A Spatial Look at Housing Bubbles

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1. Introduction

How do spatial supply conditions determine the impact of bubbles on housing markets? Since the stock of homes can be added to, a housing bubble carries within it the seeds of its own destruction. Induced production from supra-fundamental prices increases the housing stock, leading prices to eventually fall in the presence of downward sloping demand. Supply conditions must thus invariably determine the extent, the duration and the aftermath of housing bubbles.

This paper adopts a spatial perspective on supply conditions in housing markets, both within and across urban areas. *Within markets*, we distinguish between households with a longer and shorter commuting time to work. On the presumption that building is easier the further out one gets from the urban center, we expect that a given common increase in demand throughout an urban area will lead to a relatively smaller price response and relative greater quantity response the further away from the center one gets. To test for this, we ask whether households with a shorter commuting trip report relatively higher values for their homes in years when prices are high.

Using the 2005-2010 micro data of the American Community Survey, we find that to be essentially true: controlling for MSA cross year effects, we find that house values decline faster with commuting time in the years 2005-2008 than in the bust years of 2009 and 2010. This result holds when we consider various sub-samples: recent home movers, household heads that work in the central city, and those that commute by car. The flatter price gradient of the last two years is consistent with a common demand bust, with spatial variation in supply conditions. We then consider the spatial patterns of the growth in rents over the period. We find that rents also decline faster in the bust years. The change in the rate of decline is about half that of prices. That would be suggestive of there being a bubble component along with a 'legitimate' increase then dissipation of current demand, except that the difference between the two rates of decline is insignificant.

We also compare the relationship between issued permits and price changes across central city counties and outlying counties. We find that the expected increase in permits conditional upon a given increase in price growth is greater in the outlying counties than in the central ones, as one would expect if building in the center is more difficult, but the difference is insignificant.

Across markets, we distinguish between cities with longer and shorter average commuting time. Since the area of an urban area increases with the square of its radius, while the circumference increases linearly, the additional housing built in response to a given price increase is a smaller percentage of the overall stock, the larger is the city. Thus larger cities should have a less elastic supply curve, so that in response to a common demand shock across cities, prices should rise more and construction less in the larger cities. We argue that the measure of a city should be its mean commuting time.

To check this cross-market hypothesis, we regress yearly FHFA (formerly OFHEO) MSA-level price indices on year dummies and the interaction of those dummies with (demeaned) average Census 2000 commuting time in the MSA, over the 1975-2009 period, using a sample of 258 MSAs. We find a strongly significant positive correlation between the overall price level and the slope of the relationship of prices to average commuting time. In other words: when prices rise on average nationally, they rise relatively more in cities with higher average commuting time. When price growth in the mean average commuting MSA increases by one percent, price growth in an MSA with a one deviation greater average commute (2.8 minutes) is predicted to grow one-tenth of a percent more. Together, the quantity and price response is consistent with MSAs reacting differentially to a common demand shock, with supply elasticity declining in the size of the urban area.

Like Glaeser, Gyourko, and Saiz (2008), although we use the language of bubbles, nothing we present here can be considered a strict test of the presence of a bubble. Based on the analysis of prices in this paper alone, a demand story could be told. However, the rapid increase and fall of home prices in the U.S. around the 2006 peak, with no accompanying movement in general economic conditions until 2008, is certainly suggestive of the presence of a bubble.

We begin with the **within-market** analysis in Section 2. We first present our argument in detail, then present the data, the estimation procedure and then the results. In Section 3, we follow the same sequence of topics for the cross-market analysis. We relate our analysis and our findings to the existing literature in Section 4. We conclude in Section 5.

2. Within-Market Spatial Variation in House Price, Rents, and Building Permits

At any given distance from the center of an urban area, we see a mixture of developed and undeveloped land, due to differential expectations across land owners, historical accidents, local zoning variation, topographical distance and a multitude of other factors. Overall, however, since the price of housing falls as one gets further away from the center, there is likely to be a greater and greater share of undeveloped land the further out one gets. That, in turn, implies a greater possibility of a significant supply response the more distant one is from the center. That this is so empirically is the obvious inference from Burchfeld et al (2006), who show that building on previously undeveloped parcels of land in and around urban areas is far more common the less developed is the area surrounding that parcel.[1] Furthermore, where housing prices are lower, building will be less dense, and so there will be a greater opportunity to substitute higher density with lower density. Positive demand shocks that are common across an urban area, are therefore likely to be translated mostly into price increases in the city center, with little quantity increase, and translated into more development and little price change near the edge.

[1] The maps in that paper show new land development occurring overwhelmingly along the edges of the previously developed area. Their Figure VI shows an inverted U relationship between the probability of development of a previously undeveloped parcel as a function of the percentage of the surrounding square kilometer that is previously undeveloped. It is the rising part of the relationship that is most relevant for urban areas, as that is where they are located, on average (Table X in the same paper).

There are forces that may act in the opposite direction. The argument assumes that any development that does occur is at the same density of existing development (the Burchfeld et al (2006) data only reveal whether there is any development, not its density). Land use regulations may differ within an urban area, and it is possible that they are systematically more stringent in the suburbs, especially if higher income people live there and they have a greater willingness to pay for a low density environment. (CITATION) Historical development patterns may also mean that inner city structures are more depreciated and so more likely to be replaced (and at a higher density). Whether the supply response through undeveloped land is sufficiently important to outweigh these other factors is then ultimately an empirical question.

Note also that the argument for a greater quantity response and smaller price increase at greater distances from the center can not be supported by a model of homogenous households. In that case, the required indifference of occupants among all locations implies that preferences alone determine relative prices. Rather, there must be some element of heterogeneity and consequent clustering that permits local supply conditions to matter for relative prices.

Finally we note that commuting time is the appropriate measure of distance from the urban core in a within-market analysis if most of the disutility from residing at a distance from the central business district arises from the time resources devoted to going to and from work (White, 1988). Housing prices will then decline with distance from the core at a rate given by the decline in commuting *time* from the core, and the share of undeveloped land and supply possibilities should vary accordingly.

2.1. Data

The main data source used for the within-market analysis is the public use micro data samples of the American Community Surveys (ACS) for 2005 through 2010. Each year includes roughly 1.3 million owner-occupied and rental housing units. We do not use earlier years' data because in those years geographical identifiers below the state level were not available and the geographical coverage was also much smaller. The variables we take from the survey are subjects' reports on the home value if the unit is owned or annual rent if it is rented, commuting time to work, physical home attributes, utility costs associated with their residence, taxes paid (for owner-occupied homes), and the PUMA (Public Use Microdata Area) and state identifiers for both the respondent's place of residence and place of work.[2]

We take the MSA to define the urban area. Although the ACS does not include an MSA identifier, in almost all cases a PUMA can be matched to a unique MSA. We drop observations whose residents reside in a PUMA that does not belong to an MSA. Those with a residence in one of the ten PUMAs that overlap more than one MSA are dropped.[3] In part of our analysis, we distinguish between PUMAs that contain a central city of the MSA and those that don't. Not all PUMAs have a central city status identifier, however.

For part of our analysis, we restrict the sample to homeowners that report having moved to the given housing unit in the last twelve months. These are about 6.5 percent of all households. The logic of concentrating on such households is that their valuations may be closer to the market value, given that they have just recently purchased their home. However, twelve months is not necessarily 'recent' in such a volatile environment.

Our regressor of interest is commuting time, which measures the time it takes to commute from the house to work, as reported by the head of the household. This almost always equals an alternative measure calculated as the difference between the

[2] We drop vacant, occupied but neither owned nor rented, mobile home, trailer, boat, RV, and van units, homes without complete kitchen facilities or telephones, Puerto Rico and units with zero or more than nine bedrooms, or zero rooms. We also drop observations that do not report commuting time (about 2.5 percent of the data) and owner-occupied household that do not report taxes (a little over 1 percent of the data).

[3] On average, there are about 6 PUMAs per MSA. Some large MSAs, such as Log Angeles-Long Beach, contain more than 60 PUMAs.

time the respondent reports leaving the home and the time he or she gets to work. Two factors however are likely to make reported commuting time a noisy measure of the housing unit's distance in commuting time to the core.

First, households differ in how they commute, and some modes are more pleasant than others. Consequently, prices will drop more quickly with commuting time along a ray along which commuting to the center requires several buses rather than a comfortable subway ride. We handle this in part by including dummy variables for the type used. For a more thorough treatment, we redo our analysis on the subsample for which the household head drives (nearly 90% of the total sample).

Second, the household may commute in the direction of the core, but not all the way, or may not commute in the direction of the core, but rather cross-commute, i.e., around the circle and not into it. Indeed, Anas and Rhee (2007) show that most commuting is not to the central core. The resulting noise is likely to bias the coefficient on commuting time downwards in magnitude, by the reliability ratio; consequently, the difference in measured coefficients across years will also be a downward biased estimate of the true difference. To mitigate such bias, we include a dummy variable for whether the household commutes to the PUMA that contains the central core. More importantly, we redo our analysis for the subsample of households whose head commutes to that PUMA.

Note that although we speak as if there is a single center in the MSA, the presence of multiple centers in a given MSA would not in and of itself affect the quality of the commuting variable as a proxy for supply conditions. With multiple centers, prices will decline at the same rate (in commuting time) from the closest center (in a world of homogenous workers and jobs). The commuting time of households who work in the closest center to their residence will still indicate commuting time distance and so supply conditions. It is the commuting time of workers who work outside of the centers that leads to the noise in the variable.

Table 1's top panel presents the summary statistics on commuting time for homeowners. The average commuting time is at 30.89 minutes just a touch over half an hour. The median is 25 minutes. there is a large variation in commuting time across households , as seen in the standard deviation of 24 minutes, and by the 25 minute difference between the 25th and 75th percentiles, that. However, commuting time does not vary much across the samples: the average for the recent mover sample is only half a minute more, and for the driver sample, a minute less, and the 25th, 50th and 75th percentiles remain constant across the samples.

Table 2.A's two top panels presents summary statistics for the log house values by year, with the top panel corresponding to the overall homeowner sample, and the second panel to the recent mover sample. Column (1) shows the difference in the yearly average log value, averaged across the MSAs in our sample. Column (2) shows the same as a weighted (by the number of observations in the second year in each MSA) across MSAs; thus it is essentially the difference in the average log value in the entire sample. The all owner-occupants panel shows values increasing dramatically between 2005 and 2006 at about 9 percent, increasing further at half that rate over the next year to a peak in 2007, then declining over the next three years by a cumulative 9.5% or 14%. Half of the decline takes place between 2008 and 2009 alone. Column (2) shows that there is substantial variation in growth rates across MSAs.

The pattern for recent movers (about 6.5% of owner-occupants) is qualitatively similar, with values growing over the first two years and declining over the next three. Quantitatively, however, it differs substantially: the 2006-07 increase is much weaker, and the subsequent declines much greater – the latter by about 3 percent in each year. Here, too, 2008-2009 registers the greatest decline, but it stands out less. The standard deviation across MSAs is two or three times as great as that for the overall sample.

