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Drawing Inferences about Housing Supply Elasticity from House Price Responses to Income Shocks

Michelle Harter-Dreiman

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Michelle Harter-Dreiman
Office of Federal Housing Enterprise Oversight, 1700 G Street NW, Washington DC 20552
Email: sdreiman@ofheo.gov

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Abstract: The purpose of this paper is to provide information about the price elasticity of the supply of housing. I examine the relationship between the average price of single-family housing and the amount of personal income. A two-equation vector error correction system is estimated using a panel data set consisting of 76 MSAs from 1980 to 1998. The results suggest an elastic long-run supply function but a relatively slow pace of adjustment to long-run equilibrium. Hence a major demand shock can be expected to impact housing prices for several years following the shock. Differences in the responsiveness among subgroups of MSAs are examined and found to be generally minor.

I. Introduction

The answers to a variety of questions about public policies toward housing revolve around one's view about the supply adjustment process. For example, the impact of a switch to a flat tax or a consumption tax from the current income tax system upon the asset price of owner-occupied housing is a subject of some debate. Such reform would reduce the subsidies embedded in the federal income tax system and likely reduce the demand for owner-occupied housing and its asset price.[2] The extent of the ultimate decline depends upon two key behavioral parameters --the price elasticity of demand and the long-run price elasticity of supply. The literature generally places the price elasticity of the demand for owner-occupied housing near minus unity (Rosen [33])**;** unfortunately, a broad consensus about the supply elasticity of housing does not exist.

The purpose of this paper is to provide new information regarding:

- The long run supply elasticity of housing.
- The speed of supply adjustment to the steady state.
- The short run dynamics in the housing price path.

[1] This paper is a heavily revised version of an earlier paper by Dreiman and Follain (March, 2001) and draws upon my dissertation, which was supervised by Jim Follain. Helpful comments have been received from Pat Lawler, Donald Dutkowsky, Douglas Holtz-Eakin, Chi-Hwa Kao, and Michael Marschoun. The views expressed in this research are those of the author and do not represent policies or positions of the Office of Federal Housing Enterprise Oversight or other officers, agencies, or instrumentalities of the United States Government. Direct correspondence to sdreiman@ofheo.gov

The approach used here is based on a reduced form equation for housing price derived from a supply and demand model of the housing market, in which income represents the demand shift variable. The distinguishing feature of this study is the vector error correction (VEC) approach. This method enables one to investigate housing market dynamics directly, while imposing little structure. A critical part of the model is the cointegrating relationship between prices and the amount of personal income. This equation may be interpreted as the reduced form equation for the asset price of housing and, as such, it represents the long-run equilibrium condition expected to hold between the level of prices and the amount of personal income. This relationship depends critically on the demand and long-run supply curves. That is, evidence of a long-run positive relationship between house prices and income suggests the long-run supply curve is less than perfectly elastic. The reduced form supply and demand model discussed below enable the computation of a range of possible supply elasticities with some assumptions regarding price and income elasticities of demand.

The VEC model consists of equations for price and income growth. The model is based on errors from the estimation of the cointegrating relationship, as well as lagged price and income changes. Impulse response functions are utilized to examine the impact on housing prices of an unanticipated shock to income over a period of ten years. The impulse response function for the system is particularly insightful because it takes into account the likely interaction between prices and income not captured by a traditional reduced form equation.[3]

The estimates of the VEC and, in particular, the coefficient on the residuals from the cointegrating equation provide insights about the speed at which housing prices adjust to their long-run equilibrium after a shock to income. Since housing prices are dependent upon other variables, metropolitan area fixed effects are included in both the cointegrating equation and the VEC model to control for the myriad of other factors that impact housing prices at the local level.

The unit of observation is the metropolitan statistical area (MSA). Annual data from 76 MSAs for the period 1980 to 1998 are included. Housing price indexes are produced by the Office of Federal Housing Enterprise Oversight (OFHEO), and personal income comes from the U.S. Department of Commerce. All

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[2] Bruce and Holtz-Eakin [8] and Green et al [17] discuss these issues and the role of the supply elasticity in the last round of discussions of tax reform. Hendershott et al [19] and Ling [22] do the same for the tax reform debates of the 1980s.

[3] For example, Blackley and Follain [6] and others estimate structural models of the housing market and treat MSA level income as an exogenous variable; however, income may, in fact, be endogenous if the mobility of people and jobs and wage rates are responsive to the level of housing prices. In this sense, both income and housing prices are endogenous. A vector autoregression can capture such a relationship better than the traditional structural model.

variables are in real terms; the inflation adjustments are made using the national consumer price index (CPI).

While this approach does not allow for direct estimates of supply elasticity, inferences can be produced using reasonable assumptions about the income and price elasticities of demand and the reduced form estimation results from the long run equation. Indeed, the results strongly suggest that supply is less than perfectly elastic. Supply elasticity estimates in the vicinity of 1.8 to 3.2 are inferred from the parameters of the cointegrating equation and assumptions about the income and price elasticity of the demand for housing. These results are consistent with Blackley's [5] findings for the United States.

The speed of adjustment to long-run equilibrium, on the other hand, is not immediate. About 22 percent of the gap between the price level and its long-run equilibrium value is reduced each year; thus it takes about five years for housing price to get within 70 percent of its new long-run equilibrium value in response to a shock in demand. Although this is much faster than the estimates produced by Malpezzi [24] and Hort [20] for the U.S. and Miles and Andrew [30] for the United Kingdom, it is much slower than Hort [20] finds for Sweden. These results suggest that housing prices can respond substantially in response to an unanticipated income shock even though the impact on the long-run equilibrium price level would be modest.

The impulse response functions, which take into account the interaction between the level of housing prices and the amount of income, confirm these results. Lastly, there is little evidence of significant differences in the supply elasticities between two particular categorizations of MSAs -- large versus small by population density and constrained versus unconstrained by Malpezzi's regulatory index [23] described below.

The next section of the paper is a review of the literature. Section III describes the specification of the model in more detail. The data used in the paper are described in the fourth section. The results and some of their implications are discussed in Section V. The final section highlights the main conclusions of the paper.

II. Review of the Literature

The disagreement in the literature is amply demonstrated in a recent special issue of the *Journal of Real Estate Finance and Economics* edited by Rosenthal [34]. DiPasquale's [11] survey piece is exhaustive and identifies a number of different papers that support a broad spectrum of supply elasticities falling anywhere between perfectly elastic and perfectly inelastic. These studies vary in method. Muth [32], Follain [14], Malpezzi and Maclennan [25], and Meen [29] estimate reduced form models of price to draw inferences regarding supply elasticity. Follain [14] and Malpezzi and Maclennan [25] find elastic supply curves through interpretation of coefficients on demand and supply shifters in the regression equations for price. Muth [32] and Follain [14] conclude that housing supply is perfectly elastic, while Malpezzi and Maclennan [25] find that various specifications produce elasticities anywhere from 4 to 13. Meen [29] uses aggregate data to compare US and UK supply elasticities and finds both to be inelastic under the particular specification he chose. He argues that misspecification in US models is driving the higher supply elasticities cited.

