds, this approach resolves a bit of a puzzle as to why the housing bubble was so pronounced in some areas (sand states) and not others (rust belt).

Our work, however, has only just begun, as we intend to tackle several extensions. First, we plan to explore the use of different forms of credit (mortgage, auto, credit card, and student loans) to directly test the implication that household use of credit varies systematically by local perceptions of the cost of credit or other local economic conditions. If our thinking is indeed correct, not only should households leverage up on mortgage debt, but perhaps also their credit card, auto loan, and student loan debt when they perceive the cost of credit to be low. One complication, however, is that home equity withdrawal during the early to mid-2000s provided households with the ability to substitute out of these other forms of debt in favor of mortgage debt. Second, we plan to explore price-to-income models as in Gallin (2006). Third, we plan to explore asymmetric responses to local economic conditions. For example, the effects of adverse economic conditions (high local unemployment rates, too high or too low of local inflation rates, local perceptions that the cost of credit is too high) might have larger effects than when economic conditions are either benign or robust. Finally, we would like to test the robustness of our results to the Federal Reserve's bond-buying programs (specifically, how to account for bond-buying programs in a Taylor Rule setting). Currently, we take the Taylor Rule as is and do not adjust for asset purchases in the zero-lower-bound environment.

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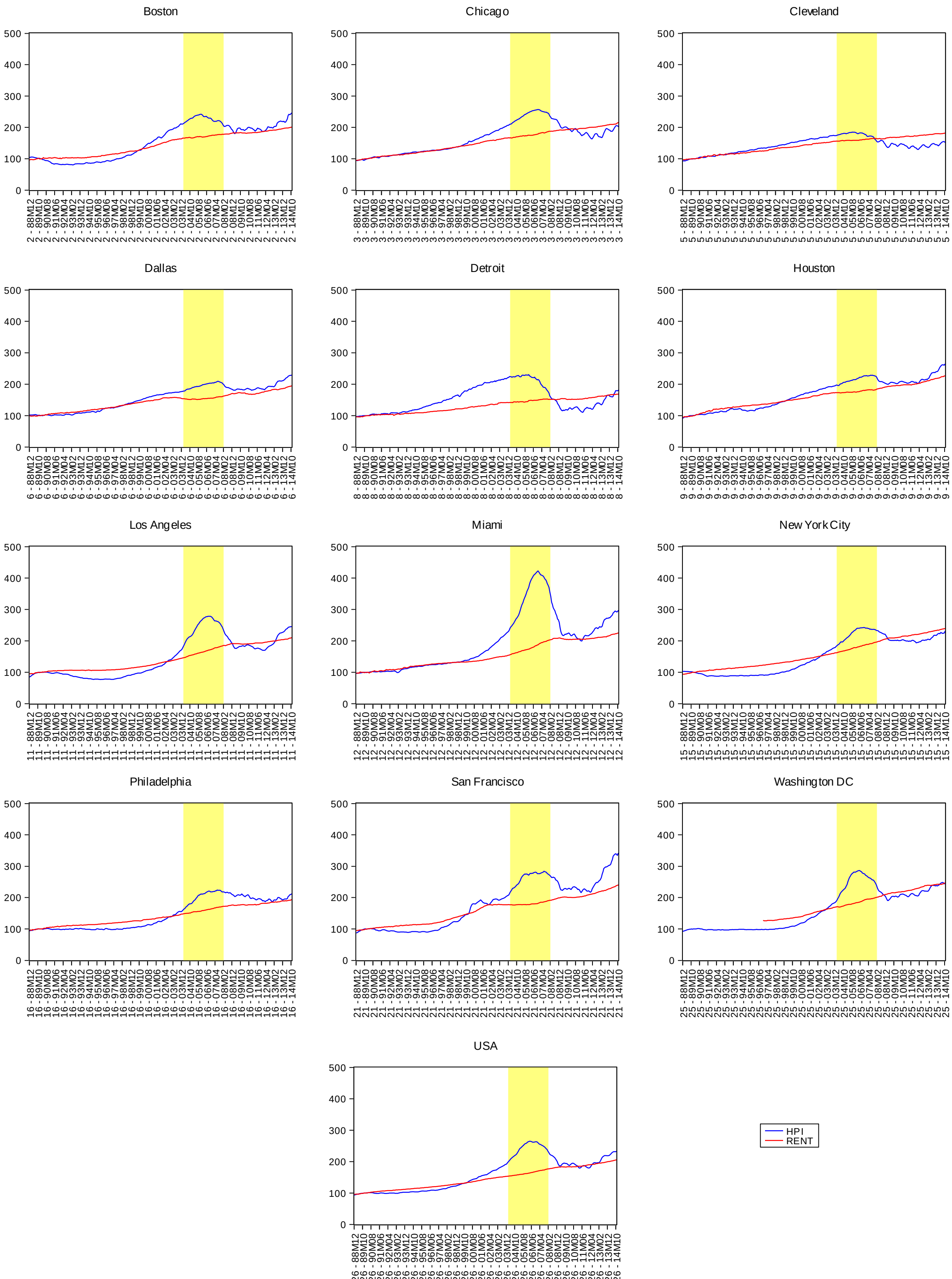
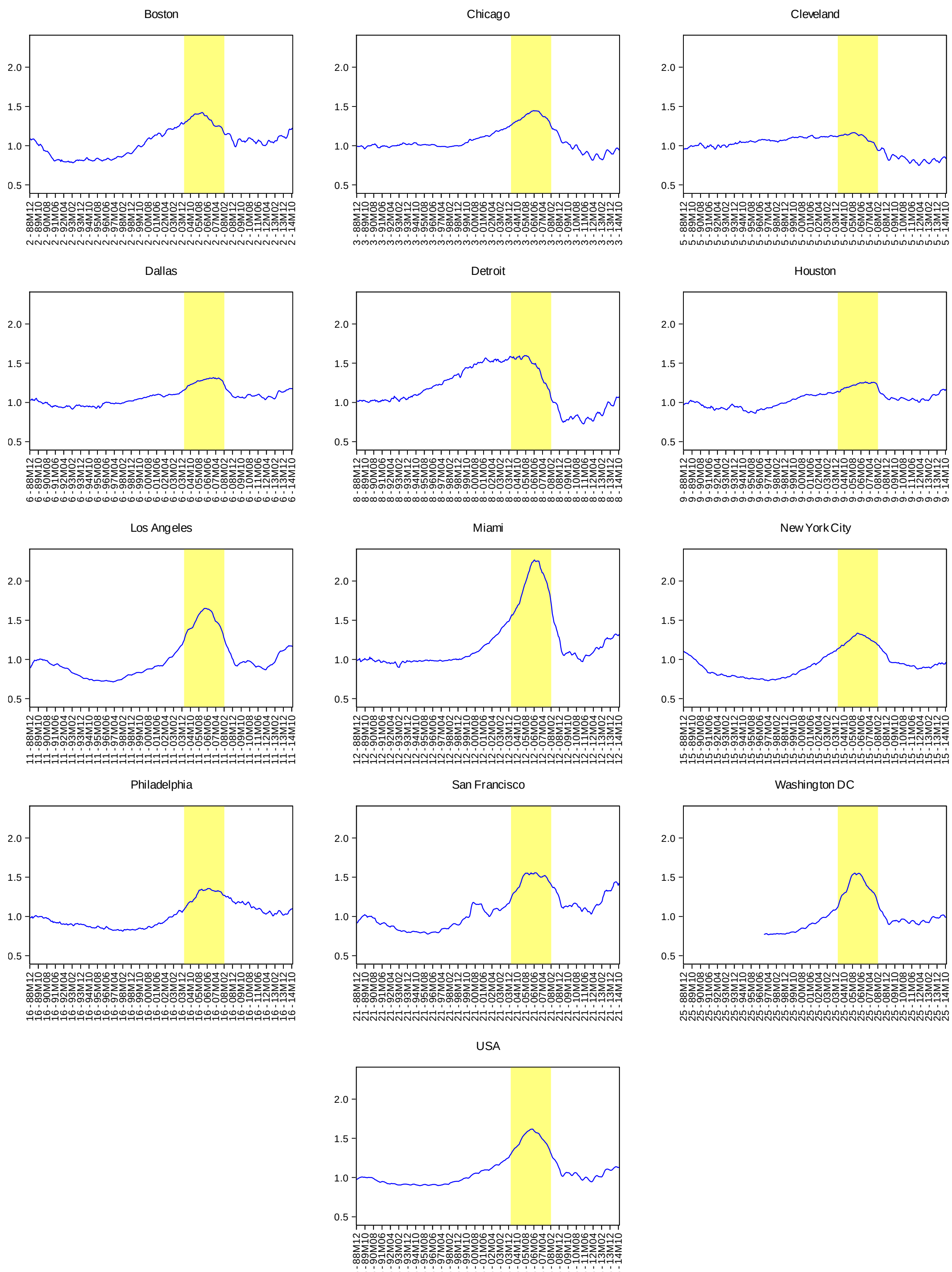
Figure 1: Local House Price and Rent Indices by MSA