What explains the difference between the two panels? It is not differences in geographical composition across MSAs between the overall and the recent mover samples, as columns (1) and (3) show the simple mean and standard deviation across MSAs.

One possible explanation is that in a downturn, recent movers are a self-selected sample of individuals that adjust to the fall in prices. The sample of recent movers is likely to have a disproportionate share of individual who are not susceptible to factors that hinder selling when prices fall, whether because they are new buyers (entirely or to an MSA market) who are not 'tied' to the recent high prices as a reference point or through portfolio composition, or because they simply are not loss averse or purchased their previous home with little debt. The loss averse may be as unwilling to admit to the loss in value when reporting it as they are unwilling to realize it financially. Equity lock-in should not affect a respondent's assessment of market conditions, but will affect his own reservation price for the property, and that may be what he reports. This would explain why the reported values for the high growth period of 2005-2006 are so similar in the two panels, while in the subsequent years, in which there is a slowdown and then a decline in prices, the growth rates are smaller for the recent mover panel.

An alternative explanation is that recent movers are more aware of market conditions than none-movers. They thus report values that are more up to date and more market specific than those reported by non-movers, whose information lags that of market conditions. Non-movers may also not carefully distinguish news that reports on their market and on the national market, and so may smooth values across MSAs as well. According to this explanation, non-movers underestimate the slowdown in the market between 2006 and 2007, don't recognize the extent of the decline over the next three years, and miss the extent of differences in growth rates across the areas.

If we are to use self reported home values to explore the movement of prices, then we need some evidence that values track prices. Others have explored this issue before (CITATION NEEDED), but given the dramatic movements in our sample, and in light of previous evidence that sellers are reluctant to recognize losses, we find it appropriate to reexamine the issue with our sample. We are unable to check the relationship at the sub-MSA level, which is the focus of the paper, as we lack any such indices, but we can at least do so at the MSA level. We begin with a comparison of the figures in Table 2A to the annual growth rates of the two leading sets of repeat sale price indices, that of the FHFA and the Case-Shiller, which we show in Table 2.B. All columns show the annual difference in the yearly average of the log of the quarterly or monthly (as appropriate) indices. Averaging over the year is appropriate since the ACS is conducted uniformly over the calendar year. The log transformation recovers the coefficient on the difference between the transaction year dummy and the previous year of sale dummy in the repeat sales regressions on which both sets of indices are based, so making them comparable to our average of log house values.

Column (1) shows the annual growth rates of the purchase-only, national level FHFA (formerly OFHEO) index, and Column (2) that for all transactions (i.e., including refinancing). In Column (3) we have taken the average growth rate of the FHFA MSA indices for MSAs that appear in our sample; in Column (4) they are weighted by the incidence of the MSA in our sample. Columns (5), (6) and (7) show the Case-Shiller National, 10 City and 20 City Composite indices. Finally in Columns (8) and (9) we re-estimate the mean and weighted mean from the first two columns in the top panel of Table 2A, using observations with a residence PUMA in one of the twenty Case-Shiller cities.

There are a number of observations to be made here. First, the Case-Shiller indices show a decline already in 2006-2007, while the FHFA indices show a small increase or a leveling off (recall that our data show a moderate increase). In the next two years, the Case-Shiller indices show huge declines; the FHFA indices also show declines but they are about ten percentage points smaller than those of Case-Shiller. Over the last pair of years, the FHFA indices continue to decline at a moderate rate, while the Case-Shiller indices level off or increase somewhat. All this is well known. What is new is that households report values whose average growth rates are much more like the FHFA figures. The higher declines in the post-bust period, and the smaller increase in 2006-07, for the all-purchase index compared to the all-transaction index are also reminiscent of the difference between the recent movers and the overall sample. However, by restricting the ACS sample to the twenty Case-Shiller cities (Columns (8) and (9)), we can generate the dramatic decline shown by that index for 2008-09[4] although not so much for the other years.

In Table 2C, we present regressions of the average log house value reported in the ACS for a given MSA and year on the log FHFA transaction index for that MSA and year, and MSA fixed effects. The regressions are weighted by the number of ACS observations in that MSA and year. There are four pairs of regressions, where the second of any pair also includes the lagged index. The four pairs cover the samples we will be looking at: all owners, recent movers, owners who work in PUMAs whose central city status is defined, and owners who commute to a central city PUMA. In the ideal case, we would have a coefficient of one on the current index in the bivariate regression. Except for the recent mover sample, we obtain coefficients very close to one: 0.96 for the overall sample, and 1.01 for the last two samples. The coefficient of 1.21 for the recent movers sample indicate that those reports substantially 'overreact' to the FHFA index. However, recall that the FHFA MSA index includes refinancing transactions, and it is not inconceivable that the assessments that underlie them smooth out purchase prices.

In all four cases, the lagged price index has a positive and significant coefficient when it is included. For other than the recent mover sample, its share of the sum of the coefficients ranges between .29 to .35; for the recent movers sample, however, it is only .025 of the sum. This reinforces our earlier that recent movers' valuation are more in line with contemporary prices (or assessments) than that of other households. The samples that looks best when considering the bivariate regression is that of households who work in the central city, for which the estimated coefficient is insignificantly different from one; but, again, the lagged index gets a large weight when it is included.

Finally, our annual building permit issuance data come from the Census Bureau, which publishes the data for about 18,000 permit-issuing places from 1990 to 2009. We

[4] That the Case-Shiller national index is so similar to its city composites throws some doubt on the representativeness of the underlying sample, the county composition of which is not known.

aggregate these place level data to create the county level data for the within-market analysis.

2.2. Estimation

To compare the within-market house price variation over the years in our sample, we estimate the following relationship:

(1) $$lnP_{jit} = \sum_{t=2005}^{2010} \gamma_{lt} I_t \times COM_j + \sum_{t=2005}^{2010} \gamma_{2t} I_t \times COM_j^2 + X_{jit}\beta + u_{it} + \varepsilon_{jit}$$

P_{jit} is self-reported house value for house *j* in MSA *i* in year t. The vector X_{jit} is a set of housing attributes, including dummies for three sizes of acreage, dummies for the number of bedrooms, dummies for ten commuting methods, whether the house is detached, the number of rooms and building age, and the log expenditures on electricity, natural gas and water. We also include a full set of MSA X year fixed effects (u_{it}), as is appropriate for a within market analysis. These fixed effects control for the overall level of prices in the MSA for that year, so, equivalently, we are regressing the deviation of log value from the mean log value for that MSA and year. This, of course, differences out any MSA level differences in local amenities, housing density, urban structure, geographical/regulation barriers etc. Some of our regressions include the log of property taxes.

The variable of interest in this regression is COM_j, which indicates the self-reported commuting time. We interact this variable and its quadratic with the year dummies. Our goal is to compare the decline in values of two physically identical homes at different proximities to the urban center, from the boom to the bust in the cycle of the second half of the 2000s.

We focus on the change in the price gradient and not on its level since we are unable to control for *all* differences in physical housing attributes and local amenities. This is likely to impart a positive bias to the effect of distance on the level of values. The monocentric model and its variants predict that per-household housing quantity or quality increases in distance from the center, in response to the decreasing price of a standardized unit. Thus the measured effect of commuting time effect on house values will include the sum of the effect on the value for some standard unit plus the effect on housing quality/quantity. However, for a given house, if the quality/quantity is relatively constant over time compared to large changes in the per standard unit value, the differences in the measured price gradient over time should come close to measuring the true changes in the price gradient. More formally, let $p_t(x)$ be the log price at distance x in year t, and $h_t(x)$ is log housing quantity/quality at distance x in year t, and specify those relationships as $p_t(x) = \alpha_t + x\gamma_t + u$ and as $h_t(x) = \alpha_t^* + x\gamma_t^* + u$. We run the regression

$$(2) \qquad v_{it} = (\alpha_t + \alpha_t^*) + x_{it}(\gamma_t + \gamma_t^*) + (u_{it} + v_{it}),$$

where $v(x)$ is the log of home value at distance x, i.e., $v(x) = p(x) + h(x)$. Basic results from the monocentric city model predict that $\gamma_t < 0, \gamma_t^* > 0$; the sign of $\gamma_t + \gamma_t^*$ depends on the utility function. We assume that γ^* is constant over the five years of our sample. Given that assumption, the differences in the measured $\gamma_t + \gamma_t^*$ across years, which we estimate by the difference in the coefficients on the interaction of commuting time and year dummies, capture differences in γ over time. Thus our approach is analagous to difference in difference estimation.

Although the long durability of housing, coupled with the random sampling of the ACS, makes a constant γ^* a reasonable assumption on which to base the empirical analysis, two factors are a cause of concern. The first is renovation and new construction at a standard, or size, different than the existing housing. If these differ systematically across locations with differing commuting times, our results will be biased. A second concern is sampling noise, especially in the smaller sub-samples we use, and especially given that we need to control for MSA year effects. To mitigate the bias, and improve precision, we include the physical home attributes in our regressions.

We also experiment with including log property taxes. In MSAs with market based assessments, taxes are likely to do an excellent job of capturing variation in value across properties in a market at a given time, thus soaking up much of the regression error and making the estimates more precise; variations in the tax rate across MSAs and time will be captured by the MSA-year fixed effect. Unfortunately, taxes may do too good a job, if they also capture variation across time within a market. This will occur if assessments are updated frequently, and are in line with market developments at the sub-MSA level. In the extreme case, if assessed values track changes in the value of individual properties (or more exactly, on average with commuting time), the estimated coefficients on commuting time will not reflect changes in the price gradient, once taxes are included. Taxes (whose coefficient should then have a coefficient of one) mask the very change we are looking for. The problem arises if assessment changes are specific to particular areas in the MSA; any common percentage change in tax assessments across the MSA that tracks changes in the average MSA price level will simply mean that changes over time in the MSA-year fixed effect for a given MSA will fail to reflect changes in the price level, but changes in the price gradient will still show up in the estimates. Ideally, we would use a given year's, say 2005's, taxes; unfortunately, we have the taxes from the year of the survey only. For this reason, we focus on regressions that do not include log taxes, but we also present regressions with it to see if doing so improves precision, being cognizant of the likely bias.

An underlying assumption behind our identification strategy is that the year-to-year growth in house prices is mostly driven by demand shocks, regardless of whether they reflect changes in economic fundamentals or a bubble. This assumption, although very strong, is consistent with the approach taken in a number of papers, including Glaeser, Gyourko, and Saiz (2008). In addition, the fact that building permits are positively associated with price changes, as evidenced later in this section, strongly suggests that much of the price increase does indeed come from changes in demand rather than supply. Finally, given that our focus is not on the price growth alone but rather on its interaction with the commuting time, the endogeneity is less of a concern here, if prices are rising due to equal tightening of supply conditions throughout the urban area.