Mayer and Somerville [28] and DiPasquale and Wheaton [12] produce direct estimates of the supply curve through stock adjustment processes based on urban spatial theory. Mayer and Somerville [28] find the lowest stock elasticity (0.08) and DiPasquale and Wheaton [12] find that the stock elasticity is a little above unity. Topel and Rosen [36] estimate the supply elasticity directly through the marginal cost curve and find that the long-run supply elasticity is around 3. Blackley [5] estimates a mixture of the above models and finds that the stock elasticities vary from 1.6 to 3. However, introducing inputs in differences rather than in levels yields better relationships between input price changes and supply. These models yield lower elasticities, around 0.8. This is more in line with Mayer and Somerville [28], who also introduce variables in differences. Intuitively, they argue, a *change* in price encourages new starts, but this is a temporary response to a price change. Eventually, the stock will reach a new equilibrium commensurate with the new price level, and starts will be zero. A benefit of this model is that it does not require estimating a series for the stock. It uses available publicly recorded data for starts.

There is a wealth of literature examining adjustment dynamics and speed. In fact, the literature finds adjustment speeds from approximately 1 year (Topel & Rosen [36], Mayer & Somerville [28], and Hort [20]) up to 35 years (DiPasquale and Wheaton [12]). Many of the recent studies utilizing metropolitan area data find adjustment speeds in the vicinity of 10 years (i.e. Abraham and Hendershott [1] and Malpezzi [24]), close to the results reported in this paper. OFHEO HPI data for most MSAs indicates that a complete cycle, including the up and down portions runs about 12 years, so this is consistent with the general pattern of the data.

Several of these more recent papers utilizing metropolitan data are similar in flavor to this one. Abraham and Hendershott [1], for example, use an error correction approach to model bubbles in coastal and inland areas. Capozza et. al [10] enhance and re-estimate this model for 62 MSAs, also citing significant error correction effects and local differences. Rosenthal [35] utilizes an error correction model that introduces a long-run equilibrium relationship between construction costs and building prices. Malpezzi [24] introduces an error correction model based on the long run relationship between house prices and income for MSAs[4]. None of these models, however, incorporate intermetropolitan migration by allowing for endogenous income. The VEC approach used in this paper is especially desirable for this purpose, as previous literature has indicated individuals do move based on house prices (Blanchard and Katz, [7]).

All of the above models have desirable and undesirable attributes. That is, no one study seems to be strikingly superior to any of the others. The problem seems to be that the data are sparse and wrought with measurement error. While many have produced clever models to make the best use of the data available, the wide range of elasticities implies that the data are the culprit in the lack of consensus. According to DiPasquale [11] the primary concern is the aggregation bias in the data. That is, there is no available data in which the unit of observation is the builder.

III. The Model: A Time-Series Approach

The VEC Model. Although a VEC is a relatively astructural approach to the modeling of a market, the specification used here is well rooted in the basic dynamic model underlying most empirical analyses of the housing market[5]. Recognizing the connection is helpful in understanding the benefits of the VEC approach relative to the traditional econometric model and in interpreting the empirical results.

According to this standard housing market model, housing demand depends on the asset price, the user cost of capital, household permanent income, and demographic characteristics of the household. Housing supply is a function of the asset price and replacement cost of housing. In this model, increases in price spurred by changes in any of the demand variables will lure new stock into the market. As long as the current asset price of housing exceeds the cost of construction, housing starts will be positive. In long-run equilibrium, the current asset price of housing depends upon the cost of construction and the levels of the exogenous drivers of housing demand. The quantity of housing, usually measured as the flow of services generated by the existing housing stock, is also a function of these variables.

[4] Gallin [15] recently challenged the results of this study by suggesting panel cointegrating tests do not confirm a long run relationship between price and income. This result, however, utilizes a null hypthesis of no cointegration, so a failure to reject may reflect the power of the particular test.
[5] This paper refers to the VEC as an astructural approach in comparison to the models discussed in the literature review. However, the VEC does impose some structure compared to the traditional vector autoregression (VAR), as the VEC includes a long-run equilibrium condition (the error correction term).

A three-equation VEC model is estimated, where the cointegrating equation represents the long-run reduced form equation for the asset price of housing in a metropolitan housing market. This equation is pre-estimated following the Engle- Granger two-step method (Banerjee et. al. [4]). The long-run relationship utilized is the one between the average level of prices and the amount of personal income in an MSA. Specifically, the cointegrating equation presumed is:

$$\ln(P_{it})= \alpha_i + \beta\ln(I_{it})+ \upsilon_{it} \tag{1}$$

where $\ln(P_{it})$ represents the natural logarithm of house price level in MSA i at time t and $\ln(I_{it})$ represents the natural logarithm of personal income level in MSA i at time t, MSA fixed effects are presumed, and υ_{it} is an idiosyncratic error. If price and income are cointegrated, this is interpreted as evidence that a long-run steady state relationship exists between the two series, and thus implies that supply is less than perfectly elastic. The logic behind this is that a long-run positive relationship between income and price is indicative that movements in demand as a result of income shocks result in some ultimate increase in price, even after supply has fully adjusted. If supply were perfectly elastic, one would expect to find no relationship between house price and income in the long-run (that is, β is not significantly different than zero).

The vector error correction system consists of an equation for price growth and an equation for income growth. The growth rates of each are modeled as functions of lagged values of price growth, income growth, and the residuals from estimation of the cointegrating equation (equation 1), as well as two year dummies[6]. The final specification is:

$$\begin{aligned}\Delta\ln(I_{it})= {} & \beta_{i0} + \beta_1\Delta\ln(I_{it-1}) + \beta_2\Delta\ln(I_{it-2}) + \beta_3\Delta\ln(P_{it-1}) \\ & + \beta_4\Delta\ln(P_{it-2}) + \lambda_1\upsilon_{it} + \beta_5\Delta 1986 + \beta_6 1991 + \varepsilon i_{it}\end{aligned} \tag{2}$$

$$\begin{aligned}\Delta\ln(P_{it})= {} & \alpha_{i0} + \alpha_1\Delta\ln(I_{it-1}) + \alpha_2\Delta\ln(I_{it-2}) + \alpha_3\Delta\ln(P_{it-1}) \\ & + \alpha_4\Delta\ln(P_{it-2}) + \lambda_2\upsilon_{it} + \alpha_5\Delta 1986 + \alpha_6 1991 + \varepsilon p_{it}\end{aligned} \tag{3}$$

The residuals from the cointegrating equation are interpreted as the departure of the current level of prices from their long-run equilibrium values. The price of an owner-occupied housing unit in the i^{th} MSA and t^{th} time period is P_{it}; I_{it} is personal income in MSA i in time period t. The α_{i0}'s and β_{i0}'s are fixed effects for each MSA and are included to capture the other MSA specific influences on the levels of prices and

[6] Attempts to include various interest rate specifications generated inconsistent results.

incomes, respectively. The dummy for 1986 represents tax reform, and the dummy for 1991 represents the recession. Other exogenous variables and other specifications were attempted, but this proved to be the most robust.

An unanticipated shock to income would spike the current value relative to price invoking disequilibrium from the long-run fundamentals. The speed at which a gap between long-run price and income is eliminated is represented by the coefficient λ_2 on the error correction term in equation 3. The lagged endogenous variables impart information about short run phenomena, such as transactions costs or house price cyclicality.

The calculation of impulse response functions from the estimated VEC provides an opportunity to examine the impact of a shock to income on housing prices that takes into account possible interactions between the two variables[7]. This seems highly desirable in a study like ours that employs MSA data because the distinction between purely endogenous and exogenous variables is sometimes difficult to make. For example, higher housing prices may impede migration into the MSA and reduce its population; alternatively, higher housing prices may also produce higher wage rates. MSAs, in other words, are small open economies in which many comparative statics result in ambiguity. As such, a model that allows for possible interaction between income and housing prices seems less restrictive than the traditional structural model of the housing market estimated with MSA level data in which income is exogenous.