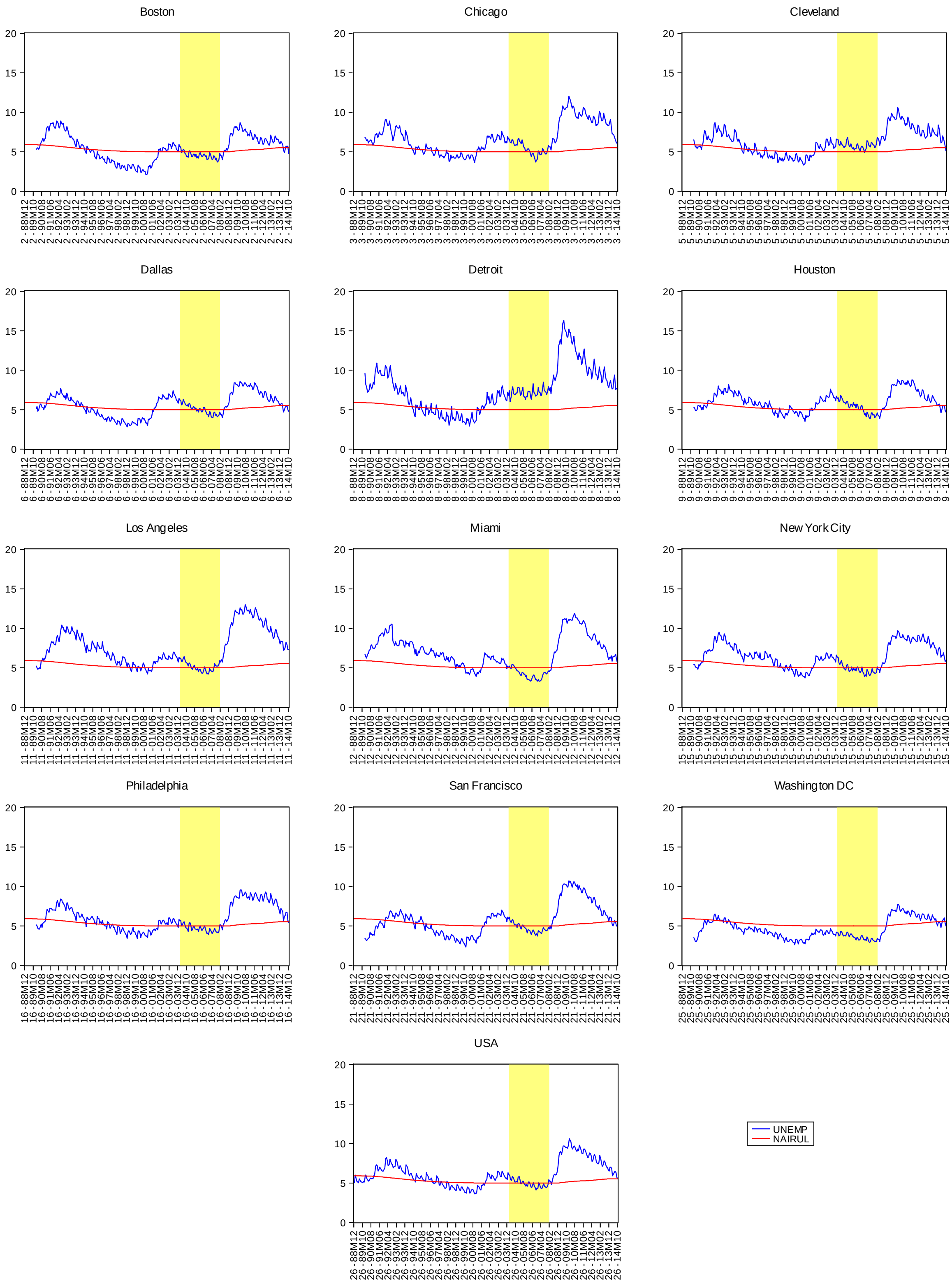
Source: For house prices, CoreLogic; for rent, Bureau of Labor Statistics.

