Drilling Down: The Impact of Oil Price Shocks on Housing Prices

Valerie Grossman,[a] Enrique Martínez-García,[a] Luis Bernardo Torres,[b] and Yongzhi Sun[c]*

ABSTRACT

This paper investigates the impact of oil price shocks on house prices in the largest urban centers in Texas. We model their dynamic relationship taking into account demand- and supply-side housing fundamentals (personal disposable income per capita, long-term interest rates, and rural land prices) as well as their varying dependence on oil activity. We show the following: (1) Oil price shocks have limited pass-through to house prices—the highest pass-through is found among the most oil-dependent cities where, after 20 quarters, the cumulative response of house prices is 21 percent of the cumulative effect on oil prices. Still, among less oil-dependent urban areas, the house price response to a one standard deviation oil price shock is economically significant and comparable in magnitude to the response to a one standard deviation income shock. (2) Omitting oil prices when looking at housing markets in oil-producing areas biases empirical inferences by substantially overestimating the effect of income shocks on house prices. (3) The empirical relationship linking oil price fluctuations to house prices has remained largely stable over time, in spite of the significant changes in the Texas' oil sector with the onset of the shale revolution in the 2000s.

Keywords: Real house prices, Real rural land prices, Panel VAR model with exogenous variables, Real oil price shocks, (Non-oil) real income shocks

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1. INTRODUCTION

Texas accounts for a large share of total fossil fuel extraction in the U.S. and is a major oil production center globally. While Texas has a large, highly diversified economy, the oil and gas industry has left its mark on the state's economy over many decades by creating hundreds of thousands of high-paying jobs and attracting much CAPEX.[1] The oil and gas sector continues to rapidly evolve and innovate, with Texas being very much at the forefront of many of the advances that have shaped the industry. More recently, the development of enhanced recovery techniques—notably hydraulic fracturing ("fracking") and multi-stage drilling—has helped reach fossil fuel deposits in

1. Texas is the second largest state economy in the U.S. both in terms of population and output, and its economy is more diversified than that of other major oil-producing U.S. states (such as Oklahoma or North Dakota). At its lowest point in 2002:Q2, Texas accounted for under 19 percent of total U.S. oil production, but its share rose to nearly 36 percent by 2016:Q2 when our sample ends. The state is also one of the major oil producers in the world (among the top 7 largest producers in 2016:Q2).

a Research Department, Federal Reserve Bank of Dallas, 75201 Dallas, Texas, USA.

b Real Estate Center, Texas A&M University, 77843 College Station, Texas, USA.

c Research Institute of Economics and Management, Southwestern University of Finance and Economics, 610074 Chengdu, China.

* Corresponding author. E-mail: emg.economics@gmail.com.

shale formations and has massively expanded the stock of proved reserves (notably of shale oil, but also of natural gas as a byproduct). For those reasons, Texas is an important testing ground for investigating the impact of exogenous fluctuations in real oil prices on the economic outcomes of oil-producing regions/countries.

In this paper, we explore the behavior of real house prices and housing fundamentals in response to real oil price shocks in Texas. While housing typically is one of the largest assets on a household's balance sheet (Emmons and Ricketts, 2017), this economically significant relationship has received only limited attention in the literature thus far.[2] The novelty of our empirical analysis of the spillover effects of real oil prices into real house prices lies in that: (a) it exploits the cross-sectional heterogeneity in the degree of oil-dependence across Texas; and (b) it is based on explicitly modeling housing demand and housing supply forces (as suggested in Grossman, et al., 2017).

A broader strand of the literature recognizes that real oil price fluctuations and, to some extent, oil price uncertainty have significant effects on overall economic activity (Hamilton, 2008; Torres, et al., 2012; Pinno and Serletis, 2013; Csereklyei, et al., 2016; Kehrig and Ziebarth, 2017) and influence energy consumption and urbanization over time (Jones, 1999; Gentry, 1994; Medlock and Soligo, 2001; Liddle, 2013; Claudy and Michelsen, 2016).[3] We contribute to this literature with a tractable model of real house prices and a novel dataset to explicitly take account of the effect that real oil price shocks have on the demand- and supply-sides of the housing market.

To empirically explore the relationship between real oil prices and real house prices, we develop a new panel dataset covering all 25 Metropolitan Statistical Areas (MSAs) in Texas at a quarterly frequency over the 1975:Q1–2016:Q2 period. The panel contains real house prices and real personal disposable income per capita for each MSA as well as rural land prices for each MSA's nearby rural land markets. We adopt a block-partitioned panel VARX (pVARX) framework to model jointly the time series and cross-sectional variation across Texas MSAs. This empirical model incorporates two common factors—U.S. real long-term interest rates and real oil prices, our variable of interest—that are largely viewed as exogenous from the point of view of each individual MSA and are treated as such in the specification. We also recognize that the response to real oil price fluctuations depends on each MSA's reliance on oil, assessing that with data on their nearest crude oil proved reserves. In doing so, we take into account the impact of technologically enabled oil supply shifts since the 2000s coming from tapping into Texas' abundant shale oil reserves.

In our findings, we highlight the impact of exogenous and common real oil price fluctuations on local housing prices across Texas' MSAs. We show the following key results:

First, the cross-sectional variation in economically viable crude oil reserves across Texas is an important part of our identification strategy that provides a rough guide of the value of the crude oil reserves underground. The impact of exogenous real oil price shocks varies considerably between more oil-wealth-dependent and less oil-wealth-dependent areas—the response of real house prices to real oil price shocks more than scales up in MSAs adjacent to areas where the concentration of the wealth endowment of crude oil reserves is the highest. Nonetheless, we find that the response of

2. Boxall, et al. (2005), and, more recently, Muehlenbachs, et al. (2015), Larson and Zhao (2017), and Kilian and Zhou (2018) investigate different aspects of the impact of the oil and gas industry on the housing market and on house prices. Abhyankar, et al. (2013), among others, explore the impact of oil price fluctuations on financial asset prices focusing instead on the relationship between oil price shocks and the stock market.

3. The aggregate effects of real oil price shocks can have significant production- and expenditure-switching consequences. In oil-producing areas in particular, an oil price increase that leads to a rise in the energy costs of production would tend to drag down non-oil production and investment while stimulating oil-related economic activity. To the extent that the degree of substitutability for energy is low (at least in the short run), increases in oil prices would tend to bring down aggregate demand while boosting oil-related incomes and consumption demand in oil-producing areas.

real house prices (and to a larger extent of real rural land prices) is comparable in magnitude to that of a real income shock even among many MSAs that are not heavily oil wealth dependent.

Second, we provide evidence of significant effects of real oil price shocks on personal disposable income per capita and a pass-through of up to 31 percent onto real rural land prices and 21 percent on real house prices after 20 quarters mostly among the most oil-dependent MSAs. Shocks to real personal disposable income per capita—capturing non-oil-related discretionary real income shocks—pull both real rural land prices and real house prices upward, with a sizeable pass-through over time (78 percent on real house prices and 76 percent on real rural land prices over the same 20-quarter horizon).

Third, our findings indicate real oil price shocks differ from (non-oil-related) discretionary real income shocks partly because—while also raising personal disposable income per capita—real oil price shocks operate also strongly through supply-side forces in the housing market.[4] Hence, omitting the spillovers into real house prices from real oil prices tends to bias upward our empirical inferences about the effect of discretionary real income shocks.

Finally, while tapping into shale formations has proven to be a major structural break for production in Texas and the U.S., our findings show the dynamic empirical relationship linking real oil prices to local real house prices has remained largely stable since the mid–1970s. We interpret this as indicating that the shale revolution has been felt in real house prices across Texas MSAs mostly because the resulting boom in the wealth endowment of crude oil reserves has shifted, concentrating more now around the major shale formations in the state.

The remainder of the paper is organized as follows. In section 2, we describe our panel dataset and lay out the empirical strategy for the paper. Section 3 reports our evidence on the estimated (block-partitioned) pVARX model and panel Granger causality test results. We use panel techniques to exploit the rich cross-sectional nature as well as the time series dimension of the MSA data we have for Texas. We explore the implications of our empirical model and assess the robustness of the results in Section 4. The last section of the paper discusses the implications from our main findings.

2. DATA AND METHODOLOGY

We model the dynamics of real house prices and key supply-side—real rural land prices (from the nearest rural land markets)—and demand-side—real personal disposable income per capita—housing market fundamentals on a panel of Texas' 25 MSAs. We also include two common factors—U.S. real long-term interest rates and our variable of interest, real oil prices—which operate both through the demand- and the supply-side of the housing market but are viewed as exogenous and largely determined in integrated financial and global commodity markets. We incorporate the cross-sectional variation in oil-dependence among MSAs into our model specification with data on the MSAs' nearest economically viable crude oil reserves.

