Essays on the Dynamics of Regional Housing and Labor Markets

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A dissertation submitted to

The Faculty of
The Columbian College of Arts and Sciences
of The George Washington University
in partial fulfillment of the requirements
for the degree of Doctor of Philosophy

May 15, 2011

Dissertation directed by

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The Columbian College of Arts and Sciences of The George Washington University certifies that William Durrett Larson has passed the Final Examination for the degree of Doctor of Philosophy as of March 23, 2011. This is the final and approved form of the dissertation.

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Abstract of Dissertation

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In this dissertation, I explore a burgeoning area of interest in the field of regional economics: the dynamics of cities and regions. I show that regional differences in the state of housing markets and the specialization of industry serve to affect the dynamic responses to local demand shocks. In particular, urban decline lowers the elasticity of housing supply, causing demand shocks to affect house prices more in declining cities than growing or stable cities. Because the housing stock constrains the labor supply in cities, decline also serves as a predictor of the effects of demand shocks on employment and wages, causing the effects on employment to decrease and those on wages to increase.

I also find that industrial specialization reduces the effects of demand shocks on the housing and labor markets. Specifically, cities with a high degree of diversification of regional exports experience stronger employment, wage, and house price effects of demand shocks compared to an equivalent shock in an industrially specialized city. When cities are highly diversified, intermediate inputs and final consumption goods are often produced locally, as opposed to specialized cities which must import these goods from other locations.

Finally, I explore the ability of simple time series models to forecast regional house price dynamics. I find that theory-driven multivariate models were best able to forecast the declines in house prices experienced in California from 2007-2009. Univariate, atheoretical models, on the other hand, forecasted quite poorly and were unable to detect turning points in the housing market.

In addition to the empirical results discussed above, this dissertation also makes methodological contributions. The essays on urban decline, industrial

specialization, and regional dynamics use a new two-step estimation procedure that acts as a substitute for panel specifications. This procedure has only recently become possible due to the high data and computing power requirements. In the first step, individual time series models are estimated for each cross-sectional unit. In the second step, characteristics of the estimates in the first step are estimated as a function of cross-sectionally varying but time-invariant variables. Bootstrapping exercises are performed spanning both steps in order to establish the statistical properties of the estimates. This two-step procedure has broad applications for further research because it enables sophisticated time-series techniques to be applied to models where panel estimators are infeasible and panel restrictions are untenable.

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Chapter 1

Introduction

1.1 A tale of four cities

In 2005, the Bureau of Labor Statistics' commodity price index rose by a dramatic 8% while its consumer price index increased by a modest 1.9%. For firms in cities that specialized in commodities and related industries, this price shock acted as a major boost to demand for their products. As the economic bases of their respective cities, demand for these urban exports led to other beneficial effects. Producers demanded intermediate inputs, and local firms that could supply those inputs felt their own increases to demand. Workers, now having higher incomes, spent money on consumer goods and housing.

Strikingly, however, cities that felt the same positive economic shock in the form of an increase in their export prices showed very different local economic responses (see Table 1.1). In cities like Charleston, West Virginia, a primary producer of coal and natural gas, employment barely increased, yet wages and house prices rose substantially. At the same time, Greeley, Colorado, a hub for local farming and ranching and home of a major meatpacking plant, experienced a large boost to employment and housing construction, but little increase to wages or house prices.

Some cities like Wichita, Kansas, with its highly specialized aerospace manufacturing, felt almost no labor market effects from the large price increases its firms received for their goods. This contrasts with Santa Barbara, California, with its diversified service economy, which experienced a huge increases in employment, wages, and house prices during the same time, even though its shock to export prices was quite small.

Table 1.1: Four representative cities' housing and labor market experences in 2005

City	Change in 2005:			
	Export Prices	Employment	Wages	House prices
Charleston, WV	5.9%	0.16%	3.58%	3.74%
Greeley, CO	12.8%	3.95%	1.76%	1.65%
Santa Barbara, CA	2.1%	3.52%	2.67%	15.99%
Wichita, KS	5.2%	0.60%	2.42%	3.94%

The obvious question is, why did these regions respond differently to similar economic shocks? This dissertation consists of three essays on the dynamics of regions. The first essay shows that in declining cities, the durable nature of the housing stock insulates employment and the housing stock from fluctuations, and causes demand shocks to be captured by workers in the form of wages, and land owners in the form of house prices. In part, this explains the differential experiences of Charleston and and Greeley, a declining and a stable city, respectively. Charleston's employment increased much slower than Greeley's, whereas Charleston's wages and house prices increased much more.

The second essay considers the effect of industrial diversification on regional dynamics. It is shown that diversified cities face magnified effects of demand shocks. While heavily specialized Wichita saw only small effects on employment, wages, and house prices from the increase in its export prices in 2005, diversified Santa Barbara felt larger effects from a smaller change. One reason for this is the industrial linkages between suppliers. The inputs in the aerospace products produced in Wichita are likely imported from other cities. This contrasts with Santa Barbara, which as a diverse service economy, supplies many of its intermediate inputs locally.

The third essay explores the experience of the housing market in California leading up to and including the declines between 2007 and 2009. Much like Santa Barbara, house prices in California increased substantially between 2000 and 2007, and subsequently crashed back to earth over the succeding two years. This essay explores the ability of simple time series models to forecast the turning point in the housing market in 2006, and forecast housing prices during the declines of 2007-2009.

This dissertation makes a number of contributions within the fields of regional science, applied econometrics, and economic forecasting. What follows in this introduction is a short summary of each of these essays, which lays out the main research questions, methodological approaches, results, and key implications.

1.2 Housing and labor market dynamics in growing vs. declining cities

There is a long-standing debate in the literature on the effects of demand shocks in regions. Some, such as Blanchard and Katz (1992), argue that regions should be modeled in a demand-driven framework, where supply is assumed to be perfectly elastic. Under this modeling framework, a demand shock will be fully incorporated into quantities such as employment, population, labor force, and the housing stock, with no changes to prices, including wages and house prices. Others, such as Bartik (1991), argue that supply considerations are essential. The source of this supply inelasticity in regional models is often land (Henderson, 1974). While the supply of land is nearly infinite in a large country such as the United States, developable land in cities can be extremely scarce. In supply constrained models, this inelasticity of the supply of land in cities causes inelasticity in the supply of housing. Because the housing stock acts as a constraint upon the labor force, these land and housing supply inelasticities ultimately define both the housing and labor dynamics of cities.

The first essay in this dissertation reconciles this apparent conflict. A model is developed where urban housing and labor markets interact with each other. Inelasticity in the supply of housing serves to increase the effect of a demand shock on wages and house prices and reduces the effect on employment and the housing stock.

Urban decline serves as a proxy for the elasticity of housing supply based on the following logic: Housing is quickly constructed and highly durable. When demand for housing in a city falls, the housing stock remains, even though house prices fall far below replacement costs. When successive positive or negative demand shocks occur in the city, the price of housing changes, but in the most depressed areas, no new construction occurs because house prices are below the threshold required to cover construction costs. What is observed is that in the face of a demand shock in a declining city, the housing stock does not change, and we observe a near-zero elasticity of housing supply. Alternatively, in a growing or stable city, house prices are at or near replacement costs, so positive demand shocks cause new housing construction. So, in growing or stable cities, the elasticity of housing supply is higher than in a declining city. Thus, a measure of urban decline serves as a proxy for the elasticity of housing supply.

This hypothesis is operationalized using a two-step procedure, following Owyang, Piger, Wall, and Wheeler (2008). In the first step, time series models for each city are estimated and impulse responses of housing and labor market variables to a local demand shock are calculated. In the second step, characteristics of these impulse responses are estimated a function of an index of urban decline.

Local demand is measured using a relatively underused variable first developed by Pennington-Cross (1997): the Export Price Index (EPI). This variable measures the prices firms in cities receive when they export to other cities and regions. Assuming cities are price-takers, this variable is an exogenous local demand determinant due to its method of construction.

Urban decline is measured using various proxies for urban decline used in the literature such as the change in center-city house values, the change in the center-city population, the average January temperature, the fraction of population in the city originally from the state, and poverty statistics. It is found that each of these decline measures can be used to predict the responses to a demand change that are consistent with the urban decline hypothesis, that cities in urban decline have different impulse response functions to demand shocks. Specifically, a positive shock raises wages and house prices but does not spur employment significantly in declining cities. In growing cities, however, an equivalent shock would increase employment but not wages or house prices.

One of the implications of this finding is that residents in growing or stable cities are not made much better or worse off by a policy or market shock. Because house prices and wages are relatively unchanging, each resident achieves nearly the national reservation utility. In contrast, in declining cities which are supply constrained, demand shocks are partially capitalized into land and house values, and the effects of a demand shock directly affect homeowners. Therefore, demand-side stimulus policies and market demand shocks have greater effects on original residents of declining city as opposed to growing or stable cities where their main effect is on employment.

1.3 Industrial specialization and regional dynamics

The second essay considers the dynamics of the housing and labor markets in cities with specialized versus diversified export sectors. There was a debate in the literature on the effects of urbanization versus localization externalities, and which one dominates in a long run context. The consensus finding is that cities with a diverse economic base experience greater long-run growth than do cities that are highly specialized (Glaeser, Kallal, Scheinkman, and Shleifer, 1992).

One question that is not often addressed in the literature is if industrial diversification affects regional dynamics in the *short run*. The second essay in this dissertation considers the relative effects of localization versus urbanization economies on the dynamic responses to regional demand shocks. The economic base model predicts that the effects of demand shocks should be larger in diversified cities versus specialized cities (Parr, Denike, and Mulligan, 1975), but this has never been adequately tested with modern time-series techniques.

This test is operationalized using the same two-step procedure as in the first essay in this dissertation. In the first stage, time series models are estimated for each city and impulse responses are calculated. In the second stage, characteristics of the impulse responses are estimated as a function of various measures of industrial specialization, including a Herfindahl-Hirschman index, a Shannon index, and a measure of the export share of the largest export industry.

It is found that, indeed, demand shocks have larger effects in diversified cities. The implications of this result for policy follow from the analysis in the first dissertation essay: in cities with large price effects, original residents benefit more because demand shocks are capitalized into land and house prices. Thus, residents in cities with a diversified industrial base benefit more from an equivalent demand shock than do residents in specialized cities.

1.4 Evaluating alternative methods of forecasting house prices: a post-crisis reassessment

The final essay considers the ability of simple time-series models to forecast the declines in house prices from 2007-2009. The academic literature is sparse concerning the forecasting performance and information content of rival house price forecasting approaches, and the third essay in this dissertaion fills this intellectual gap. This is especially important given the apparent inability of forecasters to predict the collapse in house prices over the time period considered.

This essay incorporates models traditionally found in the house price modeling literature such as Malpezzi (1999), with some advanced forecast robustification techniques such as those in Hendry (2006). The goal is to represent many of the common time series specifications found in the literature, paying particular attention to the contrast between those that are atheoretical and those that are highly motivated by theory.

Vector error correction models are of the latter, and perform the best of the models considered. They consistently outperform each of the univariate models across a battery of forecast comparison measures. Vector error correction models are able to 1) forecast the turning point in the housing market before it occurred, 2) forecast best from the first period of house price declines multiple-steps ahead, and 3) forecast the best one-step ahead from 2007-2009.

Chapter 2

Housing and labor market dynamics in growing versus declining cities

2.1 Introduction

Housing is quickly constructed but depreciates very slowly. This creates differences at the city level in the elasticity of housing supply. When demand in a city suffers a permanent decline, housing demand falls yet the housing stock remains. This led Glaeser and Gyourko (2005) to hypothesize that, in declining cities, housing is priced well below replacement costs and the primary effects of positive demand shocks, even if permanent, are to raise housing prices toward replacement costs with little or no increase in supply. The housing stock constrains the population, and the population constrains employment, so the durable nature of the housing stock decreases the citywide elasticity of labor supply in declining cities, and prevents employment from changing when local demand changes.[1]

This paper elaborates on and tests the Glaeser-Gyourko hypothesis that differences in the elasticity of housing supply caused by urban decline affect housing and labor market dynamics within cities. A general three-market regional equilibrium model of a small open city is developed and comparative statics show that urban decline reduces the effects of local demand shocks on employment and increases the effects of local demand shocks on wages and house prices. In declining cities, demand shocks are mostly capitalized into wages and house price changes instead of increasing employment.

Identification of city-level demand shocks is a major challenge. Previous methods of identification have focused on locally weighted national measures of employment following Bartik's (1991) industry mix approach.[2] However, this identification strategy suffers from the fact that national employment changes can mean a multitude of things, such as technological innovation, regional business cycles, or changes to international imports or exports, each of which has ambiguous affects on labor demand in individual locations.[3]

Instead, identification of local demand shocks (including labor) in this paper is made through the use of the Export Price Index (EPI).[4] The EPI is a measure of the prices firms receive for the goods and services they export to

[1]See Thompson (1965), Glaeser and Gyourko (2005), Glaeser, Gyourko and Saks (2005, 2006), Saks (2008), and Moretti (2010) for some notable demonstrations of this theory.

[2]Bartik (1991) uses local sectoral weights and national employment by sector to construct a variable that "prox[ies] for demand shifts for an area's exports," Bartik (1993, p. 300). Versions of this variable have been used to identify labor demand shocks at a state or local level by Bartik (1991, 1993), Blanchard and Katz (1992), Luttmer (2005), Saks (2008) and others. Guerrieri, Hartley, and Hurst (2010) employ Bartik's industry mix approach but use national wages instead of employment to identify local income shocks.

[3]For examples of variation in regional business cycles and consequences, see Owyang, Piger, and Wall (2005) and Owyang, Piger, Wall and Wheeler (2008). In particular, Owyang, Piger, and Wall (2005) find that regional employment growth during expansions primarily reflects differences in education and age as opposed to industry mix.

[4]This index is described in Pennington-Cross (1997) and Hollar (forthcoming).

other cities. It is constructed using Bartik's industry mix approach, but local weights are calculated using only export industries as opposed to all industries, and weighted values are national sectoral producer and consumer prices instead of national sectoral employment.[5] Assuming that individual industries in each city are price-takers, the EPI measures demand shocks that are exogenous to the local economy.

The empirical approach taken in this paper follows a two-step procedure. In the first step, Davis and Haltiwanger's (2001) "near-VAR" specification, which imposes a block-recursive structure on a VAR, is estimated for each of 352 U.S. cities. In the VAR, there are three blocks. The first block contains national variables, including U.S. employment, average U.S. wages, average U.S. house prices, and the U.S. intermediate goods producer price index. The second block assumes the first to be exogenous and includes only the local EPI. The third block takes both the national variables and the EPI to be exogenous and includes the local endogenous variables of employment, wages, and house prices.

In the second step, characteristics of impulse responses for each city are estimated in a cross-sectional regressions as a function of various indicators of urban decline.[6] Estimates across a battery of urban decline measures consistently indicate that decline affects the housing and labor market responses to demand shocks as predicted by the theoretical model. When subjected to a one-unit export price shock, cities in decline experience lower employment growth and larger wage and house price changes than cities with a history of

[5]The location quotient approach is used to identify export industries and employment in each city following the procedures in Brown, Coulsen, and Engle (1992).

[6]This approach follows Owyang, Piger, Wall, and Wheeler (2008), who estimate growth rates of U.S. states using time series methods in a first stage, and cross-sectional variation across states in a distinct second stage.

growth. These findings are robust to bootstrapping inference and when Bartik's (1991) industry mix-based employment variable is used in place of export prices.[7]

These results indicate labor market hysteresis is conditional on a city's recent history of growth or decline. Temporary, positive labor demand shocks cause housing construction, leading to permanently higher levels of employment in all cities. In growing cities, migration and construction increase enough to cause wages and house prices to return to previous levels, but in declining cities where house prices are often below replacement costs, little housing construction occurs, preventing net migration and keeping wages and house prices permanently higher. In growing cities, benefits of development policies go primarily to migrants, whereas in declining cities, supply constraints prevent net migration, causing benefits to go to original residents and particularly to homeowners. This reconciles a conflict in the literature between Bartik (1991) and Blanchard and Katz (1992) who disagree on the effects of local development policies and on labor market hysteresis: they are each correct in certain cases.

The finding that declining and growing areas respond differently to demand shocks should help to resolve conflicts over the choice of regional development policies and the use of supply- versus demand-driven models of regional development. In growing cities where housing and labor supply are elastic, demand-driven models such economic base, input-output, and regional econometric models are appropriate. However, in declining cities, supply is inelastic and demand driven models will tend to predict overly large responses

[7] The strategy is to compare the effects of local demand shocks–either positive or negative–in growing versus declining cities. This paper does not consider potentially asymmetric effects of demand shocks.

to policies that stimulate demand for regional exports.

This research also suggests that employment multipliers are dramatically different in growing versus declining cities, and that development policies meant to stimulate employment may be better put to use in cities that are growing rather than declining. In growing cities, positive local demand shocks primarily cause employment to increase, whereas in declining cities, employment does not increase as much. Instead demand increases are largely reflected in wages and capitalized in house prices. In declining cities, benefits to job growth go primarily to current residents as opposed to in-migrants. So, while employment multipliers in declining cities are small, benefits for original residents are relatively large.

2.2 Literature

2.2.1 The effects of local development policies

Researchers concern themselves with the theory and measurement of urban dynamics, to a large degree, because of the desire to predict the effects of local development policies. Some fundamental questions about development policies are 1) do they “create” jobs, 2) will those jobs stay, and 3) do the new jobs go to migrants or to original inhabitants? The answers to these questions in the literature tend to follow from the prior assumptions made by the researchers. On one hand, there are demand-driven frameworks where supply is perfectly elastic, leading to permanent effects of a labor demand shock on employment, but only temporary wage, unemployment, participation, and local price effects. In these models, migration and housing construction allow a region to fully adjust to demand changes in the long run. On the other hand, there are models with supply constraints, in which labor demand shocks have permanent effects on employment, but also on the unemployment rate, labor force participation, and local prices. In this section, the basic theory and empirical results of two representative demand-driven and supply-constrained approaches are considered. Blanchard and Katz (1992) is taken to represent a classic demand-driven model, whereas Bartik (1991) is selected to represent a model with supply constraints.[8]

Blanchard and Katz (1992) present a typical demand-driven regional equilibrium framework with regional labor demand and supply equations. Shocks to labor demand initially affect only wages, but over time, migration occurs until the wage effect is eliminated by the growth of population and employment. In their model, effects are symmetric and homogeneous across regions. Demand serves as the only driver of the labor market and supply is assumed to be perfectly elastic in the long run.

Blanchard and Katz's empirical results confirm their underlying theory. They estimate the effects of labor demand shocks by pooling annual data for U.S. states and estimating structural VAR models. One specification includes employment, the labor force participation rate, and the unemployment rate. Consistent with their theory, in the short run, labor demand shocks have an effect on employment, the unemployment rate, and the labor force participation rate, but in the long run, the only effect is on employment. Their interpretation of these results is that migration causes regions to fully adjust to labor demand shocks, and that the entirety of the benefits of labor demand increases go to migrants in the long run. Similarly, they estimate two bivariate

[8] Some other notable works on regional dynamics include Carlino and Mills (1987), Carlino and DeFina (1995) and Clark and Murphy (1996). Saks (2008) will be discussed later in this section.

systems, one with employment and wages, and the other with employment and house prices. In both of these models, labor demand shocks have temporary effects on prices but no long run effects. Blanchard and Katz also investigate differences in dynamics across regions, and find that states bordering Mexico have slightly larger effects of a shock to labor demand on employment.

Bartik (1991), on the other hand, begins with a model including both labor and housing markets. In the housing market, land is scarce, leading to an upward sloping housing supply curve. The predicted effect of this supply constraint is to limit in-migration, causing labor demand shocks to have permanent long-run wage, price, participation, and unemployment rate effects. In this case, as Bartik (1991, 1993) argues, benefits of local development policies go to both migrants and to original residents.

Bartik's empirical estimates show that there are indeed permanent effects of labor demand shocks on wages, house prices, and the unemployment and participation rates. He shows this by pooling annual data for U.S. cities and estimating distributed lag models, where the endogenous variable is the price of housing, wage rate, unemployment rate, or labor force participation rate, and the exogenous variables are lagged changes to employment. Bartik tests the hypothesis that small labor demand shocks only affect unemployment and labor force participation rates in "slow-growing" cities because little migration takes place. In "fast growing" cities, significant in-migration occurs, so labor demand shocks affect employment, with little effect on unemployment and participation rates. Bartik finds that there are no observable differences across slow-growing and fast-growing cities.

Both Bartik and Blanchard and Katz identify labor demand shocks using employment changes. Both assume that in the short run, labor supply is sufficiently inelastic to enable changes to employment to directly reflect a change to labor demand. As a robustness exercise, both estimate their models using Bartik's (1991) industry mix-based employment instrument. This variable uses local industry weights and national industry employment changes to identify labor demand shocks. Let i subscripts denote different industries, j denote different cities, b denote a chosen base year, and omitted subscripts denote sums.[9] The locally weighted change in national industry employment is then

$$G_{jt} = \sum_i E_{ijb} \frac{E_{it} - E_{it-1}}{E_{ib}} \tag{2.1}$$

Bartik then calculates an instrumental variable for local employment growth using equation 2.1

$$IV_{jt} = \ln(E_{jt-1} + G_{jt}) - \ln E_{jt-1} \tag{2.2}$$

The theory behind this instrument is that employment changes that are industry-specific but external to a city reflect exogenous labor demand shocks. While this approach may accurately reflect exogenous shocks to local labor demand in certain cases, there are many reasons why an increase in national employment in an industry may not reflect a local aggregate demand shock.[10]

Rickman (2010, p. 34) points out that "employment and population [are] both outcome variables and not independent measures of labor demand and supply," and highlights the difficulties of identifying labor demand shocks in

[9]For example, E_{jt} is national employment in industry j at time t.

[10]Employment outside a region can rise because that region is losing market share to the rest of the country, because exports abroad are growing, or the skill mix within the industry is changing. Additionally, the index does not attempt to distinguish between goods that are sold outside the city from those sold inside. For example, it is likely that almost all fluctuations in both retail and local service employment is endogenous to the local economy.

regional models. He argues that the Bartik (1991) and Blanchard and Katz (1992) approach to identification (following Carlino and Mills, 1987), suffers from this problem of weak instrumentation. Rickman contends that previous research has failed to answer the question of whether demand-driven models or those with supply constraints are more appropriate, in part, because of difficulties identifying labor demand shocks.

> Considerable debate exists regarding whether demand or supply forces underlie differentials in regional growth and fluctuations. The distinction matters for policymaking in terms of whether regions should focus more on attracting firms versus households to promote growth. Structural macroeconomic equilibrium models could be used to address this issue by employing more theoretically sound and empirically based assumptions than those used to date. These models also could be used to examine the dynamics of regional labor market adjustment to address economic development issues such as whether existing residents or migrants primarily benefit from job creation. Varied formulations and implementations of such models could establish the robust results regarding the workings of regional labor markets. (Rickman, 2010, p. 37)

2.2.2 Identifying local demand shocks: the Export Price Index

One approach to solving the problem of identifying local demand shocks is the Export Price Index (EPI). The EPI measures changes to the prices of goods and services that a particular region exports to other regions. The Export Price Index (EPI) is an extension of Bartik's industry mix approach and was first developed by Pennington-Cross (1997) and updated by Hollar (forthcoming). Instead of applying local industry weights to national industry employment, the EPI applies local industry weights for export industries to national prices.

It has long been recognized in the literature that changes in the prices of urban exports drives the economies of cities. Henderson (1988, pp. 33-38; 47-50) models the relation between export prices and the level of employment, wages, house prices, and other endogenous variables in cities. Economic base models (Isard, 1960), other system of cities models (Henderson, 1974), and new economic geography models (Krugman, 1991) all model city development in terms of export demand or export prices. Bartik's own industry mix-based employment instrument is meant to "prox[y] for demand shifts for an area's exports," Bartik (1993, p. 300). It is within this theoretical framework that the EPI was developed, and it seeks to measure one of the fundamental demand determinants in cities.

One key assumption underlying the EPI is that cities are small, open economies, and are price-takers on the world market for goods and services. Because prices are independent of local markets, export prices act as an exogenous local demand determinant.[11] What follows is a brief discussion of the EPI found in Pennington-Cross (1997) and Hollar (forthcoming).

