Oil Prices and Urban Housing Demand

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We develop a model of a monocentric, oil-exporting city. The model predicts a “twist” (rotation combined with a level shift) of the house price gradient with an oil price change due to the combined producer price and transportation cost effects. Empirical findings support the predictions, with house price changes positively linked to the price of oil in cities specialized in oil and gas-related industries, and negatively linked in suburban areas of all cities. These results quantify the large and differential risks to house prices associated with oil price changes both within and across cities. Overall, estimates suggest a 50% change in the price of oil results in a city-wide house price change of 15% over five years in a city specialized in the production of oil (export employment share of 50%), whereas house prices for units greater than 15 miles from the city-center change in relative terms by −1.5% over the same period.

Introduction

The steep increase in the oil price between 2000 and 2010, followed by its swift decline in the years since, has put a renewed focus on potential effects of oil price changes on house prices. This is highlighted by the run-up in real house prices in oil rich areas, such as Williston, ND, where housing assets have experienced nearly 500% real appreciation between 2000 and 2015 (see Figure 1).1 At the same time, suburban areas, which tend to have longer and more gasoline-intensive commutes, have experienced lower appreciation rates (see Figure 2) compared to the prior 15-year period. The major question

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The analysis and conclusions are those of the authors and do not necessarily represent the views of the Federal Housing Finance Agency or the United States.

1The source for house price index data is the BDL dataset (Bogin, Doerner and Larson 2016), which is published by the Federal Housing Finance Agency and can be downloaded at: http://www.fhfa.gov/papers/wp1601.aspx. The source for the oil price data is Bloomberg, and is the three-year forward price at Cushing, OK.

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motivating this research is, how are house price changes related to changes in the oil price, and do these effects vary across cities and locations within the city?

If one considers a standard household budget constraint, otherwise identical households can have differential exposure to the price of oil. Some workers are employed in businesses related to the production of oil, while others are not, leading to substantial income risk for some from oil price changes. On the expenditure side, while all households face similar effects on consumption goods, identical households can commute different distances to their place of work, leading to greater oil (via gasoline) expenditure shares for households commuting longer distances.² Because housing demand is theoretically tied to location-specific factors related to both incomes and transportation costs—a relationship highlighted in the standard urban model (SUM) of Alonso (1964), Mills (1967) and Muth (1969)—oil prices are predicted, based on theory, to have different effects on house prices in different locations.

In this article, our objective is to predict and then estimate the effects of oil price shocks on house prices both within and across cities, with a focus

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²Gillingham (2014) estimates a gasoline price elasticity of vehicle miles traveled of −0.22, in line with other estimates in the literature. This elasticity is suggestive of salience of gasoline and oil price changes to households, despite the low per-unit price of gasoline. In addition, Dodson and Sipe (2008) assert that some suburban areas in major Australian cities are vulnerable to increases in fuel costs.
on estimating both the export price and transportation cost effects. While
the transportation cost effect has received some attention in the literature,
the export price effect is almost completely absent. Our study is the first
to consider the effects of oil price changes on house prices through both
channels, over a large cross section of ZIP codes, using a sample spanning
multiple periods of both rising and falling oil, gasoline and house prices.

The income effect of oil price changes on house prices has not been con-
sidered directly in the existing literature. The link between regional incomes
and oil prices is established (e.g., Hamilton and Owyang 2012), and in other
subdisciplines of economics, oil price shocks have been used to identify ex-
ogenous local demand shocks (e.g., Acemoglu, Finkelstein and Notowidigdo
2013). But an examination of the link between oil export price shocks on
house prices across cities is conspicuously absent. Instead, the focus of
this line of inquiry in terms of housing either proceeds in an event study
framework (Smith and Tesarek 1991), or simply uses oil price changes as a
motivating stylized fact for an analysis of price changes across regions.³ In no

³For instance, Smith and Tesarek (1991) find that house prices in Houston, TX, a city
specializing in oil-related industries, fell 30% in the 1980s when the oil price fell

Notes: Large cities are defined as CBSAs with population greater than 500,000 in 1990. The
figure presents local polynomial-smoothed log differences in real (inflation-adjusted) house prices
over the respective 15-year period \( \ln HPI_t - \ln HPI_{t-15} \) at the ZIP code level.

Figure 2 ■ Fifteen-year real house price appreciation rates in large cities.
[Color figure can be viewed at wileyonlinelibrary.com]
study has the focus been on the income effect of oil price changes on house prices.

The transportation cost effect has received greater attention in the literature, but this vein remains unsettled. Coulson and Engle (1987) consider the transportation cost hypothesis and find evidence that oil price changes cause the house price gradient to rotate.\(^4\) Molloy and Shan (2013) approach the problem with a much more granular level of aggregation (ZIP code level) over a long time period (1981–2008), yet find no statistically significant effect of gasoline prices on the house price gradient. This result is perhaps surprising, given the established urban theory relating house price changes to transportation costs. We attempt to resolve this conflict in the present article.

To begin, we develop a model of an oil-exporting monocentric city in order to bring together both transportation cost and producer price effects into a cohesive theoretical framework. In this model, the city lies on a featureless plane with three concentric regions: a central business district (CBD) where firms locate and to which households commute, a residential district where households live and an agricultural hinterland, which does not contribute to the city. Households are homogeneous, consuming a composite commodity and housing. Housing quality is one-dimensional, varying by size, and is produced by profit-maximizing producers using structure and land inputs. CBD firms produce oil for export at a global price. The framework gives the classic isoultility and isoprofit conditions in the SUM, but with an added focus on the export price of the produced good. Comparative statics give predictions related to effects of oil price shocks through two channels: an earnings effect through export prices, and a transportation cost effect through higher gasoline costs, the primary input of which is oil.

We then test the predictions of the model using a new database of ZIP code-level house price indices from Bogin, Doerner and Larson (2016). We find evidence that oil prices interacted with various measures and proxies for commuting distance are predictive of house price changes. Estimates indicate that a doubling of the oil price decreases relative house prices in the suburbs (>15 miles from the CBD) by a total of 2% after three years and 3% after

\(^4\)However, their study covers six years and five cities, and they state in the last sentence of their conclusion (p. 296), “Clearly the topic needs more study with larger datasets to truly provide an answer to this classic problem in urban economics.”
five years. Estimates also suggest that when a city’s export employment share in oil-producing sectors is 50% (for context, Williston, ND, has a 60% share in 2013), a doubling of the oil price causes house prices in all areas of the city to rise by about 20% after three years and 30% after five years.

Effects of oil price changes are robust and relatively constant across time periods regarding the transportation cost effect, suggesting symmetry in terms of positive versus negative oil price changes. The oil export effect is robustly positive, though more highly variable across time periods. Additional robustness tests are broadly consistent with the theoretical model, with each additional set of estimates serving to highlight the differential sensitivities of housing demand in different locations to changes in the price of oil.

Both our theoretical predictions and empirical findings support the following view of the relation between rising oil prices and house values. In cities not linked to oil production, relative demand for housing rises in center-cities and falls in the suburbs. In oil exporting cities, however, the entire housing demand profile changes with the price of oil. Because the differential slope effects on suburban versus center-city prices are relatively small compared to the shift effect from export prices, the demand effects from oil price changes are skewed across the cross section of American cities. Overall, there is much greater potential for high-magnitude negative house price changes when the price of oil falls than when it rises. Therefore, when it comes to housing demand, house prices and mortgage credit risk, negative oil price shocks are potentially much more harmful than positive oil price shocks.

Conceptual Framework

The model presented in this section is based on the standard model of a monocentric city following Alonso (1964), Mills (1967) and Muth (1969). The city contains three distinct regions: a singularity at the center termed the CBD where export firms are located, a residential zone where households locate in order to be as close as possible to their place of employment and an agricultural hinterland that does not contribute to the city. The city is

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5These estimates are similar to Blake (2016), whose estimates imply an increase in the gasoline price of $1 per gallon leads to a house price decline of 2.1% at 15 miles from the CBD.

6Notation and derivations are based on Brueckner (1987).

7The CBD is assumed to occupy no land area in this model. This assumption can be made without effects on comparative statics as long as there is no traffic congestion.
Oil Prices and Urban Housing Demand

circular and identical at every distance from the center point of the city. This allows expression of variables in terms of the radius of an annulus (ring) or the distance to the CBD.

A representative, perfectly competitive export firm optimizes output production with respect to the price of the exported good, in this case, oil and the local labor wage. Firms produce output using labor alone. Housing producers construct housing using structure and land inputs in a perfectly competitive market. Households consume housing and a composite commodity, and undertake costly commutes to the CBD for employment. Migration of people and goods is costless. All firm and factor input owners are absentee and do not contribute profits to household incomes in the city.

In equilibrium, all households and firms are as well off at their current location as any other. The isoultility condition, along with a fixed quantity of land in each annulus, gives the familiar “Muth’s Equation” (1969, p. 22). This equation shows house prices fall at a rate equal to the ratio of marginal transportation costs to housing expenditures the further a home is from the center of the city.

In order to incorporate the price of oil into this framework, we assume that both the pecuniary price of commuting and the price of the exported good are linearly related to the oil price. Harmonizing these two parameters in the model allows for several interesting comparative static predictions. In the SUM, the price gradient results from the consumer’s maximization problem vis-à-vis bid rent curves. Therefore, instead of deriving the entire model, it is possible to arrive at comparative statics relating house prices to oil prices by analyzing only the export firm’s maximization problem and the household maximization problem. Other comparative statics from the model can be found in Brueckner (1987).

in the city. Constant transportation cost over a fixed land area for all households is simply a fixed cost of residing in the city. On the other hand, when traffic congestion is present in a city of endogenous size, it is important to model a CBD that occupies land.