Our dataset covers the period after the collapse of Bretton Woods in 1971 and the first Arab oil embargo—the 1973 oil crisis—starting in 1975:Q1 and ending in 2016:Q2 (including the period

4. Similarly, the work of Helsley and Capozza (1989) and Hardie, et al. (2000), among others, suggests that rural land prices affect land conversion and, therefore, impact urbanization (housing supply) and growth, too. The impact of real oil prices on real rural land prices, though, is tied to how mineral rights are owned (Brown, et al., 2016; Brown, et al., 2019; Boslett, et al., 2019; Covert and Sweeney, 2019). Mineral rights severance, which is quite common in Texas but not ubiquitous, potentially limits the estimated effect of real oil prices on real rural land values. Our findings, nonetheless, point out that real rural land prices are quite sensitive to real oil prices and, in areas heavily dependent on oil wealth, an important supply-side channel affecting real house prices.

of the shale revolution that took off in the 2000s) with a total of 166 quarterly observations. All the nominal series—house prices, rural land prices, real personal disposable income per capita, and oil prices—are re-expressed in real terms deflated with the seasonally adjusted quarterly U.S. headline CPI series from the U.S. Bureau of Labor Statistics to avoid the confounding effects of inflation (Hamilton, 1996). To be consistent, U.S. real long-term interest rates are computed as the nominal U.S. long-term interest rate net of long-term expected headline CPI inflation. All the data we use in this paper are publicly available.[5]

Real house prices (RHp_{it}). We employ Federal Home Loan Mortgage Corporation (Freddie Mac) house price indexes, as they provide a broad measure of the fluctuations in single-family house prices across MSAs. These are weighted, repeat-sales indexes that measure changes in market prices using repeat-sales or refinancings on the same physical properties to control for differences in the quality of the houses comprising the sample. These indexes are based on mortgage transactions on single-family properties with conforming, conventional mortgages purchased or securitized by Freddie Mac itself or by the Federal National Mortgage Association (Fannie Mae). We average the monthly Freddie Mac series to quarterly frequency and then seasonally adjust them with the standard Census X12/X13 procedure. The resulting quarterly nominal house price indexes are then deflated with U.S. headline CPI (Figure 1.A).

Real rural land prices (RLp_{it}). Still, we use the rural land prices across Texas' 33 rural land market areas and seven regional land markets computed by the RECENTER at Texas A&M University based on transaction values from the Farm Credit Bank of Texas. The RECENTER rural land prices are quarterly median values adjusted to a standardized distribution of acreages (without distinguishing among the varying uses and conditions of the land), expressed in dollars per acre and seasonally-adjusted using a simple four-quarter moving average. While we don't have urban land prices per se, rural land prices provide a quantifiable measure of the opportunity cost of turning rural land into urban land for urban development across Texas.[6] It should be noted that mineral rights ownership can be sold separately from land ownership—this is a practice common in Texas, yet transactions prices would incorporate the value of mineral rights in those cases where fee simple ownership of the land is sold. Still, we use RECENTER rural land prices per acre as the best available indicator of geographical variation and overall rural land market conditions in Texas (a gauge of the costs of developing rural land into urban land). Finally, the RECENTER rural land price series are deflated with U.S. headline CPI (Figure 1.B).

Real personal disposable income per capita ($RPDI_{it}$). Personal disposable income (PDI) is a key determinant of housing demand.[7] The U.S. Bureau of Economic Analysis reports annual total

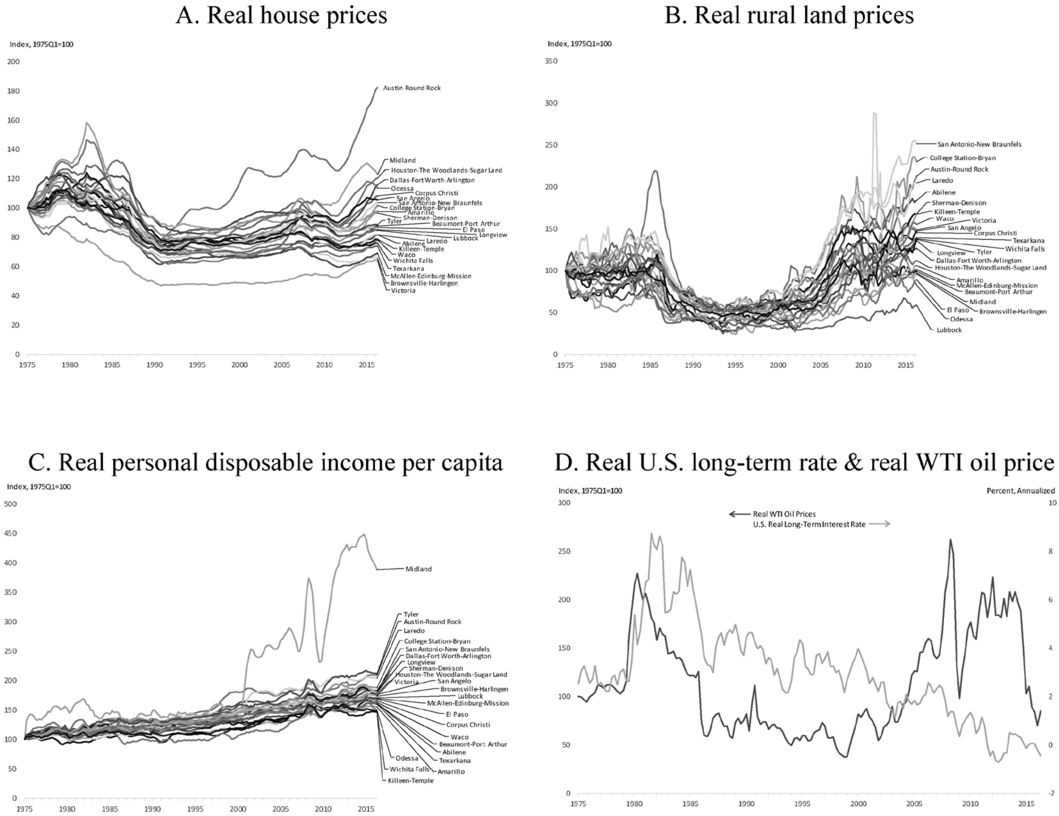
5. We obtain some of the data via the Federal Reserve Bank of St. Louis' FRED database and the Federal Reserve Bank of Dallas' Database of Global Economic Indicators (Grossman, et al., 2014) or from Haver Analytics. The boundaries of Texas' MSAs and rural land market areas/regions, the geographic location and supplementary information about the major oil and gas formations in the state as well as all primary sources and a description of our own calculations are documented in detail in the companion online appendix which can be found with the complete dataset at: https://bit.ly/2mlnK6t.

6. Rural land prices signal land scarcity and are a factor for urban development. The price of urban land, though, is only partly a function of the price of rural land and also depends on construction and other costs, the value of accessibility (commute time), and the associated expected future rent increases (Helsley and Capozza, 1989; Hardie, et al., 2000). Nonetheless, the existing empirical evidence suggests a statistically significant dynamic relationship linking real land prices to housing supply and real house prices (Ozanne and Thibodeau, 1983; Manning, 1988; Potepan, 1996; Clapp, et al., 2001; Ooi and Lee, 2006; Hwang and Quigley, 2006; Cunningham, 2006; Davis and Heathcote, 2007; Davis and Palumbo, 2008; Anari and Gilliland, 2014; Oikarinen, 2014) which we proxy for in our model with the RECENTER rural land price data.

7. On the demand-side of the housing market, the real estate literature documents a strong correlation between affordability determinants (income, long-term interest rates) and house prices (Fortura and Kushner, 1986; Mankiw and Weil, 1989; Manning, 1986; Quigley, 1999; Case and Shiller, 1989; Case and Shiller, 1990; Hort, 1998; Zhang, et al., 2014).