Formulation of prices

The EPI is a Laspeyres price index, which has two desirable properties and several potential drawbacks. A Laspeyres index uses fixed quantity weights q and time-varying prices p, with subscripts i,j, and t denoting industry, loca-

[11] There is a large literature on the effects of terms of trade shocks in small, open economies, and there are many similarities between this literature and the regional science literature. See Mendoza (1995), Broda (2001, 2004), and Kose (2002) for some examples of the effects of terms-of-trade shocks on business cycles, exchange rates, output, and prices in cross-sections of small countries. Similarly, Henderson (1974, 1988), analyzes the effects of export price shocks in cities on wages, house prices, output, and employment in cities. In many respects, cities can be viewed as small, open economies with fixed exchange rates with other cities within a currency bloc.

tion, and time.

$$P_{jt} = \frac{\sum p_{ijt} q_{ij0}}{\sum p_{ij0} q_{ij0}} \tag{2.3}$$

Since q_{ij0} is location-specific but time-invariant, the weights may be considered exogenous intertemporally. Time-varying prices in the EPI are at the national level. With the additional assumption that regions are price takers with respect to exports, national prices are exogenous with respect to a region's weights. Thus changes in the EPI are, by construction, exogenous to the city economy. Contrast this with a Paasche or chained-type index, which updates quantity weights each period, neither of which would result in an exogenous price index. The second desirable property is that only a time series for prices is required for the calculation of a Laspeyres index as long as base-period weights are known. This reduces the data requirements of the EPI and makes it computationally much easier to calculate. Laspeyres indices suffer from a documented substitution bias. Because weights are quantities and fixed across time, there can be no substitution effect for agents reacting to price changes, which results in measurement error. Ultimately, there is a tradeoff between exogeneity in the EPI and measurement error due to the Laspeyres approach.

Formulation of weights

Each location has a vector of quantity weights by industry, whose values are the fraction of the region's export employment in each industry. Export employment is calculated using Location Quotients (LQ) for industry i in region j, with omitted subscripts indicating averages over the industry or region. Location quotients measure the ratio of region's industry employment, n_{ij}/n_j compared to the national average employment in an industry, n_i/n.

$$LQ_{ij} = (n_{ij}/n_j)/(n_i/n) \tag{2.4}$$

A $LQ > 1$ indicates that sector employment in a region is greater than the national average, and that the employment in excess of the national average goes towards the production of goods and services exported to other regions. Export employment is then calculated as

$$x_{ij} = (1 - 1/LQ_{ij})n_{ij} \tag{2.5}$$

and is bounded from below at 0.

An industry is excluded even when $x_{it} > 0$ if it generally only supplies customers within the region. Industries excluded include certain retail, utility, construction, and local government activities.

Quantity weights in the EPI are calculated as the fraction of industry export employment to total export employment in the region.

$$w_{ij} = x_{ij}/x_i \tag{2.6}$$

Finally, the EPI is calculated using local industry weights and national, time-varying prices.

$$EPI_{jt} = \sum_i w_{ij} * P_{it} \tag{2.7}$$

2.2.3 The link between urban housing and labor markets

Researchers have observed for quite some time that cities often grow quickly but decline slowly. This phenomenon was dubbed the "urban size ratchet" by Thompson (1965). Glaeser and Gyourko (2005) argue that the urban size ratchet is caused by the durability of housing. Housing is both easily constructed and highly durable, making it difficult for cities to shrink in size. Effectively, durable housing creates a "kink" in the housing supply curve whereby the city has an elastic housing supply when the city is growing and an inelastic housing supply when the city is declining.[12]

Glaeser and Gyourko (2005) spawned a great deal of interest in the housing and labor market effects of the elasticity of housing supply in cities. Of particular note are the findings of Glaeser, Gyourko, and Saks (2006), who show that the citywide elasticity of housing supply affects the citywide elasticity of *labor* supply. They argue that the housing stock constrains the population and the population constrains the labor force, so the housing stock constrains the labor supply in cities. It logically follows from Glaeser and Gyourko (2005) and Glaeser, Gyourko and Saks (2006) that cities in decline have very low elasticities of both housing and labor supply compared to growing cities.[13]

Saks (2008) partially addresses Rickman's (2010) critique by imposing some structure on Blanchard and Katz' (1992) model. Saks' model extends Blanchard and Katz's model, including consideration of housing market supply conditions. She hypothesizes that housing market regulations restrict the construction of new housing, thus reducing the elasticity of housing supply and causing labor demand shocks to have different effects across cities. She iden-

[12]Glaeser and Gyourko (2005) also consider other possible causes of the urban size ratchet, including labor immobility and durable capital. They find that the durability of housing dominates both of these effects. Notowidigdo (2010) presents a model where falling local demand is absorbed by falling house prices and rising transfer payments.

[13]The idea that the elasticities of housing and labor supply are sometimes inelastic in cities is at odds with many regional "demand-driven" models such as economic base models and computable general equilibrium models, which assume that supply is highly elastic because labor and capital is geographically mobile.

tifies the elasticity of housing supply over a panel of cities with an index of housing market regulation and interacts it with an employment growth instrument constructed using Bartik's (1991) industry mix-based method. Saks finds that labor demand shocks have larger short-run effects on employment and smaller effects on house prices and wages in growing, low regulation cities versus growing, high regulation cities. However, there are no long-run effects on employment, wages, or house prices in either high or low regulation cities.

While Saks' model examines growing cites, policymakers are often concerned with declining cities. Additionally, because of the urban size ratchet, it is clear that declining cities are some of the most supply constrained in the U.S. In order to determine the effects of development policies in declining, supply constrained cities, it would make sense to extend Saks' approach to these areas. However, as Saiz (forthcoming) shows, regulation and urban decline are endogenous, so housing market regulation cannot be used to identify the elasticity of housing supply in growing versus declining cities. An extension of Saks' basic approach to declining cities is necessary in order to fully address the effects of development policies in demand-driven versus supply constrained cities.

2.2.4 Summary

There is significant debate in the literature on the short- and long-run effects of local demand shocks. This debate centers on the prior modeling assumptions researchers make on the nature of regional labor and housing supply. When supply is perfectly elastic, regions are considered to be demand-driven, and the only long-run effects are in quantities such as employment, population, and housing stock. In this case, the primary beneficiaries of demand shocks and development policies stimulating demand are migrants, not the original residents in the region. However, when supply is constrained, there are long-run effects on all regionally endogenous variables. In this case, both migrants and original residents benefit from local demand shocks.

All authors considered here find that there are short-run effects of labor demand shocks, with Saks (2008) finding that effects are different across cities. There is disagreement about the long-run effects, with Bartik (1991) finding long-run effects of labor demand shocks on house prices and wages, and Blanchard and Katz (1992) and Saks (2008) finding no long-run effects of labor demand shocks on house prices or wages.

These differences may be best resolved in two ways, according to Rickman (2010). First, estimates suffer from weak identification of labor demand shocks, and better methods of identification are necessary. The Export Price Index (EPI), as a first order demand determinant, addresses this identification concern. Second, models with structure may be better able to measure the effects of demand shocks. It is clear from the housing supply literature that one of the most important identifiable structures in cities is the housing stock. Saks (2008) identifies the housing market as a source of local inelasticity in the labor market, but does not fully incorporate the housing stock as an identifiable structure itself, in the spirit of Glaeser and Gyourko (2005). Armed with the EPI and a method of identifying supply constrained cities, this paper proceeds to address the fundamental questions about the effects of development policies.

2.3 The Comparative Statics of Regional Development

The following regional equilibrium model generates predictions about the relation among the elasticity of housing supply and the effects of demand shocks on employment, wages, and house prices. In declining cities, where the elasticity of housing supply is lower, an exogenous change to export demand has a smaller effect on employment and a larger effect on wages and house prices compared with growing cities.

This model includes product, housing, and labor markets. Following Roback (1982), Gyourko and Tracy (1991), and Brown, Hayes and Taylor (2003), representative households migrate until indirect utilities across cities are equalized. Representative firms are perfectly competitive and equilibrium profits are zero. Following the economic base model and the system of cities literature, demand for urban exports drives local economic activity [14] In each city, only one good is produced for export. The city imports all other intermediate goods used in production and consumption goods. All cities are price takers for imports and exports, following the assumptions in Henderson (1988) and Hollar (forthcoming).

Each of these markets is represented using general functional forms such as in Bartik (1991) and Gyourko and Tracy (1991), Brown, Hayes and Taylor (2003). Alternative regional models such as those found in Blanchard and Katz (1992) and Saks (2008) express the economy in a series of linear relationships. However, in order for these models to accurately reflect the data,

[14] Urban exports are goods and services exported to other cities and regions. These cities and regions can be in the same country or another country.

they rely on one particularly strong assumption: that the marginal product of labor is constant or decreasing with respect to the level of employment in a city. This assumption runs counter to the voluminous literature on agglomeration economies. There exists a tension in cities between increasing returns to additional residents and increasing costs of living, according to Henderson (1974, 1988) and Abdel-Rahman and Anas (2004). In these models, the marginal product of labor is increasing with the population of the city, which is reflected in the higher wages and rental prices of housing services found in larger cities. What is necessary is a model that derives plausible comparative statics but, at the same time, allows for increasing returns to labor. The model in this section is developed with this in mind.

The representative household derives utility from housing H and an imported composite good X.

$$U = U(H, X) \tag{2.8}$$

Consumption for each household is subject to a budget constraint, where w is the wage, r is the rental price of housing services and the price of the composite good is set equal to one. Each household supplies exactly one unit of labor, so household income is w.

$$w = rH + X \tag{2.9}$$

Combining equations 2.8 and 2.9, housing demand can be expressed as an implicit function of wages and house prices.

$$H = H^D(w, r) \tag{2.10}$$

$$H_r^D < 0,\ H_w^D > 0$$

Labor supply can be solved using the traditional regional equilibrium condition where each household receives an indirect utility $\bar{V}$ and can costlessly and immediately move to another location to achieve it if necessary.

$$L = L^S(w, r) \tag{2.11}$$

$$L_r^S < 0,\ L_w^S > 0$$

Housing is supplied by competitive firms seeking to maximize profits.

$$\Pi^H = rH - P_N N - P_S S \tag{2.12}$$

Housing is produced using structure and land inputs with constant returns to scale.

$$H = H(N, S) \tag{2.13}$$

Structure inputs are imported and have a constant price P_S. However, land is scarce, leading to an upward sloping housing supply curve as a function of N.

$$P_N = P_N(N) \tag{2.14}$$

$$P_N{}' > 0$$

Combining equations 2.13 and 2.14 with equation 2.12 and assuming long run profits for housing developers are zero, housing supply is expressed as an implicit function of rents and structure prices.

$$H = H^S(r; P_S) \tag{2.15}$$

$$H^S_r > 0,\ H^S_{P_S} < 0$$

A single good is produced in the city by competitive firms for export using labor and basket of imported intermediate inputs. Profits of these firms can be written as

$$\Pi^Q = PQ - wL - P_M M \tag{2.16}$$

Production of the export good is characterized by constant returns to scale in intermediate inputs but increasing returns to scale in labor at the city level, reflecting agglomeration economies.

$$Q = A(L)G(L, M) \tag{2.17}$$

Intermediate goods and labor are not modeled explicitly as complements or substitutes in production as this is an empirical matter.[15] The effect of a change in L on Q can be decomposed into two effects, an agglomeration effect and a private marginal product effect.

$$\frac{dQ}{dL} = A_L(L)G(L, M) + A(L)G_L(L, M) > 0 \tag{2.18}$$

This agglomeration effect is assumed to be small so that the marginal product

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15

$$Q_L > 0,\ Q_{LL} < 0,\ Q_M > 0,\ Q_{MM} = 0,\ Q_{LM} = Q_{ML} <> 0$$
$$A_L > 0,\ A_{LL} > 0,\ G_L > 0,\ G_{LL} < 0,\ G_M = 0,\ G_{MM} < 0,\ G_{LM} = G_{ML} <> 0$$

effect dominates, and

$$\frac{d^2Q}{dL^2} < 0 \tag{2.19}$$

Thus, marginal product of labor decreases in L even though there are agglomeration economies. The labor demand relation is then

$$L = L^D(w; P, P_M) \tag{2.20}$$

$$L^D_w < 0,\ L^D_P > 0,\ L^D_{P_M} < 0$$

Because city production of the export good is a small fraction of world demand, demand for the export good is perfectly elastic at the national price, P. This identifies the output supply curve as an implicit function of w alone.

$$Q = Q^S(w; P, P_M) \tag{2.21}$$

$$Q^S_w < 0,\ Q^S_P > 0,\ Q^S_{P_M} < 0$$

Equations 2.10, 2.11, 2.15, and 2.20, combined with the market clearing conditions $H_S = H_D$ and $L_S = L_D$, gives the system of equations in (2.22). Once the wage is determined, so is Q by equation 2.21.

$$(2.22)$$

$$H^D(w, r) - H^S(r; P_S) = 0$$

$$L^D(w; P_m, P) - L^S(w, r) = 0$$

Taking the total derivative of this system gives the following equation:

$$\begin{bmatrix} H_w^D & H_r^D - H_r^S \\ L_w^D - L_w^S & -L_r^S \end{bmatrix} \begin{bmatrix} dw \\ dr \end{bmatrix} = \begin{bmatrix} H_{P_S}^S dP_S \\ -L_{P_M}^D dP_M - L_P^D dP \end{bmatrix} \tag{2.23}$$

Invoking the implicit function theorem and using Cramer's rule, the effect of a change in P, P_M and P_S on wages w and the price of housing services r can each be found in turn.

The term $(H_r^D - H_r^S)(L_w^D - L_w^S)$ represents the direct effects of price changes on the respective markets and the term $H_w^D(-L_r^S)$ represents the indirect effects of price changes on other markets. For this reason, it is assumed that$(H_r^D - H_r^S)(L_w^D - L_w^S) > H_w^D(-L_r^S)$ and the determinant Δ is negative.[16]

$$\Delta = H_w^D(-L_r^S) - (H_r^D - H_r^S)(L_w^D - L_w^S) < 0 \tag{2.24}$$

The comparative static effects of an export price change are as follows. First, a positive change to export prices increase wages and house prices.

$$\frac{dw}{dP} = \frac{1}{\Delta}(H_r^D - H_r^S)L_P^D > 0 \tag{2.25}$$

$$\frac{dr}{dP} = \frac{1}{\Delta}H_w^D(-L_P^D) > 0 \tag{2.26}$$

Next, positive changes to the prices of intermediate inputs decrease wages and house prices when labor and intermediate inputs are complements, and increase wages and house prices when labor and intermediate inputs are sub-

[16]The determinant is

$$\Delta \equiv \det A \equiv \begin{vmatrix} H_w^D & H_r^D - H_r^S \\ L_w^D - L_w^S & -L_r^S \end{vmatrix}$$

stitutes.

$$\frac{dw}{dP_M} = \frac{1}{\Delta}(H_r^D - H_r^S)L_{P_M}^D <> 0 \tag{2.27}$$

$$\frac{dr}{dP_M} = \frac{1}{\Delta}H_w^D L_{P_M}^D <> 0 \tag{2.28}$$

Finally, positive changes to the price of structure inputs increase wages and house prices.

$$\frac{dw}{dP_S} = \frac{1}{\Delta}(-L_r^S)H_{P_S}^S > 0 \tag{2.29}$$

$$\frac{dr}{dP_S} = \frac{1}{\Delta}(L_w^D - L_w^S)(-H_{P_S}^S) > 0 \tag{2.30}$$

This model can be used to examine the relation between urban decline and the effects of export price shocks dP. Urban decline reduces the elasticity of housing supply, so the derivative of the comparative statics with respect to H_r^S will give the predicted effect of urban decline. First, taking the partial derivative of equation 2.25 shows that reducing the elasticity of housing supply increases the effect of export price changes on wages.

$$\frac{\partial \frac{dw}{dP}}{\partial H_r^S} = \frac{1}{\Delta^2}\left[H_w^D(-L_r^S)(-L_P^D)\right] < 0 \tag{2.31}$$

Taking the partial derivative of equation 2.26 shows that reducing the elasticity of housing supply also increases the relation between urban decline and the effects of export price shocks on the rental price of housing services.

$$\frac{\partial \frac{dr}{dP}}{\partial H_r^S} = \frac{1}{\Delta^2}\left[-H_w^D(L_w^D - L_w^S)(-L_P^D)\right] < 0 \tag{2.32}$$

The effect of urban decline on the effects of export price shocks on employment can be found from equation 2.20. Taking the total derivative of equation

2.20 with respect to P yields:

$$\frac{dL}{dP} = \frac{dL^D}{dP} = L_P^D + L_w^D \frac{dw}{dP} \tag{2.33}$$

And taking the partial derivative of equation 2.33 with respect to H_r^S gives

$$\frac{\partial \frac{dL}{dP}}{\partial H_r^S} = L_w^D \frac{\partial \frac{dw}{dP}}{\partial H_r^S} > 0 \tag{2.34}$$

Thus, the employment effect of an export price shock declines with the elasticity of housing supply. What is interesting is that the partial elasticities of labor supply (L_w^S and L_r^S) remain unchanged, but the total elasticity when considering the housing market (dL/dw and dL/dr), falls from the previous level.

This simple model formalizes the Glaeser and Gyourko (2005) argument that, in declining areas with inelastic housing supply, the effects of demand shocks on wages and house prices are large while the effects on employment are small. Additionally, this model shows that export price changes unambiguously and positively affect wages, house prices, output, and employment.

2.4 Data

2.4.1 Overview

Data exist for 352 Core-Based Statistical Areas (CBSA) in the United States.[17] Unless otherwise noted, information is gathered at the county level, and then aggregated based on the CBSA area definitions. Because CBSA/MSA bound-

[17] November 2007 definitions

aries change over time but county boundaries are stable, aggregating counties ensures a consistent area of analysis over time. The CBSA is the appropriate unit of measurement because an area of this size reflects a single labor market. Analysis at the state level is inadequate because multiple distinct labor markets exist within a state, and sometimes across states. Analysis at the county level suffers from cross-hauling, where households live in one county but work in another.

Wages and sectoral employment are from the BLS's Quarterly Census of Employment and Wages (QCEW). The QCEW uses UI data to create "near census" measures covering 99.7% of all U.S. employment.[18] The 352 CBSAs considered include 85% of national employment in 2007. Data in the QCEW are quarterly from 1990:Q1-2007:Q4, for a total of 72 observation periods.[19]

Monthly consumer price information is from the BLS's Consumer Price Index for All Urban Consumers - Current Series (CPI). Monthly producer price information is from the Producer Price Index - Industry Data (PPI-Industry) series and the Producer Price Index - Commodity Data (PPI-Commodity) series. These series are used in the creation of the export price index (EPI). Monthly data is either averaged or summed to create quarterly data, where appropriate.

Data used in the construction of the Urban Decline Index (UDI), described later in this section, are from the U.S. Census' USA Counties Data File or the U.S. Department of Housing and Urban Development's "State of the Cities Data System."[20] Housing stock, house value, and demographic data are from

[18]http://www.bls.gov/cew/cewfaq.htm

[19]This series is the limiting series in terms of the time sample used for the analysis because it begins in 1990.

[20]http://censtats.census.gov/ and http://socds.huduser.org/

these sources. Other cross-sectional data are from Saiz (forthcoming), who graciously provided his supply elasticity estimates, regulation, and topographical information. Raven (Saks) Molloy (2008) and Stephen Malpezzi (2006) also provided their regulation variables.

House prices for large cities are from the Federal Housing Finance Agency (FHFA, formerly OFHEO). FHFA house price data is quarterly at the CBSA level. This series limits the cross-sectional sample to 352 of the 940 CBSAs in the U.S.

2.4.2 Export Price Index construction

This subsection discusses the creation of the quantity weights and the price series used in the construction of the EPI. All data used are produced by the U.S. Bureau of Labor Statistics and are publicly available. The primary challenge involves matching NAICS-denoted industry codes with non-NAICS-denoted data because much of the available historical price data is denoted in SIC codes, commodity codes, and consumer price codes.

The weights are from Quarterly Census of Employment and Wages (QCEW) and the computation is straightforward. The first task is to determine the base year. Braithwait (1980) finds that the Laspeyres substitution bias increases in the amount quantities and prices differ from the base year quantities and prices. Because of this, industry weights are calculated as the average of employment in 1990, 1995, 2000, and 2005. After constructing the industry weights by location, the next steps are to calculate location quotients, export employment, and EPI quantity weights for NAICS 6-digit industries.

Prices are from the BLS's PPI and CPI tables. The PPI tables used are the PPI-Industry SIC table, the PPI-Industry NAICS table, and the PPI-

Commodity table. The CPI table used is the CPI current series for urban consumers.

The first step in creating the price panel is to map NAICS-denoted PPI-industry prices to QCEW industries. When a price is missing, the following strategy is used to fill in the missing values. Each NAICS-denoted industry for which there are missing values is sequentially matched to a SIC-denoted PPI-industry, a PPI-commodity series, or a CPI series and missing observations are filled. This matching is done based on a Census translation table in the case of SIC codes. For commodities and services, the description in the dataset is used for matching. If price data is still missing when this matched price data is used, prices from the next highest classification level are used. If price data is still missing then the CPI-All Items series is used.[21]

Figure 2.1 shows the EPI along with employment in four representative cities. In each, the EPI tracks employment to varying degrees. In New York, Austin, and Las Vegas, the EPI follows employment fairly closely, whereas in Erie, they appear to be somewhat unrelated. More generally, Table 2.1 shows the results of single-equation random coefficient models. These estimates indicate that the EPI is highly correlated with other urban variables. The EPI effect on employment, wages, and house prices in cities appears to be different, as evidenced by rejections of χ^2 tests of equal parameters across cities. Of course correlation does not imply causality, and the following empirical sections will determine the effects of export prices, but Figure 2.1 and Table 2.1

[21] One problem is that many of these series have different base years, both across industries and within industries, because some industries take prices from several price series. To address this, price growth rates are generated and a new price series is constructed based on these growth rates. This series has a value of 100 in the first period and grows at a rate of the composite industry price series. During periods of transition from one price series to another, there will necessarily be a missing growth rate. This is treated as a missing price and filled using the methods described above.

indicate that there is likely to be some relationship, and that this relationship may be different across cities

2.4.3 Measures of Urban Decline

Several indices of urban decline have been used to identify cities where house prices are significantly below replacement costs. In general, both determinants and observed characteristics of decline have been used for this purpose. Glaeser and Gyourko (2005) attempt to measure this directly by comparing asset price with an estimate of construction cost. They also argue that technological advances such as air conditioning combined with warm weather has acted as a positive amenity shock over the second half of the 20th century, and that this has had an effect on the growth or decline of cities. Saiz (forthcoming) proxies for urban decline using the population change in previous 20-year period and the fraction of migrants in the population in the first period of the estimation.

In order to parsimoniously express these measures in a single variable, an index of urban decline is created. This new measure is called the urban decline index (UDI), and is constructed by summing standardized versions of the four variables listed above. The first is the percentage change in the value of the median housing unit in the center-city between 1970 and 2000. The second is the average January temperature. The third is the fraction of the population from the same state in 1990. Finally, the fourth is the change in the population in the center-city between 1970 and 2000. The first and fourth variables are from the State of the Cities Data System (SOCDS) produced by the U.S. Department of Housing and Urban Development. The second variable is from the U.S. Department of Agriculture's Natural Amenities dataset. The third variable is from the U.S. Census' "USA Counties Data File."[22] The four variables used in the UDI encompass the variables that are noted in the literature reviewed above.

A histogram of the values in the UDI is found in Figure 2.2. Some extreme values of the UDI are found in Table 2.2. Higher values of the UDI indicate a greater degree of urban decline. Of the smallest values of the UDI, most are in warm, high-growth areas. These cities each have experienced high house price appreciation and population growth between 1970 and 2000. Of the cities with large UDI values, most are in cold, Rust Belt cities. These cities have seen declines in central-city populations and relatively flat nominal house prices.

The UDI is highly correlated with housing market regulation as shown in Figure 2.3. This provides support for Saiz's (forthcoming) contention that land use regulation varies inversely with urban decline.

2.5 Estimating a Model of Regional Dynamics

This section describes the results of using a two-step method of estimating cross-sectional differences in housing and labor market dynamics across cities. The first step involves estimating the effects of export price shocks on employment, wages, and house prices in individual cities, controlling for national variables. The housing and labor market effects are measured using impulse responses. In the second step, the characteristics of the export price impulse responses are estimated in a cross-sectional regression as a function of the state of urban decline in a city.

It is common in the literature to estimate panel models and calculate panel

[22] http://socds.huduser.org/; http://www.ers.usda.gov/Data/NaturalAmenities/; and http://www.census.gov/support/DataDownload.htm;

impulse response functions to measure the dynamic effects of shocks (see Bartik, 1991; Blanchard and Katz, 1992; and Davis, Loungani, and Madidhara, 1997), or to estimate panel models with certain variables interacted with exogenous variables in order to estimate differences across regions (see Saks, 2008; Grimes and Aitken, 2010). These empirical modeling approaches are driven by the nature of the data as having a large number of cross-sectional units and a small number of time periods. Because of this data limitation, these approaches rely on restrictions to both estimated parameters and to the cross-region error structure, and may result in incorrect inference for both parameters and impulse responses.