2.3. Results

2.3.1. Baseline Results

Table 3 presents the regression of described in equation (1) above. Column (1) presents our baseline regression, using the full sample of owner-occupants. For clarity of presentation, we group pairs of years together in the interaction terms. For example, COM*0506 is the product of a dummy variable equal to one if the year is either 2005 or 2006, zero otherwise, and the commuting time (measured in units of 10 minutes). The results predict that in 2005 and 2006, a home with a commuting time of the median 25, will have a value that is $100 \times [-.032 \times 2.5 + .0014 \times (2.5)^2] = -7.7$ percent lower than that of a similar home with a zero minute commute. As noted in the previous section, that estimate is likely to be biased. But we are interested in the difference. The results predict that in 2009 and 2010, a home with a commuting time of the median 25, will have a value that is $100 \times [-.019 \times 2.5 + .0008 \times (2.5)^2] = -4.4$ percent of a similar home with a zero minute commute. We take the difference between the 2009-10 difference in values at the median and zero commuting minutes and the 2005-06 difference as our measure of the rotation of the price gradient. As we see in the bottom panel of the table, It is 3.2 percent (rounding is responsible for the discrepancy with our calculation in the text) with a standard error of a mere 0.4 percent.

In Column (2), we add in log taxes. To recall, controlling for taxes has the potential to control for a large part of the unobserved variation in the quality and quantity of a housing unit at a given point in space and time, thus increasing the precision, but at the cost of controlling for the variation across time and space: the very effects we are looking for. As it turns out, the estimated rotation of the price gradient falls drastically to half a percent, with barely any gain in precision: the standard error on the rotation drops only one-twentieth of a percentage point to 0.35 percent. The added precision is clearly not worth the bias.

In Columns (3) and (4), we restrict the sample to recent movers. As noted earlier, we presume that their assessments will be closer to the market value. In Column (3), where taxes are not included, we obtain very similar results to those in our baseline regression of Column (1). The estimates are noisier, but far less than what one would expect from the substantially smaller sample: the standard error on the rotation of the price gradient is only doubled to 0.8 percent. The estimate itself is 3.9 percent, and so is not so different from the estimate of 3.2 that we got for the whole sample, and equality of the estimates would not fail a Hausman test. As before, adding taxes (Column (4)), reduces the estimated rotation, although much less drastically this time. It is 2.2 percent, and it is significant.

Whether or not we control for taxes, and whether or not we restrict the sample to recent movers, all four specifications show the coefficients on the linear component on commuting time are negative and significant in all years, while the coefficient on the quadratic components are positive. The marginal effect is negative up to at least 105 minutes. Although as we saw this result is not necessary for our identification strategy, it is nonetheless heartening to see that the estimates are consistent with the underlying assumption that the data are well represented by a monocentric city model, with much of the variation in housing quantity accounted for.

In order to reduce the noise in the commuting time variable due to cross-commuters and those who commute in the direction of the central city, but only partially, we next restrict the sample to that of households whose heads works in the central city. This sub-sample has only 85,200 observations, or about 4.7% of the owner-occupants. The sub-sample is so much smaller not only because it throws out those who do not commute to the central city but also because it throws out households whose head works in a PUMA whose central city status is not defined by our sources.

Table 4 presents the results. To establish a comparable baseline, we first consider the sample on which observations belong to a PUMA whose central city status is defined. This is about one-third of the sample. Our baseline regression run on this sub-sample is presented in Column (1). The estimated rotation effect is 3.6 points, little changed from the full sample result of 3.2 percent in the corresponding column from Table (3). When taxes are added, it falls, as usual, although only to 1.2 percent, and is still highly significant; indeed the precision actually falls when taxes are included. In Columns (3) and (4) we restrict the sample to those who commute to the central city. Column (3) presents the regression without taxes, and Column (4) with taxes. Restricting the sample to central city commuters increases the magnitude of all six coefficients on the linear and quadratic commuting times, consistent with the restriction reducing the errors in variable problem. The estimated rotation of the price gradient is roughly doubled, to 7.0 percent when taxes are not included, and 2.8 percent when they are; both estimates are significant.

Table 5 repeats the same exercise as in Table 4, except that here we do not pair up years, but show separate effects for each year. This table shows the evolution of the price gradient over time in finer detail. The gradient remains very nearly constant over the first four years of the sample. This is so despite the fact that those four years includes periods of growth and decline. Then, in 2009, once the markets are in the depths of the decline, the gradient becomes substantially flatter. The coefficient on the linear term is cut at least in half, and substantially more in the central city commuters sample, while the coefficient on the quadratic term drops substantially as well. 2010's gradient is flatter still (up to nearly a 50 minute commute), though the difference between it and 2010 is not significant. It is very clear that there is a substantial break in the gradient 'series' and that it takes place between 2008 and 2009.

2.3.2. Robustness Checks

An additional concern is that the commuting time may not adequately represent the disutility from commuting, which may depend on the means of transportation. We have included dummies for different commuting methods, but that obviously will not control for variations in the marginal disutility. To address this concern more fully, we have run all the above regressions with the further restriction that the household head commutes to work by driving. None of our results change in any substantive way, which is to be expected given that nearly 90% of all owner-occupants commute by car to work.

In comparing across years, the analysis has thus far implicitly used the nationwide average movement in prices or values as indicators of the state of overall market conditions. However, there are differences across cities in the extent and timing of the price appreciation and depreciation over our period of analysis. We thus check to see whether using the MSA level FHFA house price indices instead of year dummies generates the same results. To do so, we replace the interaction of commuting minutes and year dummies with the interaction of commuting minutes and the growth in the price index.

Table 6A shows the resulting regression for the sample of households whose head works in the central city. The first two columns control for MSA cross year fixed effects and physical house attributes, as usual. Without taxes, we obtain a significant and negative coefficient on the interaction of commuting time and the annual growth in the log FHFA MSA price index. (As usual, including taxes drastically cuts the estimate, which here is insignificant.) The coefficient of -.041 in Column (1) implies that when prices grow at a one percent lower rate, the absolute slope of the price gradient decreases by .04 percent per commuting minute. Thus prices at a 25 minute commute fall one-tenth of a percent more than prices at the center for every one percent decline in overall price.

At a 16 percent decline, which corresponds to the decline between 2006 and 2010, according to both the valuations reported in the ACS and the FHFA All Purchase Index, the estimated rotation is thus 1.6 percent. That is exactly one-half of our baseline estimate, and less than a quarter of that from the work in central sub-sample. Using the Case-Shiller decline of 31 percent brings the estimate in line with that of the baseline estimates, but not quite a half that of the work in central sample.

In the next two columns we replace the MSA cross year fixed effects with the price index and its lag and MSA fixed effects. The estimates on the commuting terms remain essentially unchanged. In Table 6B we consider the sample of households that are both recent movers and whose heads work in the central city. This reduces our sample size to a mere 5,837. When we includes MSA cross year fixed effects, the estimates on the commuting terms remain very much as there were, although the standard errors increase, as one would expect. When one conditions instead on the price index and its lag, the coefficients on the interaction term increase by half, and are significant, even when taxes are included.

Finally, we allow the gradient to shift with a differential magnitude according to whether growth is positive or negative, by replacing the interaction of commuting time and MSA price growth with the following two variables: $COM \times \Delta lnHPI \times I\{\Delta lnHPI > 0\}$ and $COM \times \Delta lnHPI \times I\{\Delta lnHPI > 0\}$. The results are shown in Table 6C and 6D [INCOMPLETE].

2.3.3. Within-Market Spatial Variation in Rents

We now turn to consider the rents of rented dwellings. Unlike house prices, which are driven not only by current demand and supply conditions but by expectations over future conditions as well, rents are determined by the intersection of the current demand and current housing supply only. The comparative behavior of rents to prices over a boom and bust cycle can thus give us some sense of whether the price movement was the result of a positive shock to current demand for housing services that then dissipated, or a bubble. (Of course, an increase in expected future demand that is then undone is indistinguishable from a bubble.) If it is a temporary shock to current demand, then the rent gradient should become flatter in the bust, just as for prices. If it is a bubble, than the spatial pattern of rents should remain constant over time. That is, unless there is an overhang effect, in which case, rents should fall more where supply is more elastic. Thus, for a bubble, the rent gradient should either remain constant over time, or become steeper in the bust.

We first turn back briefly to Table 2A, where the bottom panel presents the annual average growth in rents. We see that the behavior of rents is very different from that of values and price indices. In contrast to the boom and bust cycle displayed by the latter, rents increase steadily year after year, at about three and a half percent a year, until 2010, when they essentially stagnate at the 2009 level. This is clearly at odds with any explanation of the behavior of prices based on changing current demand for housing services.

Table 7 presents results from regressing log rents on the same set of regressors as in Tables 3 and 4: year dummies, their interaction with commuting time and with the square of commuting time, and attributes of the unit. The sample is restricted to households whose heads commute to the central city. Column (1) shows the results on the sample of all renters. We first note that the rent gradients are downward sloping over the vast majority of the support of commuting time. In the early years, commuting time decreases rents until 105 minutes, similarly to what we saw for values; in 2009-10, however, it turns up at 51 minutes (the 94th percentile), although the quadratic term is insignificant. The estimation rotation is 3.9 percent, and is significant. Thus we can reject the pure bubble hypothesis, under which rents would have fallen equally along the commuting time dimension, or fallen less at the center due to overhang. A weaker test is to check whether rents rotate up with the housing bust less than prices themselves. The point estimate for the rotation is about half that of the 7.0 percent we obtained for the parallel sample of owner-occupants who commute to the central city, but the difference between the two is insignificant.

The next two columns distinguish between apartments (Column (2)) and houses (Column (3)). The distinction might be an important one, since nominal rigidity in rents is much more prevalent in single family dwellings than in apartments, likely because apartments are much more likely to be owned by corporations, partnerships and large investors (Genesove, 2003). Thus we might expect that the gradient for houses would be relatively constant over time. Nonetheless, we find a positive rotation of the rent gradient in both categories, with that for houses much bigger, and only it significant.

Thus, surprisingly, although the aggregate behavior of reported rents is very different from that of both reported values and price indices, the variation in the temporal behavior of rents across commuting time is qualitatively similar to that of prices. Taken by itself, the similarity in the spatial behavior is consistent with a dramatic temporary increase in current demand in the bust period that gets undone between 2008 and 2009. It is not consistent with a bubble that gets pricked, or an increase in future expected demand that then goes away, in which case the rent gradient would have stayed constant or because of the overhang, become steeper.

2.3.4. Within-Market Spatial Variation in Building Permits

Although the focus of this paper is on prices, since our analysis does presume that building in the city center is more difficult than building outside, we now turn to investigating whether building in the urban center is indeed less responsive to price increases. We use the county level permit data to see if the number of permits increases less with price growth in central city counties than in others. That it is price growth that we should be expected to be correlated with permits and not the price levels follows naturally from the fact that permits essentially indicate the change in supply. Mayer and Somerville (1997) show that this logic follows from the standard monocentric city model, specifically Capozza and Helsley (1989). To account for replacement investment, we nonetheless allow for a price level effect by adding the current price level as well and not simply the difference. Underlying this investigation is of course an assumption that supply shifts are substantially less variable than demand shifts.