Figure 2: Price-Rent Ratios by MSA



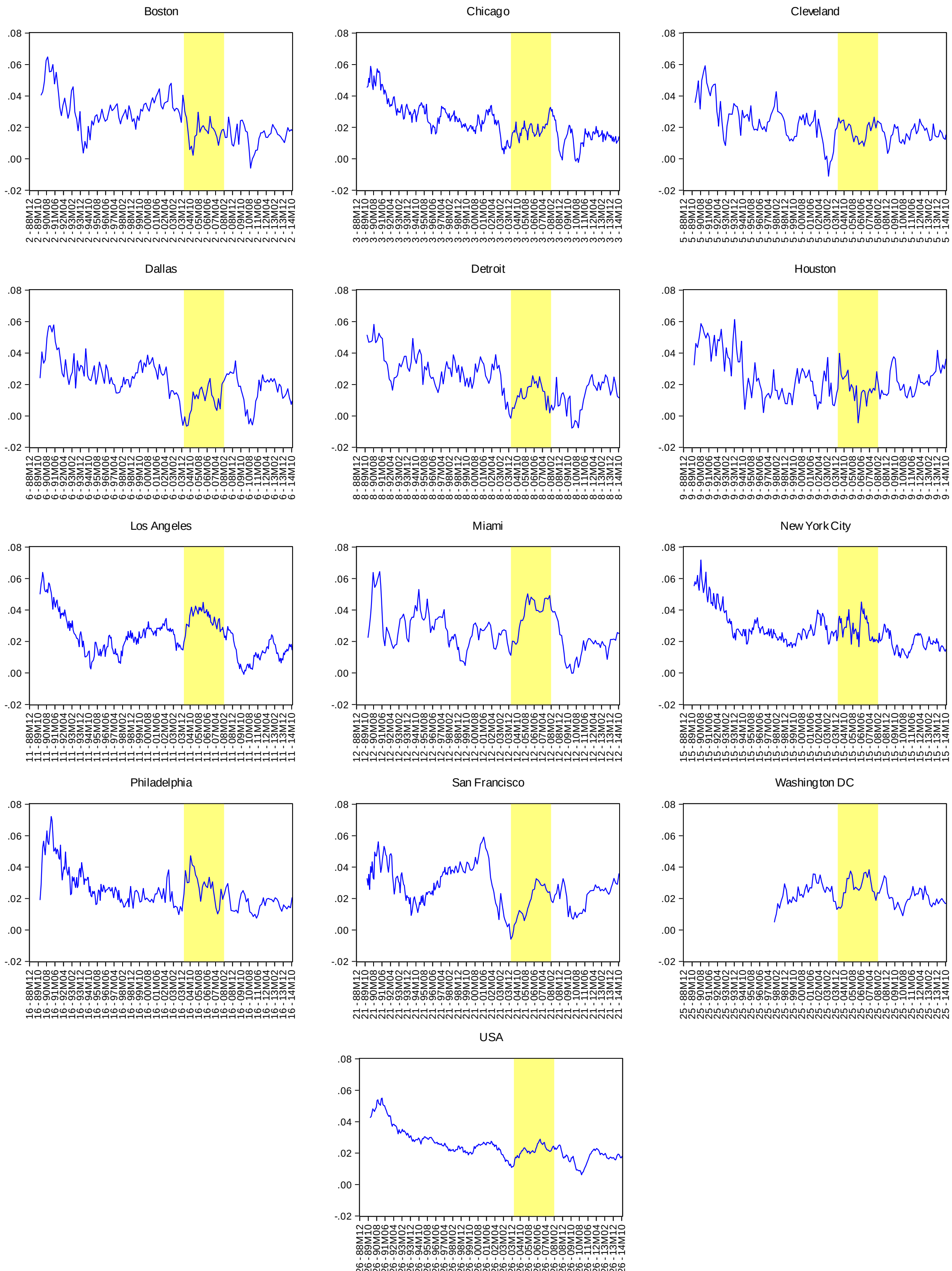
Source: Calculations from CoreLogic HPI and BLS rents data.

Figure 3: Unemployment Rates Relative to NAIRU by MSA



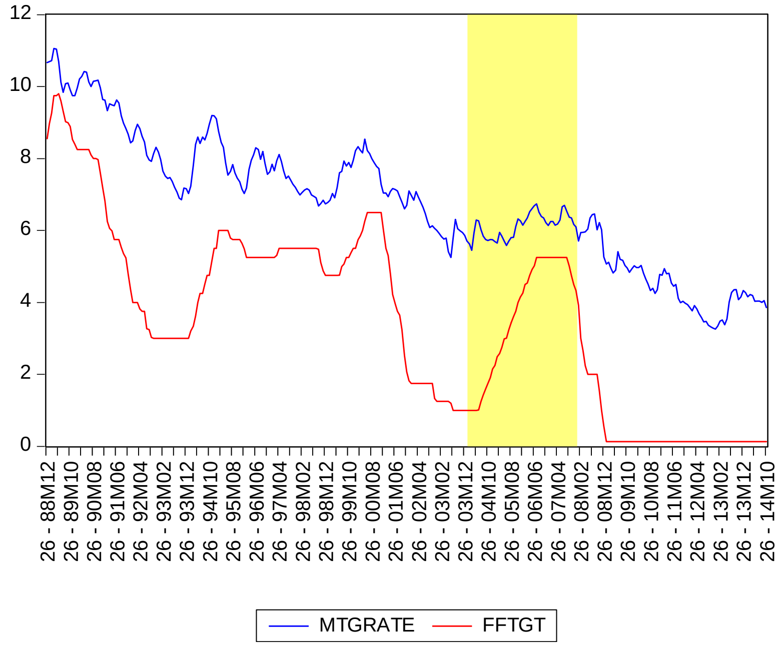
Source: For unemployment rates, Bureau of Labor Statistics Local Area Unemployment Statistics data; for NAIRU, St. Louis Fed FRED database.