Figure 1: Quarterly database for Texas MSAs from 1975:Q1 to 2016:Q2

A. Real house prices, real rural land prices, and real personal disposable income per capita



Sources: U.S. Energy Information Administration, Dow Jones & Company, U.S. Bureau of Economic Analysis, U.S. Bureau of Labor Statistics, Texas Workforce Commission, Federal Home Loan Mortgage Corporation (Freddie Mac), Real Estate Center (RECENTER) at Texas A&M University/Farm Credit Bank of Texas, Board of Governors of the Federal Reserve System, Federal Reserve Bank of Philadelphia, Haver Analytics, and authors' calculations.

personal income (including royalties from oil and gas) by MSA and annual personal current taxes for the state of Texas. We impute an annual value for each MSA's current personal taxes proportional to the share of personal income accounted for by the MSAs relative to the state's total. Each MSA's total personal income minus imputed personal current taxes divided by its corresponding annual total population from the U.S. Bureau of Economic Analysis is our imputed measure of annual PDI in per capita terms. We construct a quarterly indicator of economic conditions in each MSA based on the geometric mean of: (a) the MSA's quarterly total nonfarm employment (seasonally-adjusted) from the Texas Workforce Commission/U.S. Bureau of Labor Statistics; and (b) imputed quarterly PDI per capita for Texas based on national accounts and population data from the U.S. Bureau of Economic Analysis. We use this quarterly indicator by MSA and the standard Chow-Lin method to convert each MSA's annual PDI per capita to a quarterly frequency. The resulting series is then deflated with U.S. headline CPI (Figure 1.C).

Real long-term interest rate ($RDSG10_t$). Real long-term interest rates impact mortgage rates, housing affordability, and the demand for housing. Real long-term rates also affect the cost of financing for developers and, therefore, the demand of rural land for urban development and ultimately the supply of urban housing. To compute the U.S. real long-term interest rate, first, we use the quarterly simple average of the daily 10-year Treasury constant maturity rate (yield in percent per annum) from the Board of Governors of the Federal Reserve System (H.15 Selected Interest Rates). Second, we construct a consistent long-term inflation expectations series based on the forecast of the annual average rate of headline CPI inflation over the next 10 years from the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters extended back to 1975:Q1 with Blue Chip Economic Indicators survey data and with the Board of Governors of the Federal Reserve System FRB/US-model long-term inflation expectations series ZPI10. Finally, the U.S. real long-term interest rate is computed by netting out long-term inflation expectations from the 10-year nominal yield based on Fisher's equation (Figure 1.D).

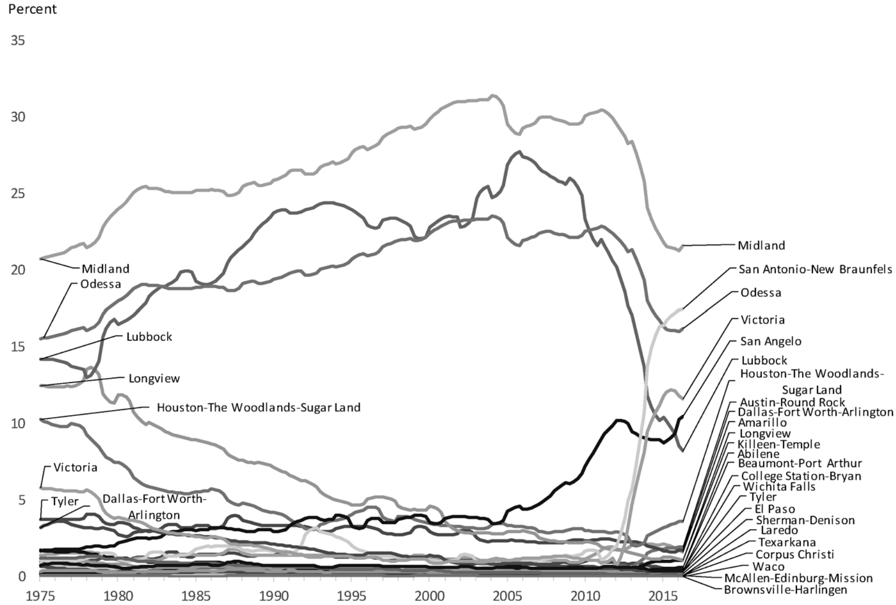
Real oil price (ROp_t). We use U.S. Energy Information Administration and Dow Jones & Company's data on the West Texas Intermediate (WTI)–Cushing, Oklahoma–crude oil spot price (dollars per barrel). The non-seasonally-adjusted series is reported at a monthly frequency and converted to a quarterly frequency by simple averaging. All remaining seasonality is removed by implementing the standard Census X12/X13 procedure on the quarterly WTI oil price series. Then, the resulting series deflated with U.S. headline CPI is our main variable of interest (Figure 1.D).[8]

Share of Crude Oil Proved Reserves by MSA ($OResShare_{it-P}$). We take account of the cross-sectional variation on oil-wealth-dependence by MSA and capture its geographical shifts over time with data on proved crude oil reserves. Specifically, we use annual data from the U.S. Energy Information Administration on crude oil (black oil, excluding lease condensate) proved reserves by Railroad Commission of Texas (RRC) district (excluding offshore), expressed in thousands of barrels (bbl). Proved reserves as of December 31 of the report year are the estimated quantities of all liquids defined as crude oil which geological and engineering data demonstrate with reasonable certainty to be recoverable in future years from known reservoirs under existing economic and operating conditions. We convert the annual series to a quarterly frequency using the quadratic sum interpolation method and re-express the series in millions of barrels (bbl) per day (b/d). Finally, we compute the nearest crude oil proved reserves by MSA apportioning the reserves on the adjacent RRC districts. We incorporate the share of each MSA's adjacent reserves over total onshore Texas reserves into the model expressed in percentages and instrumented by means of lags ($P \geq 1$)—specifically, we set $P = 8$ quarters (Figure 2).

This indicator shows great disparity across Texas MSAs with much of the crude oil reserves concentrated in parts of the state—notably around the Eagle Ford and the Permian Basin. The series also highlights two large structural shifts since 1975:Q1—first, the gradual and ongoing decline of East Texas' (Houston, Longview, Tyler) share of crude oil reserves since at least the mid–1970s and, second, the significant boost from shale oil to MSAs adjacent to the Eagle Ford (Victoria, San Antonio) and the Permian Basin (San Angelo, Midland, Odessa but less so around Lubbock) since the late 2000s.

8. We recognize that in many parts of Texas the role of natural gas prices could be equally important. Historically, oil and natural gas prices moved together even though their market structures are different. However, the relationship between them broke down over the shale revolution period (Brown and Yücel, 2008). The development of enhanced recovery techniques suitable for the Barnett Shale (Fort Worth basin in North Texas) in the late 1990s contributed to a substantial expansion in proven natural gas reserves in the 2000s—yet shale gas production gains were limited by the drag on U.S. natural gas prices from the resulting pent-up supply of shale gas. Eventually the oil and gas industry shifted its focus towards shale oil supported by the rising oil prices (and declining natural gas prices) of the late 2000s which made the efforts to tap into shale oil profitable and encouraged further technological improvements and efficiency gains. Natural gas production and shale gas in particular continue to be very important for Texas even now partly as a byproduct itself from the ongoing boom in shale oil production. We leave the exploration of the role of natural gas—and more recently of shale gas—for future research.

Figure 2: Share of nearest proven crude oil reserves by Texas MSA from 1975:Q1 to 2016:Q2



Sources: U.S. Energy Information Administration, the Texas Railroad Commission, Haver Analytics, and authors' calculations.
Notes: The shares plotted in this figure are lagged eight quarters.

2.1 Stationarity of the Data

We index the N panels of the cross-section (MSAs) as $i = 1, 2, \ldots, \mathrm{N}$ and the time periods (quarters) as $t = 1, 2, \ldots, T$. The real house prices (RHp_{it}), the real rural land prices (RLp_{it}), the real personal disposable income per capita ($RPDI_{it}$), and the real oil prices (ROp_t) are all re-expressed in log-levels and multiplied by 100 to obtain percentages when expressed in first differences. We label them $lnRHp_{it}$, $lnRLp_{it}$, $lnRPDI_{it}$, and $lnROp_t$, respectively. The real U.S. long-term interest rate ($RDSG10_t$) is retained as-is, expressed in percentages and at an annualized rate.

We consider a battery of panel unit root tests to establish the stationarity properties of the data. The Fisher-type tests (Choi, 2001), the Levin, et al. (2002) test, the Breitung (2000) test, and the Im, et al. (2003) test that we use all share the null hypothesis that all the panels contain a unit root. The tests are based on an autoregressive model specification akin to the fundamental Augmented Dickey-Fuller (ADF; Dickey and Fuller (1979, 1981), Said and Dickey (1984)) regression with a maximum number of lags which we set to four. The Fisher-type test implements a univariate unit-root test—either the ADF test or the Phillips and Perron (1988) test (PP test)—for each panel individually, and then combines the p-values from the individual tests to produce an aggregate. In contrast, all the other tests are constructed using the full panel rather than a combination of univariate tests. If the number of panels N is fixed, then the Fisher-type tests are asymptotically consistent against the alternative that at least one panel is stationary.