We first look at the aggregate time series: Figure 1 shows the time series for overall and central city single family house permits; Figure 2 shows same for overall total permits. The figures show that In general, in years where permits are generally high, central city permits are relatively lower, consistent with our conjecture.

The first two columns of Table 9 show the regressions of log permits on the OFEHEO national house price index, its lag and the interaction of each with a central city status dummy, using annual data from 1990 to 2009. We include county fixed effects. We run separate regressions for single family house and total permits. As suspected, permits in central city counties increase less with the growth rate in prices than do permits in other counties, but the difference is small: a one percent growth rate in prices is associated with 7.5 percent more permits in outlying areas, but only 7 percent greater in central city counties. [NUMBERS NEED TO BE CORRECTED].

3. Cross-Market Spatial Variation in House Price and Building Permits

So far, our analysis has focused on the spatial variation in house price growth among housing units within the same market, where the variation is collapsed to the time to commute dimension. It is natural to extend the use of commuting time as a proxy for supply conditions to the cross-market level. In this section, we first derive a theoretical relationship between average commuting time and housing supply elasticity across markets. We then empirically test this relationship by examining how house prices and building permits vary across markets with different average commuting time, and how these effects vary with the stages of the housing market cycle.

The intuition for the theoretical result is shown in Figure 3. If all the additional housing built in response to a price change is built on the margins of a circular city, then the increased stock should equal the circumference of the circle. As the total housing stock in the city is the area of the circle, the percentage change in the housing stock for a given absolute price change should be decreasing in the city radius. In considering the supply elasticity, we need to consider a given percentage increase in price, of course, and prices are higher in bigger cities. But it is only the location rents component of prices that increases with city size and in Capozza and Helsley's (1989) dynamic version of the monocentric city model, which we base our analysis on, it increases linearly. The presence of the remaining components of price, agricultural rents and construction costs, ensure then that supply elasticity is inversely proportional o the city radius. As the analysis below also shows that the proper measurement of the radius is maximum commuting time, not distance per se, we show that supply elasticity is inversely related to commuting time.

In developing our argument, we follow Mayer and Somerville (2000) and Malpezzi, Green and Mayo (2005) in deriving an elasticity of supply based on Capozza and Helsely (1989). Our presentation is, we think, somewhat more transparent, however. Consider then a set of cities that have developed in line with that model. The cities are of different sizes, perhaps because they were established at different points in the past, or perhaps because they have different transportation infrastructures that yield different commuting costs.

Now consider a shock to demand that takes the form of an enhanced willingness to pay in the city. The greater price will induce an increase in the housing stock. In line with Capozza and Helsely (1989), all new development takes place at the city edge. Assume that households are willing to pay α percent above the current fundamental price at the city edge. That means an absolute price increase at the city edge of $\Delta P = \alpha P_E$, where P_E is the current price at the edge. Capozza and Helsely (1989) show that

$$P_E = A + C + [Tf(g,r)/r]z_E$$

where A is the discounted value of land use in its undeveloped state (agricultural rent) and C is the conversion cost, which we should see here as the construction cost of the housing structure. The last term represents the discounted value of location rents, with T the time cost of commuting a unit distance, z_E is the distance from the center the edge, g population growth, r the interest rate, and f increases in g and decreases in r.

Define the absolute rate at which prices decline with distance from the city center as k. Then the city edge grows out an additional $\Delta z = k^{-1}\Delta P$ from the center. The additional area that is developed is (see Figure 3) $2\pi z_E \Delta z = 2\pi k^{-1}\alpha\{[A + C]z_E + [Tf(g,r)/r]z_E^2\}$. (Like the aforementioned papers, we assume a constant lot size.) Since the area of a circular city is z_E^2 , we obtain that the percentage increase in the housing stock is $22k^{-1}\alpha\{[A + C]/z_E + [Tf(g,r)/r]\}$. Since $k = T/r$ (a dwelling at one unit of distance closer to the center is worth the discounted value of the time cost of commuting a unit distance more), the supply elasticity of housing is

(3) $\eta = 2\{[A + C]/(Tz_E) + f(g, r)\}$.[5]

As is often done, we will assume that the opportunity cost of the land plus the construction cost, $A + C$, do not vary substantially across cities. The housing supply elasticity is thus decreasing in the maximum commuting time (Tz_E), increasing in future population grow g, decreasing in the interest rate, and increasing in the sum of the opportunity cost of land and construction costs ($A + C$).

Our focus is on commuting time. Importantly, the above argument shows us that the proper measure of a city's size as a factor of supply elasticity is in commuting minutes and not in kilometers. The term that appears in the supply elasticity is the maximum commuting time, but given the greater sensitivity of the maximum to measurement error, we substitute the average commuting time, which is two-thirds of the maximum under this model.[6]

If demand shocks are a national phenomena (Cotter, Gabriel and Roll, 2011) that add a willingness to pay to inverse demand of a constant percentage over current prices, then the foregoing implies that prices should rise relatively more in larger cities. In smaller cities, they will be undone by massive building along the edge, which will keep prices from increasing too much.

3.1 Data

To test these implications, we look at the differential movement of MSA level house prices across time according to the average commuting time of the MSA. We measure house prices with MSA level FHFA (formerly OFHEO) all transaction (i.e,

[5] Malpezzi, Green and Mayo (2005) derive the semi-elasticity of housing supply from the Capozza-Helsely model as $2(r - g)/(Tz_E)$. Multiplying this by P_E yields our result.

[6] With a fixed lot size, the mean is proportional to the maximum: since the number of dwellings at distance z from the center is $2\pi z$, mean commuting time is $2\pi T \int_0^{z_E} z^2 dz / 2\pi \int_0^{z_E} z dz = \frac{2}{3} T z_E$.

purchase plus refinancing) indices. This covers a somewhat different set of MSAs than the ACS data. We also consider a much longer window: 1976-2009. The sample of 257 MSAs is heavily unbalanced due to different starting times, which are distributed between 1975 and 1993. While the price series is at a quarterly frequency, we use the averaged annual data, as our focus is on patterns over a cycle, not on higher frequency, seasonal effects. As before, we obtain the housing permit data from the U.S. Bureau of the Census. We aggregate across places to create metropolitan-area-level aggregate permits. Annual permits data are available for 1990-2009. In some regressions, we also control for measures of growth to control for g. We also at times condition on other proxies for determinants of housing supply, notably the updated Wharton Residential Land Use Regulatory Index (WRLURI) (Gyourko, Saiz and Summers, 2008) and Saiz's undevelopable land share (Saiz, 2010).

To measure commuting time in each location, we use the average number of minutes needed for a one-way trip to work among workers 16 years and over from the 2000 Census. The mean average commuting time is 22 minutes with a standard deviation of 2.66 minutes. Examples of cities with long average commuting time are Atlanta (32 minutes), Stockton (30 minutes), Houston (29 minutes). Those with short average commuting time include Grand Forks (16 minutes) and Urbana-Champaign (18 minutes). Figure 4 reports the histogram of average commuting time. Note that the average commuting time variable does not vary over time; there should therefore be little concern of an endogeneity bias in which positive demand shocks both increase prices and increase congestion and so commuting time.

3.2 Cross-MSA variation in House Prices

The brief argument we laid out implies that when demand increases, price will increase more in markets with longer average commuting time. The argument has nothing to say about demand decreases (nor has the underlying Capozza and Helsley (1989) model), but fortunately, the period of our sample is overwhelmingly one of price increases (*Note to discussants: nominal price increases and the decline at the end of the* *period is dramatic; this will be addressed in the next draft!).* Coupled with the assumptions that (a) demand shocks are much more variable than supply shocks, and (b) demand shocks are heavily correlated across MSAs (Cotter, Gabriel and Roll, 2011), the claim implies that when overall prices increase, prices will increase more in high average commuting MSAs.

Our procedure has two stages. In the first stage, we estimate the following regression model:

$$y_{it} = \sum_{t=1975}^{2009} \alpha_t I_t + \sum_{t=1975}^{2009} \beta_t I_t \times COM_j + \sum_{t=1975}^{2009} \gamma_t I_t \times X_j + u_i + \varepsilon_{it}$$

The dependent variable is either the log of the house price index in MSA *i* at year t or its first difference.[7] I_t is a dummy variable for year t, COM_i indicates the demeaned, average commuting time in MSA i from the year 2000 Census, and X_j indicates other possible determinants of the supply elasticity. Finally, MSA fixed effects are included. When the dependent variable is the price index level, they control for, among other things, the main effects of market-specific geographical feature and regulatory constraints, and unchanging amenities. When the dependent variable is the first difference in the price index, the MSA fixed effects control for an MSA-specific trend in the same variables.

With demeaning and MSA fixed effects, the parameter α_t reflects the overall price growth in year *t*. The parameter β_t reflects, in a given year *t*, how price growth varies across markets with different average commuting time. In the second stage, we explore the relationship between β_t and α_t. If longer average commuting time indeed proxies for more inelastic housing supply, then we should expect that when overall house prices increase, that house prices increase more in the MSAs with longer

[7] The index is equal to $100 \exp(\psi_t)$, where ψ_t is the estimated coefficient on the year t variable that takes values $\{1, -1, 0\}$ according to whether t is the year of sale, previous sale, or neither, in the regression with log price as the dependent variable. Thus taking the log of the index yields ψ_t, the measured price growth, plus a constant.

commuting time than in others; that is, that β_t and α_t should be positively correlated over time. We wish to examine this relationship through the regression $E[\beta_t|\alpha_t] = a_0 + a_1\alpha_t$. The argument we outlined above implies that a_1 should be positive.