In reality, oil production is distributed unevenly across space, not just in the CBD, but the monocentric city assumption is tenable based on the following logic. While oil production itself is diffuse, support activities and endogenous local goods and services are likely to be governed by interrelationships that result in the existence of a CBD. In the monocentric model presented here, we model the production of one good for export, but this could easily be generalized to include multiple sectors that ultimately rely on the price of the goods and services produced by the economic base, in this case, oil.
Export Firms

The CBD is a single point and is occupied by a representative firm that produces output $Q$ under a constant returns-to-scale production function using labor $N$ inputs, where $a$ is a city-specific productivity parameter.\textsuperscript{9,10}

$$Q = aN.$$  

(1)

Firms maximize profits by selling output at a globally determined, exogenous price $p^O$ and hiring workers at a city-specific, endogenously determined wage rate $w$. The first-order condition of the export firm’s profit function gives the wage rate equal to labor productivity multiplied by the export price, which, in this case, is the oil price.

$$w = ap^O.$$  

(2)

Households

Households achieve utility by consuming housing $q$, a composite commodity $z$ and leisure $l$ under a strictly quasi-concave utility function $U(z, q, l)$ subject to a budget constraint. Households earn the same base income $w$ and have identical preferences. Workers must commute to the CBD by car with variable pecuniary cost $t$ per unit of distance $k$. Following Brueckner and Rosenthal (2009), it is assumed that leisure time is fixed at $\bar{l}$, with the time cost of commuting subtracted from earnings. The time spent commuting is not without some pseudoleisure benefit, so the time cost of commuting is less than the foregone income. The time cost of commuting is specified as a fraction of $\phi$ of the full work period income per unit of distance $k$, with the total time cost of transport of $\phi kw$.\textsuperscript{11} The incurred commuting cost for a household living at radius $k$ is therefore

$$T(k) = (t + \phi w)k.$$  

(3)

\textsuperscript{9}City-specific subscripts on $a$ and all endogenous variables are omitted for ease of exposition.

\textsuperscript{10}The city-specific nature of productivity induces firms to locate in particular cities. Some other mechanisms for city formation are described in Abdel-Rahman and Anas (2004), including public good provision, production agglomeration or local amenities.

\textsuperscript{11}In this model, we do not explicitly model other household transportation costs, such as shopping, recreation or trips to school or daycare. Insofar as proximity to the CBD is related to density, and density is related to proximity to these other locations, commuting costs will be highly correlated with these other noncommuting transportation costs.
Normalizing the price of $z$ to 1, the household’s utility maximization problem is

$$\max U(z(k), q(k), \bar{I}) \quad s.t. \quad w = z(k) + p(k)q(k) + (t + \phi w)k. \quad (4)$$

Marginal transportation costs are related in a linear fashion to the price of oil according to $t = bp^O$. While oil is not directly consumed while commuting, gasoline prices are highly correlated with oil prices due to input price pass-through. Substituting for $z$ in the utility function using the budget constraint, $z = w - (t + \phi w)k - p(k)q(k)$, for wages $w = ap^O$, and for marginal transportation costs $t = bp^O$, the first-order conditions give

$$\frac{U_2(p^O(a - bk - a\phi k) - p(k)q(k), q(k))}{U_1(p^O(a - bk - a\phi k) - p(k)q(k), q(k))} = p(k). \quad (5)$$

The intracity isoutility condition implies that households have identical utility levels and are indifferent between living in different locations within the city. Additionally, under the assumption of an open city, the utility level of households must equal to the prevailing utility level $u^*$, which is exogenously given,$^{12}$

$$U(p^O(a - bk - a\phi k) - p(k)q(k), q(k)) = u^*. \quad (6)$$

**An Oil Price Shock in an Oil Exporting City**

After establishing the relevant first-order conditions and urban equilibrium conditions, comparative static analysis can be conducted to predict the effects of an oil price shock on the housing price and the urban spatial structure.

First, the slope of the house price gradient can be derived by totally differentiating (6) with respect to $k$. This gives

$$-U_1((b + a\phi)p^O + p(k)q'(k) + q(k)p'(k)) + U_2q'(k) = 0, \quad (7)$$

substituting $U_2 = U_1p(k)$ from Equation (5) into Equation (7) and rearranging gives our version of Muth’s equation

$$p'(k) = \frac{-(b + a\phi)p^O}{q(k)}. \quad (8)$$

$^{12}$There are arguments in favor of both open-city and closed-city assumptions. We prefer the open-city assumption in the present context because some cities are oil exporters and some are not, with the oil price changes causing utility differentials and eventually migration between cities due to the export price effect. However, in nonoil exporting cities, an increase in the oil price unambiguously harms households because of the transportation cost effect, making a closed-city assumption potentially preferable in this context if the number of oil exporting cities is small.
This equation shows house prices falling at a rate where households are indifferent between consuming more housing at higher commuting expenditures or less housing with reduced commuting expenditure. In our rendition of the model, the marginal commuting expenditure is a constant term (pecuniary costs $b$ plus time costs $a\phi$) multiplied by the oil price $p^O$. When oil prices increase, the house price gradient steepens.

But overall, what happens to the level of house prices, not just the gradient? The effect of the oil price $p^O$ on housing prices $p(k)$ can also be derived by totally differentiating Equation (6), but this time with respect to $p^O$. This gives

$$U_1\left(a - bk - a\phi k - p(k)\frac{\partial q(k)}{\partial p^O} - q(k)\frac{\partial p(k)}{\partial p^O}\right) + U_2\frac{\partial q(k)}{\partial p^O} = 0.$$  

(9)

Substituting Equation (5) into Equation (9) gives

$$\frac{\partial p(k)}{\partial p^O} = \frac{a - bk - a\phi k}{q(k)}.$$  

(10)

The sign of $\frac{\partial p(k)}{\partial p^O}$ depends on the sign of $a - bk - a\phi k$. However, we know $a - bk - a\phi k > 0$ for every $k$ in the city due to the budget constraint. Therefore, an oil price change results in a level shift of house prices that outweighs any gradient rotation.\(^\text{13}\)

In this model, an oil price increase causes an increase in earnings and smaller increases in commuting costs. New households migrate to the city until the diseconomies of the higher population offset the rising incomes. House price increases at every $k$ indicate that the city boundary and population are increasing endogenously.\(^\text{14}\)

**An Oil Price Shock in a Nonoil Exporting City**

In most cities, oil is not produced—it is only consumed. It is therefore important to consider the case where the oil price is related only to marginal transportation cost and not household earnings. In this case, the model reduces

\(^\text{13}\)Other gradients in the SUM, such as population density, may be found recursively once the house price gradient is known. This requires solving the housing producer’s problem.

\(^\text{14}\)Derivations available upon request. As with the other gradients, this involves solving the housing production problem, which is not the focus of this section. Additionally, our model omits the effect of oil prices on the size of the CBD. Obviously, a positive oil price shock that raises demand for labor will raise demand for commercial space in the CBD, which reinforces the upward pressure on housing prices. However, this does not affect Muth’s equation governing the price gradient.
to the standard rendition of the SUM with the oil content of transportation costs substituted for marginal transportation costs as discussed in the previous section.\textsuperscript{15}

Equation (8) becomes Equation (11), where the slope of the gradient is different because earnings, and therefore the time cost of commuting, are no longer tied to the price of oil.

\[
p'(k) = \frac{-bp^O - \phi w}{q(k)}. \tag{11}
\]

Equation (10) is also modified in an important way. Because the oil price no longer enters into earnings, the total derivative of Equation (6) shown in Equation (9) becomes

\[
U_1 \left( -bk - p(k) \frac{\partial q(k)}{\partial p^O} - q(k) \frac{\partial p(k)}{\partial p^O} \right) + U_2 \frac{\partial q(k)}{\partial p^O} = 0, \tag{12}
\]

and (10) changes to

\[
\frac{\partial p(k)}{\partial p^O} = \frac{-bk}{q(k)}. \tag{13}
\]

In the case of a nonoil producing city, house prices fall everywhere, and more so when \( k \) is large such as in suburban locations. A positive oil price shock causes a rotation of the house price gradient around the CBD.\textsuperscript{16}

**Testable Predictions**

Two main testable predictions result from this model. First, an oil price change will increase house prices at every radius in an oil exporting city. While oil prices are negatively related to transportation costs, the positive income effect always dominates in our model.

Second, an oil price change will cause a fall in house prices in the suburbs relative to areas near the center-city in all cities. Because households living far from the CBD must commute farther than households near to the CBD, the isoutility condition forces house prices to fall in the suburbs in order to compensate for a loss of purchasing power when oil prices rise. This rotation

\textsuperscript{15}It is also possible to consider an export good production function that uses oil as an input. In this case, an industry with high oil input requirements would have incomes that are negatively affected by oil prices. This question is left for further research.

\textsuperscript{16}Under a closed-city assumption, utility falls in a nonoil exporting city. House price gradients rotate in a similar fashion, but at a higher average house price than in the open-city model.
in the house price gradient should occur in all cities, regardless of export industry.

**Stochastic Specification**

In order to test the predictions resulting from the theoretical model, we rely on a standard two-way fixed effects panel specification, following Blanchard and Katz (1992), Saks (2008) and others. This empirical model relates annual changes in house price appreciation, \( \Delta p_t \equiv \ln P_t - \ln P_{t-1} \), in ZIP code \( z \), in city \( i \), as a function of changes in the oil price \( \Delta p^O_t \) interacted with a city-specific oil export share \( \tilde{e} \) measure, and changes in the oil price interacted with a measure of distance to the CBD, \( k \). It may take some time for the oil price to affect the housing market, so we include lags of the oil price change variables.

We also include a within-city control variable, the change in real gross domestic product (GDP) interacted with the ZIP code-specific distance to the CBD. The importance of this control is highlighted by Molloy and Shan (2013), who argue that price gradient rotations occur in predictable ways based on household income changes, and these may be correlated with changes in transportation costs. Our baseline specification is

\[
\Delta p_{izt} = \alpha_z + \alpha_t + \sum_{h=1}^H \beta_h \Delta p^O_{t-h} \times k_z + \sum_{h=1}^H \gamma_h \Delta p^O_{t-h} \times \tilde{e}_i + \sum_{h=1}^H \delta_h \Delta GDP_{t-h} \times k_z + \epsilon_{izt},
\]

with residuals and standard errors of parameter estimates clustered by city. Equation (8), governing the house price gradient in the city, implies that when oil prices rise, the house price gradient steepens. This gives the hypothesis that \( \beta < 0 \) in Equation (14), individually and in summation. Similarly, Equation (10) predicts a city that specializes in oil exports has house prices that are

\[17\] However, due to concerns of Nickell (1981) bias, we omit lagged dependent variables in the main specification.

\[18\] For instance, a national income increase may simultaneously increase city-level demand for a center-city amenity, demand for housing and cause the oil price to rise. This necessitates the inclusion of a proxy for nontransportation factors as a control variable. We follow Molloy and Shan (2013) and include national GDP interacted with CBD distance as proxy for the sum of these factors. We will also consider other fixed effects combinations in robustness exercises as controls for state and city-specific variation in house price changes.
positively related to the price of oil due to the export price effect. But not all cities are fully specialized, so we include a continuous measure of city oil export intensity, $\tilde{e}$. Under the hypothesis in Equation (10), the share of exports dedicated to oil interacted with the oil price is positively related to house prices, or $\gamma > 0$, again, both individually and summed over time. We have no firm prediction for the sign of $\delta$, as rising incomes may cause demand for suburban units to rise through income effects, or fall due to positive interaction with possible center-city consumption amenities.