With the BLS' Quarterly Census of Employment and Wages, employment and wage data is available at quarterly intervals, giving a sufficiently large T to estimate models for individual cities.[23] Instead of estimating a panel model with interaction terms, impulse responses constructed using self-contained, city-level models can be examined later in a second stage using summary statistics or regression analysis.[24]

2.5.1 First step: VAR

This subsection describes a method of estimating regional time series models that impose theoretically justified structures on the parameters. The empirical modeling approach follows Davis and Haltiwanger (2001), who estimate a near-VAR of oil prices and employment in different manufacturing sectors. A near-VAR is a vector autoregression where block-exogeneity is imposed on certain

[23] $N = 352$ cities, $T = 72$ time periods.

[24] An example of this two-stage, "large N, large T approach" is found in Owyang, Piger, Wall, and Wheeler (2008), who estimate individual state-level growth rates in the first stage, and explain cross-sectional differences in these growth rates in the second stage.

groups of parameters. Davis and Haltiwanger's assumption that individual sectors cannot influence national variables motivates the assumption made here that individual cities cannot influence national variables. This type of modeling approach is also used by Broda (2001, 2004), who examines the effects of terms of trade shocks in small open economies in a near-VAR, with the exchange rate in the most exogenous block.

Three blocks are chosen, following the approaches of Davis and Haltiwanger (2001) and Broda (2001, 2004).[25] The first consists of national variables, including the U.S. producer price index, total U.S. employment, average U.S. wages, and average U.S. house prices.[26] The second block consists of local variables that are dependent on national conditions but exogenous with respect to other local variables. In this block is an index of local export prices. The third block includes locally endogenous variables: city-level employment, wages, and house prices.[27]

It is assumed that the variables in Y have a linear structural representation and that the parameters are unrestricted across cities.

$$\boldsymbol{B}_i(0)\boldsymbol{Y}_{it} = \boldsymbol{B}_i(L)\boldsymbol{Y}_{it} + \boldsymbol{\varepsilon}_{it} \tag{2.35}$$

[25] While each of these models only includes two blocks, the EPI necessitates a third. The EPI is exogenous with respect to local variables, but national variables are exogenous with respect to the EPI.

[26] The producer price index used is the intermediate goods PPI.

[27] The modeling approach taken here assumes that that cities are independent from one another and there are no spatial spillovers. This contrasts with other approaches in the literature including Carlino and DeFina (1995) and Canova and Ciccarelli (2009). While part of the regional data generating process for U.S. cities may be spatial in nature, it is the purpose of the research in this paper to explicitly model heterogeneous effects. Spillovers here are only modeled indirectly through national variables. This modeling approach assumes that spatial weights for each city are equivalent. One other source of spillovers is if workers in one city lived in another city. This would connect both the housing and labor markets of the two cities. The choice of MSAs as the geographic area of interest is made in order to separate housing and labor markets in different areas.

where $\boldsymbol{Y}_{it}$ consists of three blocks,

$$\boldsymbol{Y}'_{it} = [\boldsymbol{Y}_{1it},\ \boldsymbol{Y}_{2it},\ \boldsymbol{Y}_{3it}]$$

$$\boldsymbol{Y}'_{1it} = [USPPI_t,\ USEMP_t,\ USWAGE_t,\ USHPRICE_t]$$

$$\boldsymbol{Y}'_{2it} = [EPI_{it}]$$

$$\boldsymbol{Y}'_{3it} = [EMP_{it},\ WAGE_{it},\ HPRICE_{it}]$$

and $\boldsymbol{\varepsilon}_{it}$ is a vector of structural innovations for each i and t. The structural innovations can be uncovered by estimating a reduced-form model for each city $i \in I$ and placing restrictions on $\boldsymbol{B}_i(0)$ such that $\boldsymbol{B}_i(0)$ is lower triangular. Block exogeneity is imposed, following Davis and Haltiwanger (2001), such that $\boldsymbol{B}_i(L)$ is lower block-triangular. Within each block, after the period of a shock, variables are determined jointly treating prior blocks as exogenous. This ensures that feedback does not occur between local and national variables or between the export price index and other local variables.

Two lags are chosen in order to satisfy the Sims, Stock, and Watson (1990) result regarding the consistency of impulse responses when variables are in levels and cointegration is present. With so many regressors, two lags may be more than necessary. However, as Berkowitz and Kilian (2000) and Kilian (2001) note, more lags are preferable because the costs of misspecification outweigh efficiency losses due to extra lags. Also, Kilian (2001) shows that bootstrapped estimates may require more lags than originally estimated, so it is best to err on the side of too many lags. The reduced-form model estimated is

$$\boldsymbol{Y}_{it} = \boldsymbol{d}_{0i} + \boldsymbol{\alpha}_{1i}\boldsymbol{Y}_{it-1} + \boldsymbol{\alpha}_{2i}\boldsymbol{Y}_{it-2} + \boldsymbol{e}_{it} \tag{2.36}$$

where $\boldsymbol{d}_{0i} = \boldsymbol{\delta}_{0i}+\boldsymbol{Q}_{2i}+\boldsymbol{Q}_{3i}+\boldsymbol{Q}_{4i}$ and $\boldsymbol{Q}_i$ are location-specific quarterly fixed effects. *A priori* restrictions on α are made in order to recover the structural parameters $\boldsymbol{B}_i(L)$.

$$\boldsymbol{\alpha}_{ni} = \begin{bmatrix} \boldsymbol{\alpha}_{n11i} & 0 & 0 \\ \boldsymbol{\alpha}_{n21i} & \boldsymbol{\alpha}_{n22i} & 0 \\ \boldsymbol{\alpha}_{n31i} & \boldsymbol{\alpha}_{n32i} & \boldsymbol{\alpha}_{n33i} \end{bmatrix},\ n = 1, 2$$

Because the model involves simultaneous equations with different regressors in each equation, the model is estimated using SUR. This estimation approach addresses cross-equation correlation in the error terms and results in more efficient estimates than equation-by-equation OLS as is performed in a classical VAR.

The result of these estimates is a matrix of parameter estimates $\hat{\alpha} = [\hat{\alpha}_1, \hat{\alpha}_2, ..., \hat{\alpha}_I]'$ and $\hat{e} = [\hat{e}_1, \hat{e}_2, ..., \hat{e}_I]'$. The estimated error covariance matrix $\hat{e}\hat{e}' = \hat{\Sigma}$. $P \equiv B_i(0)$ is found using the Cholesky decomposition, $\Sigma = PP'$.[28] The structural disturbances are then $\varepsilon = P^{-1}e$ and the structural parameters are $B_i(L) = P^{-1}\alpha_{Li}$ for $L = 1, 2$. Orthogonalized impulse responses are calculated for each city as $\hat{\theta}_i(\hat{\alpha}, \hat{P})$.

The bootstrapping methodology for the impulse responses is described in Efron (1981), and involves several steps. First, α parameters are estimated and $\hat{\theta}$ is calculated using the observed data. Using the estimates of α, 100 error matrices are calculated by drawing a random sample of estimated residuals with replacement. For each random draw, the vector of residuals across

[28]The ordering for the Cholesky decomposition is based on Saks (2008).

all equations is taken in order to preserve the cross-equation error structure. A starting value for Y is then randomly selected and pseudo-data Y_b are recursively generated. Bootstrapped estimates of α and θ are calculated and denoted $\hat{\alpha}_b$ and $\hat{\theta}_b$ where $b \in 1, 2, ..., 100$.[29]

While Efron's bootstrapping method traditionally has lower coverage than other methods when the own lagged coefficients sum to a value close to 1 (see Kilian, 1999), the bootstrapped impulse response functions are not meant to provide confidence intervals for the impulse responses themselves. Instead, they are used in second stage regressions to establish the relationship between time invariant cross-section variables and the impulse responses.

2.5.2 Second stage: estimating differences across cities

This subsection presents a test of the hypothesis that decline causes differences in urban housing and labor market dynamics. Characteristics of the employment, wage, and house price impulse responses are estimated as a function of urban decline, and the relationship between decline and urban dynamics is tested. Of particular interest are the maximum effects, the short-run effects, and the long-run effects because these can be used to compute the time-path of responses, provide evidence of hysteresis, and for other purposes.

Consider the set of city-level impulse responses calculated in the first stage that measure the effects of a one-unit shock to the EPI on employment, house prices, or wages, and let the response characteristic c of variable v in city i be denoted as $\theta_i^{c,v}$. These characteristics are predicted to vary as a function of urban decline based on equations 2.31, 2.32, and 2.33. Assume these relationships can be can be expressed as a linear function of some index of urban

[29] This bootstrapping method is executed using STATA's IRF CREATE, BS command.

decline and a vector of controls x_i.[30] Errors are assumed to be i.i.d. and normally distributed.

$$\hat{\theta}_i^{c,v} = a + \pi \times decline_i + \boldsymbol{x_i'\beta} + \varepsilon_i \tag{2.37}$$

The distribution of the estimated π may depart from known distributions, so bootstrapping inference is undertaken. In order to perform statistical inference, the bootstrap replications of the impulse response characteristics $\hat{\theta}_{i,b}^{c,v}$ are used to re-estimate the parameter π for each bootstrapped impulse response available. The standard deviation of these bootstrapped estimates is interpreted as the standard error of $\hat{\pi}$.[31]

2.6 Results

The empirical results in this section cover some broad areas, but there are two main results.[32] First, the export price index (EPI)–a city-level variable which measures the prices firms receive for goods they export to other cities–serves as an important housing and labor demand determinant. Exogenous shocks to the EPI have positive effects on employment, wages, and house prices, controlling for national effects, but these effects vary substantially across cities.

[30]For example, it may be interesting to estimate the one-year effect of an EPI shock on employment, so $\theta_i^{c,v}$ in this case would consist of a particular city i's employment response to an EPI shock at t=4.

[31]The 90% confidence interval for π can also be computed using the 5th and 95th percentile estimates of π_b. However, due to the large number of cities and equations estimated, only 100 bootstrapping replications are feasible. Because of the small number of bootstraps, the distribution of the bootstrap estimates at the tails is extremely lumpy. For this reason, the percentile-t method of Efron (1981) is used instead.

[32]Recall that the approach is to use a two-step procedure to estimate the effect of urban decline on the effects of local demand shocks: first, VARs are estimated for each city and impulse responses (IRFs) are generated; and second, characteristics of the IRFs are estimated as a function of urban decline.

The next result shows that urban decline is one reason why these effects are different. Urban decline reduces the elasticity of housing supply, in turn, reducing the citywide elasticity of labor supply. Urban decline reduces the effect of EPI shocks on employment, and increases the effect of EPI shocks on wages and house prices. These results are similar when Bartik's (1991) industry-mix variable is used in place of the EPI, and when different measures of urban decline are used.[33]

2.6.1 Results common across cities

While impulse responses present the total effects of structural shocks, partial effects also shed some light on the dynamics of cities. These partial effects are shown in Table 2.3 and will be discussed first. In Table 2.3, median parameter estimates across 352 cities are presented, and below these values are the 5th and 95th percentile estimates. The EPI equation shows that median export prices are quite persistent, with the median lagged parameter estimates summing to 0.88. In the employment equation the EPI has a significant effect, along with U.S. employment. The EPI is a main driver of wages as well. Oddly, the lagged wage parameters sum to only 0.05. This indicates that export prices provide more information on wages than wages do, and perhaps much of the quarterly variation in the wage series is measurement error. Input prices, measured using the intermediate goods PPI, exhibit negative pressure on wages, indicating that labor is a complement to other inputs used in production. Positive U.S. employment changes also increase wages in this partial analysis. Finally, the EPI is a main driver of house prices. Besides export

[33]The estimates in this section likely suffer from attenuation bias due to measurement error in the variables, as noted by Bartik (1993). Therefore, these estimates should serve as a lower bound for the actual parameters.

prices, no other variable appears to have a systematic effect on house prices across all cities.

Using estimates found in Table 2.3 along with Cholesky-decomposed error covariance matrix, impulse responses are created and shown in Figure 2.4. These impulse responses show the total dynamic effects of structural shocks to local demand on different local housing and labor market variables. Structural shocks to the Export Price Index (EPI), a variable measuring the prices local exporters receive for their goods and services, are interpreted as local demand shocks. The line is the median impulse response at a particular time horizon and the bands are the 5th and 95th percentile estimates.

Two main conclusions flow from the results in Figure 2.4. First the EPI is a local labor and housing demand determinant, positively affecting all local variables in the model, including employment, wages, and house prices. Second, substantial differences between the 5th and 95th percentile responses indicate that there is heterogeneity in the effects of export prices across cities. As Bartik (1993) notes, measurement error often biases impulse responses of regional dynamic models towards zero. Because of the likely presence of measurement error, the magnitudes of the impulse responses should be viewed as a lower bound, especially with regard to local variables which tend to be error-prone.

Out of 352 cities, in at least one quarter after the period of the shock, the EPI has a positive effect on employment in 325 cities, a positive effect on wages in 342 cities, and a positive effect on house prices in 333 cities. These effects control for the intermediate goods producer price index, U.S. employment, average U.S. wages, average U.S. house prices, and seasonal effects.[34] The

[34]The full table of impulse responses is an 8x8 matrix of figures, and this is available in Figure 2.5. Figure 2.4 contains the local variables lower right-hand quadrant.

median impulse response of a 1-unit EPI shock on wages reaches a peak of 0.42 in quarter 2. The peak effect of an EPI shock on employment occurs a year later, with a value of 0.24 in quarter 7. By quarter 7, the effect of the EPI shock on wages falls to 0.36. This indicates that the labor supply is less elastic in the short versus the medium term, and demand shocks are initially absorbed by wages. By period 20, the effect of the EPI shock on employment falls to 0.08 and the effect of the EPI shock on wages falls to 0.10. There is a large and persistent effect of EPI shocks on house prices, which reach their peak in quarter 8 with a value of 0.59. By quarter 20, the effect of the EPI shock on house prices falls to 0.23.

2.6.2 Explaining differences across cities

One thing that is apparent from Figure 2.4 is that the impulse responses vary substantially across cities. The standard deviations of the responses are large, and the difference between the 90th and 10th percentile estimates are often the difference between a large effect and no effect whatsoever. The purpose of this section is to investigate whether these differences are random or if there are underlying structural reasons. The model developed in Section 3 predicts that the responses of wages, employment, and house prices to local demand shocks depends on the elasticity of housing supply. Because urban decline substantially reduces the elasticity of housing supply, this theory is tested by estimating the impulse responses as a function of various measures of urban decline. The main result in this section is that urban decline does indeed constrain citywide housing and labor supply, reducing the effect of local demand shocks on employment, and increasing the effects of local demand shocks on wages and house prices.

Figure 2.6 shows impulse responses in growing versus declining cities. The impulse response at each time horizon is estimated in a second-stage regression as a function of the UDI, and the figure shows the impulse response at the 5th and 95th percentiles of the index.[35] Shaded areas are confidence intervals calculated as mean estimate +/- 2*SD of the bootstrap estimates of the UDI parameter. Figure 2.6 shows that urban decline reduces the elasticity of housing supply, and alters the effects of local demand shocks, as predicted. In a growing city (the figure shows the 5th percentile of the UDI), a demand shock has a large, positive effect on employment. Conversely, a declining city (95th percentile of the UDI) has almost no employment effect. This is in contrast to the effects on wages and house prices. The wage subfigure shows that the effect of the EPI on wages is almost twice as large in declining cities as growing cities.

Other covariates are considered in Table 2.4, including the component series of the UDI. Each of the component measures of urban decline affects the dynamic responses local variables to EPI shocks as predicted. Correlations between other variables and urban dynamics are estimated as well, and these are loosely classified as traditional labor mobility determinants, various city characteristics, housing supply elasticity measures, and various measures of housing and land use regulation. Results of these regressions are meant to provide stylized facts for further research. Of particular interest is the estimate of industry specialization on regional dynamics. The effect of industry

[35] Given a one-unit impulse at t=0, at each time horizon t+h (h=1,2,...,20), a regression is estimated where the left-hand side variable is a particular response to an EPI shock and the right-hand side variable is the UDI. Using the constant and slope parameters, the 5th and 95th percentile values of the UDI are used to create a prediction for the responses at time $t + h$ in growing (5th percentile of the UDI) vs declining (95th percentile of the UDI) cities.

specialization on employment, wage, and house price responses is estimated to be negative and highly significant. This empirically verifies a canonical prediction in the economic base literature on export multipliers in specialized versus diversified regions.

Hysteresis appears to be conditional. In growing regions, there is no long-run effect of export price shocks on either wages or house prices; but in declining regions, long-run effects exist in both. The 20-quarter effect of the EPI on employment is significant in both growing and declining regions, but larger in growing regions.

There are several implications of conditional hysteresis. First, this result serves to reconcile supply- versus demand-driven models of regional growth. Economic base models, computable general equilibrium models, and others assuming a perfectly elastic regional supply curve only appear to be valid in growing regions. In declining cities, these sorts of demand-driven models are inappropriate. Cities in decline have a comparatively small elasticity of housing supply, leading to large price and small quantity effects of local demand shocks. In these regions, supply considerations are essential.

2.7 Summary and conclusions

This paper has examined the reaction of local labor and housing markets to demand shocks. Housing is durable, creating differences in the elasticity of housing supply in declining cities versus stable or growing cities. Because the housing supply constrains the labor supply in a city, urban decline also serves to prevent the labor supply from adjusting. One implication of this is that a local demand shock has different effects in growing versus declining cities. In growing cities where the elasticity of housing supply is higher, demand shocks increase employment with little effect on wages or house prices. Alternatively, in declining cities, local demand shocks do little to increase employment, and instead affect wages and are capitalized into house prices.

Local demand shocks in this paper are measured using a relatively underused regional variable, the Export Price Index (EPI). This variable uses fixed, area-specific weights and national prices to construct a price index for goods and services exported outside of a city. The EPI is shown to be an important housing and labor demand determinant in cities. Rickman (2010) forcefully argues that there is a fundamental problem in the regional dynamics literature identifying labor demand shocks, and the approach in this paper addresses this concern.

Past approaches of modeling regional dynamics focus on panel specifications. Given the increasing availability of high-frequency data for a large number of cities, this paper pursues a different approach. First, Davis and Haltiwanger's (2001) near-VAR approach is used to estimate time series models for individual cities. Using these estimates, city-level impulse responses are constructed. In a second stage, characteristics of the impulse responses are modeled as a function of different city-level cross sectional variables in order to determine why there are differences in the impulse responses across cities.

This modeling approach has been used in research examining the effects of terms-of-trade shocks in small, open economies (Broda 2001, 2004). By adopting this modeling framework for use in modeling regional economies, this paper assumes that cities behave as small, open economies that trade with each other.

A major conflict in the literature is resolved by the findings in this paper regarding the effects of local labor demand shocks. Bartik's (1991) model represents a supply-driven framework where the supply of land constrains housing and labor supply. Blanchard and Katz (1992) represent a demand-driven modeling approach where supply perfectly adjusts to changes in demand. Bartik finds that labor demand shocks have permanent effects on employment, wages, and house prices for native residents, whereas Blanchard and Katz find that labor demand shocks have no permanent effects on original residents and that all of the benefits go to migrants.

This paper argues that both approaches are correct in certain locations. In growing cities where housing supply can easily adjust through new construction, Blanchard and Katz's framework is appropriate. However, in declining cities where the housing stock cannot change quickly, Bartik's method better reflects observed urban dynamics. In general, the research in this paper shows that understanding the nature of housing supply in cities is crucial to the choice of modeling approach.

Others in the literature have formed models where the elasticity of labor supply causes the effects of demand shocks to be different across cities (Saks, 2008; Grimes and Aitken, 2010). The research in this paper supports this view, and the results in this paper are consistent with these earlier works.

The realization that demand shocks have different effects in different locations has implications for development policies meant to stimulate demand. This research suggests that employment multipliers are dramatically different in growing versus declining cities, and that development policies meant to stimulate employment may be better put to use in cities that are growing rather than declining. In growing cities, positive local demand shocks primarily cause employment to increase, whereas in declining cities, employment does not increase very much. In growing regions, the benefits to local development policies are mostly felt by migrants, as opposed to the original residents, as theorized by Blanchard and Katz (1992).

However, in declining cities where supply constraints are an essential modeling concern, benefits of development policies go largely to original residents. This paper provides evidence that temporary local demand increases provide *permanent* benefits to local firms, workers (through both employment and wage effects), and homeowners in declining cities. These results are consistent with Bartik (1991).