This model, especially the specification of the cointegrating equation, is an admittedly simple specification of the complete dynamic housing market model. Housing demand, for example, is also impacted by the changes in the user cost of capital, population movement and the relative cost of renting. New housing supply is motivated when price rises above the replacement cost of housing. A well-specified reduced form expresses price as a function of all relevant exogenous demand and supply side variables.

In the VEC framework, however, the nonlinearity of the model resulted in convoluted outcomes when too many variables were included. Although a variety of other variables were attempted, this specification proved to be the most robust.[8] As such, it allows for a rudimentary examination of the long-

[7] An impulse response function is the current and future response of the endogenous variables to a one standard deviation shock in one of the innovations.

[8] The fundamental problem is the difficulty of measuring construction costs. Available measures do not include a land price component and are usually weighted averages of a set of construction costs that do not vary widely among

run response of the price level to a shock in one of the most important demand side variables, MSA income. It does so while still providing the previously stated benefits of the VEC approach to modeling.

Inferring Supply Elasticity. This VEC model and the interpretation of the cointegrating relationship follow the essential logic underlying Muth's [32] original paper and many subsequent ones by seeking insights about the supply elasticity from estimates of the reduced form equation for price, e.g. Follain [14]. That is, results from estimation of the reduced form equation for price are used along with assumptions regarding income and price elasticities of demand and input elasticities of supply to draw inferences regarding the long-run supply elasticity. The following simplified model allows for a translation of the reduced form coefficients into specific estimates of supply elasticity. Assume the following respective log linear demand and supply equations:

$$\Delta\ln(Q_d) = \xi_d\Delta\ln(P) + \xi_i\Delta\ln(I) \quad (4)$$

$$\Delta\ln(Q_s) = \xi_s\Delta\ln(P) + \xi_w\Delta\ln(I) \quad (5)$$

where Q and P are the quantity and price of housing, respectively; I and W are the demand (income) and supply (construction wage) shock variables, respectively; ξ_d is the price elasticity of demand; ξ_i is the elasticity of demand with respect to the demand shock (I); ξ_s is the price elasticity of supply; and ξ_w is the elasticity of supply to the input price shock. The equilibrium solution to this system is:

$$\xi_s = \xi_d + \xi_i\Delta\ln(I)/\Delta\ln(P) + \xi_w\Delta\ln(W)/\Delta\ln(P) \quad (6)$$

Previous research shows that the income elasticity of demand is between .75 and 1 (Mills [31]) and the price elasticity of demand is around–1.0 (Rosen [33]). Note the price elasticity of demand may be lower (in absolute value) in the short-run (Mankiw and Weil [27]). In this approach, the demand elasticity is allowed to be as low as –0.5[9]. The wage shock in the approach used in this paper is absent. Then the price elasticity of supply (ξ_s) lies between the values calculated in the following upper and lower bound equations:

$$\xi_{su} = \Delta \ln I/\Delta \ln P - 0.5 \quad \textit{for } \xi_I = 1 \textit{ and } \xi_P = -0.5 \quad (7)$$

$$\xi_{sl} = .75*\Delta \ln I/\Delta \ln P - 1 \quad \textit{for } \xi_I = .75 \textit{ and } \xi_P = -1 \quad (8)$$

where ξ_{su} is equal to the upper bound of the range of supply elasticities and ξ_{sl} is equal to the lower bound of the range of supply elasticities.

metropolitan areas or are highly correlated with income. Also, the number of variables I can use is limited by the relatively small sample size I am working with.

The estimation results from the cointegrating equation may be used in conjunction with this model to obtain estimates of the supply elasticity. The output from the impulse response functions may also be used in tandem with this model to infer supply elasticities for any year of the simulation.

IV. Data

The measure of the housing price index is the OFHEO Weighted Repeat Sales Index, which is derived from the joint Fannie Mae/Freddie Mac loan level data. The indexes are available from the ofheo.gov web site[10]. This index has several nice qualities, including the constant quality nature of the index (housing prices are measured based on repeat transactions of the same home in the database over time), and large sample size (approximately 40% to 45% of new loans are now purchased by Fannie or Freddie). Although the index does not control for renovations in the house over time, the methodology is an improvement over indexes based upon the simple averages of sales transaction because such indexes fail to account for changing quality of homes over time (i.e. do not hold consumer preferences constant). The indexes are available from 1980 on.

The natural logarithm of the index value itself is used directly to measure log price level ($\ln(P_{it})$) in equation 1 above and all subsequent equations. Note that the index values may be converted to an actual price level series simply by normalizing the index to 1 in a chosen base year and multiplying the index in each time period by an average or median price level for the base year[11]. The values obtained in each quarter would then represent an approximation of the value of the average house sold in the chosen base year for that particular quarter. For the purposes of this paper, it is not necessary to convert the index values to actual price levels, as this only influences the fixed effects which are differenced out in the VEC procedure[12].

Aggregate personal income is obtained from Woods and Poole, but the Bureau of Economic Analysis (BEA) produces the data[13]. This variable includes wages and salaries, other labor income, proprietor's income, dividend income, rental income, personal interest income, transfer payments, and personal

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[9] Note that even a demand elasticity as low as zero has little impact on the thrust of the results in this paper.

[10] The index values used in this paper are estimated as of the first quarter of 1999. MSA index values were not available to the public at that time, and thus this exact series is not currently available on the OFHEO web site. Since historical values revise each time the index is estimated, I will make the original data available to anyone wishing to replicate this work.

[11] Levels are available from a variety of sources, such as the MIRS Survey from Federal Housing Finance Board, Census, and the National Association of Realtors.

[12] For more information on how the indexes are calculated and interpreted, please refer to the HPI Technical Description, by Charles Calhoun [9], at www.ofheo.gov.

[13] Woods and Poole, 1998, MSA Profile.

contributions for social insurance. A residence adjustment is made for persons receiving income in one area and residing in another. This series is available for 1969-1996 and projected from 1997-1998.

All of the estimation focuses on real (versus nominal) values. This is done by deflating both the price and income series by the national consumer price index for all goods less shelter.

Due to the limited length of time series available, metropolitan areas are pooled to create a panel data set[14]. Recognizing that heterogeneity is always a potential problem with panel data, the approach used here is to pool data using various subgroups of the MSAs that would have economic reason to be more homogenous. One distinction is by size; the 20 MSAs with the largest population density in 1990 constitute the "large" group, and the 20 (among the 76 in the sample) with the smallest population density make up the "small" group. Constrained or unconstrained delineation is also applied, using Malpezzi's [23] city-specific regulatory index that was constructed using Wharton data. Wharton additively constructed the index using variables of approval time, waiting time for permits, zoning regulations, and an infrastructure adequacy scale constructed by the Wharton team that provided the survey data. The MSAs with a minimum cutoff of 20 or above are defined to be in the constrained pool, and 19 or below are in the unconstrained pool[15]. This results in a subset of 49 of the original 76 MSAs, as some of the MSAs used in this paper are not evaluated in the Malpezzi index. For a list of the specific MSAs in the subgroups, please see Table 1.

All estimation is conducted for the period of 1980 to 1998. While housing prices are available quarterly, MSA income is available annually, so the model is estimated on an annual basis. Housing prices are measured as of the end of fourth quarter each year. Although earlier data are available, the earlier house price data for some metropolitan areas are unreliable due to lack of an acceptable number of transactions contributing to the construction of the index.