The Breitung and the Levin-Lin-Chu (LLC) panel tests assume that all panels have a common autoregressive parameter in the fundamental ADF regression. The Breitung and LLC tests are recommended for small-sized and moderately-sized panels (as is our case) against the alternative hypothesis that all the series are stationary. Breitung and Das (2005) also show that the Breitung test is optimal when all panels have the same autoregressive parameter, although it also has power in the heterogenous parameter case. The Im-Pesaran-Shin (IPS) panel test relaxes the assumption of a common autoregressive parameter for all panels and allows explicitly for heterogeneity across panels (even with serial correlation in the error terms). The alternative hypothesis for the IPS test is that there is at least one panel that is stationary—that is, some (but not all) of the panels may display unit roots.

Table 1 reports the p-values achieved for all panel unit root tests: the Fisher-type ADF and PP tests, the Breitung test, the LLC test, and the IPS test. We reject the unit root null in favor of stationarity when the p-value is less than or equal to a specified statistical significance level (0.01 (1%), 0.05 (5%), and 0.1 (10%)). When the p-value is larger than the specified significance level, we fail to reject the null and this suggests that the data is consistent with a unit root. All our evidence is summarized in Table 1.

Table 1: Panel unit root tests for Texas MSAs

			Tests (P-values)				
			Fisher-Type Tests		Panel Unit Root Tests		
Variable	Deterministic Terms	Panel	ADF	PP	Breitung (2000)	Levin, et al. (2002)	Im, et al. (2003)
Endogenous Variables							
• $\Delta lnRHp_{it}$	Const.	25	0.00***	0.00***	0.00***	0.00***	0.00***
• $\Delta lnRLp_{it}$	Const.	25	0.00***	0.00***	0.00***	0.00***	0.00***
• $\Delta lnRPDIp_{it}$	Const.	25	0.00***	0.00***	0.00***	0.00***	0.00***
Exogenous Variables							
• $\Delta lnROp_t$	Const.	1	0.00***	0.00***	—	—	—
• $RDSG10_t$	Const.	1	0.49 / 0.12	0.56 / 0.21	—	—	—
• $RDSG10_t$	Trend	1	0.03** / 0.18	0.10* / 0.35	—	—	—
• $\Delta RDSG10_t$	Const.	1	0.00***	0.00***	—	—	—

Notes: *, **, and *** denote statistical significance at the 10, 5, and 1 percent significance level, respectively. Reported p-values correspond to the lowest p-value achieved among competing specifications including from zero lags up to four lags. The deterministic terms included in the specification are either panel-specific fixed effects (Const.) or panel-specific linear time trends (Trend). For each test, we report the range of p-values in the following order: the full sample (1975:Q1–2016:Q2) followed by the subsample going from 1975:Q1 till 2001:Q4 (unless they both coincide up to rounding on the second decimal point). The results for the subsample going from 1975:Q1 till 2008:Q4 are similar to those of the subsample reported in Table 1 and available upon request.

We investigate the panel of all 25 MSAs in Texas and find that the first differences on real personal disposable income per capita ($\Delta lnRPDI_{it}$), real rural land prices ($\Delta lnRLp_{it}$), and real house prices ($\Delta lnRHp_{it}$) are all stationary when including panel-specific fixed-effects. In other words, the empirical evidence in Table 1 strongly supports the stationarity hypothesis of those three endogenous variables in first-differences. This finding holds true over the full sample from 1975:Q1 till 2016:Q2 and is robust for the 1975:Q1–2001:Q4 subsample which excludes the shale revolution period entirely and also for the 1975:Q1–2008:Q4 subsample which excludes only the shale oil production boom that followed.

We also find empirical support for the stationarity of the common exogenous factors. First differences on real WTI oil prices ($\Delta lnROp_t$) are stationary based on standard univariate ADF and PP tests. The evidence on the real U.S. long-term interest rate ($RDSG10_t$) including a trend component is rather weak across tests and sample/subsample periods. We choose to include first differences of the real U.S. long-term interest rate ($\Delta RDSG10_t$) in our benchmark model instead as the evidence of stationarity is shown to be a lot stronger and more robust in this case.

2.2 Empirical Framework

For our econometric analysis, we adopt the panel VARX (pVARX) framework with exogenous explanatory variables and fixed effects first proposed by Holtz-Eakin, et al. (1988). Classical ordinary least square equation-by-equation estimation methods for panel models with fixed effects do not produce unbiased estimates due to the well-known Nickell (1981) bias. One approach to deal with this bias is to use generalized method of moments (GMM) estimators instead (Hansen, 1982), as we do here. We use the GMM estimator proposed by Anderson and Hsiao (1982) and popularized by Love and Zicchino (2006) and Abrigo and Love (2016), among others.

Our dataset permits a fully balanced panel-specification across panels (that is, across the 25 Texas MSAs) over the full sample period from 1975:Q1 to 2016:Q2 as well as for the two subsamples of 1975:Q1–2001:Q4 and 1975:Q1–2008:Q4. Given the stationarity results from Table 1, we define the vector of endogenous local housing market variables as $Y_{it} = \left(\Delta lnRPDI_{it}, \Delta lnRLp_{it}, \Delta lnRHp_{it}\right)$ and the vector of exogenous common factors as $X_t = \left(\Delta lnROp_t, \Delta RDSG10_t\right)$.

We treat real oil prices and real long-term interest rates (the common factors) as exogenously given from the perspective of how local Texas housing markets operate. We model the dynamics of the (1×2) vector of common factors X_t with a simple one-panel pVAR model of order p given as:

$$X_t = X_{t-1}\Psi_1 + X_{t-2}\Psi_2 + \ldots + X_{t-p}\Psi_p + \Gamma + \epsilon_t,\ \forall t \in \{1,2,\ldots,T\}, \tag{1}$$

where the (2×2) matrices $\Psi_1, \Psi_2, \ldots, \Psi_p$ and the (1×2) matrix of intercepts Γ are parameters to be estimated. The scalar p indicates the number of lags which we set to be bounded at $p \le 4$. By assumption, the innovations satisfy that: $\boldsymbol{E}[\epsilon_t] = 0$, $\boldsymbol{E}[\epsilon_t'\epsilon_t] = \Omega$, and $\boldsymbol{E}[\epsilon_t'\epsilon_s] = 0$ for all $t > s$.

We posit that the dynamic relationship between the endogenous variables across MSAs, $\{Y_{it}\}_{i=1}^N$, is subject to shifts due to the exogenous fluctuations in the common factors, X_t, that is, due to fluctuations in the real oil price and/or the real long-term interest rate. We then adopt the canonical (homogeneous) pVARX model of order q including MSA-specific fixed effects and exogenous variables X_t in order to describe the dynamics of the endogenous variables $\{Y_{it}\}_{i=1}^N$, i.e.,

$$\begin{aligned} Y_{it} = {} & Y_{it-1}A_1 + Y_{it-2}A_2 + \ldots + Y_{it-q}A_q + X_{t-1}\breve{B}_{1it} + X_{t-1}\breve{B}_{1it} + X_{t-2}\breve{B}_{2it} + \ldots \\ & + X_{t-q}\breve{B}_{qit} + u_i + e_{it},\ \forall i \in \{1,2,\ldots,N\},\ \forall t \in \{1,2,\ldots,T\}, \end{aligned} \tag{2}$$

where Y_{it} is the (1×3) vector of dependent endogenous variables by MSA; X_t is the (1×2) vector of exogenous covariates; and u_i and e_{it} are (1×3) vectors of MSA-specific fixed-effects and idiosyncratic errors, respectively. The (3×3) matrices $A_1, A_2, \ldots, A_q$ and the possibly time-varying (2×3) panel-specific matrices $\breve{B}_{1it}, \breve{B}_{2it}, \ldots, \breve{B}_{qit}$ are to be estimated. The lag order of the pVARX specification in (2) is bounded at $q \le 6$. By assumption, the innovations satisfy that: $\boldsymbol{E}[e_{it}] = 0$, $\boldsymbol{E}[e_{it}'e_{it}] = \Sigma$, and $\boldsymbol{E}[e_{it}'e_{is}] = 0$ for all $t > s$. Moreover, the innovations in (1) and (2) are uncorrelated with each other as well (contemporaneously and at all leads and lags).