Figures

Figure 2.1: Export prices and employment: representative cities

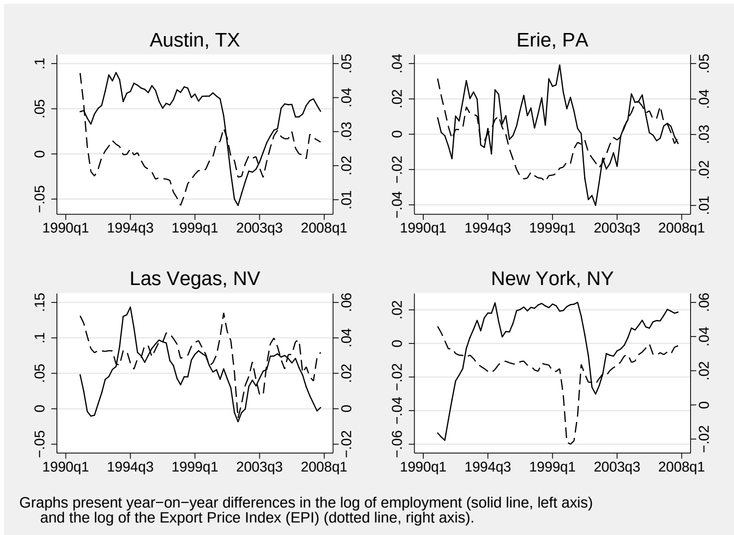


Figure 2.2: Histogram of the Urban Decline Index

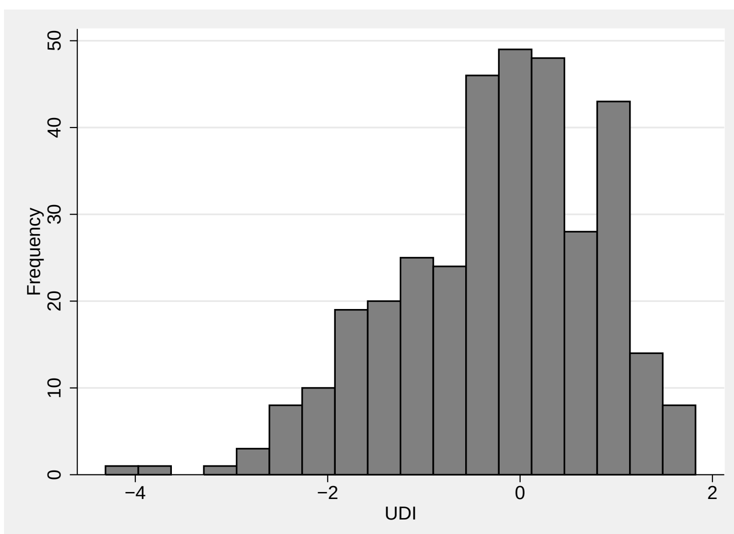


Figure 2.3: Urban decline and land use regulations

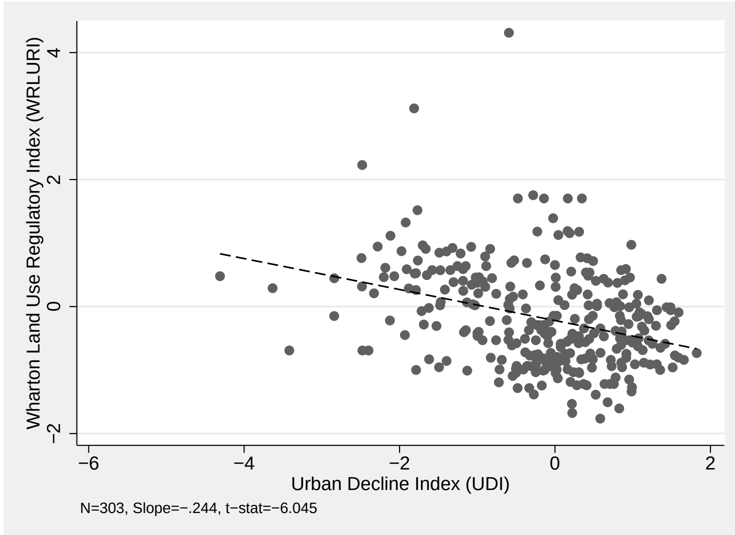
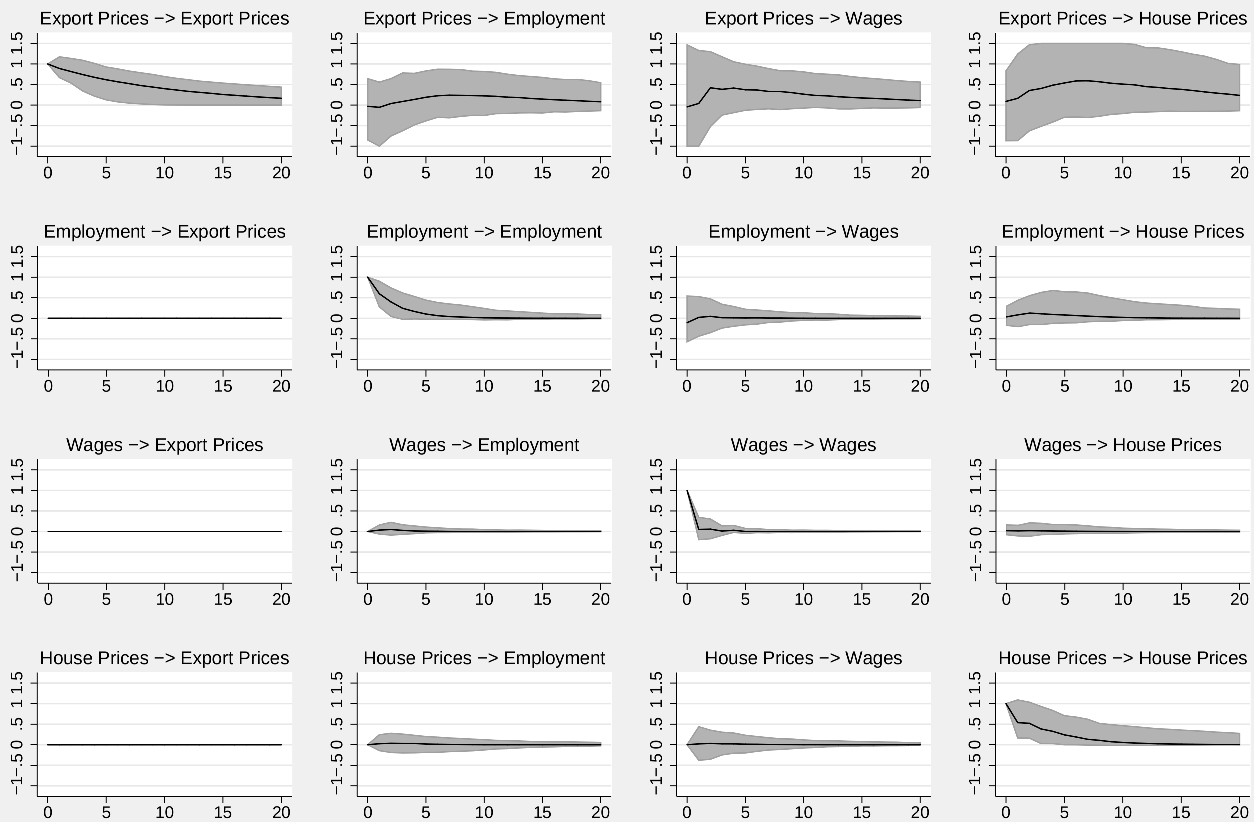
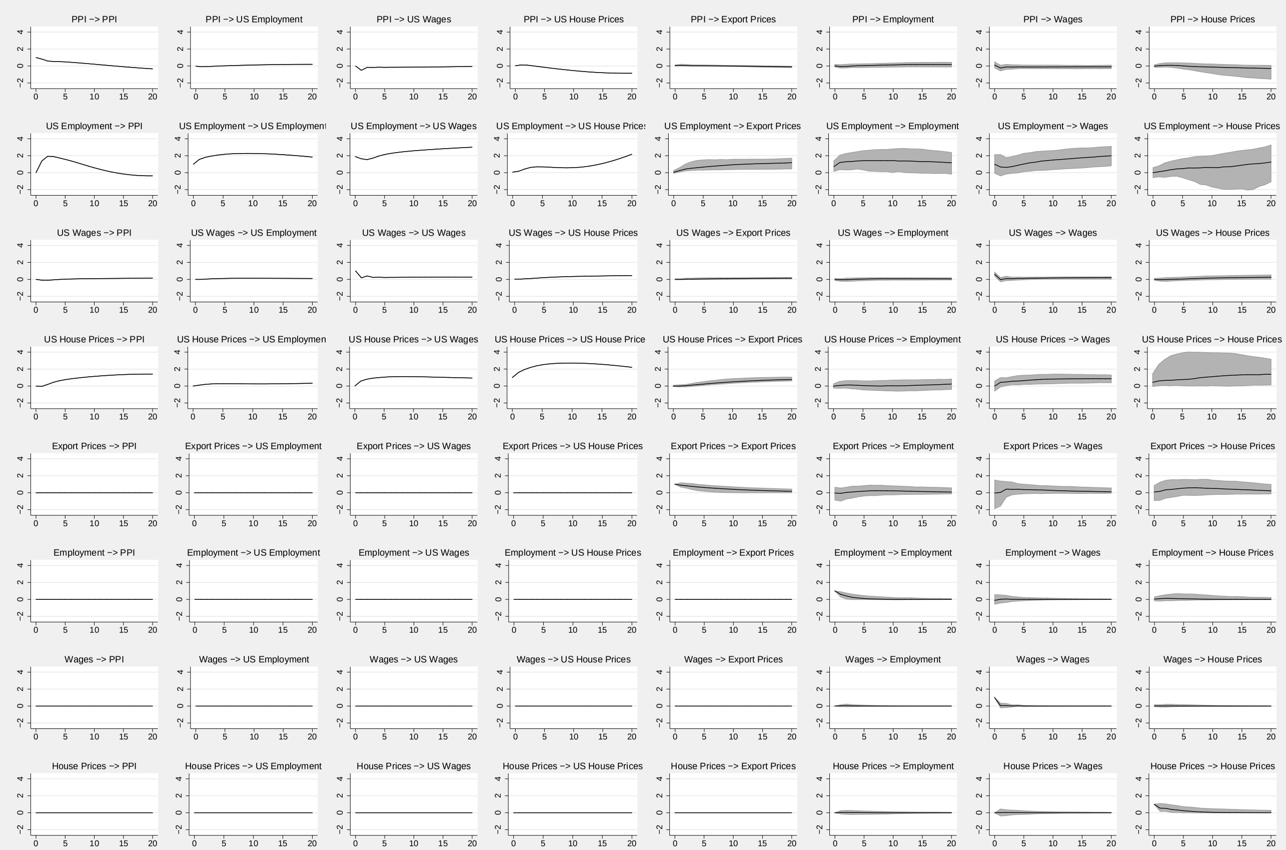


Figure 2.4: Impulse response functions (submatrix)



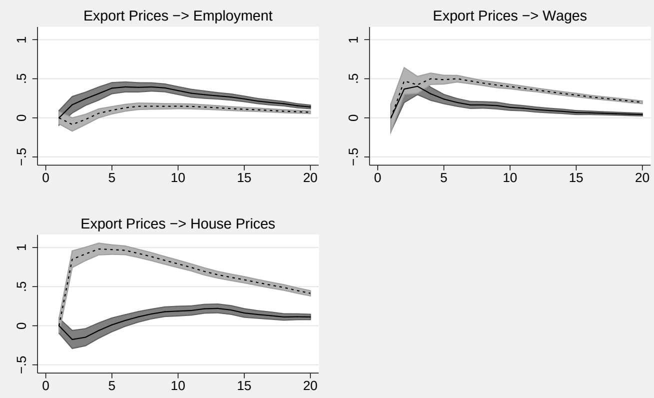
Effect of a 1 unit shock to X on Y, t quarters from the shock.
The shaded area is the 10th to the 90th percentile and the solid line is the median.

Figure 2.5: Impulse response functions (full matrix)



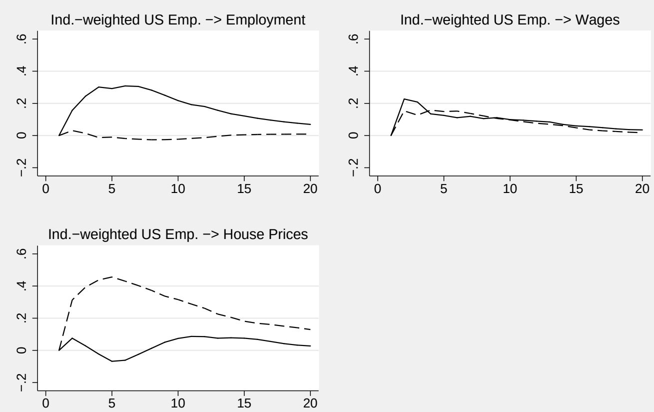
Effect of a 1 unit shock to X on Y, t quarters from the shock.
The shaded area is the 10th to the 90th percentile and the solid line is the median.

Figure 2.6: Impulse responses in growing vs. declining cities



Effect of a 1 unit shock to X on Y, t quarters from the shock.
The solid line represents a growing city (5th percentile of the Urban Decline Index).
The dotted line represents a declining city (95th percentile of the Urban Decline Index).
Shaded areas are +/− 2 SEs (bootstrapped).

Figure 2.7: Impulse response robustness check: Bartik's industry mix variable



Effect of a 1 unit shock to X on Y, t quarters from the shock.
The solid line represents a growing city (5th percentile of the Urban Decline Index).
The dotted line represents a declining city (95th percentile of the Urban Decline Index).

Figure 2.8: Impulse response robustness check: Δ median central city house value, 1970-2000

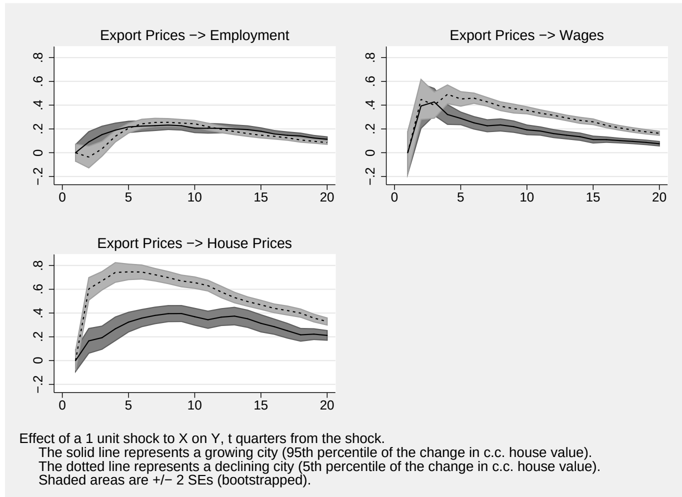


Figure 2.9: Impulse response robustness check: fraction of population from same state

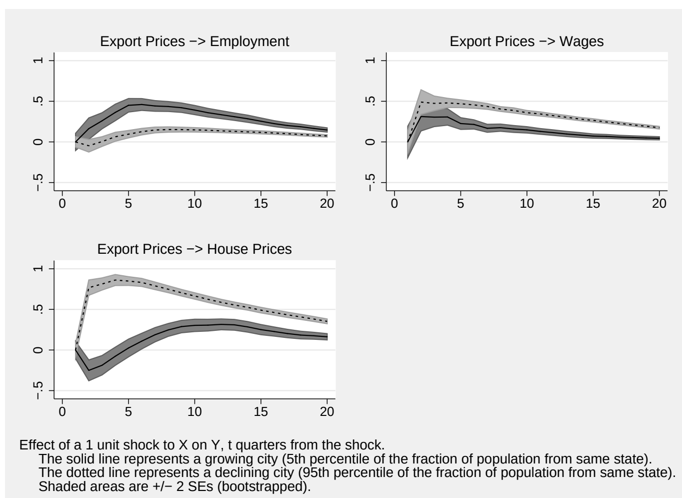
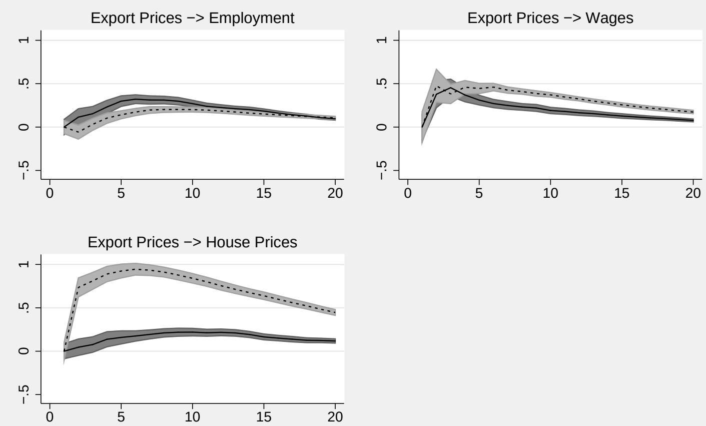
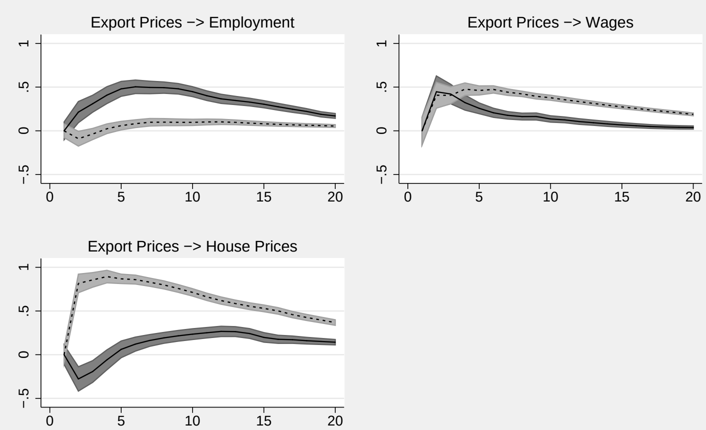


Figure 2.10: Impulse response robustness check: average January temperature



Effect of a 1 unit shock to X on Y, t quarters from the shock.
The solid line represents a growing city (95th percentile of the average January temperature).
The dotted line represents a declining city (5th percentile of the average January temperature).
Shaded areas are +/− 2 SEs (bootstrapped).

Figure 2.11: Impulse response robustness check: %Δ central city population, 1970-2000



Effect of a 1 unit shock to X on Y, t quarters from the shock.
The solid line represents a growing city (95th percentile of the change in c.c. population).
The dotted line represents a declining city (5th percentile of the change in c.c. population).
Shaded areas are +/− 2 SEs (bootstrapped).

Tables

Table 2.1: Statistical relationships between the Export Price Index (EPI) and other urban variables

	(1) ln employment	(2) ln wage	(3) ln house prices
ln Export Price Index	0.605***	1.257***	1.748***
	(0.0229)	(0.0205)	(0.0330)
Constant	8.563***	0.617***	-4.043***
	(0.135)	(0.107)	(0.160)
Observations	23472	23472	23472
T	72	72	72
N	326	326	326
χ^2 value under the null of constant parameters	2.2E+07	6.0E+06	1.7E+05
p-value	<0.001	<0.001	<0.001

Notes:
This table presents the results of three random coefficient models.
Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.2: The Urban Decline Index

Table 3. Top and bottom growing cities

CBSA code	CBSA name	Average January temperature (degrees F)	Average annual change in median house value in city center (1970-2000)	Average annual change in population in city center (1970-2000)	Fraction of population in CBSA from the same state (1990)	Urban Decline Index
Top 10 cities						
37380	Palm Coast, FL	58	7.7%	8.0%	19.7%	-4.31
34940	Naples-Marco Island, FL	65	6.8%	6.3%	19.0%	-3.63
39460	Punta Gorda, FL	64	6.2%	5.5%	13.5%	-3.22
15980	Cape Coral-Fort Myers, FL	64	6.2%	4.8%	20.8%	-2.84
38940	Port St. Lucie, FL	64	6.4%	4.7%	25.2%	-2.84
25980	Hinesville-Fort Stewart, GA	51	7.7%	4.1%	34.2%	-2.65
42680	Sebastian-Vero Beach, FL	63	6.7%	3.8%	26.6%	-2.63
39140	Prescott, AZ	36	7.6%	5.1%	28.3%	-2.58
42100	Santa Cruz-Watsonville, CA	49	9.6%	2.4%	55.6%	-2.49
36740	Orlando-Kissimmee, FL	60	6.6%	3.8%	29.1%	-2.48
Bottom 10 cities						
45060	Syracuse, NY	23	5.2%	0.1%	80.2%	1.42
40980	Saginaw-Saginaw Township, MI	21	5.5%	-0.2%	81.6%	1.44
13020	Bay City, MI	23	5.7%	-0.2%	89.7%	1.49
20260	Duluth, MN-WI	9	6.0%	-0.2%	76.8%	1.49
20220	Dubuque, IA	18	5.5%	-0.1%	81.3%	1.51
15380	Buffalo-Niagara Falls, NY	24	5.3%	-0.5%	81.4%	1.54
21300	Elmira, NY	25	4.8%	-0.4%	74.4%	1.54
13780	Binghamton, NY	22	4.8%	-0.2%	73.3%	1.59
47940	Waterloo-Cedar Falls, IA	16	5.3%	-0.1%	81.3%	1.66
46540	Utica-Rome, NY	18	5.1%	-0.4%	82.7%	1.82

Table 2.3: VAR results

VARIABLES	[1] EPI	[2] Employment	[3] Wages	[4] House prices
EPI (t-1)	0.891	-0.037	0.027	0.081
	(0.486, 1.265)	(-0.988, 0.762)	(-2.375, 1.94)	(-0.948, 1.564)
EPI (t-2)	-0.015	0.138	0.349	0.116
	(-0.375, 0.245)	(-0.721, 1.154)	(-1.452, 2.75)	(-1.128, 1.252)
Employment (t-1)		0.597	0.035	0.058
		(0.155, 1.007)	(-0.56, 0.746)	(-0.265, 0.45)
Employment (t-2)		0.002	0.020	0.022
		(-0.331, 0.28)	(-0.633, 0.637)	(-0.233, 0.374)
Wages (t-1)		0.033	0.049	0.009
		(-0.102, 0.251)	(-0.294, 0.456)	(-0.165, 0.172)
Wages (t-2)		0.029	0.004	0.009
		(-0.133, 0.231)	(-0.293, 0.293)	(-0.198, 0.168)
House prices (t-1)		0.026	0.022	0.538
		(-0.225, 0.291)	(-0.563, 0.539)	(0.067, 1.284)
House prices (t-2)		-0.013	0.011	0.131
		(-0.304, 0.242)	(-0.628, 0.591)	(-0.419, 0.422)
U.S. PPI (t-1)	0.012	-0.052	-0.244	0.019
	(-0.043, 0.201)	(-0.294, 0.158)	(-0.771, 0.267)	(-0.236, 0.293)
U.S. PPI (t-2)	-0.011	0.052	0.042	-0.043
	(-0.081, 0.118)	(-0.203, 0.31)	(-0.451, 0.649)	(-0.296, 0.234)
U.S. Employment (t-1)	0.188	0.811	0.684	0.039
	(-0.129, 0.581)	(-0.044, 2.015)	(-1.086, 2.964)	(-0.815, 1.141)
U.S. Employment (t-2)	-0.172	-0.563	-0.348	-0.147
	(-0.59, 0.152)	(-1.745, 0.382)	(-2.574, 1.453)	(-1.101, 0.746)
U.S. Wages (t-1)	0.003	-0.070	-0.052	-0.052
	(-0.022, 0.087)	(-0.31, 0.116)	(-0.493, 0.325)	(-0.271, 0.166)
U.S. Wages (t-2)	0.024	-0.014	0.069	0.008
	(-0.008, 0.118)	(-0.295, 0.212)	(-0.231, 0.53)	(-0.204, 0.225)
U.S. House Prices (t-1)	0.004	0.045	0.376	0.344
	(-0.123, 0.237)	(-0.363, 0.683)	(-0.501, 1.389)	(-0.228, 1.645)
U.S. House Prices (t-2)	0.010	-0.076	-0.158	-0.283
	(-0.231, 0.141)	(-0.644, 0.341)	(-1.144, 0.725)	(-1.338, 0.296)
N	352	352	352	352
T	71	71	71	71

A constant term and quarterly fixed effects are included in regressions, but not presented for brevity. Medians presented above the 5th and 95th percentile estimates in parentheses.

Table 2.4: Differences in impulse responses by area characteristic

Measure	EPI->Employment	EPI->Wage	EPI->House prices
Urban decline			
Urban Decline	-0.081*	0.091*	0.269*
Index	(0.014)	(0.011)	(0.016)
Change in c.c	-0.889	-9.626*	-17.998*
house value	(1.55)	(1.821)	(2.586)
Fraction of pop.	-0.61*	0.438*	1.316*
from same state	(0.091)	(0.074)	(0.115)
Average January	0.003*	-0.005*	-0.02*
temperature	(0.0009)	(0.0009)	(0.0013)
Change in c.c	10.905*	-6.902*	-19.07*
population	(1.44)	(0.992)	(1.41)
Mobility			
Fraction of pop.	-1.13*	0.126	-0.658
with some college	(0.29)	(0.363)	(0.54)
Fraction of pop.	1.914*	0.574	0.064
in poverty	(0.324)	(0.307)	(0.404)
Fraction of pop.	-0.221	1.953*	3.303*
with insurance	(0.205)	(0.224)	(0.313)
Fraction of pop.	0.242	0.94*	1.529*
homeowners	(0.214)	(0.203)	(0.29)
Median age	0.0002	0.0019	-0.0027
	(0.0053)	(0.0038)	(0.0057)
Union coverage	-0.015*	-0.001	0.007*
	(0.002)	(0.002)	(0.002)
City characteristics			
Population	-0.076*	0.067*	0.057*
density (log)	(0.01)	(0.013)	(0.018)
Median commute	-0.01*	-0.001	-0.029*
	(0.002)	(0.002)	(0.003)
Tax revenue	-0.0002*	-0.001*	-0.001*
per capita	(0.00002)	(0.00003)	(0.00003)
Industry	-0.373*	-0.248*	-0.221*
specialization	(0.112)	(0.104)	(0.106)
Elasticity measures			
Fraction of land	0.022	-0.348*	-0.539*
unavailable	(0.054)	(0.07)	(0.085)
Observed housing elasticity	1.053*	-0.342*	-1.158*
($\%\Delta H/\%\Delta P$)	(0.106)	(0.082)	(0.119)
Change in c.c.	11.061*	-5.276*	-17.553*
housing stock	(1.409)	(0.98)	(1.325)
Elasticity from	0.016	0.012	0.112*
Saiz	(0.008)	(0.011)	(0.013)
Regulation			
Regulation	-0.025	-0.127*	-0.258*
(Saks)	(0.024)	(0.029)	(0.043)
Regulation	-0.031*	-0.016	-0.024
(Malpezzi #1)	(0.008)	(0.012)	(0.016)
Regulation	0.013*	-0.028*	-0.051*
(Malpezzi #2)	(0.004)	(0.006)	(0.007)
Regulation	-0.055*	-0.039	-0.142*
(Wharton)	(0.023)	(0.034)	(0.038)
Property taxes	-0.0016*	0.0012*	-0.0002
per capita	(0.0003)	(0.0005)	(0.0005)

This table present the estimates from the following regressions:

$$\theta_i^{c,v} = a + \pi X_i + \varepsilon_i$$

where $\theta_i^{c,v}$ is variable v's 4th quarter response to an EPI shock (v listed in the column header) and X_i is a city-specific cross-sectional variable listed by row.
this equation is estimated using STATA's RREG command, which downweights extreme values.
Table cells present the mean estimate of π and the values below are standard errors.

Chapter 3

Industrial Diversity and Regional Dynamics

3.1 Introduction

Over the last fifty years, the study of the relation between externalities and growth in cities has established two key results. First, there are positive effects of specialization. Cities with established industrial clusters tend to experience further growth in those industries. This phenomenon is due to what are generally called "MAR" or "localization" externalities, as the theory was first proposed by Marshall (1890), with significant contributions by Arrow (1962) and Romer (1986). Second, there are positive effects of industrial diversification. In the model proposed by Jacobs (1969) positive spillovers between firms in different industries are the source of dynamic externalities, and are appropriately named "Jacobs" or "urbanization" externalities.

There existed a debate in the previous literature about which of these externalities–localization or urbanization–dominates in the long run. That is, do cities that are more diverse grow faster? Thus far, evidence has shown that while industrial specialization leads to productivity increases, so does diversification, and ultimately diverse cities grow faster in the long-run.[1] This belief is reflected in the efforts of several regions to diversify their economies. In particular, Nevada is pursuing development strategies aimed at expanding its renewable energy, biotechnology, aerospace, and film industries, and Michigan has developed programs to encourage businesses to develop new product lines within existing manufacturing firms.[2] Clearly, conventional wisdom is that a broadly diversified industrial base is preferable.