Of course, we do not observe β_t and α_t, but only their estimates $\hat{\beta}_t$ and $\hat{\alpha}_t$. We thus face a measurement error problem, which implies that the OLS estimate of a_1 will be biased: it converges to the sum of the attenuation of the true value (due solely to the measurement error in $\hat{\alpha}_t$) and an additional bias of the sign of the covariance between the estimation errors of the two coefficients. However, since we can estimate the distribution of those errors, using the standard asymptotic results on the distribution of OLS estimates, we can form the following consistent method of moments a la Fuller (1987) and Buonaccorsi (2010):

$$a_1^{MOM} = \{S_{\alpha\beta} - \mathrm{Q}_{\alpha\beta}\}/\{S_{\alpha\alpha} - \mathrm{Q}_{\alpha\alpha}\}$$

where $S_{\alpha\beta}$ is the sample covariance of $\hat{\beta}_t$ and $\hat{\alpha}_t$, $S_{\alpha\alpha}$ is the sample variance of $\hat{\alpha}_t$, $\mathrm{Q}_{\alpha\beta} \equiv (1 + 1999 - 1976)^{-1} \sum_{t=1976}^{1999} \sigma^2_{\alpha\beta t}$, $\mathrm{Q}_{\alpha\alpha} \equiv (1 + 1999 - 1976)^{-1} \sum_{t=1976}^{1999} \sigma^2_{\alpha\alpha t}$, $\sigma_{\alpha\alpha t}$ is the estimated standard error on $\hat{\alpha}_t$ and $\sigma^2_{\alpha\beta t}$ is the estimated covariance of $\hat{\alpha}_t - \alpha_t$ and $\hat{\beta}_t - \beta_t$. Where there are no other regressors other than the year dummies and their interaction with the commuting, $\sigma^2_{\alpha\beta t}$ equals minus the regression error variance time the product of the mean of the commuting variable divided by the variance of the same, where the mean and variance are taken over the set of MSAs in the sample for that year. Since we use the deviation of average commuting minutes from its mean, $\mathrm{Q}_{\alpha\beta}$ is very nearly zero (it is not exactly zero as the sample is not balanced). Thus in our case the method of moments estimator corrects the OLS estimator essentially for attenuation bias (the error in α).[8]

The top panel of Table 10 reports the estimates from the second-stage regressions for which the underlying first stage regression uses the FHFA house price

[8] This is not the case when we include other regressors. However, in practice, most of the bias comes from the attenuation component.

indices as the dependent variable. In the baseline specifications of Columns (1), which shows the 'naïve' (OLS) coefficient, and (2), which shows the method of moments estimator, we see that the coefficients on $\hat{\alpha}_t$ are positive and statistically significant at the 1% level, consistent with our hypothesis. The coefficient of 0.033 implies that that in a year in which house price increases on average by one percent, the price in an MSA whose average commuting time is 2-standard-deviation longer than the sample mean (that is, 28 minutes instead of 22.4 minutes) will increase by 18.48% (0.033*(28-22.4)) more than the average. The method of moments estimator is nearly exactly the same as the naïve estimator, since here the attenuation bias is small, as the year effects are precisely estimated relative to the large changes in overall housing prices over time.

The remaining columns and panel in Table 1 show a positive and significant relationship between $\hat{\beta}_t$ and $\hat{\alpha}_t$ is robust to a number of specification changes. First, in Column (3), we include the year variable in the second stage regression to control for the time trend; the trend is significant, and the estimated commuting time effect more than doubles in magnitude. (*Note to discussants: we have yet to calculate the method of moments estimator for this case.)* Second, we address the concern that the first stage regression for the baseline specification does not adequately control for other conditions that affects the elasticity of supply. We first consider the Wharton land regulation index and Saiz's undevelopable land share. We add their interaction with the year dummies to the set of regressors. The results are shown in Columns (4) through (6). Adding these indices reduces the estimated regression coefficient of $\hat{\beta}_t$ on $\hat{\alpha}_t$ by two-thirds without a trend, and by a half when there is (although the trend is insignificant). Another determinant of supply elasticity is growth, as equation (3) shows. In Columns (7) through (9) we add the interactions of population growth and average income growth to the set of regressors. That has little effect on the regression coefficients. In the last set of columns, we add in both sets of alternative supply constraints. The results are like those in columns (4)-(6), where only the land regulation index and the undevelopable share are included.

All these results are somewhat suspect, however, since as the top panel of Figure 5 shows, $\hat{\alpha}_t$, and possibly $\hat{\beta}_t$, is highly non-stationary. To correct this, we redo the first stage regressions using the first difference of the log price index as the dependent variable instead. α_t now has the interpretation as the mean differential price growth in year t around each MSA-specific trend while β_t captures the sensitivity of price growth around the specific trends to average commuting time. The bottom panel of Figure 5 shows the time series of their estimates, and we see that they are stationary. The bottom panel of Table 10 shows the second stage estimates. In none of the cases is the trend significant here, so we will focus on the bivariate regressions. The estimates in these regressions are about twice as large as those based on the level specification, which appear in the top panel. Yet moving across the columns, the same pattern is evident: adding the WRLURI and undevelopable land share indices cuts the regression coefficient in half, although it remains significant, while population and average income interactions have no effect, with or without the indices. Correcting for measurement error increases the estimate substantially.

Thus we can conclude that when prices rise overall, they rise more in high average commuting cities – a result we would expect under the monocentric model if demand shocks are highly correlated, and of similar size, across MSAs and if the variation in them dominates that of supply shocks.

3.3 Cross-MSA variation in Building Permits

We now ask whether building activity increases more with prices in markets with low average commuting time, as we argued earlier. To test this, we estimate the following regression:

$$lnPERMIT_{it} = \alpha_0 lnHPI_{it} + \alpha_1 \Delta lnHPI_{it} + \beta \Delta lnHPI_{it} \times COM_i + X_{it} + e_i + \varepsilon_{it}$$

where *i* indexes the metropolitan areas, *t* represents the year from 1990 to 2009, COM_i indicates the average commuting time in MSA *i*, $lnHPI_{it}$ indicates the log of the

FHFA house price index in MSA *i* in year t, $\Delta lnHPI_{it}$ is its first difference, X_{it} is a set of economic and demographic variables, such as income, population, and their growth rates, and e_i is an MSA fixed effect.

The coefficient α_1 indicates how construction activities are associated on average with price changes, while β captures how that association varies with average commuting time. Since the elasticity of supply is decreasing in average commuting time, we expect β to be negative. As before, we expect permits to be most strongly correlated with the price changes rather than its level (Mayer and Somerville), but we also include the price level to account for depreciation.

We present the estimates in Table 11A, with results for single family permits in Columns (1)-(3), and total permits in Columns (4)-(6). The results are similar. There is a strong correlation between the price change and permits, with every one percent increase in price growth associated with about a four percent increase in permits. The price level is irrelevant. The estimated coefficient on the interaction between price growth and average commuting time is not significant (except for Column (6), where it is nearly so). Looking at the first column, we have that a one standard deviation (2.8 minute) greater average commute decreases the predicted increase in single family home permits given a one percent greater price growth rate from 4.16 to $4.16 - 2.8 \times 0.107$ =3.86 percent.

Since housing is a durable good, the argument that we laid out depends on positive demand shocks. We thus repeat the analysis in Table 11B, where we consider observations with positive and negative growth in the price index separately. The latter are 86 percent of the sample, and yet the restriction has a major effect on the interaction coefficient. The coefficient on the commuting interaction term is now at least doubled in both panels, to around 0.22, with t-statistics of about 3 in the positive price growth panel, and about 1.5 in the negative price growth panel.

It is now always negative, with estimates an order of magnitude greater than before. The estimates are still insignificant, yet with r-values between 1.29 to 1.65, it is conceivable that there high average commuting truly is associated with a lesser sensitivity of construction with respect to positive demand shocks.

4. Related Literature

Our work is related to several strands of the housing literature. First, it relates to the literature on MSA level supply elasticity which has received increasing attention over the last few years, after having been overshadowed by a much more voluminous literature on demand (e.g., Rosenthal, 1989). Recent work has related housing supply elasticity to a number of factors, such as land use regulation (Linneman, Summers, Brooks, and Buist, 1990; Gyourko, Saiz, and Summers, 2008) and the share of buildable land (Glaeser, et al. (2008); Saiz, 2010). In our empirical cross-market analysis, we control for regulation and topography, but highlight the implications of a new supply elasticity proxy -- commuting time, which essentially stems from differences in the urban form.

Second, prior research on spatial variation in house price movements has mostly focused on across-market differences. Examples include Glaeser et al. (2008), David et al (2007), Van Nieuwerburgh and Weill (2010), and Saiz (2010). As shown in this paper and elsewhere (e.g., Guerrieri, Hartley, and Hurst, 2008), there is significant and systematic within-city variation in house price growth. Thus, both the within-market and cross-market analysis are essential to understanding house price movements. Our work adds to this literature by looking at a single indicator of supply conditions whose variation within and cross-markets determines the extent of the response of both price and quantity to demand in both contexts.

Despite its importance, the literature on within market house price movements is relatively thin. Case and Mayer (1996) and Case and Marynchenko (2002) examine house price movements during the 1980s and early 1990s across zip codes within Boston, Chicago, and Los Angeles. More recently, Landvoigt, Piazzesi and Schneider use an assignment model to explain the greater appreciation of low quality homes in San Diego. Guerrieri, Hartley, Hurst (2010) explore house price changes across neighborhoods within Chicago, and find that poor areas adjacent to rich areas appreciate more quickly than other areas. Molloy and Shan (2010) use data on a large number of ZIP codes and municipalities from 1981 to 2008, and find that a 10 percent increase in gas prices leads to a 10 percent decrease in construction in locations with a long average commuting time relative to other locations, but to no significant change in house prices.

While both of these last two papers control for commuting time in the price analysis, the within-market analysis in our paper differs from their analysis both in its focus and in its implementation. While their papers focus on the variation in demand side determinants (neighborhood gentrification opportunities and the budget share of gas prices), ours is concerned with differing supply elasticities. In the implementation, our work differs in allowing the effect of commutimg time to differ across years and MSAs, and, indeed, that is our focus.

As noted earlier, Malpezzi, Green and Mayo (2005) also derive the supply elasticity from the Capozza and Helseley (1989) model. They estimate a supply elasticity for each MSA by the OLS estimate of an MSA specific regression of permits per population on average prices, and then regress that estimate on a number of regressors, including log population, a per unit distance commuting time (i.e., T) and a land use regulation proxy. Their sample is much smaller than ours, comprising only 45 MSAs.

5. Conclusion

Recent work by Glaeser, Gyouko, and Saiz (2008) shows that house price increases more during bubbles in places where housing supply is less elastic both theoretically and empirically. In this paper, we follow their insight and explore the role of a new supply proxy – commuting time – in explaining the within-market and cross-market variation in how house price varies with stages of the market cycle.

In the within-market analysis, we use a national panel of the house-level price data between 2005-2010 to examine the relationship between the price growth of a house and its proximity to the employment center. Consistent with the notion that building is easier to build at the city edge, we find that the price gradient became flatter in the bust, implying the prices fell more in the center than at the city's edge.

In the cross-market analysis, we use the city level house price indices between 1975 and 2009, and find that when prices increase by 1% in a city where the mean average commuting time, prices increase by 1.1 percent in a city with one standard deviation greater commuting time. Turning to the quantity response, we find that an increase in price is associated with a much larger percentage increase in the total building permits in cities with shorter average commuting time.

[INCOMPLETE]

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Table 1: Summary Statistics of Commuting Time to Work (in minutes)

	Mean	S.D.	25th	Median	75th	N
			Owner-Occupant Sample			
All	30.89	23.83	15	25	40	1,817,977
Recent Movers	31.39	23.92	15	25	40	119,031
Drivers	29.82	22.31	15	25	40	1,717,938
			Renter Sample			
All	28.15	23.00	15	20	35	695,557
Recent Movers	26.75	22.07	15	20	30	251,420
Drivers	25.60	20.28	15	20	30	559,617

Note: The data source is the ACS (2005-2010).