Because the transaction price for housing is related to the expected long-run price of commuting, we specify the oil price as the expected future oil price. An expectations measure is preferable to a spot price measure in terms of shock identification because the spot price is potentially confounded by transitory and predictable price movements. On the other hand, an expectations measure only changes when new information enters the market.\footnote{While our baseline specification includes the three-year future price, our estimates are robust to the use of the spot oil price and the spot gasoline price in its place.}

We use the CBD distance, $k$, as our measure of workplace proximity, but it is well known that the distance to the CBD may be an inaccurate measure of commuting costs. This can occur in cases of city polycentricity or road networks that are nonradial (i.e., gridded or restricted due to topography). It is therefore important to include other measures as robustness checks—including the average commute time—which are presumably resilient to city polycentricity.

We prefer a panel specification over time series analysis of individual cities because the time period effects control for effects of national changes in house prices, gasoline prices, oil prices and other variables that are common to all cities. The ZIP code fixed effects also incorporate a great deal of information in this specification. For instance, persistent gasoline price differentials may exist across areas, and some areas are more or less desirable than others in ways that are capitalized into appreciation rates. In addition, the geography of a region may affect the type of vehicle purchased or the number and types of trips. This includes the existence of public transportation, or complementarities of certain vehicles with recreation or noncommuting trips. Factors that are persistent within an area over time are subsumed by the fixed effects.\footnote{In robustness tests, we examine different subsets of cities and time periods in order to determine effects of oil prices on cities of different characteristics.}

A potential concern is an endogenous response that varies within the city. For instance, high gasoline or oil prices may elicit other endogenous responses
such as the purchase of more fuel-efficient vehicles and greater utilization of public transportation. This behavior serves to flatten any price gradient effects because it mitigates the effect of the transportation cost change. Additionally, changes to gasoline prices may differentially affect house prices because land values are capitalized into local retail gasoline prices. Thus, an increase in the national gasoline price will cause prices in the suburbs to rise slower than prices in the center-city, if the gasoline price has a greater negative effect on land prices further from the CBD. All of these potential effects cause our parameter estimates to be reduced in magnitude, as they assume two countervailing effects—the first-order effect of the oil price change on house prices and a second-order effect either due to substitution, or capitalized land price effects on fuel costs at the pump that are of the opposite sign.

A final consideration is the elasticity of housing supply. Our theoretical model is long run in nature and therefore gives equivalent predictions for supply elastic versus inelastic regions. However, a large body of research has found short-run price dynamics for housing to be different in areas with high regulation (Saks 2008), topographic interruptions (Saiz 2010), urban decline (Notowidigdo 2011, Glaeser and Gyourko 2005) and other construction constraints (Glaeser et al. 2014). The general finding in this literature is that when supply is constrained, the construction response is limited in some fashion, either in the short run through regulatory barriers, or in the long run due to shifts in the long-run supply curve. This causes demand changes to be capitalized into prices to a greater degree in supply-inelastic areas.

Because oil price changes are assumed to act as housing demand shocks, based on the above theories, we would expect greater short-run price effects in areas where the supply elasticity is smaller, including large, highly regulated, topographically interrupted or declining cities. We leave a broad investigation of the interacted effects of the predictions of our model with supply elasticity factors to future research due to the numerous complications with estimating such a model. However, we do find two elasticity measures are correlated with the magnitude of the price effects observed, including city size and housing market regulation.

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21 Direct measures of housing market regulation are recent, such as the Wharton Land Use Regulatory index (WRLURI) of Gyourko, Saiz and Summers (2008), and presumably endogenous with respect to changes in house prices. Historical decline is correlated with industrial structure, which, in turn, may have interactions with the oil price beyond the export price effects we examine. Finally, large, highly regulated cities also tend to be topographically interrupted, whereas the majority of oil-producing regions are inland with low regulation and few topographic interruptions, making it difficult to identify a natural experiment given the lack of variation along these dimensions.
Data

Our unit of measure for a city is the core-based statistical area (CBSA), and for submarkets within cities, the five-digit ZIP code. Some ZIP codes span more than one city, so we restrict the sample of ZIP codes to those that exist in a single city. The data necessary to estimate the empirical model are found in various source databases. The first is the 1990 Decennial Census, which includes information on demographics, commuting patterns and housing unit counts at both the county and ZIP code level. This allows segmentation of ZIP codes into various city and neighborhood types. Other data consist of information on oil prices, oil export shares and house prices, with each described below.

Oil Prices

We assume that expected future oil prices are governed by an adaptive expectations process. This is observed using the three-year forward oil price for delivery at Cushing, Oklahoma, after 1990. Prior to 1990, we estimate this process using simple time series model relating the spot oil price to the three-year forward price.\(^{22}\) Oil price data are accessed via Bloomberg.

Figure 3A shows real oil and gasoline prices by year, deflated by the urban goods consumer price index giving prices in terms of 2015 USD. Gasoline and oil prices track each other quite precisely, with a correlation between the two of 0.88 in the level and 0.54 in the growth rate between 1975 and 2015. This figure also shows the three-year forward price, which is highly suggestive of an adaptive expectations process as it appears to be a smoothed, weighted average of the spot price.

In order to impute the expected oil price in periods prior to 1990, we model the three-year forward oil price as a weighted average of the spot oil price and three annual lags, and fit using data between 1990 and 2015. The fitted equation is

\[
p_{3yr,t}^{O} = 0.62p_{t}^{O} + 0.22p_{t-1}^{O} + 0.12p_{t-2}^{O} + 0.04p_{t-3}^{O}.
\]

This model has an estimated \(R^2\) of 0.987 over the 26 years. Our final expectations series is shown in Figure 3B.

We interpret changes in this measure as a permanent shock, following Acemoglu, Finkelstein and Notowidigdo (2013), who argue that changes to oil prices resemble a random walk. As evidence, they present a battery of Dickey–Fuller tests that “comfortably fail to reject the null hypothesis that oil prices

\(^{22}\)A national price is sufficient in most of our empirical specifications. Persistent differences in prices across regions are captured by area fixed effects.
follow a unit root.” Under this interpretation, changes in the expectations series thus represent shocks to expectations. As robustness tests, we also estimate models using the spot oil price and the gasoline price, both of which have been used in the prior literature. While spot prices may result in inefficient estimates, use is unlikely to result in biased coefficients. Robustness tests confirm this resilience.
Export Shares

Export shares are calculated using from the Bureau of Labor Statistic’s Quarterly Census of Employment and Wages (QCEW). The QCEW contains tabulations of employment for all establishments that report into national unemployment insurance programs. This includes about 97% of all civilian (both full and part time) employment in the United States.\(^2^3\)

Employment that is considered to be generating exports is calculated using the location quotient approach (see Brown, Coulson and Engle 1992, for instance). This method assumes that for each area, any employment in an industry that is in excess of the national average is used to produce goods and services for net export, for instance, by physically exporting goods, inducing tourists to visit, or provide services that are relatively unbound by geography.\(^2^4\) It also assumes that consumer preferences are Leontief and identical across locations, leading to no substitution due to differential relative prices of consumer goods.

The location quotient \(L\) for city \(i\) and industry \(j\) in time period \(t\) is calculated as follows, where \(e\) is employment and omitted subscripts denote sums:

\[
L_{ijt} = \frac{e_{ijt}}{e_{jt}} / \frac{e_{it}}{e_t}. \tag{15}
\]

A \(L_{ijt} > 1\) indicates the presence of export employment. Export employment \(x\) is then calculated as

\[
x_{ijt} = \left( \frac{L_{ijt} - 1}{L_{ijt}} \right) e_{ijt}. \tag{16}
\]

if \(L_{ijt} > 1\), otherwise \(x_{ijt} = 0\). Export employment shares are then calculated as

\[
\tilde{e}_{ijt} = \frac{x_{ijt}}{x_{it}}. \tag{17}
\]

For each three-digit NAICS sector, location quotients and export employment shares are calculated in 1990 for use in empirical specifications, and then

\(^{2^3}\) Overcounting may arise if a single worker holds jobs in more than one sector. Counts exclude self-employed, many workers on small farms, the military and other sectors where informal employment arrangements are common.

\(^{2^4}\) Many goods are produced for export even when location quotients are less than one. For instance, local households are unlikely to consume local hotels. Rather, the location quotient represents net local production versus consumption of the goods and services produced by the sector in question.
Figure 4 ■ Oil export employment shares, 2013. [Color figure can be viewed at wileyonlinelibrary.com]

again for 2013 for use in interpreting coefficients in light of present values.25

Figure 4 shows oil export shares for CBSAs in 2013 in the United States for the sum of four sectors: oil and gas extraction (NAICS 211), support activities for mining (213), petroleum and coal products manufacturing (324) and pipeline transportation (486). These sectors are chosen because they are each fundamentally related to the supply side of the oil market—when the price of oil rises, demand for extraction increases, which directly causes demand for support activities and pipeline transportation to rise.26

Shares are highest in areas commonly known to be centers of oil and gas extraction and refining, including Texas, Oklahoma, Colorado, Wyoming, North Dakota, California and Pennsylvania. In 13 of the 858 CBSAs where export shares are calculated, shares are above 30%, with a further 40 between 10% and 30%. The vast majority of all locations (722) have less than 0.1%

25While we would prefer to calculate them for our initial period (1975), 1990 is the earliest available. We therefore must make the standard weak exogeneity assumption that house price changes do not lead to changing export shares for observations in 1991–2015, but also an additional assumption that house price changes between 1975 and 1990 do not affect export shares either. While this assumption may be problematic for other locally endogenous variables, such as levels of housing stock or earnings, we do not believe this to significantly bias our estimates. Export shares are fairly stable over time and are therefore presumably not materially affected by short-run house price movements.