Figure 4: Inflation Rates by MSA



Source: Bureau of Labor Statistics.

Figure 5: Mortgage Rates and the Target Federal Funds Rate



Source: For mortgage rate, Freddie Mac Primary Mortgage Market Survey; for target federal funds rate, Federal Reserve Board.

Figure 6: Perceptions of the Cost of Credit by MSA

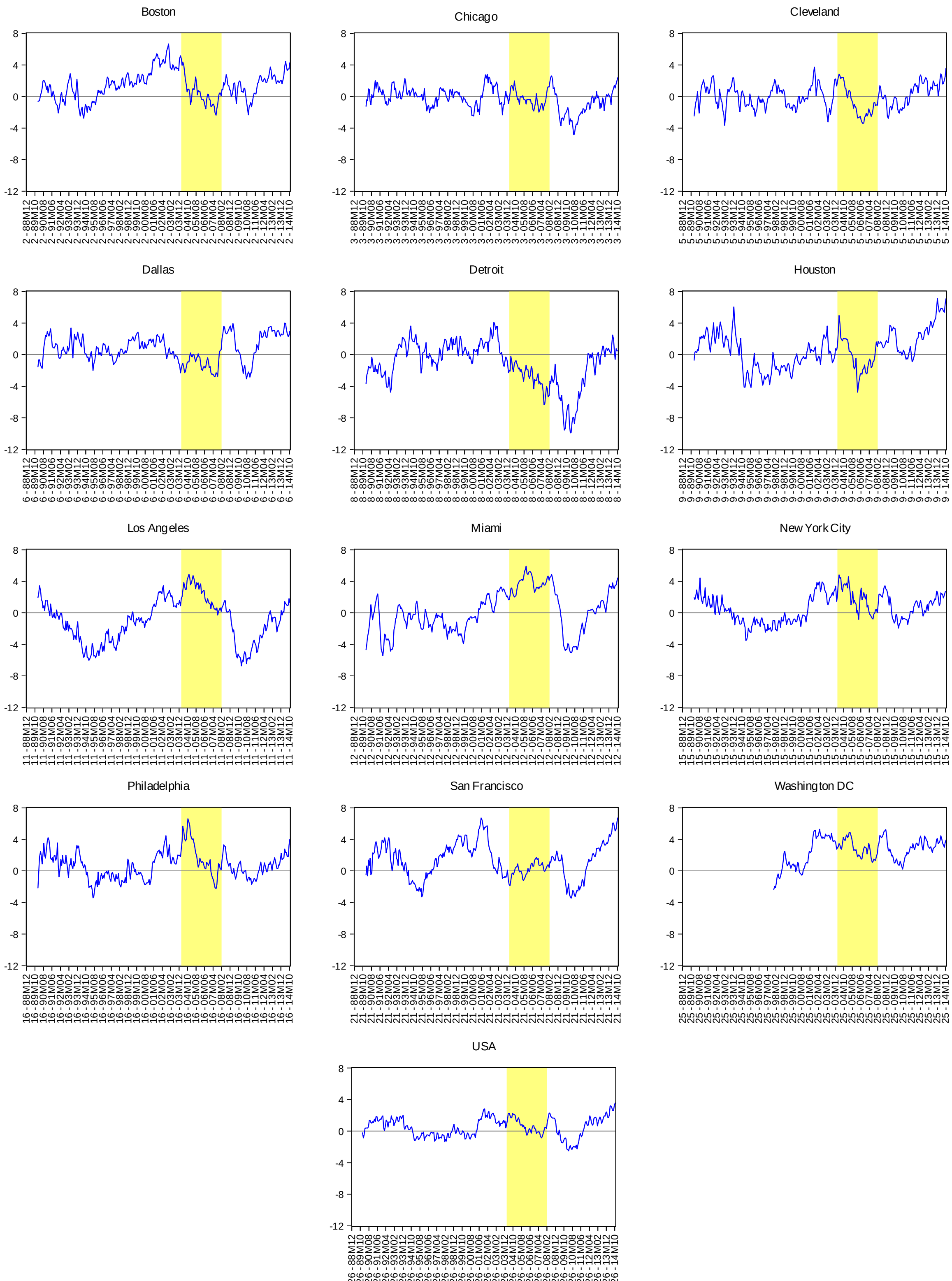


Figure 7: House Price Growth Versus Perceptions of the Cost of Credit by MSA

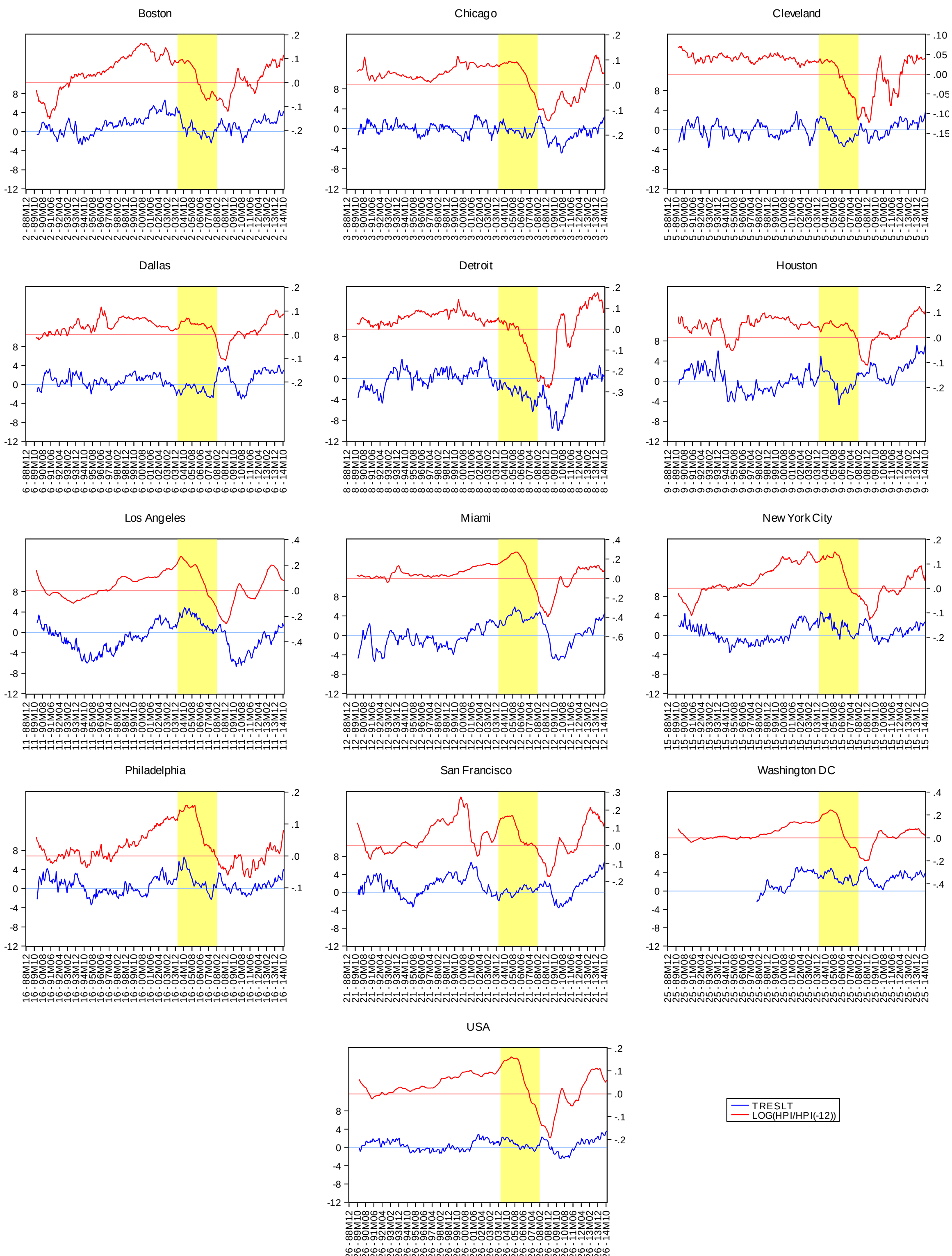


Table 1: Data Means by MSA

	UNEMP. RATE (PCT.)	INFLATION RATE (PCT., Y/Y)	TAYLOR RULE RESIDUAL (PCT.)	PRICE-RENT RATIO (1/1/90 = 1)	PRICE GROWTH (PCT., Y/Y)	RENT GROWTH (PCT., Y/Y)
USA	6.09	2.46	.49	1.08	3.38	2.93
BOSTON	5.39	2.52	1.33	1.04	3.17	2.81
CHICAGO	6.63	2.28	-.27	1.07	2.86	3.09
CLEVELAND	6.19	2.15	-.03	1.01	1.73	2.42
DALLAS	5.53	2.20	.70	1.07	3.10	2.62
DETROIT	7.51	2.27	-1.18	1.18	2.15	2.19
HOUSTON	5.96	2.40	.59	1.05	3.84	3.32
LOS ANGELES	7.44	2.37	-.96	1.00	3.71	3.03
MIAMI	6.88	2.73	.16	1.23	4.28	3.22
NEW YORK CITY	6.43	2.75	.63	.95	3.14	3.60
PHILADELPHIA	5.98	2.52	.74	1.02	2.88	2.67
SAN FRANCISCO	5.68	2.68	1.28	1.09	4.94	3.53
WASHINGTON DC	4.65	2.31	2.57	1.02	3.68	3.83

	MTG. RATE (PCT.)	FED FUNDS TGT. RATE (PCT.)
USA	6.76	3.53