Table 2A: Summary Statistics of House Price/Rent Growth (in %)

	Mean	Weighted Mean	Cross-MSA S.D.
		All Owner-Occupants (N = 1,817,283)	
2005-2006	8.85	9.09	6.12
2006-2007	4.56	4.15	4.64
2007-2008	-2.43	-3.21	7.55
2008-2009	-5.30	-7.01	9.32
2009-2010	-2.80	-3.94	6.31
		Recent Mover Owner-Occupants (N = 119,023)	
2005-2006	8.39	9.03	14.07
2006-2007	2.98	2.56	15.17
2007-2008	-5.97	-6.04	17.29
2008-2009	-6.68	-9.98	22.94
2009-2010	-6.02	-6.99	19.09
		All Renters (N=695,557)	
2005-2006	3.54	3.48	9.07
2006-2007	3.39	4.29	5.03
2007-2008	3.76	3.60	4.88
2008-2009	3.18	3.04	5.20
2009-2010	0.74	0.49	5.43

Note: The data source is the ACS (2005-2010). Column 2 presents the simple mean of the cross-MSA mean of house price growth; Column 3 presents the weighted mean, where weights equal the number of observations within each MSA for a given year; Column 4 presents the cross-MSA standard deviation around the simple mean.

Table 2B: Comparison Mean House Price Growth (in %)

	FHFA All Purchase	FHFA All Transactions	Unweighted FHFA All-Transactions (Restricted to ACS Sample)	Weighted FHFA All-Transactions (Restricted to ACS Sample)	Case-Shiller National	Case-Shiller 10 City Composite	Case-Shiller 20 City Composite	Unweighted ACS House Price Growth (Restricted to Case-Shiller Sample)	Weighted ACS House Price Growth (Restricted to Case-Shiller Sample)
2005-06	5.89	7.49	7.02	7.51	5.07	7.11	7.30	10.05	9.77
2006-07	0.22	1.56	1.74	1.45	-4.67	-4.53	-3.92	2.51	2.36
2007-08	-7.67	-2.25	-3.89	-5.16	-17.20	-18.30	-17.16	-6.50	-5.85
2008-09	-5.29	-3.56	-4.33	-5.61	-12.16	-13.86	-14.26	-13.47	-12.20
2009-10	-3.00	-2.33	-3.60	-3.82	0.20	2.08	1.23	-7.36	-7.02

Table 2C: Mean House Value Regressions on FHFA Price Index								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Overall Home Owner		Recent Mover		PUMAs w/ cent. city def.		Work in central city	
lnHPI(t)	.96	.75	1.21	1.18	1.01	.72	1.01	.79
	(.02)	(.03)	(.05)	(.06)	(.04)	(.06)	(.03)	(.04)
lnHPI(t-1)		.33		.03		.38		.32
		(.02)		(.05)		(.03)		(.04)
RMSE	.040	.028	.079	.079	.049	.041	.082	.077
# of Obs.	1200	1200	1200	1200	1199	1199	1199	1199

Table 3: House Value Regressions (Full Sample and Recent Mover Sample)

	(1)	(2)	(3)	(4)
COM*0506	-0.034	-0.022	-0.038	-0.028
	(0.0024)	(0.0021)	(0.004)	(0.003)
COM*0708	-0.036	-0.025	-0.038	-0.025
	(0.003)	(0.0021)	(0.004)	(0.003)
COM*0910	-0.019	-0.019	-0.020	-0.018
	(0.003)	(0.003)	(0.004)	(0.004)
COM^2*0506	0.0016	0.001	0.0018	0.001
	(1.38e-04)	(1.12e-04)	(1.84-04)	(1.65e-04)
COM^2*0708	0.0017	0.0011	0.0017	7.22e-04
	(1.41e-04)	(1.15e-04)	(2.09e-04)	(2.24e-04)
COM^2*0910	8.07e-04	8.77e-04	8.17e-04	7.22e-04
	(1.72e-04)	(1.48e-04)	(2.73e-04)	(2.24e-04)
Price difference at Median 2009-2010	-0.042	-0.043	-0.044	-0.040
	(0.007)	(0.006)	(0.010)	(0.008)
Price Difference at Median 2005-2006	-0.074	-0.048	-0.083	-0.062
	(0.006)	(0.005)	(0.007)	(0.006)
Difference between 2009-10 and 2005-6	0.032	0.0052	0.039	0.022
	(0.004)	(0.0035)	(0.008)	(0.008)
taxes	No	Yes	No	Yes
Sample	Full	Full	Recent	Recent
Observations	1,814,295	1,814,295	118,632	118,632

Note: The data source is the homeowner sample from the ACS (2005-2010). The dependent variable is the log of house value. All regressions include MSA x year fixed effects and house characteristics. Standard errors in parentheses are clustered at the MSA level. Commuting time is measured in a unit of 10 minutes.

Table 4: House Value Regressions

	(1)	(2)	(3)	(4)
COM*0506	-0.025	-0.013	-0.048	-0.024
	(0.003)	(0.002)	(0.008)	(0.007)
COM*0708	-0.026	-0.014	-0.050	-0.024
	(0.003)	(0.003)	(0.008)	(0.007)
COM*0910	-0.009	-0.008	-0.016	-0.011
	(0.004)	(0.003)	(0.008)	(0.008)
COM^2*0506	0.0013	6.55e-04	0.002	9.80e-04
	(1.71e-04)	(1.25e-04)	(4.64e-04)	(3.59e-04)
COM^2*0708	0.0013	6.98e-04	0.002	0.001
	(1.80e-04)	(1.37e-04)	(4.42e-04)	(3.62e-04)
COM^2*0910	4.28e-04	4.02e-04	5.72e-04	4.04e-04
	(2.14e-04)	(1.74e-04)	(4.71e-04)	(4.47e-04)
Price difference at Median 2009-2010	-0.019 (0.008)	-0.017 (0.007)	-0.038 (0.016)	-0.026 (0.016)
Price Difference at Median 2005-2006	-0.055 (0.007)	-0.029 (0.005)	-0.107 (0.017)	-0.054 (0.015)
Difference between 2009-10 and 2005-6	0.036 (0.005)	0.012 (0.005)	0.070 (0.017)	0.028 (0.012)
taxes	No	Yes	No	Yes
Sample	Full	Full	Work in Central Cities	Work in Central Cities
Observations	530,228	530,228	85,200	85,200

Note: The data source is the homeowner sample from the ACS (2005-2010). Columns (1)-(2) are restricted to observations in MSAs with a central city PUMA. Columns (3)-(4) are restricted to the sample that contains households working in central cities only. The dependent variable is the log of house value. All regressions include MSA x year fixed effects and house characteristics. Standard errors in parentheses are clustered at the MSA level. Commuting time is measured in a unit of 10 minutes.

Table 5: House Value Regressions: Separate Year Interaction Effects

	(1)	(2)	(3)	(4)
COM*05	-0.025	-0.013	-0.050	-0.027
	(0.004)	(0.003)	(0.010)	(0.008)
COM*06	-0.025	-0.014	-0.047	-0.022
	(0.004)	(0.003)	(0.009)	(0.008)
COM*07	-0.026	-0.012	-0.051	-0.021
	(0.004)	(0.003)	(0.009)	(0.007)
COM*08	-0.027	-0.016	-0.050	-0.027
	(0.004)	(0.003)	(0.011)	(0.011)
COM*09	-0.010	-0.008	-0.013	-0.006
	(0.004)	(0.003)	(0.009)	(0.008)
COM*10	-0.007	-0.007	-0.022	-0.017
	(0.004)	(0.004)	(0.009)	(0.009)
COM^2*05	0.0012	6.29e-04	0.002	0.001
	(2.12e-04)	(1.41e-04)	(6.03e-04)	(4.40e-04)
COM^2*06	0.0013	6.74e-04	0.002	8.24e-04
	(2.10e-06)	(1.73e-04)	(4.84e-04)	(4.69e-04)
COM^2*07	0.0014	6.71e-04	0.002	7.80e-04
	(2.23e-04)	(1.73e-04)	(5.60e-04)	(4.20e-04)
COM^2*08	0.0013	7.34e-04	0.002	0.0012
	(1.83e-04)	(1.53e-04)	(5.49e-04)	(5.24e-04)
COM^2*09	5.27e-04	4.62e-04	3.04e-04	1.52e-04
	(2.13e-04)	(1.74e-04)	(5.08e-04)	(4.76e-04)
COM^2*10	2.27e-04	2.53e-04	0.001	7.51e-04
	(2.88e-04)	(2.37e-04)	(5.86e-04)	(5.54e-04)
Price difference at Median 2009-2010	-0.019 (0.006)	-0.017 (0.005)	-0.039 (0.013)	-0.027 (0.013)
Price Difference at Median 2005-2006	-0.055 (0.006)	-0.029 (0.004)	-0.107 (0.014)	-0.054 (0.012)
Difference between 2009-10 and 2005-6	0.037 (0.008)	0.013 (0.007)	0.068 (0.019)	0.028 (0.018)
taxes	No	Yes	No	Yes
Sample	Full	Full	Work in Central Cities	Work in Central Cities
Observations	530,228	530,228	85,200	85,200

Note: The data source is the homeowner sample from the ACS (2005-2010). Columns (1)-(2) are restricted to the sample which contains observation with non-missing values for the variable that indicates whether households work in central cities. Columns (3)-(4) are restricted to the sample that contains households working in central cities only. The dependent variable is the log of house value. All regressions include MSA x year fixed effects and house characteristics. Standard errors in parentheses are clustered at the MSAxYear level. Commuting time is measured in a unit of 10 minutes.

Table 6A: House Value Regressions on FHFA Price indices

	(1)	(2)	(3)	(4)
COM	-0.016	-0.009	-0.015	-0.009
	(0.002)	(.003)	(0.002)	(0.003)
COM*(ΔlnHPI)	-0.041	-0.008	-0.044	-0.014
	(0.023)	(0.023)	(0.019)	(0.019)
lnHPI			1.094	1.054
			(0.054)	(0.057)
Lagged lnHPI			-0.062	-0.123
			(0.089)	(0.091)
Taxes	No	Yes	No	Yes
MSA X year fixed effects	Yes	Yes	No	No
MSA fixed effects			Yes	Yes
Sample	Work-in-Central			
Observations	85,143	85,143	85,143	85,143

Note: The ACS (2005-2010) is the main data source. The dependent variable is the log house value. HPI is the MSA FHFA house price indices. Standard errors in parentheses are clustered at the MSA level. Commuting time is measured in units of 10 minutes.