Summary statistics are presented in Table 2. Measures of dispersion, such as the minimum and maximum and the standard deviations in these subgroups reflect the price cycles that would be expected in areas less capable of adjusting quickly to demand shocks. Figure 1 illustrates the path of house price changes for the five subgroups over the sample period. All areas tend to experience booms in the mid-to-late eighties, and busts in early to mid nineties. The constrained areas experience the largest cycles

[14] When the analysis is conducted at the individual MSA level, only 16 degrees of freedom are available. I do not have confidence in results obtained with such a brief time series. However, I do attempt to run the models at the individual level for observation. These results are very briefly discussed with the empirical results.

[15] Although the Malpezzi index has received some criticism, the goal here is not to find a perfect measure by which to pool. This measure is the most current and extensive of its type, and the goal was simply to test it in this model.

during these periods, reflecting the higher measures of dispersion, followed by the large areas. The unconstrained and small areas generally experience booms and busts during the same periods, but of smaller magnitudes. The unconstrained areas, however, diverge from the mean during the early to mid-nineties. During this time period, prices were rising in the unconstrained areas while they were falling in all other subgroups and the national sample.

Panel Unit Root Tests

Of key importance in this paper is the error correction term, which is derived from the long-run relationship between house prices and income. If supply is perfectly elastic, then no long-run relationship exists, and the variables are not cointegrated. If supply were less than perfectly elastic, than one would expect to see a positive relationship between prices and income in the long run and the two variables would likely be cointegrated. A cointegrating equation is estimated using the level of price and income and a fixed effect.

In the strict Engle-Granger definition of cointegration used in this paper, the linear combination of the two (or more) variables must be integrated of order zero[16]. So unit root tests of price, income, and the residual of the linear combination of price and income are estimated and presented. Heterogeneity associated with panel data poses problems with using traditional methods for unit root testing. However, several panel unit root tests have been published. The Im, Pesaran, and Shin (IPS) [21] test touts particular usefulness for situations in which time series are short and cross sections are plentiful. Since the data are characterized as such, this paper uses the IPS test for unit roots in the income, price, and error correction variables.

The panel Augmented Dickey-Fuller (ADF) test for each of the three series takes the form:

$$\Delta y_{it} = \eta_i + \kappa y_{i,t-1} + \varpi \Delta y_{i,t-1}\ \varepsilon_{it},\ i=1,\ldots,N;\ \ t=1,\ldots,T \qquad (9)$$

The data are said to follow a unit root if κ is not significantly different than 0. In this specification, one lagged difference of the dependent variable is included for additional explanatory power[17]. The IPS test involves first conducting ADF tests at the individual MSA level and then averaging the test statistics

[16] A broader definition allows the two variables to be integrated of higher orders, but they must be the same, and the residual from their linear combination must be integrated at one order lower than the components ((Banerjee et. al. [4]).

[17] The panel unit root methods used required choosing one structural form to be applied to all MSAs. In some cases, individual MSA level Akaike information criteria required one lag, and in others 2 were indicated to be optimal. I chose to stick with one lag for all three series for this test.

across MSA. The resulting average test statistic can be converted to a standard normal random variable by subtracting the IPS simulated critical values of mean and variance for the chosen lag structure and multiplying by the square root of the number of MSAs.

The unit root tests for the panel indicate a unit root is not rejected for the income level, but is rejected for the price level at the 98 percent confidence interval with a normalized ADF test statistic of –2.12 (see Table 3). A unit root is strongly rejected for the residual series from equation 1 (ADF of –4.34), which is a necessary condition for the income and price series to be cointegrated and for applying the Engle-Granger method. Unit roots are strongly rejected when conducted on the first differences of the price and income series, which rules out integration of another order.

The fact that the unit root tests for price and income yield I(0) and I(1) results, respectively, may seem problematic at first glance. However, the residual on the linear combination of the two variables is I(0). If price and income are truly I(0) and I(1), then the residual should be I(1) (Greene [16]). The I(0) residual implies that the two series behave as I(1).

Aside from the results for the unit root tests, there is a strong case to be made for cointegration based on the supply and demand fundamentals. That is, price and income are likely to move together in the long run if the supply curve slopes even slightly upward. Given a fixed supply of land, it is not likely the long run supply curve is perfectly elastic and unlikely that price is really stationary in the long run.

V. Empirical Results

Equations 2 and 3 are estimated by ordinary least squares and weighted least squares with EVIEWS 3.1. First, the cointegrating equations are estimated via ordinary least squares (OLS) and generalized least squares (GLS). The GLS procedure applies cross section weights, using the sum of the squared residuals divided by the number of time periods as the weight for each MSA. Second, each of the two VEC equations is estimated via OLS and GLS using the same weighting methodology. GLS results are reported, although the results are not highly sensitive to the estimation technique.

Cointegrating Equations. The estimates of the cointegrating equations provide insights about the long-run relationship between the level of real housing prices and the amount of real personal income in an MSA. These are obtained directly through estimation of the coefficient β in equation 1 above. This equation is estimated separately for the national sample, the 4 subgroups, and the individual MSAs. The estimate of β represents the income elasticity of house price. This estimate is substituted into the upper and lower bound equations (7 & 8) for supply elasticity to compute ranges. The β coefficients and estimated supply elasticities are presented in Table 4.

The elasticity of price with respect to income in the national sample is 0.27; that is, a 10 percent increase in the level of real personal income increases the long-run equilibrium real price of housing by about 3 percent. The t-statistic of 25.12 confirms this is highly significant. The associated supply elasticity range is 1.8 to 3.2. The equation is also estimated for the national sample using a fixed intercept but with MSA specific coefficients of the income term. These results tell a similar story. The average coefficient of income is 0.25 and the standard deviation is 0.01. All but nine are less than 0.30 and all are less than .40. The five largest are Springfield, Vallejo, Providence, Wilmington, and Stockton; Houston has the lowest coefficient for income (0.15).

This equation is also estimated for the four selected subgroups of the full sample of MSAs. The coefficient on income is always highly significant, with t-statistics ranging from 11 to 17, depending on the subgroup. As expected, the income coefficient for the constrained MSAs is larger than the coefficient for the unconstrained MSAs (0.38 versus 0.21), which suggests that the supply elasticity is larger for the unconstrained MSAs (e.g. Houston) than among constrained MSAs (e.g. New York). Supply elasticities range from about 1.0 to 2.1 for the constrained and are between 2.6 and 4.3 for unconstrained cities. On the other hand, the estimates for the pools of large and small MSAs are not as expected. The coefficient for the group of large MSAs (0.31) is actually smaller than that for the smaller MSAs (.39). Supply elasticities thus range from about 1.4 to 2.7 for large and 0.9 to 2.1 for small MSAs. This finding suggests that MSA population density is not the defining characteristic of differences in the supply elasticity.

These equations are estimated at the individual MSA level for comparison, while cautioning that these results may be affected by the lack of available degrees of freedom. For about 15 of the MSAs, the income variable does not have the proper sign. For the other 61, however, the coefficient is properly signed and the results are often within reason. Constrained MSAs such as Honolulu (1.8 coefficient on income) and San Francisco (1.0 coefficient on income) behave as expected. Many of the unconstrained MSAs exhibit little or no relationship between price and income. For example, the coefficient on income for both Houston and Austin is zero. However, many of the results are not well behaved, so caution should be used in placing too much emphasis on the specifics of the cointegrating equation results from the individual regressions.