But what are the effects of industrial specialization in the short run? In particular, how does industrial diversity affect the dynamic responses of regional housing and labor markets to regional demand shocks? These are questions that have been ignored for some time after being of principal importance in the economic base literature and its focus on export multipliers. In the economic base model, regional exports drive demand in cities, and cause non-export employment to increase by some factor called an export multiplier. It was hypothesized that cities with a diverse industrial base experience larger multipliers because consumption goods and intermediate goods in production are acquired locally rather than imported regionally. In this paper, I test the hypothesis that industrially diverse cities experience larger short-run effects of a change in demand for a city's exports. I also determine the dynamic effects of these shocks over time in cities with different industrial concentrations.

I operationalize this test using a two-step procedure that acts as a substitute for a panel estimator. In the first step, I estimate individual time-series models for cities and compute impulse responses from a VAR. In an entirely

[1] There is a large literature on the effects of industrial scale and scope on productivity in cities. See, for example, Nakamura (1985), and Rosenthal and Strange (2003).

[2] See Velotta, Richard, "Officials choose 7 proposals in effort to diversify economy," *Las Vegas Sun*, 9-14-2011 and literature from the Michigan Economic Development Corporation, found online at *http://www.michiganadvantage.org*.

separate second step, I estimate the fourth quarter response of employment, wages, and house prices to a demand shock as a function of time invariant measures of industrial concentration. This approach follows the methods of Chapter 2 of this dissertation, which use Davis and Haltiwanger's (2001) near-VAR specification in the first stage and robust cross-sectional regressions in the second stage.

I measure demand using three variables in turn. I first consider the Export Price Index, a variable that measures the demand for goods and services sold outside the city. Next, I employ an industry-weighted measure of national employment, first used by Bartik (1991), to identify labor demand shocks in cities. Finally, I use a new variable as a demand proxy, a spatially weighted measure of national employment.

I find that cities with a diverse industrial base experience larger short-run effects of demand shocks than do cities that specialize. In particular, I find that the employment, wage, and house price effects of local demand shocks are larger in industrially diverse cities. These results are robust to different measures of industrial concentration, different local demand determinants, and to bootstrapping inference.

One implication of these results is that a local demand-side stimulus policy will tend to increase employment, wages, and house prices more in industrially diverse cities versus those that are specialized. Additionally, distributionally speaking, residents in diverse cities are made far better off by a positive demand shock than residents in specialized cities. While wages and house prices rise in an offsetting fashion in terms of overall costs of living for renters, homeowners instead benefit from both, and original residents (who tend to be homeowners) receive a double benefit from increases to local demand–their wages increase and their homes are worth more. Both of these effects are larger in diversified cities relative to specialized cities, so original residents benefit more in diversified cities.

3.2 Theory and estimation of regional dynamics

There is a long tradition in the regional science literature that investigates economic growth in cities and regions. This research dates back to at least Alfred Marshall (1890) and Werner Sombart (1907), with many critical contributions, including those by Walter Isard (1960), Kenneth Arrow (1962), Jane Jacobs (1969), Vernon Henderson (1974), and Paul Romer (1986). Two focuses of this widely arcing research agenda were to establish both the effects of short-run shocks and the long-run determinants of growth in cities. While much of the recent literature investigates the determinants of growth, the primary purpose of this section is to introduce some of the important concepts and results regarding the dynamic effects of shocks.[3]

The role of industrial specialization versus diversification has at times been a central issue. Backward linkages and export multipliers were the focus of economic base models, which have been used historically to predict the effects of demand shocks to a local economy. Sombart differentiated between *stadtebildner* and *stadtefuller* in cities; the former sell their goods and services to people outside the city and these people are relied on by the latter as drivers of the local economy. Isard formalized the economic base model in a Keyne-

[3]For an excellent overview of the determinants of growth in cities, consult Carlino and Mills (1987), Glaeser, Kallal, Scheinkman, and Shleifer (1992), and Carlino and DeFina (1995).

sian setting, giving rise to the export multiplier concept. The idea behind the export multiplier is that whenever exports exogenously change, they create some amount of local economic activity in sectors that supply the exporting firms with inputs in production and people in the city with consumer goods. It has been hypothesized that cities that are highly diversified have higher base multipliers through backward linkages (see Parr, Denike, and Mulligan, 1975, for example).[4] When demand for exports increases in a specialized city, consumer goods and intermediate inputs must be imported from other cities. In contrast, in a diversified city, some of those products are produced locally, giving rise to a higher base multiplier.

The notion that employment changes are persistent is tested in time series settings by Bartik (1991) and Blanchard and Katz (1992). This research focuses on the dynamic effects of shocks but not the effects of industrial specialization nor any other differences that may exist across regions. These papers served as a precursor to a variety of research topics exploring the dynamics of cities and regions, including the effects of shocks to different demand and supply determinants on local economies (Davis, Loungani, and Madidhara, 1997) and the relationship between employment and population growth in the face of local shocks (Clark and Murphy, 1997).[5]

More recently, investigators have sought to determine why some regions respond differently to shocks than others. For example, Owyang, Piger, Wall, and Wheeler (2008) establish some of the determinants of state-level business cycle growth rates, and Saks (2008) and Chapter 2 of this dissertation explore

[4]Input-output models arrive at the same hypothesis. Direct requirements that are not satisfied locally are imported, leading to larger local output effects in cities with highly diversified industrial structures. See Leontief (1966).

[5]Virtually all of these studies use panel estimators because they lack sufficiently long time series to estimate region-specific models.

the effects of the elasticity of housing supply on the responses to demand shocks. These papers use a variety of panel and multi-step techniques in order to investigate differences in dynamics.

I explore the dynamic effects of shocks in growing versus declining cities using a flexible two-stage procedure, following a method introduced by Owyang et al. This approach allows responses to shocks to be calculated in a first stage in a cross-section of cities, and then estimated in second stage regressions as a function of determinants of the *dynamics*.

In this way, it is possible to investigate the effects of industrial specialization on the dynamic responses of shocks. Previously, this has been difficult due to data requirements and lack of available computing resources. To undertake this method, data for a large number of time periods and a large number of cross-sectional units are necessary. Additionally, because this procedure departs from known analytically derived statistical inference, computationally intensive bootstrapping techniques are required to determine the precision of the estimates. A large quantity and quality of data are now available, as well as the necessary computing resources, so it is possible to systematically investigate the determinants of differences in dynamics across cities, and in particular, the effects of industrial specialization.

3.3 Methods

The methods used in this paper follow those used in Chapter 2, which applies the two-stage procedure of Owyang et al. (2008). In the first stage, Davis and Haltiwanger's (2001) "near-VAR" is estimated for each city, and impulse responses are calculated. Impulse responses measure the effects of a demand shock on a particular endogenous variable in a city over time. The shocks are calculated controlling for national aggregates of local variables, persistence in the different series, and correlation between contemporaneous shocks across variables. The effects include feedback effects between local variables and their persistence over time. The second stage estimates a characteristic of a particular response in the first stage as a function of cross-sectionally varying variables that are relatively stable over time.

3.3.1 First step: the time series model

The time series model applied to each city is a reduced-form VAR with several *a priori* restrictions. These restrictions impose recursive strong exogeneity on blocks of variables. This near-VAR approach has been used by Davis and Haltiwanger (2001) to estimate the effects of oil price shocks on employment in different industries and Broda (2001, 2004) to estimate the effects of different exchange rate regimes on the effects of terms-of-trade shocks. The strong exogeneity assumptions are made in order to prevent feedback between variables; in Davis and Haltiwanger's case the restrictions are made to prevent employment in a particular industry from affecting the oil price in a dynamic setting. Here, it is used to prevent feedback across two levels.

- Local variables are prohibited from affecting national variables or locationally exogenous variables

- Locally exogenous demand shocks are allowed to be influenced by national variables but not from locally endogenous variables.

The reduced form model estimated for each city has a structural representation, where X represents a locally exogenous demand determinant:[6]

$$\boldsymbol{B}_i(0)\boldsymbol{Y}_{it} = \boldsymbol{B}_i(L)\boldsymbol{Y}_{it} + \boldsymbol{\varepsilon}_{it} \tag{3.1}$$

where $\boldsymbol{Y}_{it}$ consists of three blocks,

$$\boldsymbol{Y}'_{it} = [\boldsymbol{Y}_{1it},\ \boldsymbol{Y}_{2it},\ \boldsymbol{Y}_{3it}]$$

$$\boldsymbol{Y}'_{1it} = [USPPI_t,\ USEMP_t,\ USWAGE_t,\ USHPRICE_t]$$

$$\boldsymbol{Y}'_{2it} = [X_{it}]$$

$$\boldsymbol{Y}'_{3it} = [EMP_{it},\ WAGE_{it},\ HPRICE_{it}]$$

and $\boldsymbol{\varepsilon}_{it}$ is a vector of structural innovations for each i and t. The structural innovations can be uncovered by estimating a reduced-form model for each city $i \in I$ and placing restrictions on $\boldsymbol{B}_i(0)$ such that $\boldsymbol{B}_i(0)$ is lower triangular. This would be sufficient to identify the structural innovations, but further restrictions are necessary in order to prevent feedback between local and national variables. Block exogeneity is imposed, following Davis and Haltiwanger (2001), such that $\boldsymbol{B}_i(L)$ is lower block-triangular. Within each block, after the period of a shock, variables are determined jointly treating prior blocks as exogenous. This ensures that feedback does not occur between local and national variables or between the export price index and other local variables.

[6]When X includes a weighted average of national employment (such as Bartik's local industry-weighted variable), $USEMP$ is omitted from $\boldsymbol{Y}'_1$.

Two lags are chosen in order to satisfy the Sims, Stock, and Watson (1990) result regarding the consistency of impulse responses when variables are in levels and cointegration is present. With so many regressors, two lags may be more than necessary. However, as Berkowitz and Kilian (2000) and Kilian (2001) note, more lags are preferable because the costs of misspecification outweigh efficiency losses due to extra lags. Also, Kilian (2001) shows that bootstrapped estimates may require more lags than originally estimated, so it is best to err on the side of too many lags.

3.3.2 Second stage: estimating differences across cities

In the second stage, characteristics of the local employment, wage, and house price impulse responses to a local demand shock are estimated as a function of some index of industrial specialization. Any characteristic of interest can be estimated in this manner, such as the maximum response, the long-run response, or the n-th quarter response.

Let the response characteristic c of variable v in city i be denoted as $\theta_i^{c,v}$ and assume these relationships can be can be expressed as a linear function of a measure of industrial specialization and a vector of controls x_i. Errors are assumed to be i.i.d. and normally distributed.

$$\hat{\theta}_i^{c,v} = a + \pi \times specialization_i + \boldsymbol{x_i'\beta} + \varepsilon_i \tag{3.2}$$

The distribution of the estimated π may depart from known distributions, so bootstrapping inference is undertaken. In order to perform statistical inference, the bootstrap replications of the impulse response characteristics $\hat{\theta}_{i,b}^{c,v}$ are used to re-estimate the parameter π for each bootstrapped impulse response available. The standard deviation of these bootstrapped estimates is interpreted as the standard error of $\hat{\pi}$.[7]

3.4 Data

Full data exist for sectoral employment and wages in each of the 940 Core-based Statistical Areas (CBSAs) in the U.S. using the BLS' Quarterly Census of Employment and Wages (QCEW). This data set is observed at the county level, and aggregated based on 2007 MSA definitions to create the city-level measures. The QCEW covers 99.7% of all U.S. employment, and has data at the quarterly frequency from 1990:1 through the present.

Data on house prices are available from the Federal Housing Finance Agency (FHFA, formerly OFHEO) at a quarterly frequency for 352 CBSAs from 1975:1 through the present. Thus, the intersection of the employment, wage, and house price series is the 352 cities in the FHFA index from 1990:1-present. I restrict the sample to end at 2007:4 because of the global financial crises and the associated structural shifts that have taken place since that time. The estimation sample is therefore 1990:1-2007:4. This sample covers 85% of all U.S. employment.

Several additional variables must be constructed using these data, with some additional information from other data series as well. These include various census variables found using the Census' USA Counties Datafile and HUD's State of the Cities data system, and price variables found in the BLS'

[7] The 90% confidence interval for π can also be computed using the 5th and 95th percentile estimates of π_b. However, due to the large number of cities and equations estimated, only 100 bootstrapping replications are feasible. Because of the small number of bootstraps, the distribution of the bootstrap estimates at the tails is extremely lumpy. For this reason, the percentile-t method of Efron (1981) is used instead.

PPI and CPI series.

3.4.1 Demand determinants

Three different demand determinants are considered when estimating the first-stage models: the Export Price Index, Bartik's (1991) local industry-weighted national employment variable, and a new variable which is similar to Bartik's variable but uses spatial weights instead of industry weights.

The Export Price Index (EPI) was first designed by Pennington-Cross (1997) and updated by Hollar (forthcoming), and is a variable that represents the prices exporting firms in cities receive when the export to other cities and regions. The EPI is a Laspeyres price index which uses a local industry weighted average of national producer prices.[8] Because this variable is determined in a time series setting at the national level, if one assumes that cities are price takers, then the EPI is a locationally exogenous variable by construction.

Bartik's employment variable is the precursor to the EPI. This variable uses locally weighted national employment to construct an employment instrument sterilized of all local effects. While this variable has several shortcomings, as noted by Rickman (2010), it has been used in a variety of studies as a demand instrument.[9]

The last local demand variable considered is a spatially weighted national employment variable. Owyang, Piger, and Wall (2005) show that employment growth is spatially correlated, so employment changes in surrounding cities may prove to be good predictors of future employment growth in a city.

[8]The construction has many additional details to the discussion here, which can be found in Chapter 2.

[9]See Blanchard and Katz (1992), Saks (2008), and Chapter 2, for some examples.

Weights are constructed using what Anselin (2002) calls "gravity" weights:

$$w_{ij} = \frac{1}{d_{ij}^{\alpha}} \tag{3.3}$$

where d is distance from city i to city j, and α is a dampening parameter set equal to 2. The weights are normalized to sum to one and the spatially weighted employment variable is constructed.

$$e_i = \sum \tilde{w}_{ij} e_j \tag{3.4}$$

3.4.2 Controls

One other variable that needs some discussion is one of the control variables used in the second stage regressions. This variable is called the Urban Decline Index (UDI) and is constructed as a proxy for urban decline in cities. Urban decline is notoriously difficult to quantify, so this variable takes several measures used in the literature, standardizes them, and adds them together to form the index. This variable is explained in Chapter 2. As Glaeser and Gyourko (2005) and Chapter 2 shows, urban decline dramatically reduces the elasticity of housing and labor supplies in cities, thus affecting the dynamic effects of shocks. Thus, when attempting to measure the effects of industrial specialization on urban dynamics, it is necessary to control for urban decline.

3.4.3 Industrial specialization indices

Three different industrial specialization (also known as concentration) indices are considered in this paper. In each of these three indices, a lower value indicates greater diversification among export industries. The first is the commonly used Herfindahl-Hirschman index (HHI). This variable has been used by Henderson, Kunkoro, and Turner (1995) and Rosenthal and Strange (2003) as a measure of industry concentration. The HHI for city i is computed as follows, where s is the export share of industry $n \in N$: [10]

$$HHI_i = \sum s_{in}^2 \tag{3.5}$$

Table 3.3 presents the most specialized and diversified cities ranked by the HHI. The top diversified cities are often large cities, as compared to the specialized cities which tend to be small. The diversified cities also are commonly known for their industrial breadth, whereas the specialized cities are often focused in the gambling and gaming industries or specialized manufacturing.

Another index that is popular in other branches of the sciences is Shannon's (1948) entropy index.

$$Shannon_i = \sum s_{in} \ln s_{in} \tag{3.6}$$

Finally, I consider a cruder form of concentration measure, the export share of the largest export industry. This is simply defined as

$$maxshare_i = \max\{s_{i1}, s_{i2}, ..., s_{iN}\} \tag{3.7}$$

3.5 Results

Tables 3.4 through 3.6 and Figures 3.1 through 3.3 show the effects of an export price index (EPI) shock on employment, wages, and house prices in

[10] Export employment is calculated using the location quotient approach. See Brown, Coulsen, and Engle (1992) for more information on location quotients.

cities with different levels of industrial specialization.[11] Broadly speaking, these results indicate that industrial specialization increases the effects of local demand shocks on the responses to local endogenous housing and labor market variables. These results are consistent across different measures of industrial specialization, and statistical significance is established using bootstrapped standard errors.

In particular, a 0.1 unit change to the Herfindahl-Hirschman index (about 1 standard deviation; see Table 3.2) increases the effect of a 1 unit EPI shock on employment by 2-4%, wages by 5%, and house prices by 1-3% at a time horizon of 2 years. These results imply that a change in the price of goods and services exported from a diverse city like Chicago has a 25% larger effect on employment than an equivalent shock to prices in a specialized city like Las Vegas.[12] Over time, specialization measures, demand measures, and control sets, the effects of industrial specialization are of a similar sign.

These results are consistent with the literature on export multipliers. Harvey (1973) estimates the effect of diversification on the export multiplier to be 0.23. Harvey uses a dummy variable set equal to 0 if the economy is specialized and 1 if it is diversified, and estimates total employment to base employment ratio as a function of this variable over a cross-section of cities. In the estimates in Table 3.4, a HHI change of 0.5 is required to generate the same effect as in Harvey, and this value is well within the range of HHI values in my sample.

[11] Results from the first stage time series regressions are consistent with those in Chapter 2, and so will not be discussed. Instead, in this section, I will focus on the second stage results.

[12] $0.39 \times 0.65 = 25\%$

3.6 Conclusions

This paper shows that industrial specialization affects the dynamic responses of local variables to local shocks. Cities with higher industrial diversification experience larger effects of shocks to employment, wages, and house prices relative to cities that are highly specialized.

These results are in agreement with the vast literature on the long-run determinants of growth in cities; that is, cities that are more diverse grow faster than those who specialize. These results are also consistent with prior theory and estimates of the determinants of export multipliers in economic base models.

While diversification of the economic base itself may influence the frequency and amplitude of demand shocks hitting a local economy, this paper does not speak to its effects on the *incidence* of shocks. Cities that are more diversified may experience different frequency and magnitudes of shocks than specialized cities. It is likely that cities with a diversified portfolio of export products may reduce their exposure to idiosyncratic, industry-specific risks, even while they are affected more than specialized cities to equivalent shocks. The research in this paper helps to fill the gap in the literature concerning the measurement of the short-run effects of industrial diversification. This knowledge is important when it comes to understanding the full costs and benefits of local industrial policies.

3.7 Tables

Table 3.1: Correlations between industrial specialization indices

	Herfindahl-Hirschman Index (HHI)	Shannon Index ($Shannon$)	Export share of largest export industry ($maxshare$)
HHI	1		
$Shannon$	0.8143	1	
$maxshare$	0.6639	0.6789	1

Table 3.2: Summary statistics of industrial specialization indices

	N	Mean	Std. Dev.	Min	Max
Herfindahl-Hirschman Index (HHI)	352	0.098	0.083	0.017	0.826
Shannon Index ($Shannon$)	352	-3.106	0.582	-4.886	-0.523
Export share of largest export industry ($maxshare$)	352	0.377	0.154	0.148	0.957

Table 3.3: Top 10 diversified and specialized cities

Top 10 most diversified cities

CBSA Code	CBSA Name	Population (1990)	Herfindahl-Hirschman index	Shannon index	Export share of largest export industry
16980	Chicago, IL-IN-WI	8,182,076	0.018	-4.89	0.28
19100	Dallas, TX	3,989,294	0.020	-4.55	0.28
33340	Milwaukee, WI	1,432,149	0.022	-4.35	0.41
40140	Riverside, CA	2,588,793	0.025	-4.40	0.21
15380	Buffalo, NY	1,189,288	0.026	-4.16	0.18
31100	Los Angeles, CA	11,273,720	0.026	-4.82	0.34
33100	Miami, FL	4,056,100	0.027	-4.33	0.16
26420	Houston, TX	3,767,335	0.027	-4.31	0.21
39740	Reading, PA	336,523	0.028	-3.92	0.23
35620	New York, NY-NJ-PA	16,846,046	0.028	-4.32	0.26

Top 10 most specialized cities

CBSA Code	CBSA Name	Population (1990)	Herfindahl-Hirschman index	Shannon index	Export share of largest export industry
23540	Gainesville, FL	191,263	0.276	-2.25	0.58
22220	Fayetteville, AR-MO	239,464	0.292	-1.88	0.50
23580	Gainesville, GA	95,428	0.307	-1.99	0.57
39900	Reno, NV	257,193	0.400	-1.85	0.62
25060	Gulfport-Biloxi, MS	207,875	0.403	-1.75	0.77
25500	Harrisonburg, VA	88,189	0.528	-1.31	0.73
48620	Wichita, KS	511,111	0.534	-1.48	0.84
19140	Dalton, GA	98,609	0.553	-1.17	0.85
29820	Las Vegas, NV	741,459	0.670	-1.11	0.83
12100	Atlantic City, NJ	224,327	0.827	-0.52	0.92

Table 3.4: Second stage regression results: Herfindahl-Hirschman index

Equation	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Response Variable	Emp-loyment	Wage	House Prices	Emp-loyment	Wage	House Prices	Emp-loyment	Wage	House Prices
Herfindahl-Hirschman index	-0.061 0.139	-0.705*** 0.107	-0.379** 0.210	-0.225* 0.144	-0.607*** 0.109	-0.116 0.217	-0.393*** 0.146	-0.525*** 0.106	-0.202 0.220
Urban Decline Index				-0.080*** 0.016	0.076*** 0.012	0.222*** 0.016	-0.079*** 0.016	0.076*** 0.012	0.223*** 0.016
Population (log, 1990)							-0.057*** 0.012	0.040*** 0.013	-0.038** 0.020
N	352	352	352	347	347	347	347	347	347

Notes: This table presents the results from nine different equations. The dependent variable is the 8th quarter response of the variable in the column to a 1-unit EPI shock. Estimates are calculated using STATA's rreg command. Standard errors are bootstrapped. Constant term estimated but not presented. *, **, and *** indicate 10%, 5% and 1% significance based on one-tailed tests.

Table 3.5: Second stage regression results: Shannon index

Equation	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Response Variable	Emp-loyment	Wage	House Prices	Emp-loyment	Wage	House Prices	Emp-loyment	Wage	House Prices
Shannon Index	0.026* 0.020	-0.114*** 0.019	-0.021 0.034	0.011 0.020	-0.105*** 0.019	0.001 0.035	-0.075*** 0.026	-0.088*** 0.021	-0.056 0.046
Urban Decline Index				-0.077*** 0.015	0.079*** 0.012	0.224*** 0.016	-0.076*** 0.015	0.080*** 0.012	0.224*** 0.016
Population (log, 1990)							-0.075*** 0.015	0.018 0.015	-0.053** 0.025
N	352	352	352	347	347	347	347	347	347

Notes: This table presents the results from nine different equations. The dependent variable is the 8th quarter response of the variable in the column to a 1-unit EPI shock. Estimates are calculated using STATA's rreg command. Standard errors are bootstrapped. Constant term estimated but not presented. *, **, and *** indicate 10%, 5% and 1% significance based on one-tailed tests.

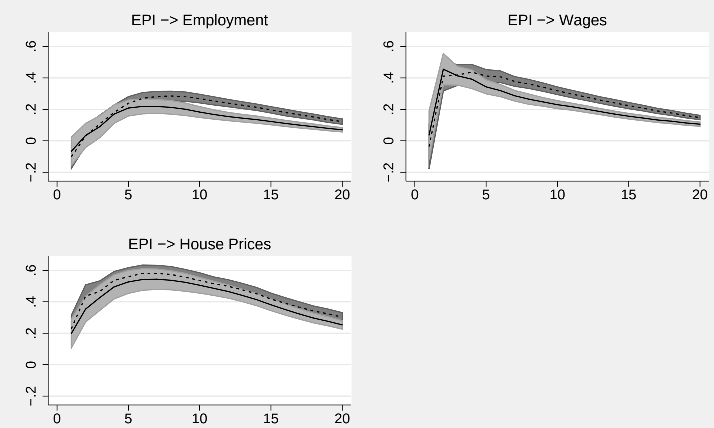
Table 3.6: Second stage regression results: export share of largest export industry

Equation	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Response Variable	Emp-loyment	Wage	House Prices	Emp-loyment	Wage	House Prices	Emp-loyment	Wage	House Prices
Export share of largest ex. industry	-0.134**	-0.458***	-0.417***	-0.242***	-0.372***	-0.206**	-0.380***	-0.310***	-0.305***
	0.061	0.053	0.097	0.068	0.055	0.102	0.070	0.061	0.108
Urban Decline Index				-0.084***	0.071***	0.217***	-0.083***	0.073***	0.216***
				0.016	0.012	0.017	0.012	0.012	0.017
Population (log, 1990)							-0.067***	0.032***	-0.048***
							0.016	0.014	0.020
N	352	352	352	347	347	347	347	347	347

Notes: This table presents the results from nine different equations. The dependent variable is the 8th quarter response of the variable in the column to a 1-unit EPI shock. Estimates are calculated using STATA's rreg command. Standard errors are bootstrapped. Constant term estimated but not presented. *, **, and *** indicate 10%, 5% and 1% significance based on one-tailed tests.