26Other sectors are presumably related to the price of oil through demand for oil inputs. For instance, oil is a primary input in production for transportation services, rubber manufacturing and gas stations. In this case, all else equal, oil demand, labor demand and therefore housing demand, should fall when oil prices rise. Other industries may also have a procyclical correlation with the price of oil due to aggregate demand factors.
export employment in these sectors. A list of export shares by CBSA is available in Table 1.

House Prices

The source for house price information is the Bogin, Doerner and Larson (2016) (BDL) house price database produced by the Federal Housing Finance Agency. The BDL database includes constant-quality, repeat-sales house price indices at an annual frequency, calculated for 914 CBSAs, including all 381 MSAs and 533 MicroSAs. It also includes 17,936 ZIP-code-level house price indices, including nearly 9,000 prior to 1990, making it ideally suited to measure the effects of oil prices on house price changes within cities over long time horizons. The BDL database also includes a measure of the distance to the CBD of the CBSA, allowing this to enter as a covariate in empirical specifications.27

Figure 1 shows oil and house prices in Williston, ND, which has seen a rise in oil production in recent years due to innovations related to hydraulic fracturing (“fracking”) and horizontal drilling. This figure illustrates the high correlation between the oil price level and house prices in this city. Figure 5 shows that this case may be generalizable, as house price appreciation by CBSA between 2000 and 2015 appears to have a high partial correlation with oil export shares, controlling for rapid appreciation in California, the mid-Atlantic and the Sun Belt states.

Figure 2 shows 15-year appreciation rates for two periods, 1985–2000 and 2000–2015, as a function of the distance to the CBD, averaged over all ZIP codes available. House price gradients are steepening more between 2000 and 2015 than between 1985 and 2000. In the context of Figure 3A, which shows higher oil price levels in the later period, house price gradients appear steepen as the same time as oil prices are high. This is suggestive of a relationship similar to Equation (8), which posits that an increase in oil prices steepens the house price gradient.

Main Results

This section presents estimates of Equation (14), calculated over the full panel of ZIP codes in 781 CBSAs between 1975 and 2015. These estimates enable

27The distance-to-CBD measure in the BDL database is constructed as the distance between the ZIP code’s centroid and the CBD centroid. The CBD ZIP code is identified using the standardized sum of two density measures. The first is the standardized fraction of housing units in 20+ unit structures. The second is the (negative) standardized land area of the ZIP code. Because ZIP codes have roughly similar numbers of postal customers, the area gives an approximate measure of density.
Table 1 ■ Oil export employment shares.

| CBSA Code | CBSA Name | State | Oil Export Employment Share (2013) | CBSA Code | CBSA Name | State | Oil Export Employment Share (2013) |
|-----------|-----------|-------|-----------------------------------|-----------|-----------|-------|-----------------------------------|
| 11260     | Anchorage | AK    | 9%                                | 14620     | Bradford  | PA    | 26%                               |
| 20980     | El Dorado | AR    | 15%                               | 48700     | Williamsport | PA    | 16%                               |
| 42620     | Searcy    | AR    | 13%                               | 42380     | Sayre     | PA    | 11%                               |
| 31620     | Magnolia  | AR    | 11%                               | 48780     | Sayre     | PA    | 2%                                |
| 12540     | Bakersfield | CA | 14%                               | 38300     | Pittsburgh | PA    | 2%                                |
| 41860     | San Francisco | CA | 1%                                | 33260     | Midland   | TX    | 59%                               |
| 24300     | Grand Junction | CO | 24%                               | 30220     | Levelland  | TX    | 55%                               |
| 24540     | Greeley    | CO    | 24%                               | 10860     | Alice     | TX    | 53%                               |
| 20420     | Durango    | CO    | 6%                                | 11380     | Andrews   | TX    | 48%                               |
| 19740     | Denver     | CO    | 4%                                | 37420     | Pampa     | TX    | 45%                               |
| 16460     | Centralia  | IL    | 7%                                | 14420     | Borger    | TX    | 42%                               |
| 30580     | Liberal    | KS    | 30%                               | 36220     | Odessa    | TX    | 39%                               |
| 24460     | Great Bend | KS    | 22%                               | 23620     | Gainesville | TX    | 34%                               |
| 25700     | Hays       | KS    | 15%                               | 26420     | Houston   | TX    | 29%                               |
| 23780     | Garden City | KS | 7%                                | 33420     | Mineral Wells | TX    | 27%                               |
| 29180     | Lafayette  | LA    | 48%                               | 30980     | Longview  | TX    | 27%                               |
| 34020     | Morgan City | LA | 28%                               | 47020     | Victoria  | TX    | 26%                               |
| 26380     | Houma      | LA    | 22%                               | 18580     | Corpus Christi | TX    | 25%                               |
| 29340     | Lake Charles | LA | 15%                               | 32220     | Marshall  | TX    | 25%                               |
| 43340     | Shreveport | LA    | 13%                               | 20900     | El Campo  | TX    | 21%                               |
| 35020     | Natchez    | LA    | 10%                               | 13060     | Bay City  | TX    | 19%                               |
| 35880     | New Orleans | LA | 9%                                | 13300     | Beeville  | TX    | 19%                               |
| 36660     | Opelousas  | LA    | 8%                                | 29500     | Lamesa    | TX    | 18%                               |
| 29860     | Laurel     | MS    | 24%                               | 13700     | Big Spring | TX    | 18%                               |
| 13740     | Billings   | MT    | 6%                                | 13140     | Beaumont  | TX    | 17%                               |
| 48780     | Williston  | ND    | 60%                               | 37300     | Palestine | TX    | 17%                               |
| 19860     | Dickinson  | ND    | 48%                               | 45020     | Sweetwater | TX    | 15%                               |
Table 1  ■  Continued.

| CBSA Code | CBSA Name | State | Oil Export Employment Share (2013) | CBSA Code | CBSA Name | State | Oil Export Employment Share (2013) |
|-----------|-----------|-------|-----------------------------------|-----------|-----------|-------|-----------------------------------|
| 33500     | Minot     | ND    | 15%                               | 33500     | Minot     | ND    | 15%                               |
| 26020     | Hobbs     | NM    | 60%                               | 26020     | Hobbs     | NM    | 60%                               |
| 16100     | Carlsbad  | NM    | 54%                               | 16100     | Carlsbad  | NM    | 54%                               |
| 22140     | Farmington| NM    | 28%                               | 22140     | Farmington| NM    | 28%                               |
| 40740     | Roswell   | NM    | 6%                                | 40740     | Roswell   | NM    | 6%                                |
| 21220     | Elko      | NV    | 11%                               | 21220     | Elko      | NV    | 11%                               |
| 45780     | Toledo    | OH    | 3%                                | 45780     | Toledo    | OH    | 3%                                |
| 12780     | Bartlesville| OK    | 73%                               | 12780     | Bartlesville| OK    | 73%                               |
| 49260     | Woodward  | OK    | 51%                               | 49260     | Woodward  | OK    | 51%                               |
| 21120     | Elk City  | OK    | 48%                               | 21120     | Elk City  | OK    | 48%                               |
| 20340     | Duncan    | OK    | 38%                               | 20340     | Duncan    | OK    | 38%                               |
| 36420     | Oklahoma City| OK    | 30%                               | 36420     | Oklahoma City| OK    | 30%                               |
| 32540     | McAlester | OK    | 26%                               | 32540     | McAlester | OK    | 26%                               |
| 21420     | Enid      | OK    | 21%                               | 21420     | Enid      | OK    | 21%                               |
| 44660     | Stillwater| OK    | 18%                               | 44660     | Stillwater| OK    | 18%                               |
| 11620     | Ardmore   | OK    | 17%                               | 11620     | Ardmore   | OK    | 17%                               |
| 46140     | Tulsa     | OK    | 12%                               | 46140     | Tulsa     | OK    | 12%                               |
| 38620     | Ponca City| OK    | 10%                               | 38620     | Ponca City| OK    | 10%                               |
| 43060     | Shawnee   | OK    | 6%                                | 43060     | Shawnee   | OK    | 6%                                |
| 25100     | Guymon    | OK    | 5%                                | 25100     | Guymon    | OK    | 5%                                |
| 22900     | Fort Smith| OK-AR | 8%                                | 22900     | Fort Smith| OK-AR | 8%                                |
| 26860     | Indiana   | PA    | 28%                               | 26860     | Indiana   | PA    | 28%                               |

Note: Oil export employment shares are calculated using methods described in the text. Data are from the BLS’ Quarterly Census of Employment and Wages, and include CBSA-level employment in the following four NAICS sectors in 2013: oil and gas extraction (NAICS 211), support activities for mining (213), petroleum and coal products manufacturing (324) and pipeline transportation (486). Cities in bold have greater than 250,000 housing units. Cities are included if the share is greater than 5%, or both greater than 1% and the population is greater than 250,000.
hypothesis tests of both the export price effect, estimated using the city export employment share for oil, and the transportation cost effect, estimated based on several different commuting cost measures. Table 2 presents the estimates and the results of these tests. The presentation of this table includes each lag of the interacted variables, along with the sum of the lagged coefficients and $F$-tests of the null hypothesis of no effect.\(^{28}\)

Column 1 presents parameter estimates where the commuting cost variable is defined as the log of the distance to the CBD. The oil export share interaction terms start small at one lag, rise to a peak at three lags and remain positive and significant through lag five. The sum of the lags is approximately 0.64, indicating a five-year oil price—house price elasticity of 0.32 in a city where the export employment share for oil is 50%. All individual parameters are positive and most are statistically significantly different than zero, indicating support for the first prediction of our theoretical model. These estimates are not statistically different than in the other three models, with the sum of lags varying between 0.632 and 0.646.