VEC Model Overview. The preferred method for analyzing the VEC is the impulse response function because of the nonlinearity of the relationship between income and price inherent in a VEC. The VEC is essentially a restricted vector autoregression (VAR) containing an error correction component; however, like a VAR it is an endogenous system of equations containing lagged endogenous variables. Each equation in the VEC system is estimated separately, and the system is forward solved for each of the endogenous variables (equations 2 and 3 in this case).

The interpretation of the impulse response is then straightforward. The impulse response measures the change in the endogenous variables with respect to changes in other endogenous variables over a chosen time horizon. This is why impulse responses are a convenient tool for analyzing VAR/VEC results. Nonetheless, direct examination of the coefficients of the lagged variables does provide some insights about the short-run response of price to demand shocks. The full set of estimates is reported in Table 5. Indeed, a consistent picture does emerge from the estimates based upon all MSAs -- the speed of adjustment of housing prices to demand shocks is not immediate. The sum of the coefficients of the lagged income variables is significant and sum to about 0.35. This implies a long-run multiplier of almost 3 absent the incorporation of interactions with the other two equations; that is, about half of the impact of a demand shock is realized in the first couple of years. The coefficients of the lagged price growth rates for the sample of all cities are both positive and significant and sum to 0.45 , which also implies that the full response of housing prices to a shock of any type lasts well beyond two years. Similar conclusions are drawn from the estimates of the large and small MSAs.

The interpretation of the estimates of the lagged variables for the constrained and unconstrained MSAs seems less clear. The sum of the coefficients on lagged price terms for the constrained region is about 0.46 versus 0.24 for the unconstrained region. While this *is* consistent with the evidence that supply in constrained areas is less able to respond quickly and efficiently to a shock, the sum of the coefficients on income in the unconstrained group is 0.53 while this number is only 0.34 for the constrained group. One would expect that both the lagged price terms and income terms would impact the price equation more heavily in constrained areas, since supply is slower to respond. Therefore, this is just the opposite of what intuition would suggest for these subgroups. The differences in coefficients for the large and small MSAs were very small.

Error Correction Coefficient. A key part of the VEC results is the coefficient of the cointegrating equation residual (λ_2 in equation 3 above). It indicates the speed at which housing prices respond to disequilibrium in the housing market. As expected, the estimates of the coefficient are all negative and significant among a variety of specifications; that is, housing price growth is slower, all else equal, in

MSAs in which housing price levels are above those consistent with long-run equilibrium. The coefficient estimate for all MSAs is -0.22, which suggests that 22 percent of the gap between housing prices and their fundamental determinants is reduced each year. Furthermore, it takes three years to eliminate half of the gap; even after 10 years about ten percent of the gap remains. This appears to be a relatively slow adjustment period because it suggests that the short-run response of price to a shock in demand will exceed the long run by substantial amounts. On the other hand, the estimated response speed is significantly faster than those estimated by Malpezzi [24] and Hort [20]. Both of these studies report coefficient estimates of the EC term to be in the vicinity of 0.05.

The estimates of the EC coefficient are virtually the same for the subgroups as the national (about -0.20 to -0.22), with the exception of the unconstrained group (-0.14). This again suggests an adjustment speed of about 10 years for the first 3 subgroups. The unconstrained group, however, does not reach 10 percent of equilibrium value for 15 years. This is opposite of what would be intuitively expected.

The behavior of the error correction term in the VEC model was perhaps the most robust result when conducted for comparison at the individual MSA level. Of the 61 MSAs that contained the proper sign on income in the cointegrating equation, about half of them were characterized by EC coefficients that ranged between -.10 and -.39, not enormously different from the ranges estimated with the pooled data. Most often, these numbers were highly significant, and when they were not, the t-statistics were almost always greater than 1.0. The average EC coefficient for the sample of 61 was -0.49 and the median was -0.42. While not wishing to focus on the individual level MSA results, the most important finding here was that the EC term was the only variable that was almost always significant and properly signed. This would indicate that generally the long-run relationship is a strong driver of house price movement. Expected regional variation, however, is not easily detected here. Often, the less constrained and smaller MSAs are slower to adjust and vice-versa. Again, these results are obtained using too few degrees of freedom to merit much attention.

Impulse Response Analysis. The impulse response analysis sheds light on the short-run and long run responses of each of the variables to various shocks in a way that takes into account the nonlinearity of the VEC and the correlation between the errors in the two equations. Recall that the impulse response analysis computes the path of changes in the two variables to a one standard deviation change in one of the two variables. The system is ordered with personal income being the driving force. This ordering scheme was chosen based on the causal path of variables outlined in the basic dynamic housing model. That is, shocks to relatively exogenous demand variables directly impact short and long-run housing prices and quantities. For further justification of this logic, see Atesoglu and Dutkowsky [3].

The results are summarized in Figures 2 and 3. For the group of all cities, a shock to personal income results in house price change with a ratio of about 0.21; that is, a ten percent increase in the demand variable (a shock to personal income growth) increases housing prices by 2.1 percent after ten years (see Figure 2). The ratio of price to the demand shock continues to grow over the first 4 years, peaking at 0.79 before beginning to decline. This response is consistent with the presence of positive autocorrelation in housing price growth as found by Abraham and Hendershott [1]. However, the final ratio of 0.21 is consistent with a highly elastic supply curve over the long-term. The inferred long-run supply elasticity after 10 years is between 2.6 and 4.3, a little higher than the range computed directly from the cointegrating equation (1).

According to the IRF, it takes approximately 9 years for prices to reach 70 percent of their equilibrium value. Short run dynamics or disturbances resulting from the positive and significant lagged price and income terms are responsible for the longer adjustment period implied by the complete VEC as opposed to just the cointegrating equation.

Also shown on Figures 2 and 3 are impulse response functions for the subgroups. The relative price response for each of the subgroups peaks in year 4 of the simulation, before beginning to decline. By year 4, the small subgroup had cumulated the most price growth, followed by unconstrained, constrained, and large groups. At the end of the simulation, net price response was largest in the unconstrained group and smallest in the large group but the differences were small. Depending on subgroup, the range of lower to upper bound supply elasticities by the end of 10 years fell somewhere between 0.7 to 2.6. Refer to the figures for explicit ranges for each group.

The subgroup results are somewhat counterintuitive with respect to expected regional differences. This mirrors the inconsistency seen in the cointegrating equation for the small and large groups. In the case of the higher elasticity for the constrained versus unconstrained, this is a result of the slow adjustment speed estimated for the unconstrained group. In other words, prices are not close to their equilibrium values for the unconstrained group after 10 years.

VI. Conclusion.

Results from the cointegrating equations, VEC model estimation, and impulse response analyses are presented to develop a story regarding the responsiveness of housing supply to demand stimuli. First, the cointegrating equations are estimated and used with the price and income elasticity assumptions to solve for long-run supply elasticity ranges. Nationally, this yields a supply elasticity between 1.8 and 3.2 depending on assumptions of income and own price elasticities of demand. These results are quite consistent with evidence presented by Blackley [5].

The residuals from this equation are then used in a two-equation VEC model of income and house prices. The coefficient on the error correction term in the price equation gives us direct information about speed of adjustment. Essentially, adjustment to equilibrium takes many years; 70 percent of the adjustment occurs with the first 5 years and 90 percent within 10 years. While seemingly slow, they are faster than those estimated by Hort [20] and Malpezzi [24]. Also the model estimation implies that lagged price and income do affect current prices and therefore will influence the path to equilibrium.