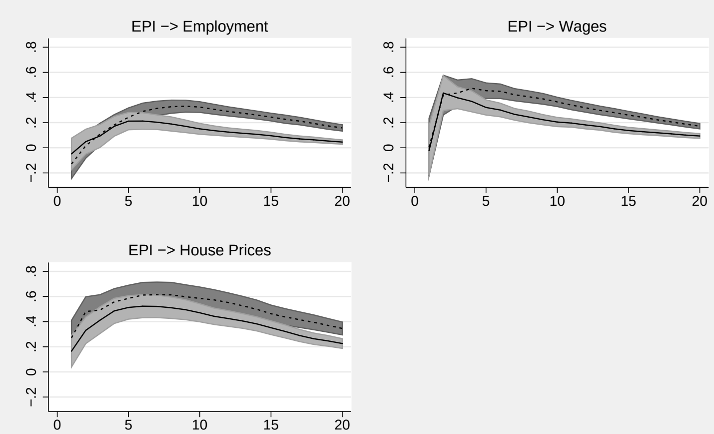
3.8 Figures

Figure 3.1: Industrial diversification (HHI) and the effects of local demand shocks



Effect of a 1 unit shock to X on Y, t quarters from the shock.
The solid line represents a highly specialized city (5th percentile of the Herfindahl−Hirschman index).
The dotted line represents a highly diversified city (95th percentile of the Herfindahl−Hirschman index).
Shaded areas are +/− 2 SEs (bootstrapped).

Figure 3.2: Industrial diversification (Shannon Index) and the effects of local demand shocks



Effect of a 1 unit shock to X on Y, t quarters from the shock.
The solid line represents a highly specialized city (5th percentile of the Shannon index).
The dotted line represents a highly diversified city (95th percentile of the Shannon index).
Shaded areas are +/− 2 SEs (bootstrapped).

Figure 3.3: Industrial diversification (Maximum export share) and the effects of local demand shocks

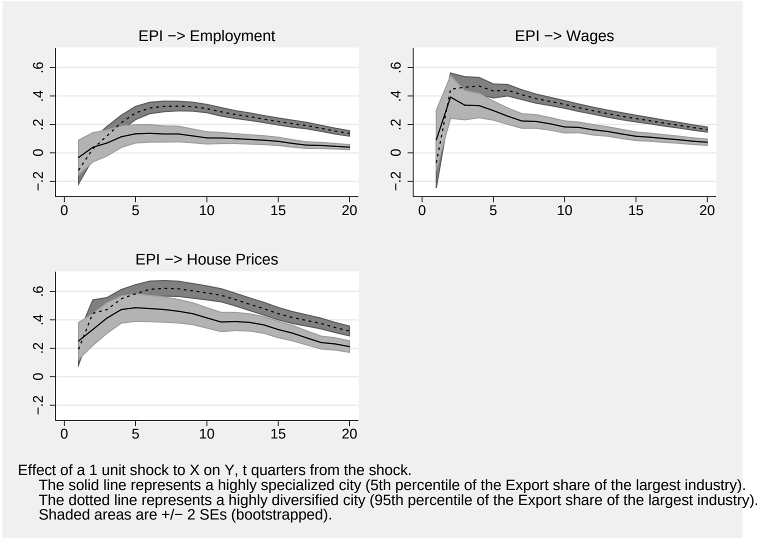
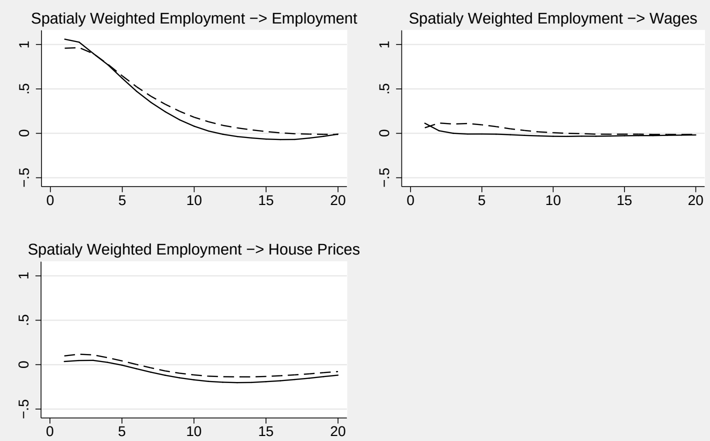


Figure 3.4: Industrial diversification robustness check: local industry-weighted national employment

Figure 3.5: Industrial diversification robustness check: spatially weighted national employment



Effect of a 1 unit shock to X on Y, t quarters from the shock.
The solid line represents a highly specialized city (5th percentile of the Herfindahl−Hirschman index).
The dotted line represents a highly diversified city (95th percentile of the Herfindahl−Hirschman index).

Chapter 4

Evaluating Alternative Methods of Forecasting House Prices: A Post-Crisis Reassessment

4.1 Introduction

Despite the importance of the residential sector of the U.S. economy, relatively few studies have assessed the performance of alternative time series models that forecast the price of housing services. This is surprising, given the importance of house price forecasts in predicting mortgage defaults, property taxes, and a number of other consumption, investment, and policy decisions (Kochin and Parks, 1982; Demyanyk and Van Hemert, forthcoming) Furthermore, there is evidence that house prices are forecastable to a certain degree (Case and Shiller, 1989, 1990; Crawford and Fratantoni, 2003). Accordingly, it is useful to determine which forecasting models are best able to capture the future movements of house prices.

This paper reconsiders the existing evidence on which classes of simple time-series models best forecast house prices: theory-driven multivariate models or atheoretical univariate models. In particular, I ask three questions:

- Which class of models was able to predict a turning point in the housing market before house price declines occurred?
- Which class of models forecast best from the peak of house prices from 2006, multiple steps ahead, over the next three years?
- Which class of models had the lowest error and unique information in forecasts one step ahead during the period of house price declines?

In order to answer these questions, eight different empirical house price models are estimated using Federal Housing Finance Agency (FHFA, formerly OFHEO) house price data for California.[1] Pseudo *ex ante* forecasts are then computed and these forecasts are evaluated along a number of dimensions.[2]

Models are chosen to reflect different variable transformations (levels vs. first- or second-differences), information sets (incorporating non-house price series), and parameter restrictions (e.g. cointegration). In total, five univariate models are considered: two autoregressive (AR) models, an autoregressive fractionally integrated moving average (ARFIMA) model, an unobserved components (UC) model, and a random acceleration model. Three multivariate models are considered as well: a vector autoregression (VAR) in levels with house prices, personal incomes, and rental prices, a vector error correction (VEC) model with house prices and personal incomes, and a VEC model with house prices and rental prices. The literature suggests that there should be, *a priori*, a cointegrating relation between incomes and house prices and between

[1]California is the subject of study because three other works in the literature, Crawford and Fratantoni (2003), Miles (2008), and Gupta and Miller (2010), consider California as well. Additionally, data on personal incomes are available at the state level but not at the city level.

[2]Pseudo *ex ante* forecasts are constructed using only information that was available at the time of the forecast. For example, a model used to produce forecasts in 2005:Q4 would only include data up to 2005:Q4.

rental and house prices (Malpezzi, 1999; Gallin, 2008). It is therefore plausible that VEC models would forecast quite well when the housing market is at a state of long-run disequilibrium such as at the peak of a house price bubble.

I find that multivariate models are best able to forecast the turning point in the California housing market. As far back as 2004, error correction models predicted that the growth in house prices in California was unsustainable, and retrenchment would occur. This suggests that expanding the model information set to include other variables and imposing cointegration restrictions helps to predict turning points.

I also find that from the peak in house prices in 2006, n-step forecasts constructed using multivariate models perform the best over the next three years. While all models exhibit bias, the multivariate models are substantially closer to the true decline in house prices than the univariate models.

Finally, I find that multivariate models also have the lowest 1-step ahead forecast error during the period of house price declines, though the differences between these and the univariate models are small. Forecast encompassing tests show that in none of the 45 tests performed, does any multivariate model fail to encompass any univariate model. However, no model's 1-step forecasting error is as small as its in-sample estimation error, suggesting that either each of the forecasts considered leaves out some valuable information, or that structural shocks during the forecasting period were of higher variance than during the estimation period.

4.2 Stylized facts from the literature on housing markets

This section describes some of the broad characteristics of the housing market and several popular methods of modeling house prices. There are two stylized facts regarding the movement of house prices that motivate much of the house price literature. The first is that house price changes are highly persistent from one period to the next (Case and Shiller, 1989, 1990; Meese and Wallace, 1991; Glaeser and Gyourko, 2006). The second is that the housing market is prone to large boom periods followed by painful corrections (Muellbauer and Murphy, 1997; Glaeser and Gyourko, 2006).

Case and Shiller (1989, 1990) find that house price changes are highly persistent, and that house prices are forecastable over short time horizons. This has since become a well-known time series property of house prices, and has influenced much research on the subject, ranging from its implications for the efficiency of the housing market to the effect of this persistence on house price cycles. Glaeser and Gyourko (2006) remark that in the U.S. between 1980 and 2005, a $1 increase in real house prices in one year is associated with a $0.71 increase in house prices the following year. Various explanations exist as to why this is the case. Muellbauer and Murphy (1997), for example, argue that credit rationing, uncertainty, and transaction costs all contribute to the persistence of house price changes.

Muellbauer and Murphy (1997) go on to argue that it is this persistence in house price changes that contributes to the boom-bust nature of the housing market. While yearly house price changes are positively correlated, Glaeser and Gyourko (2006) show that five-year house price changes are negatively correlated, with a \$1 increase in house prices in one year being correlated with a \$0.32 decrease in house prices over the next five years.

Malpezzi (1999) shows that this reversion in house prices can be modeled as a reversion to a long-run relationship of house prices and incomes. Malpezzi estimates a panel equilibrium correction model of house prices in U.S. cities and finds that house prices correct to a long-run, area-specific, house price-income ratio. Similarly, it is a standard in user cost theory that house prices and rental prices share a long-run error correcting relationship. This link is related to the dividend pricing hypothesis in that the discounted stream of monthly user costs should approximate the price of the unit. Gallin (2008) estimates both a quarterly differenced model and a four-year differenced model and finds that house prices adjust to a constant long-run rental price-asset price ratio.[3]

Models where house prices correct to established long-run relationships may depend on the sample over which the relationship is measured. For example, while Gallin (2008) finds strong evidence of equilibrium correction in house prices and rents, Verbrugge (2008) describes how user costs have diverged from rents for quite some time, and that perhaps an equilibrium correcting relationship does not exist. However, Verbrugge's estimation sample ends at the peak of the house price bubble, making it clear in hindsight why he found no evidence of equilibrium correction.

4.3 Previous house price forecast comparisons

There are few papers comparing different house price forecasts in the literature. In general, forecast comparison exercises focus on univariate models

[3]Davis and Palumbo (2008) find that land prices drive house prices to a large degree, but this approach is difficult to implement because of the difficulty of measuring land prices.

and are compared on the basis of MSFEs. Many studies of house price dynamics have considered periods where prices were increasing and have not had to deal with problems created by major turning points. Under the circumstances considered, research has mostly found that univariate time series models perform better than multivariate VAR and error correction models motivated by economic theory. Other, more recent evidence suggests, however, that multivariate models may be able to predict turning points and produce good forecasts during periods of disequilibrium in the housing market.

One of the first house price forecast comparisons in the literature is Brown, Song, and McGillivray (1997). They consider UK house prices and consider a univariate time-varying coefficients model, an error correction model, an AR and a VAR model. Brown, Song, and McGillivray find that a time-varying coefficients model outperforms all others based on the MSFE of the different forecasts.

Crawford and Fratantoni (2003) consider house price forecasts of different U.S. states using the FHFA repeat-sales house price indices. They compute forecasts based exclusively on univariate house price models and evaluate their forecasts using MSFE and mean absolute deviation (MAD). Models considered include ARIMA, GARCH, and Markov-switching models. They find that ARIMA models are best able to forecast house price changes 1-step ahead based on MSFE comparisons. While Markov-switching models offer the best fit in-sample, this class of models performs quite poorly in out of sample forecasting tests compared to the other models considered. Miles (2008) closely follows Crawford and Fratantoni and finds that generalized autoregressive (GAR) models outperform ARIMA models.

Guirguis, Giannikos, and Anderson (2005) examine forecasts of the U.S.

housing market using GARCH, AR, Kalman filters, and VEC models. They find the Kalman filters and the GARCH models forecast best on the basis of MSFE comparisons. However, the VEC forecasts they consider are based on a cointegrating relation covering the forecasting period as well as the estimation period. This approach is not a realistic forecasting exercise because forecasts are generated based on information unobtainable at the time of the forecast.

Gupta and Miller (2010) provide a recent study of MSA-level house prices in California. They consider a variety of specifications, including spatial VAR, spatial VEC, and spatial BVAR models. They find that different models forecast better in different locations, and that the best model in terms of overall RMSE in each location is able to predict turning points in the respective housing markets four quarters ahead with reasonable accuracy.

In general, the literature finds that univariate time series models are able to forecast better than theory-driven multivariate models. These evaluations are mostly performed over periods of increasing house prices. All of the papers' primary comparison measures are MSFEs, and they do not consider other forecast comparison metrics such as the ability to predict turning points (with the exception of Gupta and Miller) or the relative information content of rival forecasting models.

The approaches in the literature can be extended in two main ways. First, researchers who model house prices successfully do so using models that are able to capture both persistence and equilibrium correction. While all of the papers considered are able to model persistence, models able to represent equilibrium-correcting systems such as vector error correction models have not been fully explored. Many of those who have forecasted using VEC models have either done so over periods of increasing house prices (Brown, Song, and McGillivray, 1997) or they are conditional forecasts (Guirguis, Giannikos, and Anderson, 2005). Gupta and Miller's (2010) success in modeling house prices and predicting turning points shows that VEC models should be given a closer look, and that they may be able to predict turning points farther back in time and forecast well during periods of declining prices. Because error correction models are, by definition, able to model equilibrium-correcting systems, it is plausible that VEC models could perform well during periods of disequilibrium.

There are a number of different ways of comparing forecasts beyond MSFEs. For example, forecast encompassing tests can evaluate the relative information content of forecasts and parameter constancy tests can establish the adequacy of forecasting models during the forecasting period. These tools are readily available and should be utilized to compare and contrast the various characteristics of forecasts.

4.4 Statistical forecast comparison methods

Beyond the previously noted MSFE comparisons, there are several other ways of comparing rival forecasts. This section describes three of these means of comparison: bias tests, parameter constancy tests and forecast encompassing tests. When it is not obvious which forecasts are better than others, these comparison statistics, along with usual measures of MSFE and bias, can be used to establish rankings and evaluate the relative information content of a set of rival forecasting models.

Suppose a set of data over which a model is estimated on observations $t = 1, ..., T$ and forecasts $\tilde{Y}_t$ are generated from $t = T+1, ..., T+H$. Actual values are denoted as Y_t, and subtracting the actual from the forecast yields forecast errors ε_t. Mincer and Zarnowitz (1969) propose a bias test where, for a set of 1-step ahead forecasts, equation 4.1 is estimated and the joint hypothesis $\{\alpha = 0; \beta = 1\}$ is tested. A rejection of this null hypothesis is interpreted as evidence of bias in the forecasts.[4]

$$Y_{T+h} = \alpha + \beta \tilde{Y}_{T+h|T+h-1} + e_{T+h} \tag{4.1}$$

While the Mincer and Zarnowitz approach tests for *average* bias, Hendry's (1974) parameter constancy test establishes the *expected* bias of the individual forecast errors. This test can detect systematic biases that on average, are offsetting. Hendry's test statistic is the ratio of the mean squared forecast error and the in-sample residual variance.

$$\frac{MSFE}{\sigma^2} \sim F(H, T-k) \tag{4.2}$$

Under the null, the ratio of these variances follows an F distribution with H and $T-k$ degrees of freedom, where H is the number of forecasts used to compute the MSFE, T is the number of observations in the estimation sample, and k is the number of parameters estimated. This is equivalent to testing

$$E\left[(\varepsilon_{T+1}, \varepsilon_{T+2}, ..., \varepsilon_{T+H})'\right] = \mathbf{0} \tag{4.3}$$

A rejection of this null hypothesis indicates that 1), the parameters that define the relationship between exogenous variables and Y are non-constant between the estimation period and the forecasting period, and 2), that the

[4] Holden and Peel (1990) show that such a rejection is a sufficient but not necessary characteristic of a biased forecast.

expected bias of the individual forecast errors is nonzero.

Forecast encompassing tests are also used to evaluate and compare different forecasts. These tests were formalized by Chong and Hendry (1986) and extended by Ericsson (1992, 1993). They extend the Mincer and Zarnowitz's (1969) bias test to incorporate information from a rival forecast $\hat{Y}$, and test the relative information content of $\tilde{Y}$ versus $\hat{Y}$. When comparing two forecasts, if a first model contains information relevant to forecasting that a second model does not, the first model is said to "forecast encompass" the second.

Ericsson's (1993) test of forecast encompassing is selected over Chong and Hendry's version because it has higher power when Y, $\tilde{Y}$ and $\hat{Y}$ are I(1) and $Y - \tilde{Y}$ is I(0). Under these circumstances, the Chong and Hendry test involves estimating a regression of unbalanced order, whereas the Ericsson test addresses this issue. In the Ericsson test, the base equation is:

$$Y_{T+h} - \tilde{Y}_{T+h|T+h-1} = \alpha + \gamma(\hat{Y}_{T+h|T+h-1} - \tilde{Y}_{T+h|T+h-1}) + e_{T+h} \tag{4.4}$$

There are three tests that can be performed based on the above equation. Each of these tests represents slightly different assumptions, hypotheses, and has different resulting implications. The first two variants estimate equation 4.4, but the encompassing test is performed under different null hypotheses. The first is that $\hat{Y}$ contains no unique information that could be used to forecast Y that $\tilde{Y}$ does not provide. Under this null, $\{\gamma = 0\}$. The second test is the same as the first, but simultaneously tests that $\tilde{Y}$ is an unbiased forecast. Under this second null, $\{\alpha = 0; \gamma = 0\}$. Another way of interpreting the second test is as a forecast encompassing test versus *two* rival forecasts: a constant forecast and $\hat{Y}$.

The third test assumes *a priori* that $\alpha \equiv 0$ and tests that $\{\gamma = 0\}$. This forces the Ericsson regression through the origin and thus risks omitting a potentially critical deterministic component. However, this equation saves one degree of freedom relative to the regression in the first two tests, and thus has higher power, especially in small sample sizes and when $\tilde{Y}$ is an unbiased forecast.

A rejection of tests one or three indicates that the rival model contains information useful to forecasting that the encompassing model does not. This is classified as a *failure to encompass*. A rejection of test two may indicate a failure to encompass $\hat{Y}$, but may instead indicate that $\tilde{Y}$ is a biased forecast. A failure to reject, in any case, indicates that there is no unique information in the rival forecast and that $\tilde{Y}$ *encompasses* $\hat{Y}$.

4.5 Alternative forecasting models

This section describes the eight models used to compute the house price forecasts evaluated in this paper.[5] Of these models, five are univariate and three are multivariate, and each is shown in Table 4.1. The set of models considered is meant to reflect the wide number of choices based on the literature reviewed above, including different variable transformations (levels vs. first or second differences), information sets (incorporating non-house price series), and parameter restrictions (e.g. cointegration).

The first model considered is a random acceleration model. The forecast of a non-seasonal, second-differenced model is $\Delta^2 \hat{Y}_{T+1|T} = 0$, or equivalently

[5]When models are of first- or second- differences, the log-level of house prices is constructed using the difference equation identities.

that $\Delta\hat{Y}_{T+1|T} = \Delta Y_T$, and $\hat{Y}_{T+1|T} = Y_T + \Delta Y_T$. Second-differenced models are robust to changes in deterministic constant terms, trends, and long-run equilibria. A random acceleration model's forecasts may be hard to beat in terms of RMSE because it immediately incorporates shifts in the first and second derivatives of house prices into forecasts for the next period, thus eliminating forecast bias due to deterministic shifts. However, this extreme adaptability comes at cost of a higher expected forecast error variance, as Hendry (2006) shows.

An AR(1) model of the level of house prices is the second model considered. Because house prices are highly persistent, this will be nearly equal to a random walk-with-drift model. The AR(1) model has some different characteristics than the random acceleration model. Assuming the data generating process is also AR(1), it has a lower expected forecast error variance provided there are no changes in the deterministic components of the model during the forecast period.[6] Additionally, the AR(1) model does not allow for persistence in growth rates. Because house prices exhibit persistent growth rates, as seen in Figure 2, the AR(1) model is likely to forecast poorly.

An AR(p) model shares many of the same characteristics as the AR(1) model, but is better specified because the optimal number of lags are included.[7] This eliminates autocorrelation that is likely to exist in an AR(1) model and therefore will produce more unbiased and consistent parameter estimates. Autocorrelation is likely to exist based on the well-established finding

[6] However, if deterministic components change, then large biases could result, pushing the MSFE higher than the random acceleration model.

[7] The choice of $p = 6$ lags is made based on estimating the model with $p + m$ lags for some chosen p and m and then testing if each of the lags $\rho_{p+1} = \rho_{p+2} = ... = \rho_{p+m} = 0$. If this hypothesis is rejected, p is increased by one and the test is redone. This continues until the hypothesis is not rejected, which in this case, occurs when $p = 6$.

that house price changes are persistent.

An ARFIMA(2,d,2) model allows for fractional differencing and persistence in the error terms, in addition to autoregressive parameters. However, without second-differencing, its forecasts will not be robust to deterministic shifts in trend and equilibrium shifts. If $d > 1$, then the ARFIMA model's forecasts are robust to deterministic constant term shifts.

A standard unobserved components model includes level, trend, seasonal, and irregular components that are allowed to change over time. The trend is defined based on a linear dynamic system that encompasses a linear trend model, a random walk model, and a random walk with drift model. Without deterministic shifts, the UC model is likely to forecast well because of its incorporation of changes to the first derivative of house prices in the trend component. However, because the UC is explicitly based on deterministic (albeit evolving) components, it is particularly susceptible to deterministic shifts during the forecasting period.

VEC models of rental prices of housing services and house prices, and personal incomes and house prices impose a long-run relationship on the ratio of a particular variable with house prices. In VEC models, house price changes are modeled as a function of the current deviation from this relationship.[8] Because they are differenced with proper lag selection, these models are robust to constant shifts and can model persistence in growth rates. Also, due to the error correction term, these models incorporate long-run mean reversion. The fact that short-run growth persistence and long-run mean reversion are two of the defining characteristics of house prices indicates that VEC models should

[8] Justification for these restrictions is based on Johansen (1988) cointegration tests based on the literature described in Section 2, which confirm the presence of cointegration.

be used to forecast house prices.[9]

The final model is a VAR(5) consisting of the levels of house prices, rental prices of housing services, and personal incomes. This unrestricted VAR in levels generalizes the two VECs considered previously. Perhaps there are other interrelationships at work than error correction, or error correction is of an alternative form to that which is parameterized in the VEC models.

4.6 Data

The house price data are from the Federal Housing Finance Agency (FHFA, formerly OFHEO) and are quarterly from 1975:Q1 to 2009:Q4, yielding 140 observations. Personal income data is from the Bureau of Economic Analysis. The rental price data are from the Bureau of Labor Statistics' Rent of Shelter index for the West Urban geographic area.

House prices are notoriously difficult to measure because of the need to control for substantial heterogeneity in the quality of the housing stock. Each measure is different and none is perfect, so it is important to consider each when choosing an index of study. The FHFA index is a repeat-sales index, and thus does not consider prices of new home sales. It also only includes houses whose mortgages have been securitized or purchased by Freddie Mac or Fannie Mae. The Case-Shiller index is also a repeat-sales index, but it includes all types of transactions, including those with subprime mortgages or fraudulent transactions. The National Assoication of Realtors produces a median sales price index, but this index is not constant-quality. The FHFA index is used in this paper due to the length of the time series and to make this research

[9] Gupta and Miller (2010) consider a spatial VEC where city-level house prices converge to a regional equilibrium. This type of equilibrium correction is not considered in this paper.

comparable to past reaserch using this index. Furthermore, due to the rise in subprime loans in the early 2000s, using the FHFA index keeps the sample of homes in the index somewhat consistent in terms of loan type.