Table 6B: House Value Regressions on FHFA Price indices

	(1)	(2)	(3)	(4)
COM	-0.015	-0.010	-0.011	-0.008
	(0.005)	(0.004)	(0.006)	(0.005)
COM*(ΔlnHPI)	-0.044	-0.037	-0.068	-0.047
	(0.036)	(0.031)	(0.029)	(0.026)
lnHPI			1.721	1.679
			(0.148)	(0.087)
Lagged lnHPI			-0.457	-0.598
			(0.221)	(0.163)
Taxes	No	Yes	No	Yes
MSA X year fixed effects	Yes	Yes	No	No
MSA fixed effects			Yes	Yes
Sample	Work-in-Central and Recent Movers			
Observations	5,837	5,837	5,837	5,837

Note: The ACS (2005-2010) is the main data source. The dependent variable is the log house value. HPI is the MSA FHFA house price indices. Standard errors in parentheses are clustered at the MSA level. Commuting time is measured in units of 10 minutes.

Table 6C: House Value Regressions on FHFA Price indices

	(1)	(2)	(3)	(4)
COM	-0.013	-0.004	-0.016	-0.009
	(0.000)	(0.002)	(.002)	(0.002)
COM*(ΔlnHPI)*I{ΔlnHPI>0}	-0.075	-0.086	-0.021	-0.007
	(0.031)	(0.021)	(0.025)	(0.023)
COM*(ΔlnHPI)*I{ΔlnHPI<0}	-0.007	0.072	-0.069	-0.022
	(0.035)	(0.041)	(0.028)	(0.028)
lnHPI			1.097	1.055
			(0.056)	(0.058)
Lagged lnHPI			-0.054	-0.120
			(0.089)	(0.091)
Taxes	No	Yes	No	Yes
MSA X year fixed effects	Yes	Yes	No	No
MSA fixed effects			Yes	Yes
Sample		Work-in-Central		
Observations	85,143	85,143	85,143	85,143

Note: The ACS (2005-2010) is the main data source. The dependent variable is the log house value. HPI is the MSA FHFA house price indices. Standard errors in parentheses are clustered at the MSA level. Commuting time is measured in units of 10 minutes.

Table 7: Rent Regressions Restricted to Households Working in Central Cities

	(1)	(2)	(3)
COM*0506	-0.019	-0.022	-0.009
	(0.009)	(0.012)	(0.011)
COM*0708	-0.013	-0.018	-0.001
	(0.007)	(0.008)	(0.008)
COM*0910	-0.001	-0.009	-0.015
	(0.009)	(0.009)	(0.008)
COM^2*0506	8.50e-04	8.42e-04	2.33e-04
	(6.87e-04)	(4.90e-04)	(8.31e-04)
COM^2*0708	5.26e-04	8.45e-04	-1.61e-04
	(4.12e-04)	(4.90e-04)	(5.44e-04)
COM^2*0910	9.81e-05	7.92e-04	-0.0011
	(6.34e-04)	(5.36e-04)	(0.0011)
Price difference at Median 2009-2010	-0.002 (0.019)	-0.017 (0.018)	0.030 (0.029)
Price Difference at Median 2005-2006	-0.041 (0.019)	-0.050 (0.025)	-0.021 (0.023)
Difference between 2009-10 and 2005-6	0.039 (0.021)	0.033 (0.027)	0.051 (0.025)
Sample	All Rentals	Rented Apartments	Rented Houses
Observations	28.285	16,323	11,962

The data source is the home renter sample from the ACS (2005-2010). The dependent variable is the log of rent value. All regressions include MSA x year fixed effects and house characteristics. Standard errors in parentheses are clustered at the MSA level. Commuting time is measured in a unit of 10 minutes.

Table 8: Summary Statistics of Building Permits

	Single Family House Permits		Total Permits	
	Mean	S.D.	Mean	S.D.
Central county	1378.59	2366.64	1429.66	2418.62
Outlying county	480.06	752.39	480.21	758.21

Note; The building permits are obtained at the county level from the Census (1990-2009).

Table 9A: The Relationship Between Permits and Prices

	Single Family Permits	Single Family Permits	Total Permits	Total Permits
Price index	7.48	8.09	7.39	7.74
	(0.26)	(0.28)	(0.26)	(.28)
Lagged price index	-7.373	-1.32	-7.302	-1.01
	(0.26)	(0.33)	(0.26)	(0.32)
Central City*price Index	-0.594	-0.59	-0.480	-0.48
	(0.32)	(0.32)	(0.32)	(0.32)
Central City*lagged price index	0.417	0.42	0.33	0.33
	(0.328)	(0.32)	(0.32)	(0.32)
Year Dummies	No	Yes	No	Yes
Number of Observations	14,827	14,827	14,827	14,827

Note; The building permits are obtained at the county level from the Census (1990-2009). The house price index is the U.S. national house price index. Standard errors in parentheses are clustered at the county level.

Table 9B: The Relationship Between Permits and Prices

	Single Family Permits	Single Family Permits	Total Permits	Total Permits
Price index	7.27	7.26	0.17	0.15
	(0.42)	(0.42)	(0.13)	(0.13)
Δprice index	0.53	0.20	0.86	0.89
	(0.46)	(0.46)	(0.44)	(0.45)
Central City*price Index	-0.22	-0.19	-0.37	-0.37
	(0.07)	(0.07)	(0.13)	(0.13)
Central City*Δ price index	0.27	0.36	-0.50	0.53
	(0.41)	(0.40)	(0.45)	(0.46)
House price indices	National	National	MSA	MSA
Number of Observations	16,427	16,440	13,819	13,832

Note; The building permits are obtained at the county level from the Census (1990-2009). All regressions include year dummies and county fixed effects. Standard errors in parentheses are clustered at the county level.

Table 10: Second-Stage of the Cross-MSA Price Variation Analysis

β_t	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Dependent Variable in the first stage: lnHPI											
$\hat{\alpha}_t$	0.031	0.031	0.073	0.012	0.012	0.037	0.033	0.033	0.058	0.013	0.014	0.006
	(0.003)	(0.002)	(0.018)	(0.003)	(0.0005)	(0.017)	(0.003)	(0.002)	(0.018)	(0.003)	(0.0006)	(0.015)
Time Trend	No	No	-0.002	No	No	-0.001	No	No	-0.001	No	No	0.0003
			(0.001)			(0.001)			(0.0008)			(0.0007)
Population and Income Controls	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Other Supply Constraints	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Estimation Method	OLS	MOM	OLS	OLS	MOM	OLS	OLS	MOM	OLS	OLS	MOM	OLS
	Dependent Variable in the first stage: ΔlnHPI											
$\hat{\alpha}_t$	0.058	0.061	0.057	0.022	0.030	0.018	0.046	0.063	0.044	0.019	0.036	0.015
	(0.018)	(0.002)	(0.018)	(0.012)	(0.002)	(0.017)	(0.015)	(0.003)	(0.015)	(0.010)	(0.002)	(0.011)
Time Trend	No	No	-2.82e-06	No	No	-0.00004	No	No	-0.00002	No	No	-0.00006
			(0.0007)			(0.00005)			(0.00005)			(0.00004)
Population and Income Controls	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Other Supply Constraints	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Estimation Method	OLS	MOM	OLS	OLS	MOM	OLS	OLS	MOM	OLS	OLS	MOM	OLS

Note: The independent variable is $\hat{\alpha}_t$, the estimated coefficient on I_t, the dummy variable for year t. The dependent variable is $\hat{\beta}_t$, the estimate of the coefficient on the interaction of the (demeaned) average commuting time with I_t. Data sources for first stage: (1) MSA level FHFA (OFHEO) house price indices (1976-2009), time averaged over the year. (2) Average commuting time from the 2000 Census data. The first stage regression regresses lnHPI or ΔlnHPI on year MSA fixed effects, dummies, the interactions of average commuting time and year dummies. Population and Income Controls refers to the interaction of population and average income with year dummies. Other Supply Constraints refers to the interaction of the WRLURI and Saiz's undevelopable land share with year dummies.

Table 11A: Permit Regressions

	Single Family Permits	Single Family Permits	Single Family Permits	Total Permits	Total Permits	Total Permits
lnHPI	0.07	0.11	0.12	0.06	0.11	0.12
	(0.07)	(0.08)	(0.08)	(0.07)	(0.08)	(0.08)
Δ lnHPI	4.16	4.18	4.08	4.13	4.15	4.04
	(0.20)	(0.20)	(0.19)	(0.19)	(0.19)	(0.18)
Δ lnHPI*COM	-0.107	-0.087	-0.080	-0.098	-0.079	-.071
	(0.046)	(.0044)	(0.045)	(0.046)	(0.044)	(.046)
Other Controls		Income, Population	Income, Population Δ Income Δ Pop		Income, Population	Income, Population Δ Income Δ Pop
Year Effects	No	No	No	No	No	No
MSA Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,559	2,559	2,559	2,559	2,559	2,559

Note: The building permits are obtained at the MSA level from the Census (1990-2009).

Table 11B: Permit Regressions

	Single Family Permits	Single Family Permits	Single Family Permits	Total Permits	Total Permits	Total Permits
	Sample with Positive HPI Growth					
lnHPI	0.30	0.31	0.31	0.29	0.30	0.30
	(0.08)	(0.09)	(0.09)	(0.08)	(0.09)	(0.09)
Δ lnHPI	2.35	2.33	2.28	2.35	2.33	2.30
	(0.36)	(0.34)	(0.31)	(0.34)	(0.32)	(0.30)
Δ lnHPI*COM	-0.225	-0.216	-0.21	-0.207	-0.196	-0.194
	(0.078)	(0.070)	(.072)	(0.078)	(0.074)	(0.074)
Other Controls		Income, Population	Income, Population Δ Income Δ Pop		Income, Population	Income, Population Δ Income Δ Pop
Year Effects	No	No	No	No	No	No
MSA Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,209	2,209	2,209	2,209	2,209	2,209
	Sample with Non-Positive HPI Growth					
lnHPI	-0.07	0.07	0.05	-0.05	0.09	0.08
	(0.13)	(0.15)	(0.17)	(0.13)	(0.05)	(0.17)
Δ lnHPI	5.78	5.88	5.52	5.77	5.85	5.46
	(0.76)	(0.73)	(0.76)	(0.75)	(0.72)	(0.75)
Δ lnHPI*COM	-0.24	-0.26	-0.18	-0.24	-0.26	-0.17
	(0.16)	(0.16)	(0.17)	(0.16)	(0.16)	(0.15)
Other Controls		Income, Population	Income, Population Δ Income Δ Pop		Income, Population	Income, Population Δ Income Δ Pop
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
MSA Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	350	350	350	350	350	350

Note: The building permits are obtained at the MSA level from the Census (1990-2009).