The inclusion of MSA-specific fixed effects in (1)-(2) allows us to take care of all (time-invariant) location-specific characteristics not explicitly accounted for in the specification. We model the cross-sectional and time series variation of the matrices $\breve{B}_{1it}, \breve{B}_{2it}, \ldots, \breve{B}_{qit}$ in (2) as reflecting varying degrees of oil-wealth-dependence across Texas MSAs. In turn, we assume that there is no cross-sectional variation or time-dependence on the sensitivity to real long-term interest rates of the endogenous variables of model (2). We describe the sensitivity to real oil price fluctuations across MSAs with varying degrees of oil-dependence as an interaction between oil price changes and the share of pre-existing proved crude oil reserves (reserves that are economically viable at a given point in time). We favor this data as a gauge of the potential oil-related wealth of a given area because it is less subject to change with current real oil price changes than actual production would. The share of crude oil reserves across local areas largely depends on the geology of the terrain which is exogenously given—although shifting patterns can arise in the share of crude oil reserves over extended periods of time (Figure 2) due to depletion of existing reserves (East Texas) and technological advancements (notably the shale oil boom in the Eagle Ford shale and the Permian Basin). We instrument oil-wealth-dependence using pre-existing shares of crude oil reserves adjacent to each MSA lagged eight quarters ($OResShare_{it-P}$, $P = 8$).[9]

We define a transformed vector of exogenous variables $\breve{X}_{it} = (OResShare_{it-P} \cdot \Delta lnROp_t, \Delta RDSG10_t)$ (with $P = 8$) to incorporate the interaction between real oil prices in first differences and the pre-existing share of nearest crude oil reserves. The lagged share of crude oil reserves ($OResShare_{it-P}$) is divided by 100 to re-express it in units rather than percentages. Then, we estimate a simplified variant of the canonical model (2) where we replace the exogenous component $\{X_{t-j}\breve{B}_{jit}\}_{j=1}^{q}$ with $\{\breve{X}_{it-j}B_j\}_{j=1}^{q}$ where the corresponding (2×3) matrices $B_1, B_2, \ldots, B_q$ are the re-defined coefficients to be estimated. We explore the presence of structural breaks in the coefficients $B_1, B_2, \ldots, B_q$ resulting from the onset of the shale revolution in the 2000s—although, in a preview of our later discussion of the findings, the evidence does not provide much support for the hypothesis that these coefficients are unstable over our sample period.

We estimate the pVARX model in (1)-(2) by blocks. The procedure involves first transforming the data with the forward mean-differencing transformation—the so-called Helmert transformation—introduced by Arellano and Bover (1995) in order to remove the panel fixed-effects. The Helmert transformation subtracts the average of all available future observations which we denote with a superscript H.[10] Since past realizations are not included in this transformation, the Helmert transformed variables remain valid instruments. Stacking observations over panels and then over time, the GMM estimator for (1)-(2) is generically given by $C = ((\bar{G}^H)'Z\widehat{W}Z'(\bar{G}^H))^{-1}((\bar{G}^H)'Z\widehat{W}Z'Y^H)$. The exogenous block in (1) implies $G_{it}^H = ((OResShare_{it-P} \cdot \Delta lnROp_t)^H, \Delta RDSG10_t^H)$, $\bar{G}_{it}^H = [\breve{X}_{it-1}^H, \breve{X}_{it-2}^H, ..., \breve{X}_{it-p}^H]$, and $C' = [\Psi_1', \Psi_2', ..., \Psi_p']$. The vector of $m \geq p$ instruments Z contains m lags of the two exogenous variables. Similarly, the local housing market block in (2) is characterized by $G_{it}^H = (\Delta lnRPDI_{it}^H, \Delta lnRLp_{it}^H, \Delta lnRHp_{it}^H)$, $\bar{G}_{it}^H = [Y_{it-1}^H, Y_{it-2}^H, ..., Y_{it-q}^H, X_{t-1}^H, X_{t-2}^H, ..., X_{t-q}^H]$, and $C' = [A_1', A_2' ..., A_q', B_1', B_2' ..., B_q']$. The set of instruments Z in this case includes the q lags of the two exogenous variables as well as $n \geq q$ lags of the three endogenous variables in model (2). We use Hansen (1982)'s robust conforming weighting matrix $\widehat{W}$. The lags of the Helmert transformed variables selected for inclusion in the model (p and q, respectively) are instrumented by lags of the variables in levels (that is, untransformed). In our analysis, we set the number of instruments to be $m = 4$ for the exogenous variables in (1) and $n = 6$ for the endogenous variables in (2), respectively.

The block-partitioning aspect of our estimation strategy is aimed at imposing block-specific restrictions on the dynamics of the model. First, we use distinct sets of instruments for the endogenous local housing variables and for the exogenous common factors in order to achieve more

9. The contemporaneous real oil price shocks propagate for at most four quarters and ought to be uncorrelated with (and unpredictable based on) any prior information—including that from the lagged (eight quarters or more) shares of proved crude oil reserves adjacent to each MSA. Similarly, the contemporaneous shocks from (2) can only propagate for at most six quarters and, therefore, should be uncorrelated with the lagged (eight quarters or more) shares for the same reason.

10. For any given variable g_{it}, the corresponding Helmert transformation g_{it}^H is given by $g_{it}^H = \sqrt{\frac{T-t}{T-t+1}}\left(g_{it} - \frac{1}{T-t}\sum_{n=t+1}^{T} g_{in}\right)$.

efficient GMM estimates. This also implements a more parsimonious strategy that limits the problem of lag proliferation in the instruments and the specification (Roodman, 2009).

Second, our specification also establishes that the propagation of exogenous real oil price shocks (and shocks to real long-term interest rates) into local real house prices occurs only through the spillovers estimated via fluctuations in the exogenous variables as shown in the pVARX form in (2). Furthermore, the partitioning also allows us to impose cross-equation restrictions on the dynamics of the model preventing developments in local housing markets across Texas MSAs from having a spurious impact on the real U.S. long-term real interest rate or on globally-determined real oil prices. We argue that those restrictions provide a plausible description of the relationship between local real house prices and real long-term interest rates and global oil prices.

Finally, the proposed partitioning introduces restrictions on the variance-covariance matrix of the shock innovations that permit us to identify shocks to real oil prices and real personal disposable income per capita that are exogenous through an appropriate Cholesky ordering on the local housing market block and the common factors block in (1)–(2).[11] This ensures that the innovations of the housing variables are uncorrelated with the innovations on the common factors. As an important corollary, this identification scheme is also useful to better understand what makes real oil price shocks different from real personal disposable income per capita shocks—that are orthogonal to real oil price shocks—in how they impact the dynamics of local real house prices (and their demand- and supply-side determinants).

3. MODEL ESTIMATION

To explore the effects of exogenous real oil price shocks on real house prices, taking stock of the cross-sectional heterogeneity within Texas, we use the two-block model given by (1)–(2). In this section, we discuss the selection of the appropriate lag structure for the model, and then proceed with the estimation results. We also explore the stability properties of the estimated model. Our benchmark specification in (1)–(2) is estimated using the full sample, but we also consider two alternative specifications. First, we consider the case where we impose zero-restrictions on the matrices $B_1, B_2, \ldots, B_q$ in order to investigate how omitting real oil price fluctuations alters our perception of the dynamics in the local real estate block of the model (that is, in (2)). Second, we re-estimate the model with two subsamples that exclude the onset of shale gas and oil in the early 2000s and the heyday of the shale oil boom in Texas since the late 2000s to assess the hypothesis of parameter instability in the model due to the shale revolution.

3.1 Model Selection

We choose the optimal lag order and moment condition separately for each block of the model given by (1)–(2). For systems that are just-identified or overidentified (that is, whenever $p \leq m = 4$ and/or $q \leq n = 6$), the overall coefficient of determination (CD) can be computed to evaluate the proportion of variation explained by the pVARX model (Abrigo and Love, 2016). For overidentified systems (that is, whenever $p < m = 4$ and/or $q < n = 6$), apart from the overall CD, we can also deploy Andrews and Lu (2001)'s set of moment and model selection criteria for GMM

11. We should note here that the exogenous real oil price shocks in our framework do not necessarily have a structural interpretation and likely reflect a varying combination of global supply and global demand shocks. However, given that the propagation of these shocks goes through fluctuations in the real price of oil, these reduced-form exogenous shocks still help us assess the response of real house prices to the mix of demand and supply shocks that drives real oil price fluctuations.

estimation based on Hansen's (1982) J-statistic. These are viewed as the counterpart of well-known maximum likelihood-based model selection criteria: MBIC can be viewed as the GMM counterpart of the Bayesian information criteria (BIC), MAIC as the counterpart of the Akaike information criteria (AIC), and MHQIC as the counterpart of the Hannan-Quinn information criteria (HQIC).