Figures 1a and 1b illustrate the several stylized facts that were previously noted, including the tendency for persistence in growth rates and mean reversion over long periods. Figure 1a indicates that there may be a long-run statistical relationship between house prices and incomes as Malpezzi (1999) finds. Figure 1b shows that there may be a similar long-run relationship between house prices and rents, as Gallin (2008) suggests. Case and Shiller (1989) show that house price growth rates show substantial autocorrelation across time, and Figure 4.2 shows this to be true in California, at least recently.

The FHFA price index is a repeat sales house price index. The construction method of this variable may affect certain test statistics, especially parameter constancy tests. A repeat sales house price index is based on transaction data for individual homes that have sold at least twice. The index is constructed by first estimating the change in appreciation for a pair of transactions for some unit i as a function of dummy variables set at -1 and 1 at the time of the first and second transactions.

$$\Delta V_i = \sum \beta_t D_{it} + \varepsilon \tag{4.5}$$

Errors are heteroskedastic as a function of the distance between transactions, so this regression is estimated using an FGLS procedure following Case and

Shiller (1989)[10]. The index is then computed as

$$I_t \equiv e^{\hat{\beta}_t} \tag{4.6}$$

This correction does not address a different sort of heteroskedasticity: measurement error. Because the index relies on pairwise transactions, as new sales occur, past index values are revised. Therefore, a repeat sales price index calculated from time $t = 1...T$ has measurement error variance increasing with t and is highest at time T. [11]

$$var(I_t) = \sigma_t^2;\ d\sigma_t^2/dt > 0 \tag{4.7}$$

4.7 Forecast results and comparisons

4.7.1 Model fit

Table 4.2 presents a number of different model and forecast evaluation measures. The standard deviation of the errors of the RACC model is 0.012, which is only slightly larger than the standard deviation of the errors in models with many estimated parameters, which are .011 or .012 for six of the other seven models considered. In contrast to the other models, the AR(1) model fits the data relatively poorly, with an in-sample residual standard deviation of 0.025.[12]

[10]See Pennington-Cross (2005) for a concise explanation of repeat sales indices.

[11]Because the measurement error variance is predicted to be larger during the forecasting period than the estimation period, parameter constancy tests using repeat sales data may over-reject the null and a GLS procedure that addresses this known form of heteroskedasticity may perform better than unweighted tests.

[12]Full model results are available online at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1709647 in the appendix.

4.7.2 Forecasting the turning point

Next, I consider which models were able to forecast the turning point in the housing market. The *turning point* is defined as the period in which house prices first decline, which occurs in 2006:Q3. Before this period, house prices in California had risen continuously since 1996. Figure 4.3 presents rolling-window, pseudo *ex ante* forecasts.[13] The figure is representative in that the error correction model was able to predict the declines in house prices experienced in California before declines were ever observed. These results are broadly consistent across the three multivariate models.

The AR(6) model forecasts house price increases in perpetuity until the quarter before the decline in house prices. While this model predicts a flattening of house prices in the 2006:Q2 and 2006:Q4 forecasts, it never predicts any significant house price declines until declines are actually observed. These results are similar to the other four univariate models considered, and suggest univariate models were unable to forecast the turning point in the housing market.

In general, error correction models were relatively successful in predicting that a turning point would occur, though concordance with the actual turning point is weak. The VEC-INC model is substantially better at forecasting the turning point than the AR(6) model, predicting a future turning point in every forecast going back as far back as 2003:Q4. Even in 2004, the high growth rate was pushing house prices on such a trajectory that future declines were

[13] A rolling window forecast is meant to simulate a sequence of forecasts generated by a researcher in real-time, using only data available at that point in time. In Figure 4.3, the first forecast is generated by estimating a model using data up until 2003:Q4, and forecasting each quarter from 2004:Q1 until 2009:Q4; the second forecast is generated by estimating a model with the same specification using data up until 2004:Q2 and forecasting each quarter from 2004:Q3 until 2009:Q4; and so on.

inevitable. Predictions of the exact time of the turning point were fairly inaccurate, especially as the housing bubble inflated ever larger in 2005. However, some forecasts were on the mark, with the 2004:Q2 forecast predicting the turning point exactly.

What is important in these figures is that regardless of the date of the forecast, univariate models were unable to predict declines in house prices prior to actually observing a decline. While the forecast accuracy of the multivariate forecasts is mixed, some of them were able to forecast turning points in the housing market. In particular, each of the VEC-INC forecasts foreshadowed sustained future house price declines. A stylized interpretation of these results is that atheoretical time series models were unable to forecast turning points in the housing market, but theory-driven multivariate models were somewhat successful.

4.7.3 Forecasting from the turning point

After the turning point in 2006:Q3, I consider which forecasts were able to forecast well from a fixed point in 2006:Q4, and forecasting over the next three years. Figure 4.4 shows dynamic forecasts, multiple steps ahead, and Figure 4.5 shows some of these forecasts with confidence intervals.

Multivariate error correction models outperform the univariate models. Visually, it is immediately apparent that the VAR, VEC-INC, and VEC-RENT forecasts outperform the univariate forecasts, and both the VEC-INC and VEC-RENT forecasts do better than the VAR forecast. The RACC forecast outperforms all univariate models and is the only one to forecast even a slight decline in house prices over the forecasting window.

Table 4.3 shows estimates of the n-step ahead MSFEs, Theil's U statistics (relative to the RACC model) and average bias statistics. Multiple steps ahead, the VEC-RENT and VEC-INC models both have much lower MSFEs than any rival model. U-statistics for these forecasts are very low, both about 0.18. The VAR also does well relative to the naive forecast with a U-statistic of 0.46.

Multi-step forecasts show substantial systematic deviations from actual house prices. The bias of the RACC model is the lowest of the univariate models with an average bias of 19% of the value of an average home. Other univariate models perform even worse, with the AR(1) model over-forecasting by 32%. The multivariate models do better, with both VEC models showing an average bias of 8% and the VAR with an average bias of 13%. The bias in the multi-step forecasts serves to drive the MSFEs. Even the VEC-INC and VEC-RENT forecasts, which both have much lower MSFEs than other forecasts, have biases are about six times that of the forecast error variance.

In general, these results are consistent with the previous exercise examining which models were best able to forecast the turning point. Theory-driven specifications outperform all atheoretical specifications across each of the comparison methods considered.

4.7.4 Forecasting after the turning point

The final forecasting exercise is to see which models are best able to forecast over the period of declining house prices, between 2007:Q1 and 2009:Q4. Figure 4.6 shows each model's 1-step ahead forecasts from just after the turning point in the housing market through 2009. Visually, all of these forecasts appear to be quite similar, with the exception of the AR(1) forecasts, which are biased. Because these forecasts are visually indistinguishable, it is necessary to proceed with analysis of forecast comparison statistics and tests.

MSFE comparison

Table 4.4 presents the different MSFEs of 1-step for each model, as well as MSFE comparisons versus the naive RACC model in the form of Theil's U-statistic. 1-step MSFEs indicate that the VEC-RENT model has the lowest MSFE among the models considered. The AR(6), ARIMA(2,d,2), VEC-RENT, VEC-INC and the vector autoregression with house prices, incomes, and rental prices (VAR) each have a lower MSFE than the naive RACC model. The AR(1) and the UC models both perform worse than the naive model, as indicated by U-statistics greater than one. Generally speaking however, each of the set of forecasts are indistinguishable from one another besides the AR(1) model, which performs much worse.

Bias test results

The 1-step forecasts appear to be mostly unbiased. Mincer and Zarnowitz's (1969) tests show that only the AR(1) model produces biased forecasts.

All F-tests reject Hendry's (1974) version of the Chow test for parameter constancy, indicating that there may be bias in the expectation of individual forecast errors in all models. These tests indicate that, while all of the models besides the AR(1) are similar in terms of MSFE and average bias, no model is able to forecast as well as the model fit in-sample. There are two possible reasons for this finding. Either some part of the data generating process changed over the forecasting period relative to the estimation sample, and modeling this change would produce better forecasts; or the structural error variance was higher in the forecasting period relative to the estimation period.[14]

Forecast encompassing test results

Table 4.5 presents a summary of the three different encompassing tests performed for each of the forecast pairs. Each of these individual tests is found in Tables 4.6-4.8. Because there are seven rival model for each forecast and three tests, there are $7 \times 3 = 21$ total encompassing tests for each forecast. The main concern, however, is to compare the relative performance of theory-driven multivariate and atheoretical univariate models. There are five univariate models and three multivariate models, so of the 21 possible tests, there are 15 relevant encompassing tests for the multivariate models and nine tests for the univariate models.

Of the univariate models, for only the AR(6) model is forecast encompassing of a rival multivariate model never rejected at the 10% level.[15] Each of the other univariate models fails encompassing in at least three of the nine tests. The UC and the AR(1) models perform the worst, with the RACC and the ARFIMA models in the middle.

No multivariate model ever fails to encompass a rival univariate model in any of the 15 encompassing test for the three multivariate models (45 tests, total). This indicates that incorporating additional non-house price information into the forecasts does not make forecasts any worse, and can add value relative to many of the univariate models when forecasting 1-step ahead during periods of declining house prices.

[14] As mentioned in Footnote 11, the nature of the repeat sales index may cause the structural error variance during the forecasting period to be higher then during the estimation sample.

[15] Though there are three rejections out of nine tests at the 15% level, and the AR(6) model fails to encompass one of the univariate models in one of the tests.

While MSFE, bias, and parameter constancy tests indicated that forecasts were indistinguishable (with the exception of the AR(1) model), forecast encompassing tests give a clearer picture of which models are better than others. Each of the multivariate models never fails to forecast encompass a rival model, and the AR(6) model fails to forecast encompass only one rival model and none of the multivariate models. The ARFIMA and the RACC models perform the next best, followed by the UC model. The AR(1) model, as with the other tests, performs the worst.

4.8 Conclusion

With the exception of the rolling window forecasts presented in Figure 4.3, all models listed in Table 4.1 are estimated using data on house prices from 1975:Q1-2006:Q4, and forecasts are generated over 2007:Q1-2009:Q4.[16] Each of these models is evaluated and compared using the battery of statistical measures described in Section 4. Five of these models were univariate models and three were multivariate models. The univariate models were selected to provide a range of different, commonly used time series specifications, and the multivariate models were selected based on theoretical economic relationships between house prices, incomes, and rental prices.

There are three main results responding to the research questions presented in the introduction. First, error correction models of house prices and incomes and house prices and rental prices are able to forecast large house price declines multiple steps ahead before any house price declines were observed. In every

[16] The rental price series begins at 1982:Q4, so if the model includes rental prices, the estimation sample starts in 1982:Q4. Results for other models estimated from 1982:Q4 to 2006:Q4 do not vary substantially from models estimated using the full sample, from 1975:Q1-2006:Q4.

forecast using the VEC-INC model, a future turning point in house prices was identified, though the concordance of the actual turning point with the predicted turning point was weak. In contrast, univariate models consistently predicted continued increases in house prices far out into the future. The best univariate forecasts predicted a flattening of house prices, but never significant declines.

Second, multivariate models all outperform univariate models when forecasting from the turning point multiple steps ahead over the next three years. While all forecasts considered under-predict the magnitude of house price declines, the multivariate models are not as bad as the univariate models.

Third and finally, several models are able to forecast well 1-step ahead during the period of falling housing prices. Each of the multivariate models, the RACC, and the AR(6) model are able to produce unbiased forecasts (on average) that are rarely encompassed by rival forecasts. The AR(1) and the unobserved components models each performs worse than the naive model and are often forecast encompassed. All models fail parameter constancy tests, indicating that the data generating process changed from the estimation sample to the forecasting period.

In general, the theoretically motivated multivariate models performed much better than the univariate time series models across a variety of comparison and evaluation metrics. The multivariate models were best able to forecast turning points in the housing market, were best able to forecast from the turning point over the succeeding three year window, and were best able to forecast 1-step ahead over the period of declining house prices.

This paper is a natural extension of the prior literature on house price forecast comparisons. The relative success of the VEC models with income and rental prices reinforces the finding of Gupta and Miller (2010), who show that spatial VEC models outperform non-spatial VAR models. It is clear from this work and theirs that it is crucial to model house prices using specifications that allow for long-run mean reversion in addition to short-run persistence of growth rates.

While past works compared MSFEs and other measures of fit across models, this research also compares forecasts multiple steps ahead, and evaluates forecasts based on average bias, tests of parameter constancy, and forecast encompassing. The past literature has also only compared forecasts over periods of growth in house prices, as opposed to periods of decline. Finally, this model considers an unobserved components model and a univariate random acceleration model, which past comparisons had not included.

4.9 Tables and Figures

Table 4.1: Forecasting models

Model(short)	Model (long)	Specification
M1	RACC	$\Delta^2 Y_t = \alpha + \varepsilon_t$
M2	AR(1)	$Y_t = \alpha + \rho Y_{t-i} + \varepsilon_t$
M3	AR(6)	$Y_t = \alpha + \sum_{i=1}^{p} \rho_i Y_{t-i} + \varepsilon_t$
M4	ARFIMA(2,d,2)	$\Delta^d Y_t = \alpha + \sum_{i=1}^{p} \rho_i \Delta^d Y_{t-i} + \sum_{i=1}^{q} \theta_i \Delta^d \varepsilon_{t-i} + \varepsilon_t$
M5	UC	$Y_t = \mu_t + \psi_t + \varepsilon_t$
M6	VEC-RENT(4)	$\Delta \boldsymbol{Y}_t = \boldsymbol{\alpha\beta}' \boldsymbol{Y}_{t-1} + \sum_{i=1}^{p} \boldsymbol{\Pi}_i \Delta \boldsymbol{Y}_{t-i} + \boldsymbol{\varepsilon}_t$
M7	VEC-INC(5)	$\Delta \boldsymbol{Y}_t = \boldsymbol{\alpha\beta}' \boldsymbol{Y}_{t-1} + \sum_{i=1}^{p} \boldsymbol{\Pi}_i \Delta \boldsymbol{Y}_{t-i} + \boldsymbol{\varepsilon}_t$
M8	VAR(5)	$\boldsymbol{Y}_t = \boldsymbol{\alpha} + \sum_{i=1}^{p} \boldsymbol{\Pi}_i \boldsymbol{Y}_{t-i} + \boldsymbol{\varepsilon}_t$

Table 4.2: Model fit

Model	observations(T)	parameters(k)	σ
RACC	126	4	0.012
AR(1)	127	5	0.022
AR(6)	122	10	0.011
ARIMA(2,d,2)	128	10	0.011
UC	128	3	0.012
VEC-RENT	92	19	0.011
VEC-INC	122	15	0.011
VAR	92	13	0.011

Table 4.3: Multi-step forecast statistics

Model	RMSFE	Theil's U[1]	Average bias[2]
RACC	0.225	1	-0.190**
AR(1)	0.382	2.885	-0.329**
AR(6)	0.248	1.217	-0.210**
ARIMA(2,d,2)	0.298	1.752	-0.254**
UC	0.243	1.168	-0.206**
VEC-RENT	0.096	0.184	-0.080**
VEC-INC	0.097	0.188	-0.084**
VAR	0.154	0.467	-0.132**

One and two asterisks indicates significance at the 10% and 5% level, respectively.

[1] relative to RACC

[2] Rejections based on the null hypothesis that $\{\alpha = 0; \beta = 1\}$ in equation 4.1.

Table 4.4: 1-step forecast statistics

Model	RMSFE	Theil's U[1]	Average bias[2]	Parameter constancy[3]
RACC	0.024	1	0.007	4.133**
AR(1)	0.055	5.019	-0.049**	6.379**
AR(6)	0.022	0.834	0.004	3.986**
ARIMA(2,d,2)	0.023	0.905	0.002*	4.646**
UC	0.025	1.043	0.000	4.698**
VEC-RENT	0.020	0.675	0.002	3.487**
VEC-INC	0.023	0.872	0.002	4.451**
VAR	0.022	0.827	-0.011	4.368**

One and two asterisks indicates significance at the 10% and 5% level, respectively.

[1] relative to RACC

[2] Rejections based on the null hypothesis that $\{\alpha = 0; \beta = 1\}$ in Equation 4.1.

[3] Column presents the ratio $RMSFE^2/\sigma^2$ where σ is the in-sample residual standard deviation found in Table 4.2. Under the null that $RMSFE/\sigma = 1$, this ratio follows a χ^2 distribution with $(T-k, H)$ degrees of freedom, where $H = 12$ is the number of periods forecasted and T and K are found in Table 4.2.

Table 4.5: Forecast encompassing test summary

Encompassed by a multivariate model[1]	Test A	Test B	Test C	Total
RACC	2 of 3	1 of 3	1 of 3	4 of 9
AR(1)	2 of 3	3 of 3	3 of 3	8 of 9
AR(6)	0 of 3	0 of 3	0 of 3	0 of 9
ARIMA(2,d,2)	2 of 3	0 of 3	1 of 3	3 of 9
UC	2 of 3	2 of 3	2 of 3	6 of 9

Encompassed by a univariate model[1]	Test A	Test B	Test C	Total
VEC-RENT	0 of 5	0 of 5	0 of 5	0 of 15
VEC-INC	0 of 5	0 of 5	0 of 5	0 of 15
VAR	0 of 5	0 of 5	0 of 5	0 of 15

[1] at the 10% level

Table 4.6: Forecast-encompassing test statistics: test A

$$Y_{T+n|T+n-1} - \tilde{Y}_{T+n|T+n-1} = \alpha + \gamma(\hat{Y}_{T+n|T+n-1} - \tilde{Y}_{T+n|T+n-1}) + e_{T+n|T+n-1}$$

Forecast in row denoted $\tilde{y}$. Forecast in column denoted $\hat{y}$.
The value in each cell below is the p-value of the restriction $\{\gamma = 0\}$.

Encompassing	Model to be encompassed							
model	M1	M2	M3	M4	M5	M6	M7	M8
M1		0.240	0.199	0.547	0.399	0.072*	0.447	0.054*
M2	0.137		0.091*	0.083*	0.185	0.037**	0.132	0.029**
M3	0.560	0.394		0.892	0.038**	0.145	0.379	0.120
M4	0.750	0.167	0.303		0.691	0.091*	0.531	0.062*
M5	0.169	0.147	0.009**	0.206		0.017*	0.105	0.023**
M6	0.667	0.503	0.537	0.788	0.220		0.480	0.415
M7	0.975	0.352	0.220	0.782	0.349	0.085*		0.073*
M8	0.941	0.630	0.887	0.851	0.619	0.941	0.780	

Table 4.7: Forecast-encompassing test statistics: test B

$$Y_{T+n|T+n-1} - \tilde{Y}_{T+n|T+n-1} = \alpha + \gamma(\hat{Y}_{T+n|T+n-1} - \tilde{Y}_{T+n|T+n-1}) + e_{T+n|T+n-1}$$

Forecast in row denoted $\tilde{y}$. Forecast in column denoted $\hat{y}$.
The value in each cell below is the p-value of the joint restriction $\{\alpha = 0; \gamma = 0\}$.

Encompassing	Model to be encompassed							
model	M1	M2	M3	M4	M5	M6	M7	M8
M1		0.322	0.280	0.550	0.458	0.122	0.491	0.095*
M2	0.000**		0.000**	0.000**	0.000**	0.000**	0.000**	0.000**
M3	0.694	0.567		0.822	0.086*	0.273	0.553	0.233
M4	0.907	0.351	0.547		0.880	0.213	0.778	0.154
M5	0.370	0.331	0.028**	0.432		0.049**	0.251	0.068*
M6	0.869	0.757	0.784	0.922	0.435		0.737	0.675
M7	0.977	0.620	0.444	0.939	0.617	0.206		0.181
M8	0.244	0.217	0.243	0.241	0.215	0.244	0.235	

Table 4.8: Forecast-encompassing test statistics: test C

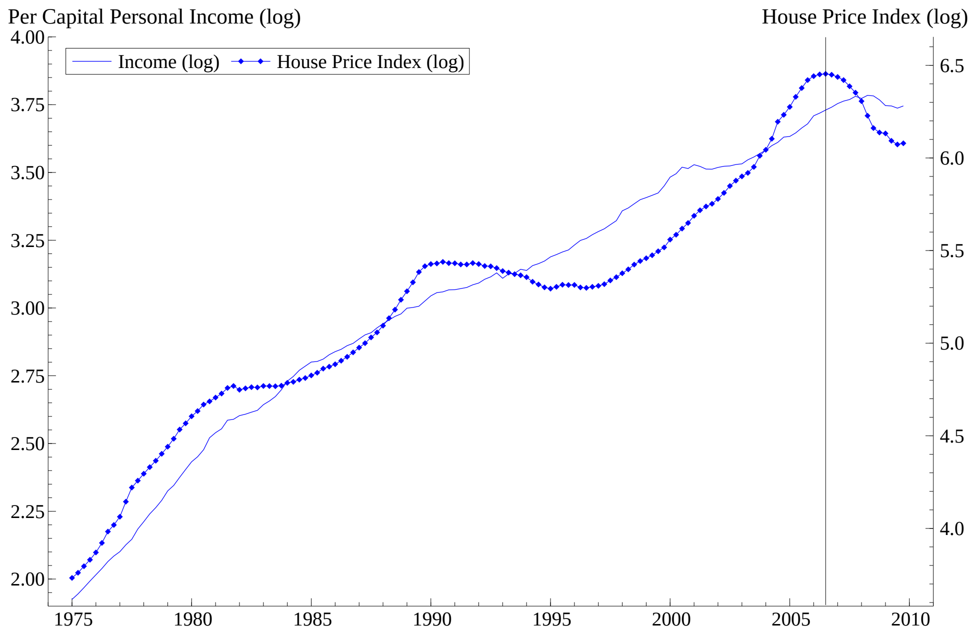
$$Y_{T+n|T+n-1} - \tilde{Y}_{T+n|T+n-1} = \gamma(\hat{Y}_{T+n|T+n-1} - \tilde{Y}_{T+n|T+n-1}) + e_{T+n|T+n-1}$$

Forecast in row denoted $\tilde{y}$. Forecast in column denoted $\hat{y}$.
The value in each cell below is the p-value of the restriction $\{\gamma = 0\}$.