Table 11C: Permit Regressions

	Single Family Permits	Single Family Permits	Single Family Permits	Total Permits	Total Permits	Total Permits
lnHPI	-0.02	0.09	0.15	0.05	0.16	0.22
	(0.18)	(0.17)	(0.18)	(0.18)	(0.17)	(0.17)
Δ lnHPI	2.58	2.59	2.34	2.53	2.54	2.29
	(0.19)	(0.18)	(0.19)	(0.18)	(0.18)	(0.19)
Δ lnHPI*COM	0.011	0.011	0.006	-0.005	0.015	0.010
	(0.037)	(0.037)	(0.035)	(0.038)	(0.037)	(0.036)
Other Controls		Income, Population	Income, Population Δ Income Δ Pop		Income, Population	Income, Population Δ Income Δ Pop
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
MSA Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,559	2,559	2,559	2,559	2,559	2,559

Note: The building permits are obtained at the MSA level from the Census (1990-2009).

Table 11D: Permit Regressions

	Single Family Permits	Single Family Permits	Single Family Permits	Total Permits	Total Permits	Total Permits
			Sample with Positive HPI Growth			
lnHPI	0.04	0.12	0.18	0.05	0.17	0.22
	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	(0.18)
Δ lnHPI	1.93	1.87	1.67	1.91	1.87	1.69
	(0.38)	(0.35)	(0.33)	(0.36)	(0.35)	(0.33)
Δ lnHPI*COM	-0.13	-0.10	-0.10	-0.11	-0.09	-0.09
	(0.08)	(0.07)	(0.07)	(0.075)	(0.07)	(0.07)
Other Controls		Income, Population	Income, Population Δ Income Δ Pop		Income, Population	Income, Population Δ Income Δ Pop
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
MSA Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,209	2,209	2,209	2,209	2,209	2,209
			Sample with Non-Positive HPI Growth			
lnHPI	0.08	0.29	0.45	0.30	0.53	0.71
	(0.06)	(0.58)	(0.56)	(0.54)	(0.54)	(0.51)
Δ lnHPI	3.17	3.30	3.13	3.13	3.28	3.10
	(0.94)	(0.90)	(0.91)	(0.94)	(0.89)	(0.88)
Δ lnHPI*COM	0.005	-0.005	0.002	-0.013	-0.03	-0.016
	(0.197)	(0.19)	(0.18)	(0.20)	(0.19)	(0.17)
Other Controls		Income, Population	Income, Population Δ Income Δ Pop		Income, Population	Income, Population Δ Income Δ Pop
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
MSA Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	350	350	350	350	350	350

Note: The building permits are obtained at the MSA level from the Census (1990-2009).

Figure 0: Total Permits and FHFA All Purchase Price Index

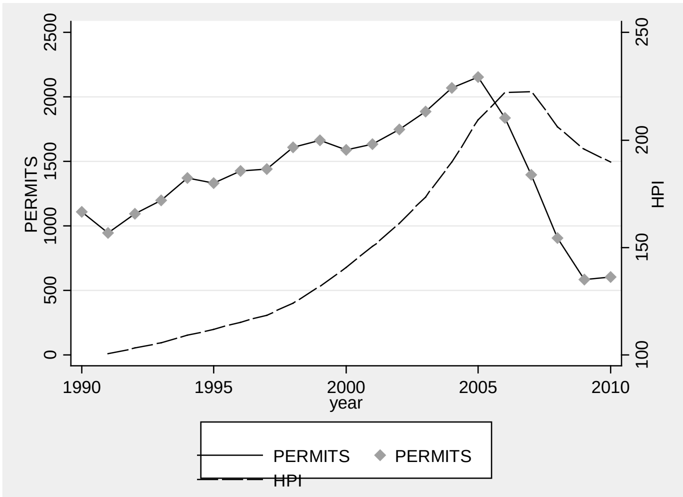
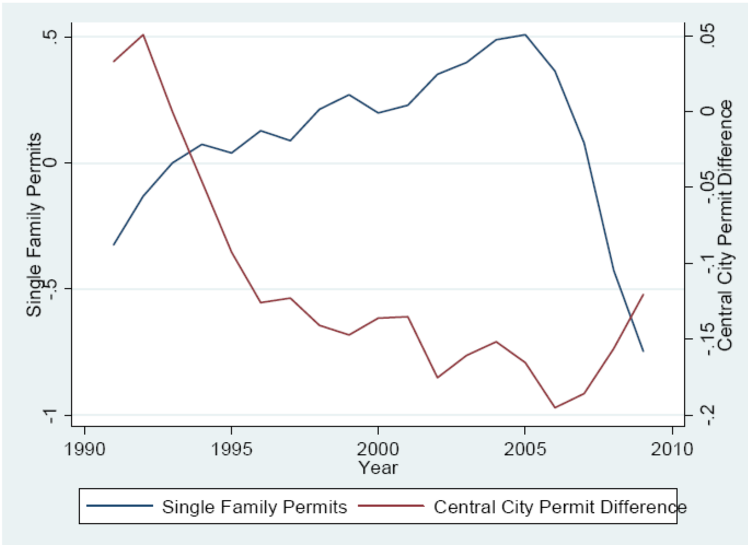
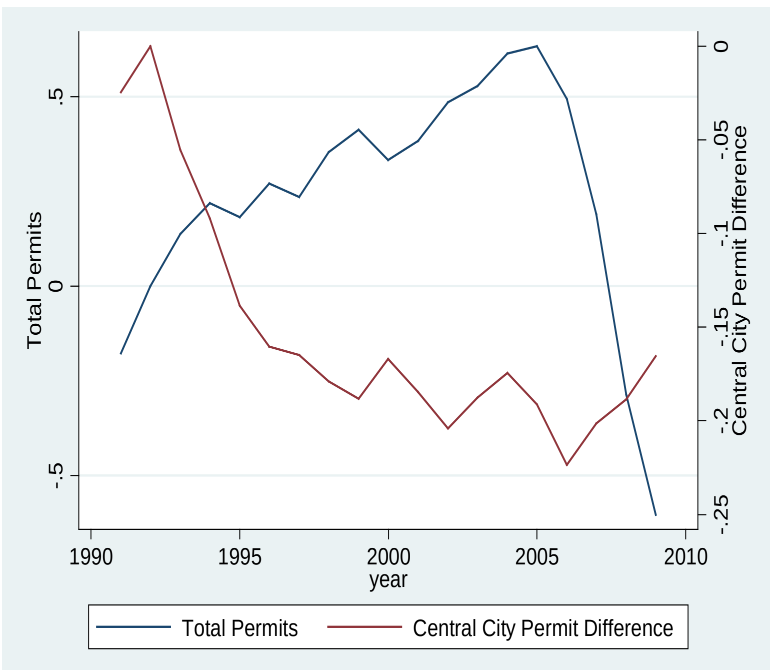


Figure 1: Single Family Home Permits: All and Central City



The blue line shows total single family home permits on a log scale, with 1992 normalized at zero. The red line shows the log share of central city permits.

Figure 2: Total House Permits: All and Central City



The blue line shows total permits on a log scale, with 1992 normalized at zero. The red line shows the log share of central city permits.

Figure 3: Graphical Illustration of Supply Elasticity With Respect to City Size

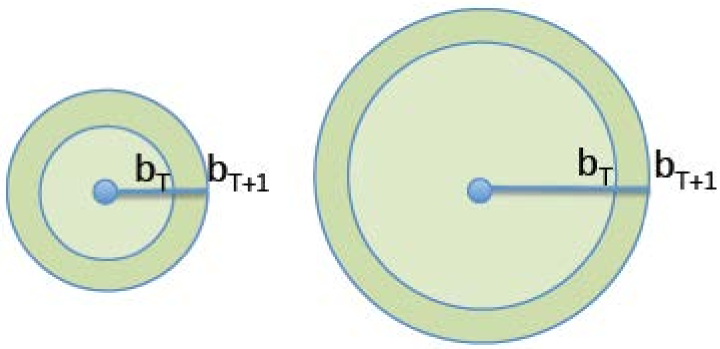


Figure 4: Histogram of Average Commuting Time

(Mean = 22.39 min, sd = 2.66 min)

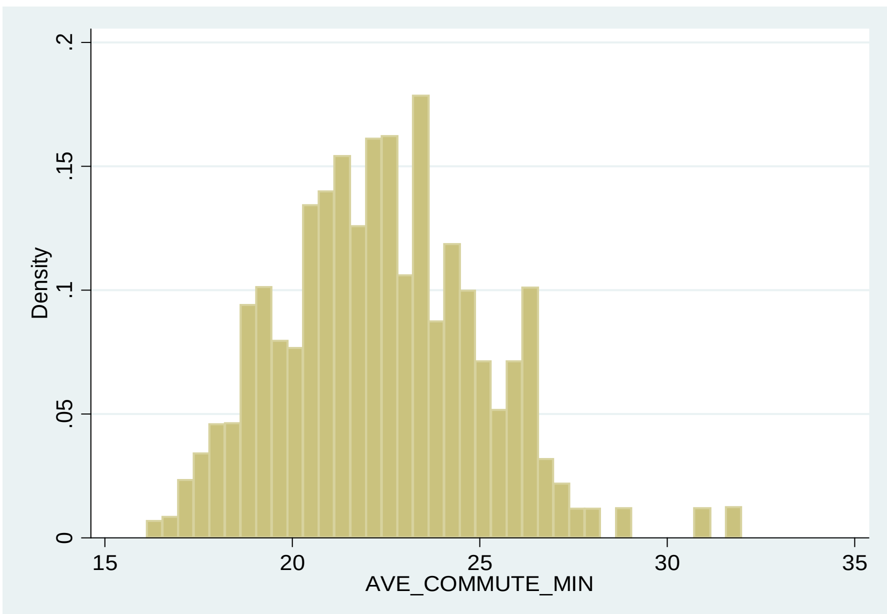
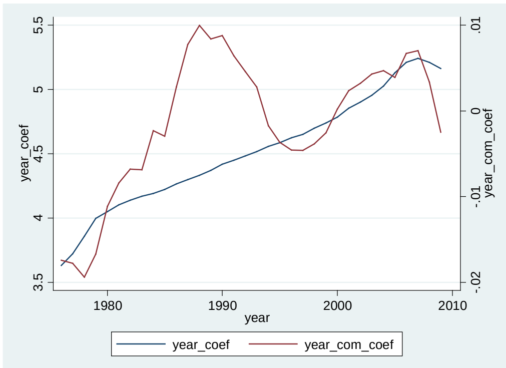


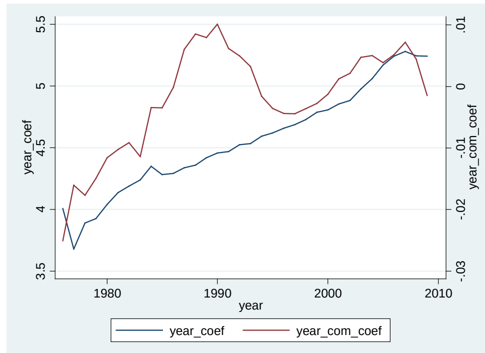
Figure 5: Cross-MSA House Price Analysis

First-stage Dependent Variable: lnHPI

Without Income and Population Controls

With Income and Population Controls





First-stage Dependent Variable: ΔlnHPI

Without Income and Population Controls

With Income and Population Controls