Our key findings from this battery of tests are reported in Table 2 below. Based on the overidentified model selection criteria by Andrews and Lu (2001), a first-order pVAR is the preferred model for the exogenous block in (1) since this has the smallest MBIC, MAIC, and MHQIC. The p-value of Hansen's (1982) J-statistic fails to reject the joint null hypothesis that the instruments are valid instruments, i.e., uncorrelated with the error term. Therefore, we retain $m = 4$ and adopt $p = 1$ for equation (1). We would reach a similar conclusion had we used the long-term real interest rate in levels with or without a trend instead in this block of the model.

Table 2: Lag selection criteria: Hansen's (1982) J-statistic and Andrews and Lu (2001)

Lag	IV	CD	*J*-statistic P−value	MBIC	MAIC	MHQIC
Local Housing Block						
$q=1$	$n=6$	0.59 / 0.61	0.00 / 0.00	259.40 / 185.31	542.06 / 447.84	441.80 / 352.58
2	$n=6$	0.63 / 0.66	0.00 / 0.00	159.37 / 140.83	385.50 / 350.85	305.29 / 274.64
3	$n=6$	0.66 / 0.70	0.00 / 0.00	66.23 / 31.87	235.83 / 189.39	175.67 / 132.23
4	$n=6$	0.74 / 0.76	0.00 / 0.00	–18.10 / –13.45	94.96 / 91.57	54.86 / 53.46
5	$n=6$	0.75 / 0.77	0.00 / 0.00	–18.76 / –8.81	37.78 / 43.70	17.72 / 24.64
6	$n=6$	0.77 / 0.75	—	—	—	—
Common Factors						
$p=1$	$m=4$	–0.09 / –0.09	0.21 / 0.26	–42.85 / –40.97	–8.35 / –9.35	–22.37 / –22.16
2	$m=4$	–0.10 / –0.10	0.72 / 0.78	–33.61 / –32.34	–10.61 / –11.26	–19.96 / –19.79
3	$m=4$	–0.02 / –0.03	0.72 / 0.30	–17.40 / –13.69	–5.90 / –3.15	–10.58 / –7.42
4	$m=4$	0.24 / 0.26	—	—	—	—

Notes: The table reports the three selection criteria proposed by Andrews and Lu (2001): MBIC, MAIC, and MHQIC. The Hansen's (1982) J-statistic on the validity of overidentifying restrictions is reported indirectly in terms of p-values. The overall coefficient of determination (CD) that accounts for the variation explained by the model is also included. For each, we report the values for the full sample that ends in 2016:Q2 followed by the values for the subsample going from 1975:Q1 to 2001:Q4. The results are fairly similar for the subsample that ends in 2008:Q4 (available upon request). We only report here the findings for the common factor specification where the U.S. real long-term interest rates are given by $\Delta RDSG10_t$. The results using the level ($RDSG10_t$) with and without a time trend are available upon request, but qualitatively point to the same lag and instrument (IV) specification.

For the local housing markets block specified in (2), the smallest MBIC, MAIC, and MHQIC values for overidentified models are obtained when we set q to be equal to 5. However, for all overidentified specifications where $q < 6$, the p-value of Hansen's (1982) J-statistic rejects the joint null hypothesis that the instruments are valid. The overall CD reaches its highest value whenever just-identified and $q = n = 6$. We therefore retain $n = 6$ and adopt $q = 6$ for equation (2). We should note that these model selection results are robust whether we consider the full sample or the subsamples that exclude the onset of shale gas or the later shale oil boom period.

3.2 Model Estimation

We fit a first-order pVAR for the exogenous common factor block in (1) and a sixth-order pVARX specification with exogenous common factors interacted with the pre-existing share of crude oil reserves for the local housing market block in (2). Our findings on the first-order pVAR used to estimate the dynamics of $X_t = \left(\Delta lnROp_t, \Delta RDSG10_t\right)$ over the full sample and the subsample that excludes the shale revolution (1975:Q1–2001:Q4) are reported in Table 3. Table 4 documents the estimation of the local housing market block in (2) over the full sample period (column (A)), for the subsample that excludes the period of the shale revolution (column (B)), and for an alternative specification estimated over the full sample that sets the local housing market spillovers from real oil prices to zero (column (C)).[12]

As seen in Table 3, the evidence suggests there is little explanatory power for the lagged common factors on the equation for the real long-term interest rate in first differences. The alternative specifications that consider the real long-term interest rate in levels with and without trend also tend to validate the hypothesis that the real long-term rate is well-described as a unit-root process without any spillovers. As a result, we retain the variable $\Delta RDSG10_t$ in our preferred benchmark specification of the model. The findings in Table 3 also indicate that real oil prices in first differences appear to follow a simple first-order autoregressive process. All of this implies that changes in the real long-term interest rate are purely transitory and show neither own-persistence nor significant spillovers from real oil prices, while the growth rate in real oil prices displays some degree of own-persistence that we need to take into account in our subsequent empirical analysis.[13]

Table 4 provides the full set of estimates for the pVARX(6) model for the local housing

Table 3: pVAR(1) model of the exogenous common factors

	$\Delta lnROp_t$		$\Delta RDSG10_t$	
	1975:Q1–2016:Q2	1975:Q1–2001:Q4	1975:Q1–2016:Q2	1975:Q1–2001:Q4
$\Delta lnROp_t$	0.24***	0.26***	0.00	0.01*
$\Delta RDSG10_{t-1}$	1.01	1.36	0.05	0.03
	$\Delta lnROp_t$		$RDSG10_t$	
	1975:Q1–2016:Q2	1975:Q1–2001:Q4	1975:Q1–2016:Q2	1975:Q1–2001:Q4
First Alternative Specification				
$\Delta lnROp_{t-1}$	0.25***	0.27***	0.00	0.00
$RDSG10_{t-1}$	0.17	–0.07	1.00***	1.00***
Second Alternative Specification				
$\Delta lnROp_{t-1}$	0.31***	0.30***	0.00	0.00
$RDSG10_{t-1}$	–2.05	–0.18	0.98***	0.87***
t	–0.08	–0.00	–0.00	–0.01

Notes: *, **, and *** denote statistical significance at the 10, 5, and 1 percent significance level, respectively. GMM estimates for the benchmark pVAR(1) are reported for the full sample (1975:Q1–2016:Q2) and for the subsample that excludes the shale revolution (1975:Q1–2001:Q4). The results for the subsample ending in 2008:Q4 are similar to those reported here and available upon request. The first alternative specification only satisfies the stability condition for the full sample. Initial weight matrix: Identity. GMM weight matrix: Robust. Instruments: lags(1/4) for ($\Delta lnROp$ $\Delta RDSG10$) and, alternatively, lags(1/4) for ($\Delta lnROp$ $RDSG10$) with or without the deterministic time trend.

market block in (2). The coefficient estimates for the subsample that excludes the shale revolution period (column (B)) are fairly similar to those we obtain over the full sample (column (A)). Hence, this evidence suggests that, once we account for the interaction of real oil price fluctuations with the share of pre-existing crude oil reserves, the shale revolution has not led to significant parameter instability—a structural break—in the dynamic relationship linking real oil prices to real house

12. The findings in Table 3 and Table 4, when we exclude only the shale oil boom years starting in 2009:Q1, are similar to those reported here and available upon request. The results in Table 4 are robust if we replace $\Delta RDSG10_t$ in the vector of exogenous common factors with the level of the long-term interest rate and a time trend $(RDSG10_t, t)$ instead.

13. The pVAR(1) model given in (1) is, in practice, like estimating a VAR(1) process for the exogenous common factors. The GMM estimates we report here are also very similar to the OLS (seemingly unrelated regressions) estimates and to the conditional maximum likelihood estimates of the VAR(1) specification.