Table 2: Mortgage Rate Model Estimates

	LOG(RENT)	MTG. RATE
ALL 12 CITIES	2.054*	.101*
	(.053)	(.007)
NORTHEAST REGION	2.013*	.088*
	(.080)	(.011)
MIDWEST REGION	1.875*	.111*
	(.146)	(.016)
SOUTH REGION	1.882*	.070*
	(.102)	(.013)
WEST REGION	2.201*	.110*
	(.115)	(.017)
SAND STATES	2.155*	.103*
	(.109)	(.016)
RUST BELT STATES	1.864*	.110*
	(.229)	(.022)
USA	2.140*	.101*
	(.206)	(.026)

* denotes statistical significance at the .05 level (Newey-West HAC standard errors in parentheses).

Table 3: Unemployment Rate Model Estimates

	LOG(RENT)	MTG. RATE	UNEMP. RATE
ALL 12 CITIES	1.905*	.064*	-.043*
	(.044)	(.006)	(.003)
NORTHEAST REGION	1.906*	.062*	-.017*
	(.079)	(.011)	(.005)
MIDWEST REGION	1.644*	.066*	-.052*
	(.109)	(.013)	(.005)
SOUTH REGION	1.683*	.028*	-.054*
	(.081)	(.011)	(.005)
WEST REGION	2.097*	.065*	-.042*
	(.100)	(.016)	(.006)
SAND STATES	2.003*	.056*	-.050*
	(.089)	(.014)	(.005)
RUST BELT STATES	1.582*	.062*	-.058*
	(.158)	(.016)	(.005)
USA	1.976*	.064*	-.045*
	(.186)	(.024)	(.011)

* denotes statistical significance at the .05 level (Newey-West HAC standard errors in parentheses).

Table 4: Enhanced Unemployment Rate Model Estimates

	LOG(RENT)	MTG. RATE	UNEMP. RATE - NAIRU
ALL 12 CITIES	1.927* (.044)	.063* (.006)	-.045* (.003)