The impulse response functions go one step further by using the parameters of the VEC to compute the path to equilibrium of both price and income following a shock. Supply elasticities may also be generated from the results of the IRFs. The supply elasticities generated after 10 years are very close to the estimates inferred from the cointegrating equation. This is because the effects of the lagged price and income terms virtually die out in the long run, and the long-run response of price to the shock is a direct result of the error correction coefficients. The speed of adjustment implied by the impulse response functions also roughly reflects that which would be interpreted directly from the error correction coefficient in the VEC. This would indicate that income is not highly endogenous, even at the metropolitan area level. This is a key finding, as the purpose of the VEC approach was to allow for income endogeneity, which is often the result of intermetropolitan migration.

Estimation of the model for subgroups did not produce substantial differences, for the most part. And differences were often counterintuitive. However, the general ranges of elasticities and adjustment speeds from cointegrating equations, error correction terms, and IRFs are consistent with the national estimates.

Together, the results suggest that housing prices would be affected by a major shock to demand. For example, housing prices would likely decline in response to the enactment of a major tax reform plan that reduced the subsidy to owner-occupied housing, all else equal. However, much of the impact would dissipate and housing prices would recover much of the lost value over time. This conclusion seems to highlight the potential benefits of phasing in the provisions of any such plan because a phase in would likely mitigate the short-run impact on housing prices.

An obvious shortcoming of this paper is the lack of sufficient explanatory variables. As was stated earlier, many other supply and demand side variables were attempted but results were convoluted. This is likely due to the highly nonlinear nature of the VAR model. A nice extension would be the introduction of additional demand or supply side variables in a manner such that a cohesive story would emerge.

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Table 1: Pool Definitions

TOP 20[1]	*BOTTOM 20*[2]	*CONSTRAINED*[3]	*UNCONSTRAINED*[4]
Atlanta	Akron	Akron	Buffalo
Baltimore	Albuquerque	Allentown	Chicago
Boston	Allentown	Atlanta	Dallas
Chicago	Ann Arbor	Baltimore	Dayton
Cleveland	Augusta	Birmingham	Denver
Dallas	Bakersfield	Boston	Detroit
Detroit	Birmingham	Charlotte	Gary
Houston	Columbia	Cincinnati	Grand Rapids
Los Angeles	Fresno	Cleveland	Greensboro
Minneapolis	Gary	Columbus	Greenville
Nassau	Harrisburg	Fort Lauderdale	Hartford
New York	Honolulu	Honolulu	Kansas
Orange County	Omaha	Indianapolis	Minneapolis
Philadelphia	Springfield	Los Angles	New Orleans
Phoenix	Stockton	Miami	Oklahoma City
Pittsburgh	Syracuse	New York	Phoenix
Riverside	Toledo	Newark	Portland
St. Louis	Vallejo	Orlando	Richmond
San Diego	Wichita	Philadelphia	Salt Lake City
Washington	Wilmington	Pittsburgh	St. Louis
		Providence	Tampa
		Rochester	
		Sacramento	
		San Diego	
		San Francisco	
		San Jose	
		Syracuse	
		Toledo	

[1]20 MSAs with largest population density in sample
[2]20 MSAs with lowest population density in sample
[3]MSAs that are most supply constrained using Malpezzi definition
[4]MSAs that are least supply constrained using Malpezzi definition

Table 2: Summary Statistics

	All Cities		*Constrained Cities*		*Unconstrained Cities*		*Large Cities*		*Small Cities*	
	I_{it}	P_{it}	I_{it}	P_{it}	I_{it}	P_{it}	I_{it}	P_{it}	I_{it}	P_{it}
Mean	5.14	0.05	5.41	0.08	5.28	-0.03	6.13	0.09	4.27	0.05
Median	5.04	0.00	5.36	0.02	5.12	-0.03	5.98	0.02	4.28	0.00
Maximum	7.46	0.90	7.46	0.81	7.24	0.30	7.46	0.90	4.90	0.80
Minimum	3.56	-0.73	4.07	-0.73	4.11	-0.37	5.08	-0.47	3.56	-0.73
Std. Dev.	0.80	0.21	0.81	0.21	0.70	0.13	0.54	0.25	0.28	0.20
Observations	1444	1444	494	494	361	361	380	380	380	380
Cross sections	76	76	26	26	19	19	20	20	20	20

All Variables in Real Terms and in Logarithms

Table 3: ADF Test Statistics					
	Price		Income		EC Term
	Level	*First Difference*	*Level*	*First Difference*	
Standardized t-bar statistic*	-2.12	-8.42	7.62	-4.96	-4.34
Individual ADF Test Statistics					
Akron	-0.06	-3.59	0.23	-3.40	-0.31
Albuquerque	-2.11	-2.25	-0.30	-3.20	-1.76
Allentown	-2.66	-1.93	-0.72	-2.23	-2.56
Ann Arbor	-0.66	-4.16	-1.24	-2.87	-0.97
Atlanta	-1.64	-1.68	-0.90	-1.95	-1.59
Austin	-1.99	-2.02	-0.24	-2.33	-1.45
Bakersfield	-0.83	-2.07	-1.27	-1.66	-0.69
Baltimore	-1.46	-2.16	-1.32	-1.51	-1.62
Birmingham	-0.87	-4.53	-0.13	-3.18	-2.55
Boston	-3.56	-1.78	-1.35	-1.52	-3.66
Buffalo	-1.40	-2.20	-0.61	-2.13	-1.37
Charlotte	-1.35	-2.93	-0.51	-2.18	-3.98
Chicago	-0.90	-3.32	0.41	-2.49	-1.12
Cincinnati	-0.65	-2.77	-0.15	-2.35	-1.64
Cleveland	0.08	-4.19	-0.08	-2.56	-0.17
Columbia, SC	-1.66	-2.09	-0.94	-1.78	-1.67
Columbus, OH	-0.19	-3.96	-0.98	-2.82	-1.79
Dallas	-1.21	-1.39	0.18	-1.55	-1.01
Dayton	-0.92	-2.19	-0.75	-2.93	-1.16
Denver	-0.62	-1.61	1.66	-0.78	-1.35
Detroit	-0.55	-4.93	-0.90	-3.62	-0.87
Fort Lauderdale	-2.11	-3.10	-0.81	-2.16	-1.48
Gary	-0.54	-2.10	0.37	-3.54	-0.90
Grand Rapids	-0.46	-2.55	-0.20	-3.42	-1.65
Green Bay	-1.96	-2.55	-0.64	-2.28	-1.89
Greenville	-0.85	-4.81	-0.49	-2.73	-3.66
Harrisburg	-2.66	-4.30	-1.03	-1.52	-3.10
Hartford	-3.09	-1.87	-1.95	-1.31	-2.80
Honolulu	-3.52	-2.41	-2.03	-1.43	-3.42
Houston	-2.03	-1.67	1.72	-2.80	-1.90
Indianapolis	-0.97	-3.99	0.04	-4.24	-4.85
Jacksonville	-2.43	-3.75	-0.57	-1.33	-1.47
Kansas City	-1.79	-2.58	-0.33	-2.12	-1.72
Las Vegas	-2.22	-4.05	0.86	-3.12	-0.96
Los Angeles	-2.28	-1.63	-1.36	-1.18	-2.39
Louisville	-0.29	-2.89	0.40	-3.18	-0.93
Miami	-1.42	-2.57	-0.60	-2.64	-2.17