Table 4: pVARX(6) model of local housing variables with spillovers from exogenous common factors

	$\Delta lnRPDI_{it}$			$\Delta lnRLp_{it}$			$\Delta lnRHp_{it}$		
	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
$\Delta lnRPDI_{it-1}$	0.29***	0.24***	0.31***	–0.10*	–0.07	–0.08	–0.06***	0.01	–0.04***
$\Delta lnRPDI_{it-2}$	0.15***	0.11***	0.16***	0.13**	0.08	0.12**	0.03**	0.04***	0.03***
$\Delta lnRPDI_{it-3}$	–0.06**	–0.05*	–0.06**	0.00	–0.11*	0.01	–0.01	–0.02	0.00
$\Delta lnRPDI_{it-4}$	–0.14***	–0.04	–0.15***	–0.04	–0.06	–0.03	0.07***	0.07***	0.07***
$\Delta lnRPDI_{it-5}$	–0.09***	–0.10***	–0.09***	–0.02	–0.12*	–0.01	0.01	0.01	0.00
$\Delta lnRPDI_{it-6}$	–0.04	–0.05*	–0.03	–0.10*	–0.20***	–0.11**	–0.04***	–0.02*	–0.04***
$\Delta lnRLp_{it-1}$	0.01***	0.01***	0.01***	0.11***	0.14***	0.11***	0.00	0.01**	0.00
$\Delta lnRLp_{it-2}$	0.01**	0.01**	0.01***	0.23***	0.21***	0.24***	0.00	0.00	0.00
$\Delta lnRLp_{it-3}$	0.00	0.01	0.01	0.03	0.05**	0.03	0.00*	0.00	0.00*
$\Delta lnRLp_{it-4}$	–0.01*	–0.00	–0.01*	–0.42***	–0.40***	–0.41***	0.00**	0.00	0.00*
$\Delta lnRLp_{it-5}$	0.01*	0.00	0.01**	0.14***	0.15***	0.14***	0.00	0.01	0.00
$\Delta lnRLp_{it-6}$	0.00	0.00	0.00	0.09***	0.11***	0.09***	0.00	0.00	0.00
$\Delta lnRHp_{it-1}$	–0.01	–0.02	–0.03	0.43***	0.64***	0.44***	0.50***	0.39***	0.50***
$\Delta lnRHp_{it-2}$	–0.12***	–0.06**	–0.15***	0.15	0.18	0.15	0.20***	0.26***	0.18***
$\Delta lnRHp_{it-3}$	0.14***	0.15***	0.14***	–0.20*	–0.30**	–0.22*	0.28***	0.33***	0.28***
$\Delta lnRHp_{it-4}$	0.11***	0.08***	0.16***	0.01	–0.13	0.03	–0.23***	–0.24***	–0.23***
$\Delta lnRHp_{it-5}$	–0.04	–0.13**	–0.03	0.23**	0.37***	0.23**	0.04*	–0.00	0.05**
$\Delta lnRHp_{it-6}$	–0.06*	–0.03*	–0.05	0.31***	0.30**	0.30***	0.01	0.02	0.02
$S\_\Delta lnROp_{t-1}$	0.19***	0.15**	—	0.06	–0.10	—	0.03***	–0.00	—
$S\_\Delta lnROp_{t-2}$	0.08**	0.01	—	0.03	0.11	—	0.10***	0.11***	—
$S\_\Delta lnROp_{t-3}$	0.11***	0.16***	—	0.05	0.11	—	0.02	0.00	—
$S\_\Delta lnROp_{t-4}$	–0.07*	–0.05	—	0.01	–0.07	—	0.02	0.01	—
$S\_\Delta lnROp_{t-5}$	0.10***	0.27***	—	0.01	0.10	—	0.04***	0.07***	—
$S\_\Delta lnROp_{t-6}$	0.04	0.04	—	0.18***	0.12	—	0.01	0.00	—
$\Delta RDSG10_{t-1}$	–0.40***	–0.33***	–0.36***	–0.08	0.12	–0.04	–0.13***	–0.26***	–0.12***
$\Delta RDSG10_{t-2}$	–0.06	–0.12**	–0.03	0.44***	0.58***	0.45***	0.22***	0.24***	0.24***
$\Delta RDSG10_{t-3}$	0.15***	0.14***	0.17***	0.64***	0.69***	0.63***	0.11***	0.21***	0.12***
$\Delta RDSG10_{t-4}$	0.32***	0.32***	0.34***	0.16	–0.04	0.17	–0.12***	–0.11***	–0.11***
$\Delta RDSG10_{t-5}$	–0.16***	–0.22***	–0.16***	0.69***	0.75***	0.70***	0.21***	0.21***	0.22***
$\Delta RDSG10_{t-6}$	–0.17***	–0.25***	–0.17***	0.24	0.34*	0.28	–0.11***	–0.19***	–0.11***

Notes: *, **, and *** denote statistical significance at the 10, 5, and 1 percent significance level, respectively. Notice also that $S\_\Delta lnROp \equiv OResShare \cdot \Delta lnROp$. GMM estimates for the benchmark pVARX model (column (A)), the benchmark model excluding the shale revolution (from 2002:Q1 onwards) years (column (B)), and the model excluding spillovers from real oil prices (column (C)). The results for the subsample ending in 2008:Q4 are similar and available upon request. Initial weight matrix: Identity. GMM weight matrix: Robust. Instruments: lags(1/6) for ($\Delta lnRPDI$ $\Delta lnRLp$ $\Delta lnRHp$) and, if included, lags(1/6) for ($OResShare \cdot \Delta lnROp$ $\Delta RDSG10$).

prices. In Table 4, we also consider a scenario whereby spillovers from real oil prices into real house prices are omitted (column (C)). The direct implication of this assumption is that real oil price shocks do not have any direct effect on real house prices. We find that this particular omission tends to bias somewhat our coefficient estimates and, therefore, also our empirical inferences about the propagation of shocks (notably because it magnifies the response elicited by fluctuations in personal disposable income per capita).

Our coefficient estimates in all three scenarios (columns (A), (B), and (C)) reported in Table 4 suggest that the estimated spillovers from lagged real rural land prices on real personal disposable income per capita and real house prices are rather modest. Moreover, the impact of real oil price fluctuations interacted with pre-existing crude oil reserves appears weak and mostly statistically insignificant. All of this indicates that real rural land prices—proxying for supply-side factors in the housing market—play only a limited role in the transmission of real oil price shocks into real house prices.

In short, our estimates suggest that the shale revolution has had a limited effect on the dynamic relationship given in (2); that ignoring the spillovers from real oil prices may lead us to overstate the impact of demand-side fundamentals (particularly of real personal disposable income per capita shocks); and that the supply-side channel via real rural land prices appears weaker than the demand-side channel primarily through real personal disposable income per capita but partly through real long-term interest rates as well.

Finally, we should point out that we also check the stability condition of the estimated block-system in (1)–(2). Hamilton (1994) and Lütkepohl (2005) show that stability requires all eigenvalues of the companion matrix of the estimated model to be inside the unit circle. Exploring the eigenvalues confirms that the estimates reported in Table 3 and Table 4 are all stable for our preferred benchmark. Given that the estimated benchmark model satisfies this stability condition, the pVARX specification is invertible and has an infinite-order vector moving-average (VMAX) representation including the exogenous variables.

3.3 Panel Granger Causality

Panel Granger causality is based on performing Wald exclusion tests for each equation of the underlying pVARX model for (1)-(2). A variable y_{it} is said to "Granger-cause" another variable g_{it} if, given all the lags for g_{it}, we find that the lags of y_{it} are jointly statistically significant in the equation for g_{it}. The panel VAR-Granger causality Wald test evaluates the null that the coefficients of all the lags are zero (the excluded lagged variables do not Granger-cause the dependent variable of the corresponding equation) against the alternative that at least one coefficient is not equal to zero.[14] The Granger causality test results for our benchmark model over the full sample are summarized in Table 5.

Table 5 shows the p-value is above the conventional statistical significance thresholds for the common factor equations in (1). With this evidence, we can say that there is no empirical support for the hypothesis that real long-term interest rates Granger-cause real oil prices or for the hypothesis that real oil prices Granger-cause real long-term interest rates. This is consistent with the estimates in Table 3, which also show that the spillovers in the exogenous common factor block of the model are statistically insignificant.

In turn, Table 5 shows that real oil price fluctuations interacted with the share of pre-existing crude oil reserves—as well as real long-term interest rates—Granger-cause real house prices and real personal disposable income per capita across MSAs in Texas. However, real oil price changes interacted with the share of pre-existing reserves fail to Granger-cause real rural land prices while real rural land prices only weakly Granger-cause real personal disposable income per capita and real house prices at the 10 percent statistical significance level. These findings are consistent with the results in Table 4, which also shows weak real oil price spillovers into real house prices via real rural land values.

Still, the results in Table 5 clearly show real oil price changes do affect the local housing markets in Texas—and house prices in particular—even after we account explicitly for demand-side forces like real personal disposable income per capita and supply-side forces like real rural land prices that are themselves also affected to some degree by real oil price fluctuations. In addition, our evidence shows most of the variables in the local housing block strongly Granger-cause each other at the 1 percent statistical significance level. This provides further support for the variables included and

14. Notice that by construction, given the block-partitioned specification of (1)–(2), the lags of the local variables in $Y_{it} = \left(\Delta lnRPDI_{it}, \Delta lnRLp_{it}, \Delta lnRHp_{it}\right)$ do not Granger-cause the exogenous common factors in $X_t = \left(\Delta lnROp_t, \Delta RDSG10_t\right)$.