For some context, estimates in Smith and Tesarek (1991) imply an elasticity of about 0.5, with a 60% fall in the oil price in the 1980s reducing house prices in Houston by 30% over the time period. Our elasticity estimate is about 0.2 for a city with 30% export share, such as Houston. While our estimates are lower than the special case of Houston in the 1980s, our estimates are still large, significant and are generalizable across different locations and time periods.

\(^{28}\)The lag length of 5 is chosen based on a sequence likelihood ratio tests comparing the sum of squared residuals with $n$ versus $n+1$ lags. When there is no statistical difference in fit, which occurs at $n = 5$, $n$ lags are deemed sufficient.
Table 2  ■ Effects of oil prices on house prices—main results.

| Commuting Variable: | Dependable Variable: Δ ln HPI(t) |
|---------------------|----------------------------------|
|                     | [1] CBD Distance (log, Miles) | [2] CBD Distance > 15 Miles | [3] Commute (log, Minutes) | [4] Commute > 24 Minutes |
| City Oil Export Share ×: Δ ln Oil Price (t - 1) | -0.0965 [0.0657] | -0.0973 [0.0659] | -0.0841 [0.0732] | -0.0857 [0.0701] |
| Δ ln Oil Price (t - 2) | 0.226*** [0.0381] | 0.229*** [0.0395] | 0.237*** [0.0384] | 0.235*** [0.0377] |
| Δ ln Oil Price (t - 3) | 0.301*** [0.0402] | 0.303*** [0.0402] | 0.303*** [0.0397] | 0.300*** [0.0398] |
| Δ ln Oil Price (t - 4) | 0.135*** [0.0498] | 0.137*** [0.0496] | 0.123*** [0.0484] | 0.119** [0.0480] |
| Δ ln Oil Price (t - 5) | 0.0723* [0.0350] | 0.0719* [0.0355] | 0.0682* [0.0366] | 0.0634* [0.0358] |
| Sum of coefficients  | 0.638***  | 0.644***  | 0.646***  | 0.632***  |
| F-Statistic         | 33.58     | 34.23     | 32.94     | 36.42     |
| p-Value             | <0.001    | <0.001    | <0.001    | <0.001    |

Commuting variable (in column header) ×: Δ ln Oil Price (t - 1) | 0.00205** [0.000998] | 0.0116 [0.00786] | 0.0568*** [0.0156] | 0.0186** [0.00814] |
| Δ ln Oil Price (t - 2) | -0.00391*** [0.000933] | -0.0163*** [0.00589] | -0.0260*** [0.00738] | -0.0162*** [0.00493] |
Table 2  ▬ Continued.

| Commuting Variable:                | [1] CBD Distance (log, Miles) | [2] CBD Distance > 15 Miles | [3] Commute (log, Minutes) | [4] Commute > 24 Minutes |
|------------------------------------|-------------------------------|-----------------------------|---------------------------|--------------------------|
| $\Delta \ln \text{Oil Price } (t-3)$ | $-0.00081$                    | $-0.0131^{**}$              | $-0.0263^{***}$           | $-0.0180^{***}$          |
|                                    | [0.000908]                    | [0.00596]                   | [0.00722]                 | [0.00503]                |
| $\Delta \ln \text{Oil Price } (t-4)$ | $-0.00237^{**}$               | $-0.0102$                   | $-0.0243^{***}$           | $-0.0138^{**}$           |
|                                    | [0.000793]                    | [0.00643]                   | [0.00787]                 | [0.00573]                |
| $\Delta \ln \text{Oil Price } (t-5)$ | $0.000971$                    | $-0.00269$                  | $0.00434$                 | $-0.00151$               |
|                                    | [0.00127]                     | [0.00949]                   | [0.0124]                  | [0.00916]                |
| Sum of coefficients                | $-0.00407^{**}$               | $-0.0307^{**}$              | $-0.0155^{**}$           | $-0.0309^{**}$           |
| $F$-Statistic                      | 4.969                         | 5.254                       | 4.049                     | 5.644                    |
| $p$-Value                          | 0.0261                        | 0.0222                      | 0.0445                    | 0.0178                   |
| Sum of $\Delta \text{GDP} \times$ |                              |                             |                          |                          |
| CBD distance coefficients          | 0.0614^{**}                   | 0.0586^{**}                 | 0.057^{***}              | 0.0632^{***}             |
| ZIP code FEs                       | Yes                           | Yes                         | Yes                       | Yes                      |
| Time period FEs                    | Yes                           | Yes                         | Yes                       | Yes                      |
| Observations                       | 336,076                       | 336,076                     | 309,273                   | 309,273                  |
| $R$-squared                        | 0.314                         | 0.314                       | 0.309                     | 0.308                    |

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors (CBSA) in brackets. Cross section includes all ZIP codes for which house prices are available that span a single CBSA. Data are at an annual frequency between 1975 and 2015. Model 2 also includes a category for ZIP codes between 5 and 15 miles from the CBD. These estimates sum to $-0.015$ and are jointly significant at the 10% level. Sum of $\Delta \text{GDP} \times$ CBD distance parameters includes $\sum_{t-1}^{t-5} \beta_t$. Electronic copy available at: https://ssrn.com/abstract=3694521
Figure 6 ■ Dynamic effects of oil price changes on house prices.

Note: Figures are based on coefficient estimates from Table 2, column 1. Panel (A) considers the partial effect of an oil price change (log difference) on house prices in a city with a 50% oil export employment share. Panel (B) considers the partial effect of on house prices in a ZIP code 15 miles from the central business district.

In column 1, the distance-to-CBD measure’s interacted effect is zero at the first lag, peaking at period two and declining through period 5. The sum of the lags is −0.004 giving an estimated elasticity of 0.011 at 15 miles from the CBD after five years. Evaluated at these values, this transportation cost effect is nearly 30 times smaller than the export price effect, though both are statistically and economically relevant given the values of the assets. Overall, it appears that oil prices increase relative house prices in oil producing areas, and decrease relative house prices slightly in suburban areas.

A clear pattern emerges when each of the lagged interaction term parameters are graphed in Figure 6. Effects start small after one year, peak in year 2 or 3 and slowly fall through year 5. Combined, these suggest that a permanent change in oil prices results in a permanent change in house prices. While construction is likely to mitigate some of this effect in the long run, these short-run effects appear to be robust across a variety of specifications.

We also estimate house price changes as a function of location in one of three concentric rings around the CBD: the center-city from 0 to 5 miles to the CBD; the mid-city, from 5 to 15 miles; and the suburbs, which are defined as 15+ miles from the CBD. The base estimate is the center-city area, so parameter estimates in column 2 are interpreted as appreciation relative to this group. The sum of the interacted variable coefficients for mid-city areas is negative (−0.015) and significant at the 10% level. In the suburbs, the sum of the coefficients is −0.031, highly significant and in line with the log-distance estimate.
While these first two models give significant estimates of the predicted sign, CBD distance alone may be imprecise due to city polycentricity, suburbanization of employment or other factors. We therefore attempt to determine the robustness of results in columns 1 and 2 with an alternative measure of commuting costs—the commute time itself. Columns 3 and 4 show that this measure gives similar results to the CBD measure, with log commute time and commute times greater than 24 minutes (the measure used by Molloy and Shan 2013) associated with negative relative house price effects when the price of oil rises.

These results echo those in Coulson and Engle (1987), who found that the increase in gasoline prices in the late 1970s led to steepening price gradients in cities, and Molloy and Shan (2013), who use ZIP code data and find negative but insignificant effects of gasoline prices interacted with commute times on house prices. Molloy and Shan’s (2013) specification estimates differences in house prices as a function of the 0/1 indicator for commute times interacted with changes in gasoline prices, with 1–4 lags. The sum of these four coefficients is negative as predicted by our theoretical model, but at −0.009, it is only about 1/3 the magnitude of our estimate and is not statistically significant. In later sections, we delve into some of the possible reasons for this difference in estimated effects.

Robustness Exercises

City-Level Industry Models

In the baseline model, observations are at the ZIP code level, yet the oil export share variable is measured at the city level. It is therefore useful to consider a more direct, city-level model that only attempts to measure the export price effect. Additionally, while it has been assumed that four NAICS sectors sum to give the “oil export employment share” in Table 2, it is certainly possible that these industries have a differential effect on oil prices.

In order to isolate cross-city effects, we model CBSA-level house prices rather than ZIP code house prices as a function of export employment shares of the baseline export employment variable (or respective industries) interacted with oil price changes, and CBSA and time period fixed effects. Summed parameters from this set of estimates are found in Table 3 for the baseline export employment variable, and each of the four NAICS sectors 211, 213, 324 and 486.

Column 1 presents the city-level rendition of the baseline model. All within-city factors are subsumed into the city fixed effect. The point estimate
Table 3  ■ Effects of oil prices on house prices—city-level industry estimates.

| Sector Name                      | Model [1] | Model [2] |
|----------------------------------|-----------|-----------|
| All Oil Sectors (Baseline)       |           |           |
| Oil and Gas Extraction           | 0.667***  | 0.655***  |
| Support Activities for Mining    | 0.715***  | 0.698***  |
| Petroleum and Coal Products      | 0.112     | 0.0514    |
| Manufacturing                    | 0.004     | 0.821     |
| Pipeline Transportation          |           |           |
|                                 | F-Statistic |          |
|                                 | 143.7     | 21.69     |
|                                 | p-Value    | 0.001     |
|                                 | <0.001    | <0.001    |
|                                 | CBSA FE     | Yes       |
|                                 | Yes       |           |
|                                 | Time period FE | 28,913 |
|                                 | Yes       | 28,913    |
|                                 | Observations |          |
|                                 | 28,913    | 28,913    |
|                                 | R-squared | 0.276     |
|                                 |           | 0.277     |

Note: *** p < 0.01, ** p < 0.05, * p < 0.1. Cross section includes all CBSAs for which house prices are available. Data are at an annual frequency between 1975 and 2015. Export employment shares are calculated using methods described in the text. Model 1 includes the export employment share summed over the four component NAICS sectors. Model 2 allows each sector to enter the model independently.

of the sum of the 5 lags of the export price effect is 0.67, which is slightly higher than the 0.63–0.64 point estimates found in columns 1–4 of Table 2. This finding validates the estimated effects in models with a ZIP-code-level specification, despite its exclusive reliance on cross-city variation.