NORTHEAST REGION	1.911* (.078)	.061* (.012)	-.018* (.006)
MIDWEST REGION	1.720* (.112)	.071* (.013)	-.052* (.005)
SOUTH REGION	1.714* (.082)	.029* (.011)	-.056* (.006)
WEST REGION	2.097* (.098)	.060* (.016)	-.047* (.006)
SAND STATES	2.009* (.087)	.052* (.014)	-.055* (.005)
RUST BELT STATES	1.694* (.163)	.069* (.017)	-.059* (.006)
USA	1.994* (.187)	.061* (.025)	-.048* (.012)

* denotes statistical significance at the .05 level (Newey-West HAC standard errors in parentheses).

Table 5: Inflation Rate Model Estimates

	LOG(RENT)	MTG. RATE	UNEMP. RATE - NAIRU	INFLATION RATE
ALL 12 CITIES	1.915* (.041)	.055* (.006)	-.044* (.003)	1.727* (.412)
NORTHEAST REGION	1.900* (.068)	.036* (.011)	-.023* (.005)	5.069* (.764)
MIDWEST REGION	1.598* (.112)	.077* (.013)	-.054* (.005)	-4.074* (1.061)
SOUTH REGION	1.686* (.080)	.020 (.011)	-.055* (.005)	1.921* (.705)
WEST REGION	2.062* (.086)	.053* (.015)	-.043* (.006)	1.161 (.963)
SAND STATES	1.951* (.081)	.039* (.013)	-.050* (.005)	2.098* (.878)
RUST BELT STATES	1.502* (.162)	.071* (.016)	-.062* (.006)	-4.896* (1.232)
USA	2.009* (.193)	.053 (.028)	-.051* (.013)	1.856 (2.850)

* denotes statistical significance at the .05 level (Newey-West HAC standard errors in parentheses).