Encompassing	Model to be encompassed							
model	M1	M2	M3	M4	M5	M6	M7	M8
M1		0.737	0.108	0.303	0.733	0.042*	0.225	0.140
M2	0.000**		0.000**	0.000**	0.000**	0.000**	0.000**	0.000**
M3	0.412	0.806		0.957	0.336	0.132	0.836	0.375
M4	0.916	0.746	0.354		0.773	0.078*	0.469	0.158
M5	0.453	0.547	0.070*	0.208		0.014**	0.100	0.086*
M6	0.892	0.597	0.824	0.883	0.229		0.469	0.564
M7	0.869	0.596	0.478	0.718	0.368	0.073*		0.184
M8	0.665	0.192	0.402	0.305	0.474	0.116	0.270	

Figure 4.1: House prices, personal incomes, and rental prices: California

(a) House prices and incomes



(b) House prices and rental prices

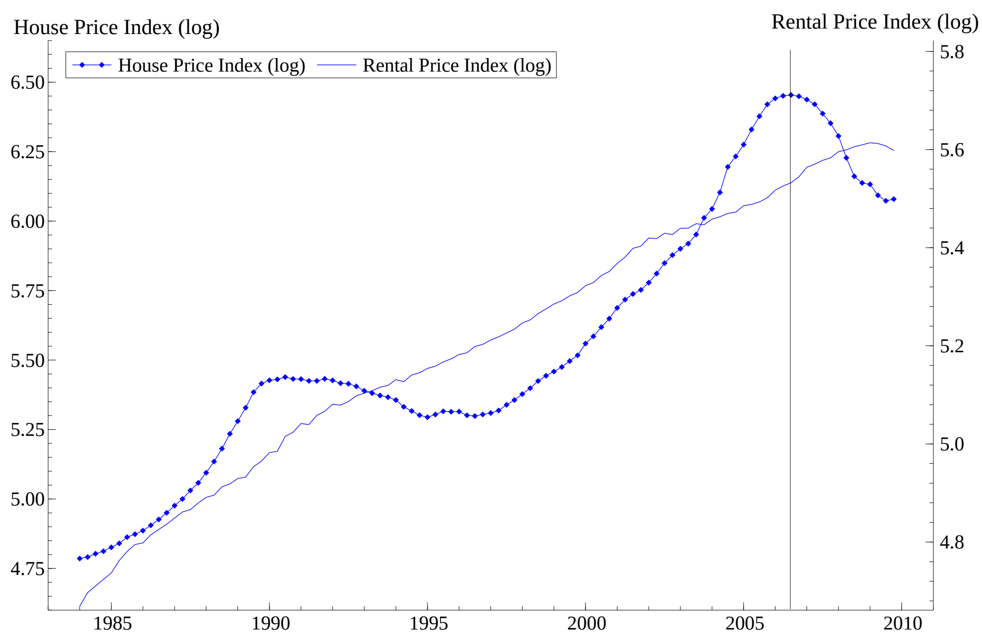


Figure 4.2: Change in house prices: California

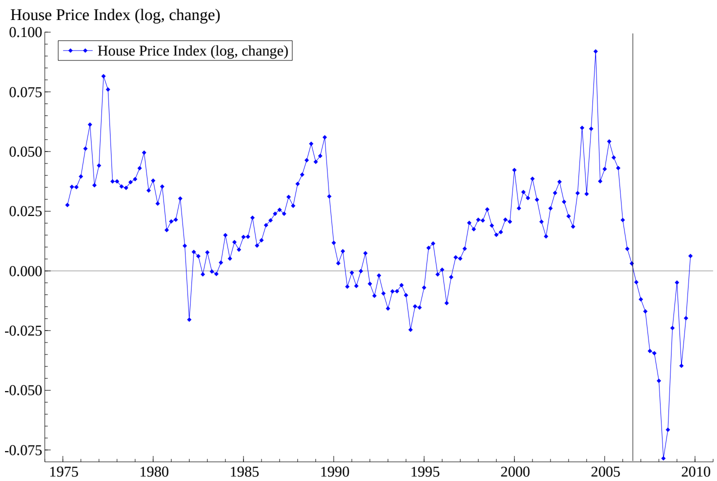
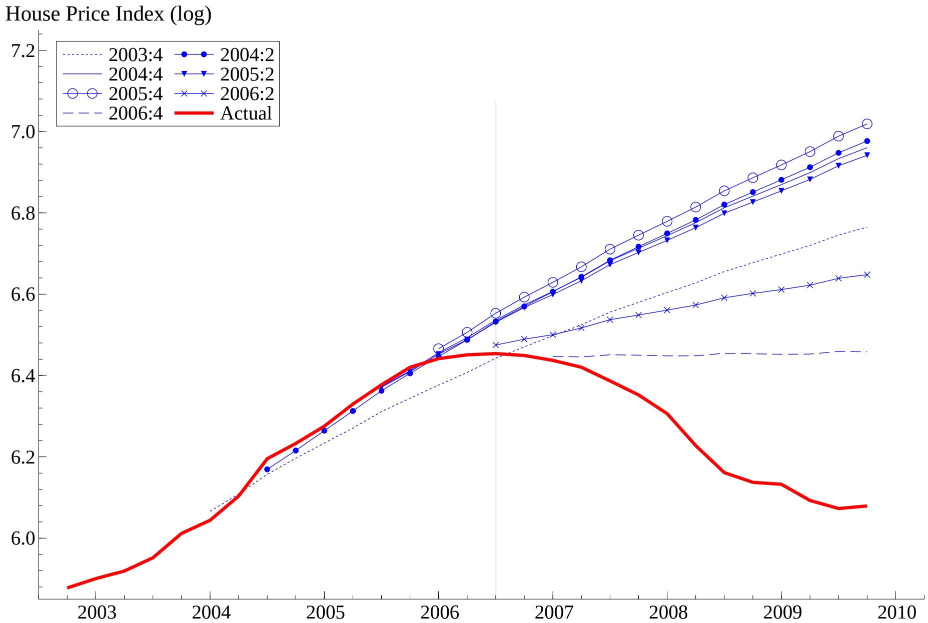


Figure 4.3: Pseudo ex-ante forecasts: univariate vs. multivariate models

(a) AR(6)



(b) VEC-INC

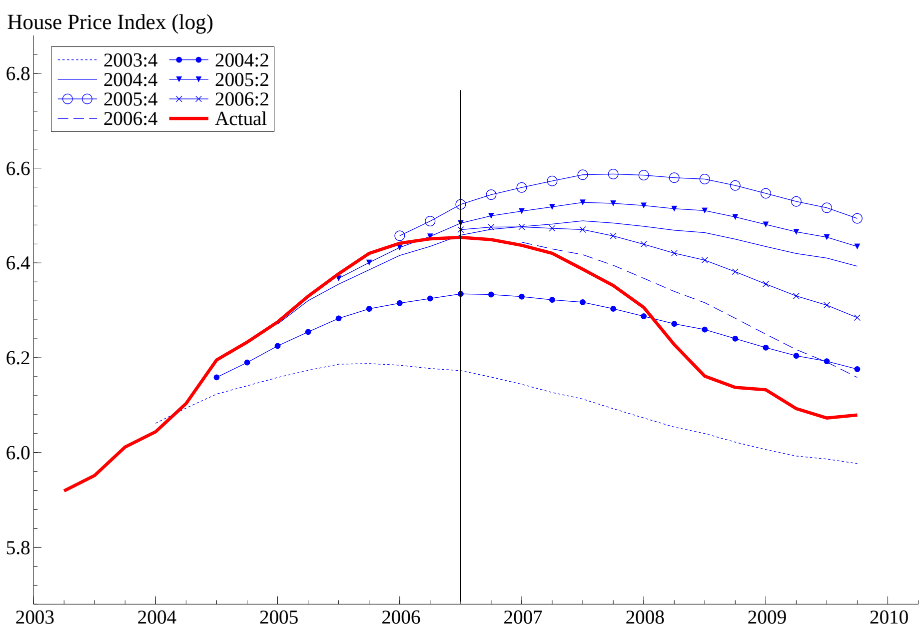


Figure 4.4: multi-step dynamic forecasts

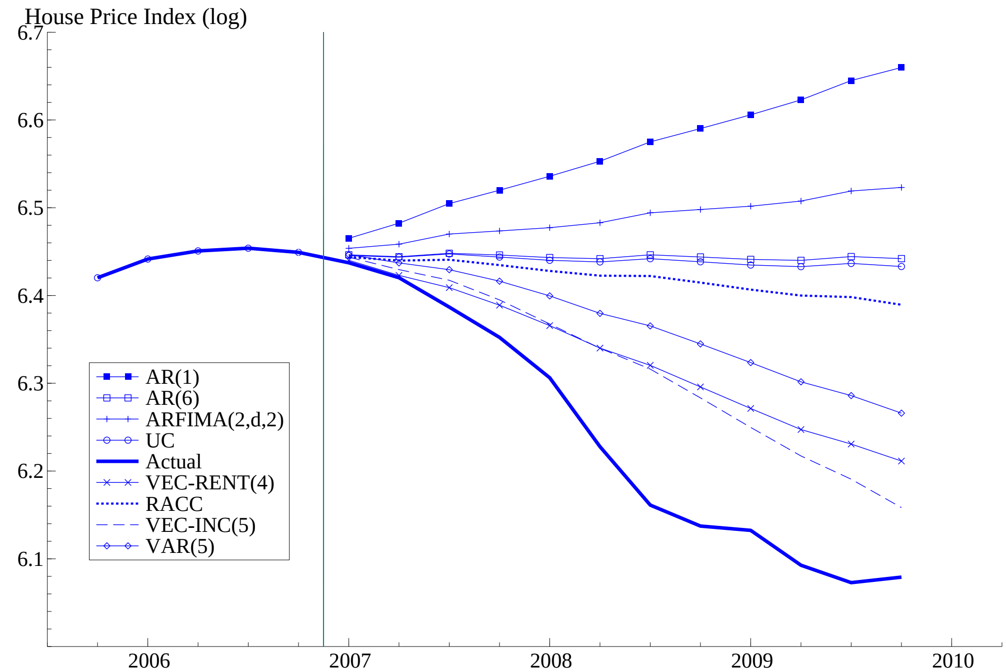
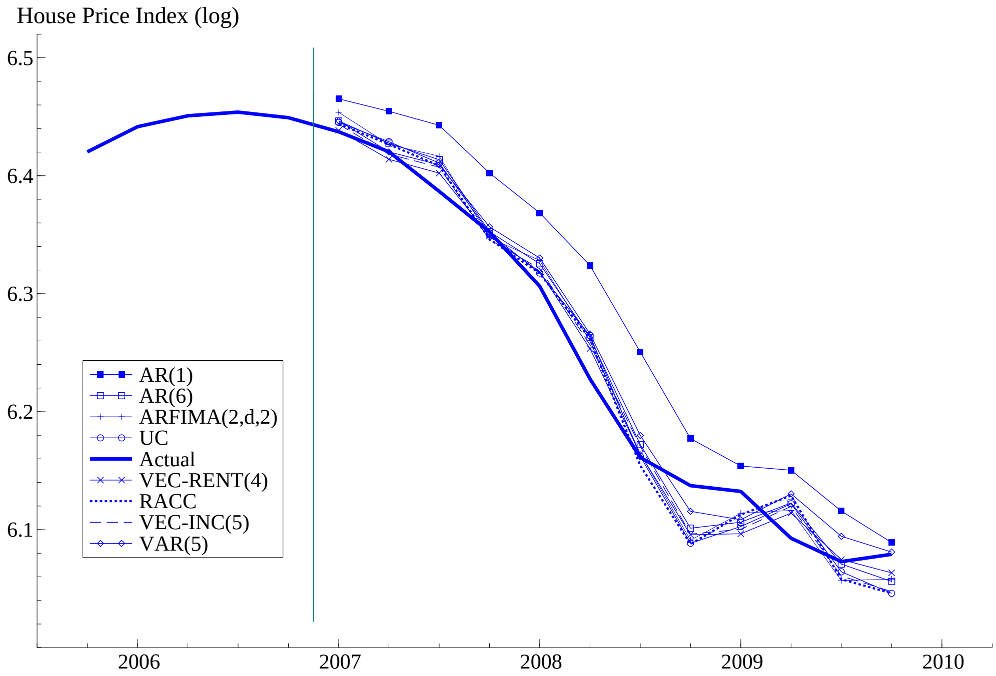


Figure 4.5: Confidence intervals of select multi-step dynamic forecasts

Figure 4.6: 1-step forecasts



4.10 Appendix

Table A1: Random acceleration model estimation results

$$\text{DDCASTHPI} = \underset{(0.00107)}{-0.0002435} + \underset{(0.00303)}{0.006934}\ \text{CSeasonal}_t + \underset{(0.00303)}{0.008977}\ \text{CSeasonal}_{t-1} + \underset{(0.00301)}{0.01262}\ \text{CSeasonal}_{t-2}$$

$N = 126,\ \sigma = [0.012024],\ LL = 380.273498,\ Smpl : 1975 : 3 - 2006 : 4$

Table A2: AR(1) estimation results

$$\text{LCASTHPI} = \underset{(0.00306)}{0.9947}\ \text{LCASTHPI}_{t-1} + \underset{(0.0163)}{0.0463} + \underset{(0.00541)}{0.0002082}\ \text{Seasonal}_t + \underset{(0.00537)}{0.001881}\ \text{Seasonal}_{t-1} + \underset{(0.00537)}{0.007238}\ \text{Seasonal}_{t-2}$$

$N = 127,\ \sigma = 0.02147,\ LL = 310.165,\ Smpl : 1975 : 2 - 2006 : 4$

Table A3: AR(6) estimation results

$$\begin{aligned}\text{LCASTHPI} = {} & \\ & \underset{(0.0935)}{1.82}\ \text{LCASTHPI}_{t-1} - \underset{(0.192)}{0.9912}\ \text{LCASTHPI}_{t-2} + \underset{(0.203)}{0.5907}\ \text{LCASTHPI}_{t-3} \\ & - \underset{(0.202)}{0.7218}\ \text{LCASTHPI}_{t-4} + \underset{(0.194)}{0.4032}\ \text{LCASTHPI}_{t-5} - \underset{(0.0961)}{0.1027}\ \text{LCASTHPI}_{t-6} \\ & + \underset{(0.00979)}{0.003727} + \underset{(0.00326)}{0.006603}\ \text{Seasonal}_t + \underset{(0.00316)}{0.00536}\ \text{Seasonal}_{t-1} \\ & + \underset{(0.00317)}{0.01415}\ \text{Seasonal}_{t-2}\end{aligned}$$

$N = 122,\ \sigma = 0.0111822,\ LL = 380.305,\ Smpl : 1976 : 3 - 2006 : 4$

Table A4: ARFIMA(2,d,2) estimation results

	Coefficient		Std.Error	t-value	t-prob
d parameter	1.32477		0.2757	4.8	0
AR-1	0.483542		0.1911	2.53	0.013
AR-2	0.386105		0.1358	2.84	0.005
MA-1	0.147896		0.1335	1.11	0.27
MA-2	-0.60418		0.1798	-3.36	0.001
Constant	3.80971		0.1739	21.9	0
Seasonal	-0.00237		0.001324	-1.79	0.075
Seasonal_1	-0.0028		0.001857	-1.51	0.134
Seasonal_2	0.002409		0.001325	1.82	0.072
log-likelihood	400.1725				
no. of observations	128	no. of parameters		10	
AIC.T -	780.3449	AIC		-6.09644	
mean(LCASTHPI)	5.17594	var(LCASTHPI)		0.397383	
sigma	0.010787	σ^2		0.000116	

Smpl: 1975:1-2006:4

Table A5: Unobserved components model estimation results

T	128	Variances of disturbances:		
p	3		Value	(q-ratio)
std.error	0.011519	Level	3.46E-05	0.4476
Normality	10.55	Slope	7.74E-05	1
H(41)	1.4741	Seasonal	0.00E-05	0.00E-05
DW	1.909	State vector analysis at period 2006(4)		
r(1)	0.037426		Value	Prob
q	13	Level	6.44845	[0.00000]
r(q)	-0.00066524	Slope	-0.00135	[0.89524]
Q(q,q-p)	11.852	Seasonal chi2 test	16.34984	[0.00096]
$Rs\hat{2}$	0.71842			

Log-Likelihood: 537.546 Smpl: 1975:1-2006:4

Table A6: VEC-RENT(4) estimation results

DLCASTHPI =

$$\underset{(0.109)}{0.762}\ \text{DLCASTHPI}_{t-1} - \underset{(0.226)}{0.2916}\ \text{DLRENT}_{t-1} - \underset{(0.13)}{0.03325}\ \text{DLCASTHPI}_{t-2}$$
$$- \underset{(0.23)}{0.3469}\ \text{DLRENT}_{t-2} + \underset{(0.131)}{0.434}\ \text{DLCASTHPI}_{t-3} - \underset{(0.228)}{0.006322}\ \text{DLRENT}_{t-3}$$
$$- \underset{(0.119)}{0.2115}\ \text{DLCASTHPI}_{t-4} + \underset{(0.225)}{0.0223}\ \text{DLRENT}_{t-4} - \underset{(0.006)}{0.01054}\ \text{CIa}_{t-1}$$
$$+ \underset{(0.0186)}{0.03135} + \underset{(0.00379)}{0.004008}\ \text{Seasonal}_{t} + \underset{(0.00332)}{0.000686}\ \text{Seasonal}_{t-1}$$
$$+ \underset{(0.00372)}{0.01021}\ \text{Seasonal}_{t-2}$$

DLRENT =

$$- \underset{(0.05)}{0.04321}\ \text{DLCASTHPI}_{t-1} - \underset{(0.103)}{0.1547}\ \text{DLRENT}_{t-1} + \underset{(0.0596)}{0.0761}\ \text{DLCASTHPI}_{t-2}$$
$$+ \underset{(0.105)}{0.1764}\ \text{DLRENT}_{t-2} - \underset{(0.0597)}{0.02048}\ \text{DLCASTHPI}_{t-3} + \underset{(0.104)}{0.04282}\ \text{DLRENT}_{t-3}$$
$$+ \underset{(0.0546)}{0.05458}\ \text{DLCASTHPI}_{t-4} + \underset{(0.103)}{0.399}\ \text{DLRENT}_{t-4} - \underset{(0.00274)}{0.004228}\ \text{CIa}_{t-1}$$
$$+ \underset{(0.00852)}{0.01516} + \underset{(0.00173)}{0.0004115}\ \text{Seasonal}_{t} - \underset{(0.00152)}{0.001019}\ \text{Seasonal}_{t-1}$$
$$+ \underset{(0.0017)}{0.000657}\ \text{Seasonal}_{t-2}$$

$N = 92,\ \sigma = [0.0106267, 0.0048618],\ LL = 922.614282$
$Smpl : 1984 : 1 - 2006 : 4$

Table A7: VEC-INC(5) estimation results

DLCASTHPI =

$$
\begin{aligned}
&\underset{(0.0925)}{0.7936}\ \mathrm{DLCASTHPI}_{t-1} - \underset{(0.122)}{0.01286}\ \mathrm{DLCAINC}_{t-1} - \underset{(0.116)}{0.1745}\ \mathrm{DLCASTHPI}_{t-2} \\
&- \underset{(0.123)}{0.1025}\ \mathrm{DLCAINC}_{t-2} + \underset{(0.11)}{0.4398}\ \mathrm{DLCASTHPI}_{t-3} + \underset{(0.132)}{0.07195}\ \mathrm{DLCAINC}_{t-3} \\
&- \underset{(0.116)}{0.2656}\ \mathrm{DLCASTHPI}_{t-4} + \underset{(0.126)}{0.08464}\ \mathrm{DLCAINC}_{t-4} + \underset{(0.0984)}{0.2033}\ \mathrm{DLCASTHPI}_{t-5} \\
&- \underset{(0.124)}{0.2319}\ \mathrm{DLCAINC}_{t-5} - \underset{(0.00806)}{0.02537}\ \mathrm{CIa}_{t-1} + \underset{(0.0136)}{0.03665} \\
&+ \underset{(0.00329)}{0.007836}\ \mathrm{Seasonal}_{t} + \underset{(0.00323)}{0.006639}\ \mathrm{Seasonal}_{t-1} + \underset{(0.00313)}{0.0145}\ \mathrm{Seasonal}_{t-2}
\end{aligned}
$$

DLCAINC =

$$
\begin{aligned}
&\underset{(0.0731)}{0.0788}\ \mathrm{DLCASTHPI}_{t-1} + \underset{(0.0966)}{0.1441}\ \mathrm{DLCAINC}_{t-1} + \underset{(0.0916)}{0.01208}\ \mathrm{DLCASTHPI}_{t-2} \\
&+ \underset{(0.0972)}{0.377}\ \mathrm{DLCAINC}_{t-2} - \underset{(0.0867)}{0.04833}\ \mathrm{DLCASTHPI}_{t-3} + \underset{(0.104)}{0.09225}\ \mathrm{DLCAINC}_{t-3} \\
&+ \underset{(0.0921)}{0.09231}\ \mathrm{DLCASTHPI}_{t-4} + \underset{(0.0993)}{0.0449}\ \mathrm{DLCAINC}_{t-4} - \underset{(0.0779)}{0.1023}\ \mathrm{DLCASTHPI}_{t-5} \\
&- \underset{(0.0981)}{0.01506}\ \mathrm{DLCAINC}_{t-5} + \underset{(0.00637)}{0.002279}\ \mathrm{CIa}_{t-1} + \underset{(0.0107)}{0.002446} \\
&- \underset{(0.0026)}{0.0001563}\ \mathrm{Seasonal}_{t} - \underset{(0.00256)}{0.003823}\ \mathrm{Seasonal}_{t-1} - \underset{(0.00247)}{0.004077}\ \mathrm{Seasonal}_{t-2}
\end{aligned}
$$

$N = 122,\ \sigma = [0.0108183, 0.00855774],\ LL = 804.117306$
$Smpl : 1976 : 3 - 2006 : 4$

Table A8: VAR(5) estimation results

LCASTHPI =

$$\underset{(0.116)}{1.712}\ \text{LCASTHPI}_{t-1} - \underset{(0.217)}{0.7948}\ \text{LCASTHPI}_{t-2} + \underset{(0.226)}{0.4961}\ \text{LCASTHPI}_{t-3}$$
$$- \underset{(0.218)}{0.6702}\ \text{LCASTHPI}_{t-4} + \underset{(0.125)}{0.2419}\ \text{LCASTHPI}_{t-5} + \underset{(0.146)}{0.04758}\ \text{LCAINC}_{t-1}$$
$$- \underset{(0.214)}{0.08139}\ \text{LCAINC}_{t-2} - \underset{(0.212)}{0.1235}\ \text{LCAINC}_{t-3} + \underset{(0.222)}{0.3698}\ \text{LCAINC}_{t-4}$$
$$- \underset{(0.17)}{0.07638}\ \text{LCAINC}_{t-5} - \underset{(0.293)}{0.4798}\ \text{LRENT}_{t-1} - \underset{(0.308)}{0.1447}\ \text{LRENT}_{t-2}$$
$$+ \underset{(0.314)}{0.2974}\ \text{LRENT}_{t-3} + \underset{(0.302)}{0.09472}\ \text{LRENT}_{t-4} + \underset{(0.267)}{0.0876}\ \text{LRENT}_{t-5}$$
$$+ \underset{(0.299)}{0.4052} + \underset{(0.00385)}{0.003177}\ \text{Seasonal}_{t} + \underset{(0.00349)}{0.0002053}\ \text{Seasonal}_{t-1}$$
$$+ \underset{(0.00381)}{0.01038}\ \text{Seasonal}_{t-2}$$

LCAINC =

$$\underset{(0.0891)}{0.03273}\ \text{LCASTHPI}_{t-1} - \underset{(0.167)}{0.07873}\ \text{LCASTHPI}_{t-2} - \underset{(0.175)}{0.03144}\ \text{LCASTHPI}_{t-3}$$
$$+ \underset{(0.168)}{0.1795}\ \text{LCASTHPI}_{t-4} - \underset{(0.0964)}{0.1056}\ \text{LCASTHPI}_{t-5} + \underset{(0.112)}{1.069}\ \text{LCAINC}_{t-1}$$
$$+ \underset{(0.165)}{0.2645}\ \text{LCAINC}_{t-2} - \underset{(0.163)}{0.3988}\ \text{LCAINC}_{t-3} + \underset{(0.171)}{0.05721}\ \text{LCAINC}_{t-4}$$
$$+ \underset{(0.131)}{0.07809}\ \text{LCAINC}_{t-5} - \underset{(0.226)}{0.1991}\ \text{LRENT}_{t-1} - \underset{(0.237)}{0.06757}\ \text{LRENT}_{t-2}$$
$$- \underset{(0.242)}{0.09053}\ \text{LRENT}_{t-3} - \underset{(0.233)}{0.1996}\ \text{LRENT}_{t-4} + \underset{(0.206)}{0.469}\ \text{LRENT}_{t-5}$$
$$+ \underset{(0.231)}{0.2679} + \underset{(0.00297)}{0.001981}\ \text{Seasonal}_{t} - \underset{(0.00269)}{0.002409}\ \text{Seasonal}_{t-1}$$
$$- \underset{(0.00294)}{0.002643}\ \text{Seasonal}_{t-2}$$

LRENT =

$$
\begin{aligned}
& - \underset{(0.0456)}{0.07484}\ \text{LCASTHPI}_{t-1} + \underset{(0.0856)}{0.1108}\ \text{LCASTHPI}_{t-2} - \underset{(0.0893)}{0.08389}\ \text{LCASTHPI}_{t-3} \\
& + \underset{(0.086)}{0.04549}\ \text{LCASTHPI}_{t-4} + \underset{(0.0494)}{0.004924}\ \text{LCASTHPI}_{t-5} - \underset{(0.0575)}{0.01308}\ \text{LCAINC}_{t-1} \\
& + \underset{(0.0846)}{0.07082}\ \text{LCAINC}_{t-2} + \underset{(0.0835)}{0.103}\ \text{LCAINC}_{t-3} - \underset{(0.0875)}{0.06876}\ \text{LCAINC}_{t-4} \\
& + \underset{(0.0672)}{0.06061}\ \text{LCAINC}_{t-5} + \underset{(0.116)}{0.4888}\ \text{LRENT}_{t-1} + \underset{(0.122)}{0.2222}\ \text{LRENT}_{t-2} \\
& - \underset{(0.124)}{0.08982}\ \text{LRENT}_{t-3} + \underset{(0.119)}{0.3959}\ \text{LRENT}_{t-4} - \underset{(0.106)}{0.208}\ \text{LRENT}_{t-5} \\
& + \underset{(0.118)}{0.4953} + \underset{(0.00152)}{0.0008408}\ \text{Seasonal}_{t} - \underset{(0.00138)}{0.0005055}\ \text{Seasonal}_{t-1} \\
& + \underset{(0.0015)}{0.0007145}\ \text{Seasonal}_{t-2}
\end{aligned}
$$

$N = 92,\ \sigma = [0.0106387, 0.00820626, 0.00420011],\ LL = 1005.57355$
$Smpl : 1984 : 1 - 2006 : 4$

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