Estimates in models using single industries likely suffer from positive omitted variable bias, as firms in these sectors tend to cluster spatially near to each other. Model 2 simultaneously estimates the dynamic effects of each of the industries, with results presented in columns 2–5. These results suggest a remarkably similar effect of export specialization in NAICS sectors 211, 213 and 324, with each effect summing to between 0.65 and 0.70. Pipeline transportation has an uncertain effect and the point estimate is small. The fact that each of the first three sectors have such similar effects helps to justify the pooling of each of the variables into a single oil export employment share variable. The fourth sector’s effect is not statistically different from the prior three, making the pooling of all four permissible.
Table 4  ■  Effects of oil prices on house prices—time period sensitivity.

| Time period sample: | 1975–1980 | 1981–1998 | 1999–2010 | 2011–2015 |
|---------------------|-----------|-----------|-----------|-----------|
| Oil price change:   | Positive  | Negative  | Positive  | Negative  |
| City Oil Export Share × Δ ln Oil Price ($t - 1, t - 2, \ldots, t - 5$): | | | | |
| Sum of coefficients | 0.339     | 1.821***  | 0.584***  | 0.0666    |
| F-Statistic         | 2.055     | 44.5      | 13.71     | 0.9937    |
| p-Value             | 0.153     | <0.001    | <0.001    | 0.76      |
| ln CBD distance × Δ ln Oil Price ($t - 1, t - 2, \ldots, t - 5$): | | | | |
| Sum of coefficients | -0.00694**| 0.0111    | -0.00876***| -0.0141***|
| F-Statistic         | 4.477     | 1.79      | 18.73     | 15.37     |
| p-Value             | 0.035     | 0.181     | <0.001    | <0.001    |
| Sum of Δ GDP × CBD distance coefficients | | | | |
| Time period FEs     | Yes       | Yes       | Yes       | Yes       |
| CBSA FEs            | Yes       | Yes       | Yes       | Yes       |
| City ring FEs       | Yes       | Yes       | Yes       | Yes       |
| Observations        | 10,070    | 125,025   | 141,027   | 59,954    |
| R-squared           | 0.33      | 0.142     | 0.452     | 0.452     |

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Cross section includes all ZIP codes for which house prices are available that span a single CBSA. Data are at an annual frequency between 1975 and 2015. Sample time-period cutoffs are based on periods of largely increasing (1975–1980 and 1999–2010) or decreasing (1981–1998 and 2011–2015) oil prices. For some samples, there are too few time periods available to estimate a full battery of ZIP code fixed effects. In their place, for each sample, we use CBSA and ring fixed effects, where ring fixed effects are defined based on three concentric 5 mile annuli from the CBD and a final 15+ mile category.

Robustness across Time Periods

It may be possible for the relationship between oil prices and house prices to change over time, with asymmetric effects in periods of increasing versus decreasing prices. Table 4 presents estimates from four different time periods, delineated based on periods of roughly monotonic rising or falling prices. Overall, estimates show the city oil export share interacted with the price of oil to have a positive effect on house prices in periods of both rising and falling prices, though the effect is not statistically significant for some. In addition, the effect of the oil price on the house price gradient is negative in most time periods considered.

Because of the small number of observations in some samples, we alter our fixed effects strategy in this exercise. The ZIP code fixed effects are replaced...
with CBSA and city ring fixed effects for each 5-mile annulus. Ring fixed effects are used by Ahlfeldt et al. (2015) as a way to capture nonlinearities in the changes in house prices within cities. In the present context, ring fixed effects serve as controls capturing differential within-city appreciation rates that are common across all cities. This effect was previously captured by the ZIP code fixed effect, but now is captured by the ring fixed effect.

Column 1 presents estimates calculated using the sample of house price observations from 1975 through 1980. This period is defined by the large increase in oil prices due to Middle Eastern supply disruptions. In this subsample, the sum of the city oil export share coefficients is positive but not statistically different from zero. The sum of the CBD proximity coefficients is negative and significant.

Column 2 considers the decrease in oil prices from 1980 through the late 1990s. The export price effect is positive and statistically significant, and the commuting effect is positive but insignificant. The export price effect is larger than the estimates from Table 2, indicating a higher degree of sensitivity during this period of real oil price declines. On the other hand, price gradients do not appear to be significantly affected by the slow, steady decline in real oil prices.

Parameters estimated during the rapid rise in oil prices in the first decade of the 2000s are presented in column 3. The sum of the oil export share parameters is about 1/3 of the prior period, but the proximity effect becomes negative and highly significant.

Finally, the 2011–2015 period considers a set of years where the price of oil is first high, at approximately $100 per barrel in 2011, eventually falling to $50 per barrel in 2015. Much like the 1975–1980 period, the point estimates are of the correct sign and the transportation cost effect is significant. The GDP control variable is also interesting to consider. For the first time in any specification, the sum of the coefficients is negative and significant, rather than positive. This indicates that rising incomes are correlated with increased demand for center-city locations in this period, as opposed to suburbanization.29

Overall, these results suggest oil price effects on house prices to be somewhat noisy concerning both effects. The effect of oil prices on suburbs is

29We leave further examination of other determinants and precise mechanisms of price gradient rotations to further research. For an excellent survey of potential causes, see Edlund, Machado and Sviatchi (2015).
particularly noteworthy because the last 30 years has been broadly identified as one with steepening house price gradients in large cities. Our estimates here suggest that recent oil price declines have served to mitigate some of this steepening, making suburban locations relatively more attractive places to live between 2010 and 2015.

In light of these results, a major question is why house prices in areas like Williston, ND, have remained persistently high in the recent period. This city has a high elasticity of housing supply, and estimates in prior periods of declining oil prices predict steep declines in the face of falling oil prices. Williston is not alone. For the 2011–2015 period, the sum of the export price coefficients falls dramatically relative to the prior period from 0.58 to 0.07, indicating that the export price mechanism, at least for this period, substantially weakened. It is therefore reasonable to conclude one of two possibilities: either the level of real house prices in these cities is unsustainable, or the relationship between oil and house prices has somehow fundamentally changed between the 2000s and the 2010s.

**Effects of City Size and Regulation**

The size of a city may affect the extent to which oil prices affect house prices for three main reasons. First, at a given distance, commute times in a large city will likely be higher due to road congestion. Second, cities that are larger tend to have more diverse economies, leading to greater indirect effects of oil price changes. Finally, as discussed previously, the elasticity of housing supply is often lower in larger cities, leading to potentially larger export price effects in larger cities.

Housing market regulation may also affect how oil price changes interact with house prices. In a highly regulated city, it is more difficult to quickly construct new housing, altering price dynamics compared to an unregulated city. By reducing housing construction in response to a housing demand shock, housing market regulation can increase the magnitudes of the dynamic effects of oil price changes on house prices.

In this section, we split our sample of ZIP codes into large and small cities in 1990, defined as greater than or less than 500,000 housing units. We then do the same for housing market regulation, splitting the sample based on values of the Wharton Land Use Regulatory Index (WRLURI) described in Gyourko, Saiz and Summers (2008). We split the sample based on this index as in Molloy and Shan (2013) so that positive values indicate a highly regulated city and low values indicate a lightly regulated city, and estimate the same model on each subsample. We recommend caution in our interpretation.
Table 5  ■  Effects of oil prices on house prices—effects of city size and regulation.

| City Sample: | [1] | [2] | [3] | [4] |
|--------------|-----|-----|-----|-----|
| City Oil Export Share × Δ ln Oil Price \((t - 1, t - 2, \ldots, t - 5)\): | City | City | Regulation | Regulation |
| Sum of coefficients | 0.636*** | 0.683*** | 0.46*** | 0.678*** |
| \(F\)-Statistic | 40.86 | 13.16 | 13.46 | 25.11 |
| \(p\)-Value | <0.001 | <0.001 | <0.001 | <0.001 |
| In CBD distance × Δ ln Oil Price \((t - 1, t - 2, \ldots, t - 5)\): | | | | |
| Sum of coefficients | −0.00106* | −0.00164 | −0.00162 | −0.00469** |
| \(F\)-Statistic | 3.514 | 0.0341 | 1.039 | 4.089 |
| \(p\)-Value | 0.0612 | 0.855 | 0.31 | 0.0436 |
| Sum of Δ GDP × CBD distance coefficients | | | | |
| ZIP code FEs | Yes | Yes | Yes | Yes |
| Time period FEs | Yes | Yes | Yes | Yes |
| Observations | 167,698 | 168,378 | 111,190 | 224,886 |
| \(R\)-squared | 0.26 | 0.393 | 0.235 | 0.376 |

Note: *** \(p < 0.01\), ** \(p < 0.05\), * \(p < 0.1\). Cross section includes all ZIP codes for which house prices are available that span a single CBSA. Data are at an annual frequency between 1975 and 2015. Small and large cities are defined based on a cutoff at 500,000 housing units in 1990. Low and high regulations are defined based on WRLURI values < 0 and > 0, respectively.

Empirical findings in Table 5 give mixed evidence suggesting larger cities are more sensitive to oil price changes. The parameter estimate of the effect of the oil price interacted with distance is slightly higher in large cities than small cities. Smaller effects of physical distance in small cities are consistent with lower fuel consumption per mile compared to large cities, and suggest that physical proximity matters more in large cities. On the other hand, the export price effect is similar in small versus large cities, suggesting city size does not matter along this particular dimension of the effects.

Housing market regulation, on the other hand, is highly correlated with the effects of oil price changes on house prices, with results echoing Saks (2008).
Both export price and transportation cost effects are larger in more highly regulated cities. There are two ways to interpret these results. Either housing supply inelasticity is preventing housing construction and increasing the degree to which oil price increases are capitalized into house prices, or areas experiencing a high degree of sensitivity to oil price changes end up having highly regulated cities by 2008. As discussed in “Stochastic Specification” section, we do not pursue this subject further, instead leaving causal examination to further research due to the myriad issues in attributing causality.