Middlesex	-3.48	-2.17	-0.92	-1.44	-3.39
Minneapolis	0.00	-1.55	-0.48	-1.91	-1.57
Monmouth	-3.21	-2.23	-1.98	-1.65	-3.34
Nashville	-2.12	-2.16	-0.53	-2.65	-2.34
Nassau	-3.14	-1.50	-1.90	-1.26	-3.19
New Haven	-1.67	-1.70	-1.01	-1.99	-1.60
New Orleans	-1.77	-1.89	0.99	-2.21	-1.96
New York	-2.40	-1.68	-1.25	-1.57	-2.42
Newark	-3.56	-2.02	-1.80	-1.79	-3.54
Norfolk	-2.67	-1.90	-1.48	-1.31	-1.31
Oakland	-1.63	-1.89	-1.30	-1.88	-2.01
Omaha	-0.91	-2.26	0.78	-1.83	-1.99
Orlando	-1.04	-2.20	-0.95	-1.40	-0.41
Philadelphia	-2.78	-2.09	-1.20	-1.51	-2.77
Phoenix	-1.34	-1.53	-0.14	-2.16	-1.65
Pittsburgh	-0.88	-5.87	1.40	-1.89	-1.45
Portland	0.59	-1.50	1.44	-3.59	0.20
Providence	-3.18	-1.71	-1.67	-1.62	-3.16
Raleigh	-1.92	-1.98	-0.84	-2.52	-1.82
Richmond	-1.91	-2.99	-0.85	-1.80	-1.97
Riverside	-1.96	-1.82	-1.43	-1.38	-1.86
Rochester	-3.34	-1.78	-1.43	-2.28	-2.70
Sacramento	-2.12	-2.23	-1.68	-1.96	-3.02
Salt Lake City	-0.72	-1.46	1.00	-1.17	-1.12
San Diego	-1.86	-1.67	-1.27	-1.29	-2.42
San Francisco	-2.23	-2.06	-0.21	-1.03	-2.50
San Jose	-1.30	-2.32	0.41	-1.46	-1.74
Seattle	-0.47	-2.22	0.84	-1.88	-1.03
Springfield, MA	-2.65	-1.50	-1.52	-1.56	-2.63
St. Louis	-3.12	-2.86	-0.93	-1.63	-1.99
Stockton	-2.32	-1.73	-1.07	-1.86	-2.65
Syracuse	-3.31	-1.49	-2.54	-1.81	-2.54
Tampa	-2.36	-4.06	-0.83	-1.53	-1.37
Toledo	-2.14	-3.93	-0.58	-2.67	-3.44
Vallejo	-1.67	-1.85	-2.24	-1.68	-2.33
Washington, DC	-2.19	-1.83	-1.79	-1.46	-2.31
West Palm Beach	-1.50	-2.47	-2.21	-0.82	-1.63
Wichita	-2.10	-1.73	1.00	-2.29	-2.13
Wilmington	-2.66	-1.69	-0.80	-1.92	-2.53

**t-bar represents the average of the Dickey Fuller statistics for all MSAs. The standardized t-bar statistic above is computed using critical values of mean and variance simulated by IPS for 18 time series and 76 cross sectional observations. The simulated values of mean and variance for this data are -1.514 and .923, respectively.*

Table 4: Results from Cointegrating Equation

		LN(Iit)	Range of Supply Elasticity
	Dependent Variable		
All Cities	LN(Pit)	0.27	[1.8 - 3.2]
		0.01	
		25.12	
Constrained Cities	LN(Pit)	0.38	[0.97 - 2.1]
		0.02	
		17.26	
Unconstrained Cites	LN(Pit)	0.21	[2.6 - 4.3]
		0.02	
		11.00	
Large Cities	LN(Pit)	0.31	[1.4 - 2.7]
		0.03	
		11.61	
Small Cities	LN(Pit)	0.39	[0.92 - 2.1]
		0.03	
		15.12	

Note: t-statistics in bold; standard errors in italics.

Table 5: Coefficients from VEC Estimation

	Dependent Variable	d(LN(Pit-1))	d(LN(Pit-2))	d(LN(Iit-1))	d(LN(Iit-2))	EC_{it-1}	YR7	YR11	*Weighted R^2*	*Unweighted R^2*
All Cities	d(LN(Iit))	0.06	0.03	0.25	-0.02	-0.05	0.02	-0.03	0.59	0.46
		0.01	*0.01*	*0.03*	*0.03*	*0.00*	*0.00*	*0.00*		
		6.16	**2.96**	**9.17**	**-0.70**	**-9.32**	**9.19**	**-13.68**		
	d(LN(Pit))	0.30	0.15	0.10	0.25	-0.22	0.05	-0.05	0.62	0.57
		0.02	*0.02*	*0.05*	*0.05*	*0.01*	*0.00*	*0.00*		
		13.88	**6.92**	**2.04**	**4.53**	**-20.71**	**12.08**	**-14.08**		
Constrained Cities	d(LN(Iit))	0.05	0.03	0.21	-0.01	-0.05	0.02	-0.02	0.55	0.44
		0.02	*0.01*	*0.05*	*0.05*	*0.01*	*0.00*	*0.00*		
		3.40	**1.81**	**4.43**	**-0.10**	**-5.54**	**5.44**	**-7.26**		
	d(LN(Pit))	0.34	0.12	0.02	0.32	-0.22	0.06	-0.05	0.64	0.60
		0.03	*0.03*	*0.08*	*0.09*	*0.02*	*0.01*	*0.01*		
		9.83	**3.64**	**0.21**	**3.39**	**-11.48**	**7.79**	**-8.45**		
Unconstrained Cites	d(LN(Iit))	0.06	0.00	0.28	-0.11	-0.01	0.02	-0.03	0.48	0.47
		0.03	*0.03*	*0.05*	*0.07*	*0.01*	*0.01*	*0.00*		
		2.33	**0.05**	**5.26**	**-1.60**	**-0.72**	**4.12**	**-8.03**		
	d(LN(Pit))	0.12	0.12	0.16	0.37	-0.14	0.03	-0.05	0.54	0.41
		0.05	*0.04*	*0.08*	*0.11*	*0.02*	*0.01*	*0.01*		
		2.57	**2.63**	**1.96**	**3.48**	**-6.77**	**3.23**	**-8.32**		
Large Cities	d(LN(Iit))	0.05	0.02	0.30	0.05	-0.06	0.02	-0.03	0.63	0.54
		0.02	*0.02*	*0.06*	*0.06*	*0.01*	*0.00*	*0.00*		
		2.22	**0.95**	**5.35**	**0.76**	**-6.83**	**4.26**	**-6.84**		
	d(LN(Pit))	0.32	0.17	0.09	0.22	-0.21	0.05	-0.06	0.69	0.67
		0.04	*0.04*	*0.10*	*0.12*	*0.02*	*0.01*	*0.01*		
		7.33	**4.09**	**0.93**	**1.85**	**-11.73**	**5.51**	**-8.59**		
Small Cities	d(LN(Iit))	0.08	0.05	0.16	-0.09	-0.05	0.02	-0.02	0.53	0.41
		0.02	*0.02*	*0.06*	*0.06*	*0.01*	*0.00*	*0.00*		
		3.89	**3.41**	**2.92**	**-1.51**	**-4.78**	**5.34**	**-6.44**		
	d(LN(Pit))	0.34	0.13	0.01	0.25	-0.20	0.05	-0.05	0.58	0.55
		0.04	*0.04*	*0.10*	*0.12*	*0.02*	*0.01*	*0.01*		
		7.94	**3.36**	**0.11**	**2.17**	**-9.13**	**5.79**	**-6.75**		

Note: t-statistics in bold; standard errors in italics.
*The weighted R-squared is calculated using a cross-section weighted fitted residual, and the unweighted R-squared is calculated using unweighted residuals (from the original data). Both fitted residuals are computed using the parameter estimates from the weighted regression.