Table 6: Perceived Cost of Credit Model Estimates

	LOG(RENT)	MTG. RATE	UNEMP. RATE - NAIRU	INFLATION RATE	PERCEIVED COST CREDIT
ALL 12 CITIES	1.928*	.081*	-.031*	-1.818*	.025*
	(.039)	(.006)	(.003)	(.614)	(.003)
NORTHEAST REGION	1.895*	.056*	-.016*	1.987	.021*
	(.064)	(.011)	(.005)	(1.081)	(.006)
MIDWEST REGION	1.713*	.114*	-.034*	-7.563 *	.030*
	(.110)	(.014)	(.006)	(1.342)	(.007)
SOUTH REGION	1.682*	.038*	-.047*	-.624	.018*
	(.076)	(.012)	(.006)	(1.121)	(.006)
WEST REGION	2.049*	.068*	-.033*	-1.681	.020*
	(.083)	(.015)	(.007)	(1.506)	(.008)
SAND STATES	1.952*	.065*	-.033*	-1.508	.027*
	(.075)	(.014)	(.006)	(1.279)	(.007)
RUST BELT STATES	1.649*	.109*	-.042*	-8.076 *	.027*
	(.160)	(.018)	(.008)	(1.585)	(.008)
USA	2.055*	.075*	-.041*	-.634	.031
	(.185)	(.030)	(.013)	(3.226)	(.016)

* denotes statistical significance at the .05 level (Newey-West HAC standard errors in parentheses).

Table 7: Enhanced Perceived Cost of Credit Model Estimates

	LOG(RENT)	MTG. RATE	UNEMP. RATE - NAIRU	INFLATION RATE	Σ(PERCEIVED COST CREDIT)
ALL 12 CITIES	1.880* (.037)	.069* (.006)	-.033* (.003)	-.709 (.473)	.030* (.003)
NORTHEAST REGION	1.821* (.056)	.046* (.009)	-.019* (.004)	1.735* (.794)	.035* (.004)
MIDWEST REGION	1.788* (.112)	.111* (.013)	-.032* (.006)	-4.879* (1.149)	.033* (.006)
SOUTH REGION	1.603* (.073)	.027* (.010)	-.050* (.005)	-.125 (.804)	.024* (.005)
WEST REGION	1.950* (.082)	.045* (.014)	-.035* (.006)	-1.112 (1.150)	.023* (.006)
SAND STATES	1.834* (.074)	.038* (.012)	-.036* (.005)	-.164 (.963)	.029* (.005)
RUST BELT STATES	1.713* (.160)	.107* (.017)	-.039* (.007)	-5.618* (1.342)	.028* (.007)
USA	2.031* (.178)	.063* (.026)	-.045* (.012)	.943 (2.970)	.050* (.015)

* denotes statistical significance at the .05 level (Newey-West HAC standard errors in parentheses).

Table 8: Enhanced Perceived Cost of Credit Model Estimates (including interpolated cities)

	LOG(RENT)	MTG. RATE	UNEMP. RATE - NAIRU	INFLATION RATE	Σ(PERCEIVED COST CREDIT)
	--- Include partially interpolated series ---				
ALL 16 CITIES	1.843* (.033)	.058* (.005)	-.030* (.002)	-.756 (.400)	.022* (.002)
	--- Include all interpolated cities ---				
ALL 25 CITIES	1.891* (.027)	.059* (.004)	-.031* (.002)	-1.192* (.330)	.014* (.002)
NORTHEAST REGION	1.816* (.047)	.054* (.007)	-.016* (.004)	.419 (.641)	.033* (.004)
MIDWEST REGION	1.920* (.064)	.093* (.008)	-.027* (.003)	-4.673* (.632)	.014* (.003)
SOUTH REGION	1.669* (.060)	.022* (.008)	-.034* (.004)	1.074 (.637)	.017* (.004)
WEST REGION	1.913* (.049)	.042* (.008)	-.044* (.004)	-1.777* (.688)	.006 (.004)
SAND STATES	1.856* (.054)	.046* (.009)	-.037* (.004)	1.182 (.735)	.025* (.004)
RUST BELT STATES	1.632* (.091)	.082* (.010)	-.033* (.004)	-5.145* (.784)	.031* (.004)

* denotes statistical significance at the .05 level (Newey-West HAC standard errors in parentheses).