Spot Oil and Gasoline Prices

While thus far we have followed our preferred identification strategy, it is reasonable to argue that households may respond more directly to spot gasoline or oil prices when making location decisions. This might occur due to issues of salience—the average homebuyer may observe the spot price and infer it to be equal to the future expected value despite the presence of future, statistically predictable movements. To understand the effects of this modeling choice, we substitute spot gasoline prices and oil prices for our oil price expectations measure in the main specification and estimate the model parameters.

For gasoline, we use a national average gasoline price series from the U.S. Department of Energy. This series appends the price for regular leaded gasoline before 1990, and regular unleaded gasoline through the end of the sample. ZIP code fixed effects capture cross-city variation in gasoline prices, but the issue of within-city gasoline price gradients remains. Insofar as land prices are capitalized into gasoline prices, gas prices would be higher, the closer the location to the center of the city. Were this to be the case, and assuming households consume gasoline near to their residential location, this effect would serve to flatten the house price gradient. Any observed gradient rotation is therefore a lower bound.

Table 6, column 1, mimics Table 2, which presents the baseline estimates of the export price and transportation cost effects. The marginal effect of gasoline price changes is nearly three times higher than changes to the oil price. Clearly, gasoline prices are more important for the average homebuyer than oil prices when considering the relative desirability of different locations. While gasoline prices are highly correlated with oil prices, they are not perfectly correlated. The oil price essentially sets the floor for the gasoline price because of its status as a primary input in production. But there are periods when gasoline prices depart from oil prices, such as during the aftermath of Hurricane Katrina in 2005, when demand for gasoline outstripped refining
Table 6 ■ Effects of spot oil and gasoline prices on house prices.

| Transportation Cost Measure: | Dependent Variable: Δ ln HPI(t) | [1] | [2] |
|------------------------------|---------------------------------|-----|-----|
| City Oil Export Share × Δ ln Oil Price \((t−1, t−2, \ldots, t−5)\): | | | |
| Sum of coefficients | 0.638*** | 0.718*** |
| F-Statistic | 33.57 | 57.83 |
| p-Value | <0.001 | <0.001 |
| ln CBD distance × Δ ln Oil Price \((t−1, t−2, \ldots, t−5)\): | | | |
| Sum of coefficients | −0.0108*** | −0.00329** |
| F-Statistic | 19.16 | 6.257 |
| p-Value | <0.001 | 0.0126 |
| Sum of Δ GDP × CBD distance coefficients | 0.0502*** | 0.0632*** |
| ZIP code FEs | Yes | Yes |
| Time period FEs | Yes | Yes |
| Observations | 336,076 | 336,076 |
| R-squared | 0.314 | 0.314 |

Note: *** \(p < 0.01\), ** \(p < 0.05\), * \(p < 0.1\). Cross section includes all ZIP codes for which house prices are available that span a single CBSA. Data are at an annual frequency between 1975 and 2015.

capacity. This result highlights the channel through which oil prices affect house prices—that is, via gasoline prices. It is therefore perhaps unsurprising that oil prices have a smaller marginal effect.

Column 2 reports parameters from a model using the spot oil price. The export price effect is somewhat larger using this measure compared to the expectations measure, but the transportation cost effect is slightly smaller. In general, it appears that for oil, changes to both the spot price and expected future prices have similar effects on house prices.

Do Particular States Drive the Results?

Certain states tend to dominate discussions of the oil industry in the United States. Oklahoma and Texas have been major oil producers since the early 1900s, and North Dakota, Montana and Pennsylvania have seen increasing oil production due to the “fracking” boom of the early 2000s. Due to this geographic concentration, it is possible that state-level house price changes are related to state-specific factors that drive estimates for the entire sample.
Table 7 ■ Effects of oil prices on house prices—do certain states drive results?

| Dependent Variable: Δ ln HPI(t) | North Dakota | Texas | Oklahoma |
|---------------------------------|-------------|-------|----------|
| State Omitted:                  | [1]         | [2]   | [3]      |
| City Oil Export Share × Δ ln Oil Price (t − 1, t − 2, ..., t − 5): | | | |
| Sum of coefficients             | 0.639***    | 0.693*** | 0.601*** |
| F-Statistic                     | 33.38       | 24.99  | 32.15    |
| p-Value                         | <0.001      | <0.001 | <0.001   |
| ln CBD distance × Δ ln Oil Price (t − 1, t − 2, ..., t − 5): | | | |
| Sum of coefficients             | -0.00405**  | -0.00387** | -0.004** |
| F-Statistic                     | 4.851       | 4.036  | 4.681    |
| p-Value                         | 0.0279      | 0.0449 | 0.0308   |
| Sum of Δ GDP × CBD distance coefficients | | | |
| ZIP code FEs                    | Yes         | Yes    | Yes      |
| Time period FEs                 | Yes         | Yes    | Yes      |
| Observations                    | 335,546     | 319,966 | 332,426  |
| R-squared                       | 0.315       | 0.33   | 0.317    |

Note: ***p < 0.01, **p < 0.05, *p < 0.1. Cross section includes all ZIP codes for which house prices are available that span a single CBSA. Data are at an annual frequency between 1975 and 2015.

Therefore, we sequentially exclude three states from the samples in order to determine the sensitivity of estimates.

Table 7 shows that omission of Texas, Oklahoma and North Dakota does not significantly affect estimates of the commuting variables, suggesting these results are robust. Estimates for local export shares indicate that Texas may be less sensitive along this dimension, as the parameter rises by about 10% when Texas ZIP codes are omitted. None of these effects are statistically significant, however, so we conclude that no particular state is driving any of the reported results.

Specification Robustness

There are several specification issues we consider in this section. The first investigates the magnitude of omitted variable bias in the transportation cost parameters when the GDP × CBD distance variable is omitted. Column 1 shows the magnitude of the point estimate of the treatment increasing by about 75%, from −0.040 to −0.068. This result highlights the importance of the GDP control in accounting for variation in within-city price dynamics.
Table 8 ■ Effects of oil prices on house prices—further robustness tests.

| Specification Alternative: | Dependent Variable: $\Delta \ln HPI(t)$ |
|----------------------------|--------------------------------------|
|                           | [1] No GDP × Dist                      |
| $\Delta \ln HPI(t - 1)$   | 0.198***                              |
|                           | [0.0168]                               |
| City Oil Export Share ×   |                                      |
| $\ln$ Oil Price $(t - 1)$ |                                      |
|                           | 0.0986***                              |
|                           | [0.0148]                               |
| $\Delta \ln$ Oil Price $(t - 1, t - 2, \ldots, t - 5)$: | |
| Sum of coefficients       | 0.638***                               |
| $F$-Statistic              | 33.52                                 |
| $p$-Value                  | <0.001                                |
| $\ln$ CBD distance ×      |                                      |
| $\ln$ Oil Price $(t - 1)$ |                                      |
|                           | −0.000744***                           |
|                           | [0.000236]                             |
| $\Delta \ln$ Oil Price $(t - 1, t - 2, \ldots, t - 5)$: | |
| Sum of coefficients       | −0.00683***                            |
| $F$-Statistic              | 23.33                                 |
| $p$-Value                  | <0.001                                |
| Sum of GDP × CBD coefficients | 0.0366**                               |
| ZIP code FEs               |                                      |
| Time period FEs            |                                      |
| Observations               | 336,076                               |
| $R$-squared                | 0.313                                 |
|                           | 322,175                               |
|                           | 0.35                                  |
|                           | 336,076                               |
|                           | 0.311                                 |

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors (CBSA) in brackets. Cross section includes all ZIP codes for which house prices are available that span a single CBSA. Data are at an annual frequency between 1975 and 2015. GDP coefficients are the sum of 5 lags in the difference equations, and the lagged level in the level equation.

Next, it is common in the empirical regional economics literature to include lagged dependent variables in panel models. While a lagged dependent variable is potentially an important control variable, it also may result in endogeneity bias when it is included along with fixed effects. This occurs because the calculation of the area fixed effects rely on data for all periods, including the contemporaneous error, leading to correlation between the lagged dependent variable and the error (Nickell 1981). We do not anticipate this bias to be substantial in practice, because we have a fairly large number of time periods, a large number of ZIP codes, and we also include time period fixed effects. Column 1 of Table 8 presents estimates of Equation (14) with lagged change in house prices as an independent variable.

Electronic copy available at: https://ssrn.com/abstract=3694521
Estimates in this model are similar to the baseline. The sum of the lags of the city oil export employment share falls from 0.64 to 0.51. While the estimate is smaller, its effects accumulate by virtue of the lagged dependent variable, with almost zero cumulative difference ($1 - 0.51 = 0.638$). The sum of the coefficients for CBD proximity is slightly smaller, at about $-0.036$ versus the baseline estimate of $-0.040$, giving a cumulative effect of 0.045. These results suggest that the lagged dependent variable provides potentially useful explanatory power while introducing negligible endogeneity bias. This is an important insight for applications where the objective is to produce a maximally fitting model, including forecasting exercises.

The third specification-related robustness exercise we perform is related to the differencing of the oil price change. Rather than modeling house price changes as the sum of the lags of oil price changes and interactions, it is possible to collapse the changes into a single-level variable. This specification does not allow for dynamics, but is potentially more efficient due to the smaller number of parameters estimated. A difference-level parameter is interpreted as follows: a change in the level of the real oil price causes an acceleration in house prices. That is, as long as oil prices are high, house prices will grow above mean levels in every year. The converse is also true—when the level of oil prices is low, house prices fall each year.

The level estimate of the export price effect is 0.10. To compare this estimate to the differenced estimates, consider a five-year oil price change, which leads to an interacted effect of 0.50 over five years. This is similar (0.14 smaller) to the sum of the differenced estimates. The estimate of the CBD distance effect is $-0.00075$, or $-0.0038$ after five years, which is near sum of the differenced estimates of $-0.004$. Overall, level estimates appear to give similar quantitative and qualitative results.

The final set of robustness tests relates to the choice of the fixed effects to include as controls. While we argue ZIP code and time period fixed effects are adequate by means of the robustness of our results, Molloy and Shan (2013) include additional fixed effects for each CBSA × time period. These additional controls are necessary if omission causes bias in the estimated transportation cost coefficients. This can occur if unaccounted for annual city-level variation in appreciation rates is correlated with transportation costs interacted with changes in oil prices.