Figure 1: Real House Price Movements Among Groups

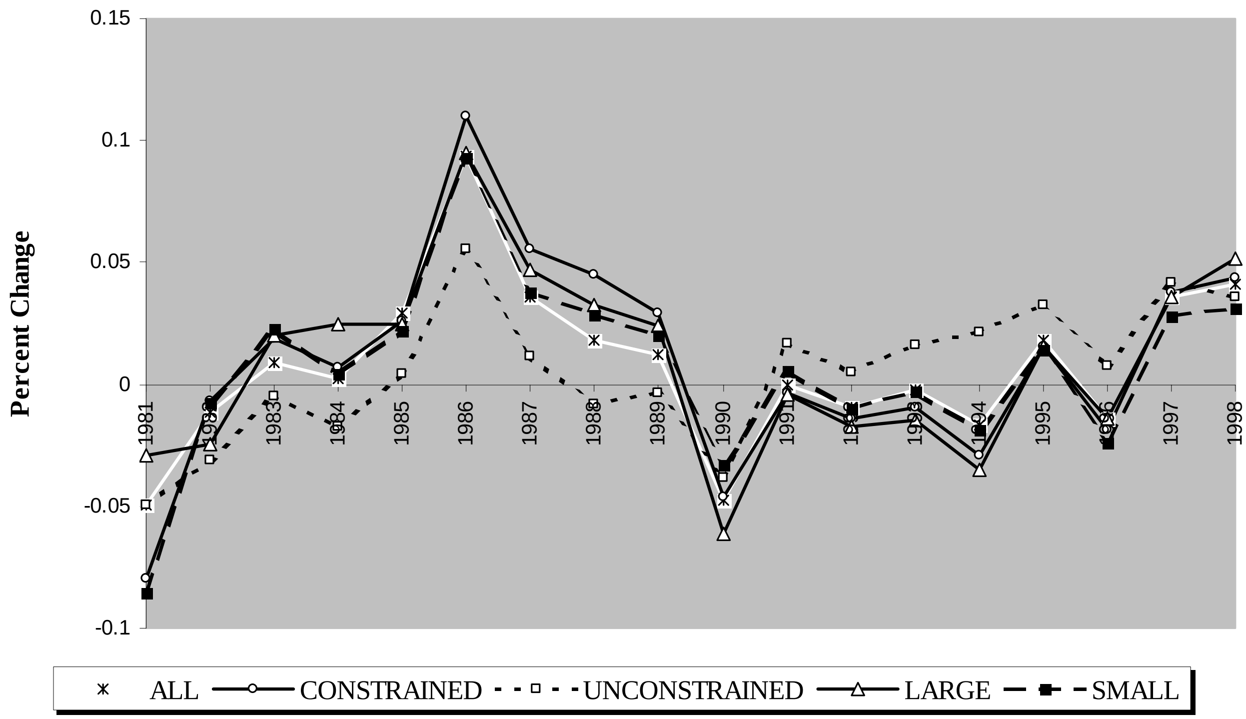

Figure 2: Net Response of Price to Shock in Personal Income
All, Constrained, and Unconstrained

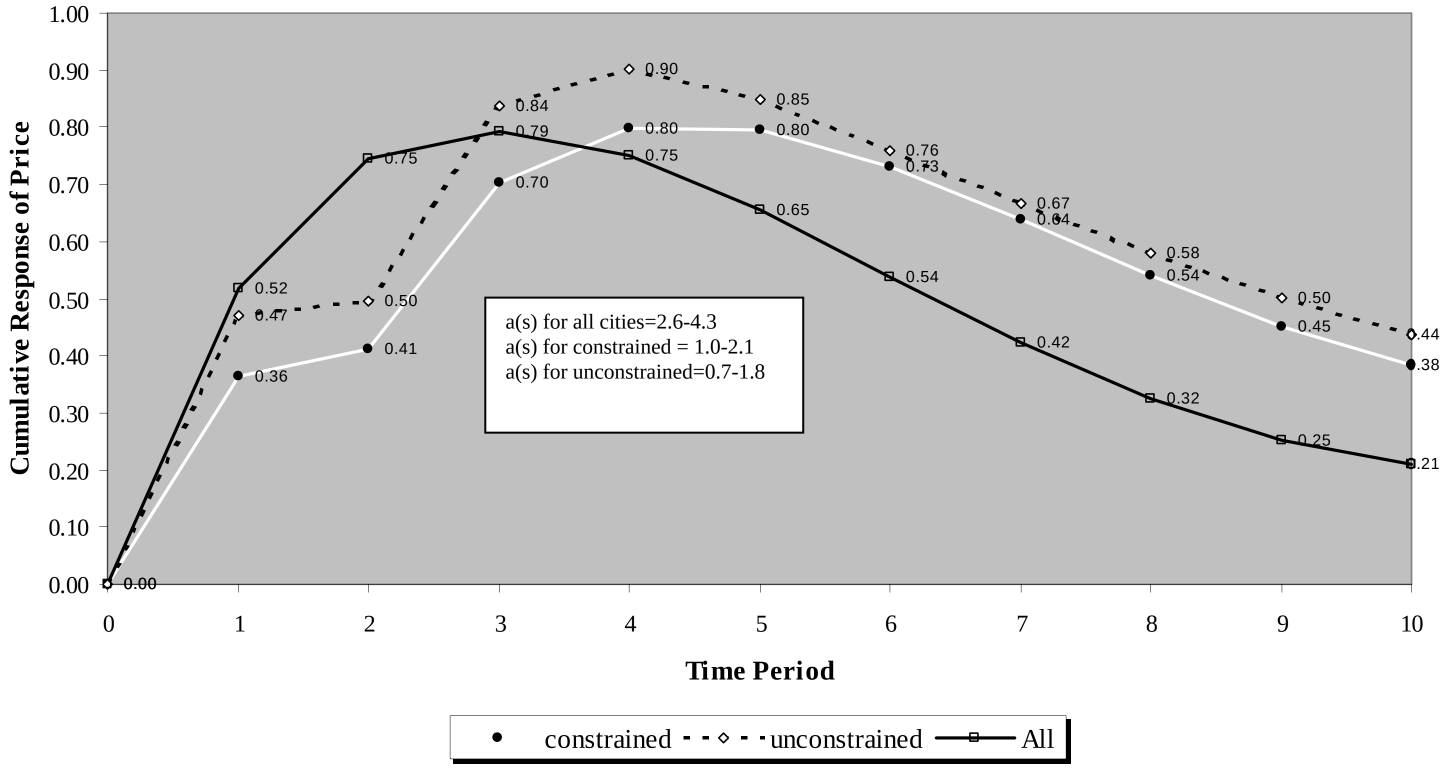

Figure 3: Net Response of Price to Shock in Personal Income
All, Large, and Small