However, confounding the desire to include additional controls as insurance against omitted variable bias is the measurement error in the house price indices, and attenuation caused by repeated differencing of right-hand side
variables that are imperfect measures of the desired treatment. House price indices are estimated based on housing unit transactions that are increasingly sparse at low levels of geographic aggregation. Repeated differencing of these indices causes noise to dwarf the signal in the data. We therefore are cautious throughout the paper in our inclusion of large numbers of fixed effects, as each severely affects the power of the estimator. Our current strategy of ZIP code and time period fixed effects results in about 12,000 fixed effects that are removed through differencing the series along the two dimensions. A third difference is required because we consider appreciation rates. The Molloy and Shan (2013) fixed effects strategy requires 36,000 fixed effects in our sample. These extra fixed effects are particularly problematic in small cities, where the number of ZIP codes is small.

Table 9 presents estimates for 15 models that are meant to explore how fixed effects alter the estimates of treatment parameters. These models consist of three different transportation cost variables: (1) the baseline CBD distance interacted with the change in the oil price measure; (2) a dummy variable set equal to 1 if the ZIP code is beyond 15 miles from the CBD interacted with the change in the oil price measure and (3) CBD distance interacted with the change in the spot gasoline price. These three measurement approaches are then used to estimate five models: (1) the baseline approach with ZIP code and time period fixed effects, (2) time period effects by state instead of national time period effects, (3) state × time period effects but omitting the GDP × distance interaction term, as this control is often no longer significant with additional fixed effects, and (4) and (5) mimicking (2) and (3), but with MSA × time period fixed effects for metropolitan statistical areas, and state × time period fixed effects in their place for micropolitan statistical areas. Effectively, this treats all micropolitan areas within a state as a single “non-CBSA area.”

The first thing that is apparent from the estimates is that fixed effects alter the effects of the oil export price effect in a substantial way. We are not concerned with these estimates, as their inclusion is interpreted as a control in this context—much of the explanatory power is subsumed within state × time period fixed effects. The inclusion of GDP × distance as a control, while necessary in models 1, 6 and 11, is often unnecessary as additional fixed effects are added. This suggests that the GDP × distance variable is capturing some cross-state variation in annual house prices in models 1, 6 and 11.

The treatment variable of concern is the CBD proximity measure interacted with the change in the oil price. Throughout the paper, this estimate has been small in magnitude relative to the export price effect. While it has been
Table 9  ■ Effects of oil prices on house prices—fixed effect robustness.

| Models with CBD Distance, Sums of Coefficients (t – 1 + ⋯ + t – 5) | [1] | [2] | [3] | [4] | [5] |
|---------------------------------------------------------------|-----|-----|-----|-----|-----|
| City Oil Export Share ×:                                      |     |     |     |     |     |
| Δ ln Oil Price                                                | 0.638*** | 0.0391 | 0.0393*** | 0.405*** | 0.405*** |
| ln CBD distance ×:                                            |     |     |     |     |     |
| Δ ln Oil Price                                                | –0.00407** | –0.00468*** | –0.00388*** | –0.00108** | –0.00067 |
| Δ ln GDP                                                      | 0.0614** | 0.00893 | 0.405*** | 0.405*** | 0.405*** |
| ZIP code FEs                                                  | Yes | Yes | Yes | Yes | Yes |
| Time period FEs                                               | Yes |     |     |     |     |
| State × Time period FEs                                       | Yes |     |     |     |     |
| MSA/State × Time period FEs                                   |     |     |     |     |     |
| Observations                                                  | 336,076 | 336,076 | 336,076 | 336,076 | 336,076 |
| R-squared                                                     | 0.314 | 0.573 | 0.573 | 0.664 | 0.664 |

Models with CBD Distance > 15 Miles Indicator, Sums of Coefficients (t – 1 + ⋯ + t – 5)

| Models with CBD Distance > 15 Miles Indicator, Sums of Coefficients (t – 1 + ⋯ + t – 5) | [6] | [7] | [8] | [9] | [10] |
|------------------------------------------------------------------------------------------|-----|-----|-----|-----|-----|
| City Oil Export Share ×:                                                                 |     |     |     |     |     |
| Δ ln Oil Price                                                                             | 0.643*** | 0.0434 | 0.0437*** | 0.409*** | 0.409*** |
| CBD distance > 15 Miles ×:                                                                 |     |     |     |     |     |
| Δ ln Oil Price                                                                             | –0.0205** | –0.0192*** | –0.0172*** | –0.00581* | –0.00519 |
| Δ ln GDP                                                                                   | 0.0615*** | 0.0159*** | 0.00753* | 0.00753* | 0.00753* |
| ZIP code FEs                                                                              | Yes | Yes | Yes | Yes | Yes |
| Time period FEs                                                                            | Yes |     |     |     |     |
| State × Time period FEs                                                                   | Yes |     |     |     |     |
| MSA/State × Time period FEs                                                               |     |     |     |     |     |
| Observations                                                                              | 336,076 | 336,076 | 336,076 | 336,076 | 336,076 |
| R-squared                                                                                 | 0.314 | 0.573 | 0.573 | 0.664 | 0.664 |
### Table 9  ■  Continued.

| Models with Gasoline Prices, Sums of Coefficients $t-1 + \cdots + t-5$ | [11] | [12] | [13] | [14] | [15] |
|---|---|---|---|---|---|
| Δ ln Oil Price | 0.638*** | 0.0379 | 0.0379*** | 0.406*** | 0.406*** |
| Δ ln Gasoline Price | −0.0108*** | −0.00837*** | −0.00667*** | −0.00229** | −0.00138 |
| Δ ln GDP | 0.0502*** | 0.00959 | 0.00743* | 0.00743* | 0.00743* |
| ZIP code FE | Yes | Yes | Yes | Yes | Yes |
| Time period FE | Yes | Yes | Yes | Yes | Yes |
| State × Time period FE | Yes | Yes | Yes | Yes | Yes |
| MSA/State × Time period FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 336,076 | 336,076 | 336,076 | 336,076 | 336,076 |
| R-squared | 0.314 | 0.573 | 0.573 | 0.664 | 0.664 |

**Note:** ***p < 0.01, **p < 0.05, *p < 0.1. Cross section includes all ZIP codes for which house prices are available that span a single CBSA. Data are at an annual frequency between 1975 and 2015. “MSA/State” gives MSA-specific dummy variables if the ZIP code is in an MSA. If the ZIP code is not in an MSA, the fixed effect is assigned to a state.
robust across samples, we wish to consider its robustness to additional fixed effects. In Table 9, results show that point estimates are always negative, but additional fixed effects reduce the estimate of the CBD proximity measures. In some cases, additional fixed effects render the transportation cost effect not statistically different than zero. The estimates in columns 5, 10 and 15 are similar conceptually to those in Molloy and Shan (2013)—estimates of an effect that are of the correct sign but not statistically different than zero.

Overall, we cannot conclude if the declining point estimate is due to measurement error, attenuation, or the elimination of omitted variable bias. However, we have reason to continue with the ZIP code and time period fixed effect strategy for the following reasons: first, our results are robust to state × year fixed effects, which should capture similar effects as city × year fixed effects (only omitting within-state cross-city variation); and second, our results have been shown to be robust with respect to a battery of alternative variable definitions, cross-sectional samples, time period samples and other modeling assumptions. Finally, the estimates in all specifications are likely a lower bound. There are many dimensions over which substitution may take place at the household or firm level, including the modal choice of commuting, vehicle fuel efficiency and even the location of employment in response to changing fuel prices. In all cases, substitution serves to attenuate our measurement of the partial effect of transportation cost changes on house prices.

Conclusion

This paper makes two primary contributions. The first is theoretical and brings together local oil export production and oil-related transportation costs into the SUM of Alonso (1964), Mills (1967) and Muth (1969). While the structure of this model is similar to prior renditions, it has never been explicitly derived in terms of the oil price. Harmonizing the export price and transportation cost parameters facilitates concise derivation of comparative static effects of exogenous oil price changes on house prices in cities of different industrial structures and at different locations within the city.

The theoretical model predicts that an oil price change has two main effects. In a city that specializes in oil supply—that is the production, refining and transportation of oil—there is a positive export price effect of increasing oil prices on wages, leading to house price appreciation in the city relative to other cities. However, because oil is also indirectly consumed by commuters in the form of gasoline, an increase in the price of oil increases the differential commuting costs between the center-city and suburban locations. This transportation cost effect steepens the house price gradient. Overall, the model predicts a “twist” in house prices due to an oil price change—a level shift
combined with a rotation of the house price gradient. In cities that do not specialize in oil production, the model predicts the transportation cost effect will remain, but without the export price effect, leading to a rotation that leaves house prices below prior levels in all locations, but more substantially in the suburbs.

Our second contribution is empirical. We test predictions from the theory using a new ZIP-code-level house price index (the Bogin, Doerner and Larson 2016, dataset produced by the FHFA) along with measures of export employment shares from the Bureau of Labor Statistics’ Quarterly Census of Employment and Wages. Export shares are calculated using location quotients. Proximity measures to the CBD are calculated as well.

Overall, estimates suggest oil price and house price changes to be positively related to the oil export employment share, and negatively related to the distance to the CBD, conditional on other factors. The estimates are robust with respect to the time periods and states considered, different CBD proximity measures, city size and model specifications. In terms of our direct contribution, findings here are the first large-scale evaluation of the export price effect of oil on house prices in the literature. Estimates regarding the transportation cost effect contribute to the ongoing debate between those who have found that house prices and transportation costs are unrelated, and those who have found an empirical link. Our findings present evidence in favor of the notion that oil price changes, vis-à-vis transportation costs, rotate house price gradients, though some questions remain.

While we have demonstrated the robustness of these effects versus a battery of sampling and measurement exercises, several useful extensions are apparent. For instance, it may be possible to build within this framework to incorporate dynamics related to the elasticity of housing supply and more structurally account for spatial spillovers. We also assume identification by using changes in an expectations measure, but it may be possible to achieve identification through other means. Because the transportation cost estimate is small, it is particularly sensitive to measurement error in the house price index and attenuation of the estimator caused by repeated differencing. These issues limit our ability to include a full vector of fixed effects as controls for unobserved factors. We leave further examination and extensions to future research.

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