Table 5: Panel Granger causality tests

Equation	Excluded Variables	Chi-square Statistic	Degrees of Freedom	Prob > Chi-square
$\Delta lnRPDI_{it}$	$\Delta lnRLp_{it-1},\ldots,\Delta lnRLp_{it-6}$	18.27	6	0.01***
$\Delta lnRPDI_{it}$	$\Delta lnRHp_{it-1},\ldots,\Delta lnRHp_{it-6}$	36.06	6	0.00***
$\Delta lnRPDI_{it}$	$S\_\Delta lnROp_{t-1},\ldots,S\_\Delta lnROp_{t-6}$	45.50	6	0.00***
$\Delta lnRPDI_{it}$	$\Delta RDSG10_{t-1},\ldots,\Delta RDSG10_{t-6}$	111.17	6	0.00***
$\Delta lnRLp_{it}$	$\Delta lnRPDI_{it-1},\ldots,\Delta lnRPDI_{it-6}$	11.00	6	0.09*
$\Delta lnRLp_{it}$	$\Delta lnRHp_{it-1},\ldots,\Delta lnRHp_{it-6}$	68.64	6	0.00***
$\Delta lnRLp_{it}$	$S\_\Delta lnROp_{t-1},\ldots,S\_\Delta lnROp_{t-6}$	9.00	6	0.17
$\Delta lnRLp_{it}$	$\Delta RDSG10_{t-1},\ldots,\Delta RDSG10_{t-6}$	51.61	6	0.00***
$\Delta lnRHp_{it}$	$\Delta lnRPDI_{it-1},\ldots,\Delta lnRPDI_{it-6}$	91.02	6	0.00***
$\Delta lnRHp_{it}$	$\Delta lnRLp_{it-1},\ldots,\Delta lnRLp_{it-6}$	11.78	6	0.07*
$\Delta lnRHp_{it}$	$S\_\Delta lnROp_{t-1},\ldots,S\_\Delta lnROp_{t-6}$	67.82	6	0.00***
$\Delta lnRHp_{it}$	$\Delta RDSG10_{t-1},\ldots,\Delta RDSG10_{t-6}$	235.24	6	0.00***
Common Factors				
$\Delta lnROp_{t}$	$\Delta RDSG10_{t-1}$	0.53	1	0.47
$\Delta RDSG10_{t}$	$\Delta lnROp_{t-1}$	1.32	1	0.25

Notes: *, **, and *** denote statistical significance at the 10, 5, and 1 percent significance level, respectively. Notice that $S\_\Delta lnROp \equiv OResShare \cdot \Delta lnROp$. The panel Granger tests reported are computed as Wald tests of the excluded variables for the benchmark pVARX model by blocks given by (1) and (2). The test statistics are computed based on the full sample estimates for the benchmark specification reported in Table 3 and Table 4.

the pVAR structure adopted here as it clearly helps us capture the dynamic endogenous relationships among the variables in $Y_{it} = \left(\Delta lnRPDI_{it}, \Delta lnRLp_{it}, \Delta lnRHp_{it}\right)$ and the role played by the exogenous common covariates in $\breve{X}_{it} = \left(OResShare_{it-P} \cdot \Delta lnROp_{t}, \Delta RDSG10_{t}\right)$.

4. EMPIRICAL FINDINGS

In this section, we evaluate the dynamic relationships modeled in (1)-(2) tracing out the effects of shocks—particularly shocks to real personal disposable income per capita and to real oil prices—on the endogenous local housing market variables. Our block-partitioning of the system (1)–(2) already imposes key identifying restrictions and requires that residual innovations ϵ_t and e_{it} for all $i = 1, 2, \ldots, \mathrm{N}$ be uncorrelated at all leads and lags. Apart from that, we rely on a recursive structure for our pVARX specification to impose additional identifying restrictions on the residual innovations of each block. That is, we orthogonalize the residual innovations of each block with a Cholesky decomposition (Sims, 1980).

The Cholesky decomposition is not unique and critically depends on the ordering of the variables in each block—what we do here is to impose a plausible ordering with which to recover block-exogenous shocks to real personal disposable income per capita and to real oil prices. This is useful because we are particularly interested in disentangling the effects of discretionary real income shocks that are otherwise orthogonal to real oil prices from the effects of real oil price shocks. Here: (a) for the exogenous common factor block, our Cholesky identification assumes that real oil price shocks can impact real long-term interest rates contemporaneously but not the other way around; and (b) for the local housing market block, we assume that real house prices can respond contemporaneously to real rural land price shocks and to real personal disposable income per capita shocks, real rural land prices respond contemporaneously to real personal disposable income per capita shocks but not to real house price shocks, and real personal disposable income per capita responds contemporaneously only to its own shocks.[15]

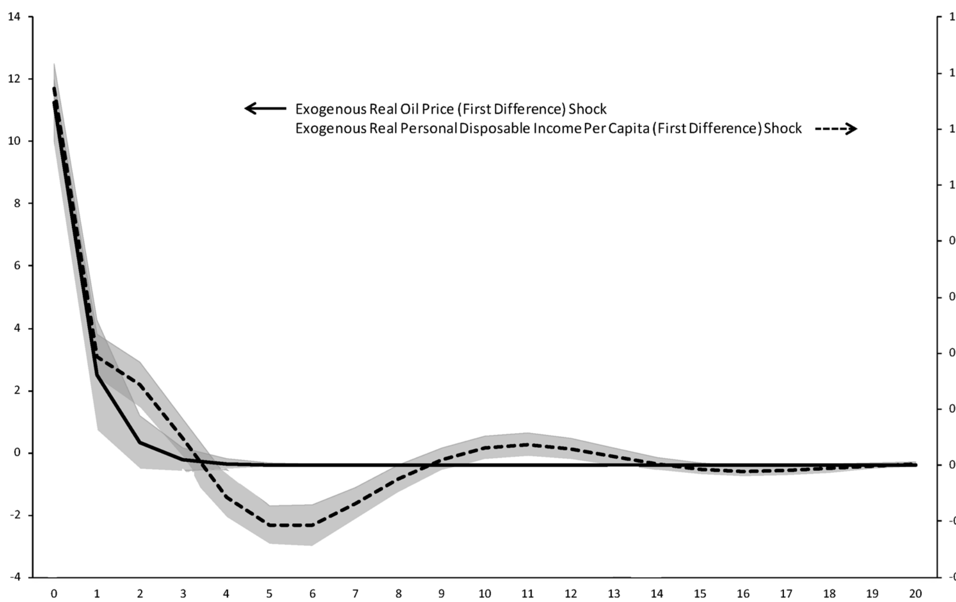
15. We also consider an alternative ordering whereby real rural land prices respond contemporaneously to both real personal disposable income per capita and real house prices, while real house prices only respond contemporaneously to real personal disposable income per capita shocks. The results we obtain are largely unchanged, and available upon request.

Because common factors are included as common exogenous covariates in the local housing market system in (2), identified innovations to real oil prices obtained from the estimated system in (1) can propagate into (2) interacted with pre-existing crude oil reserves and affect the dynamics of the local housing market variables. The same can be said of exogenous innovations to the real long-term interest rate estimated with the common factors system in (1). Also, we should note that fluctuations in the common factors propagate into the housing block in (2) with a lag of at least one quarter under our timing assumptions.

4.1 Impulse Response Functions

Real oil price shocks as well as real personal disposable income per capita shocks tend to dissipate fairly quickly, as seen in the impulse response functions (IRFs) plotted in Figure 3. Real oil price shocks, however, are an order of magnitude larger than exogenous shocks to real personal disposable income per capita (that are orthogonal to real oil price shocks in our benchmark specification). This difference in the magnitude of the impact of each shock is consistent with the fact that real oil prices are also similarly more volatile unconditionally than real personal disposable income per capita is in the data. Moreover, the dynamic responses of the (non-oil) discretionary real income shocks and the real oil price shocks that we have identified (and illustrated for the full sample in Figure 3) are robust to: (a) alternative orderings of the variables in the local housing block (keeping the assumption that real personal disposable income per capita responds contemporaneously to own shocks alone), and (b) to a subsample that excludes the period since either the onset of the shale revolution or the shale oil boom years.

Figure 3: Real personal disposable income per capita shocks vs. real oil price shocks

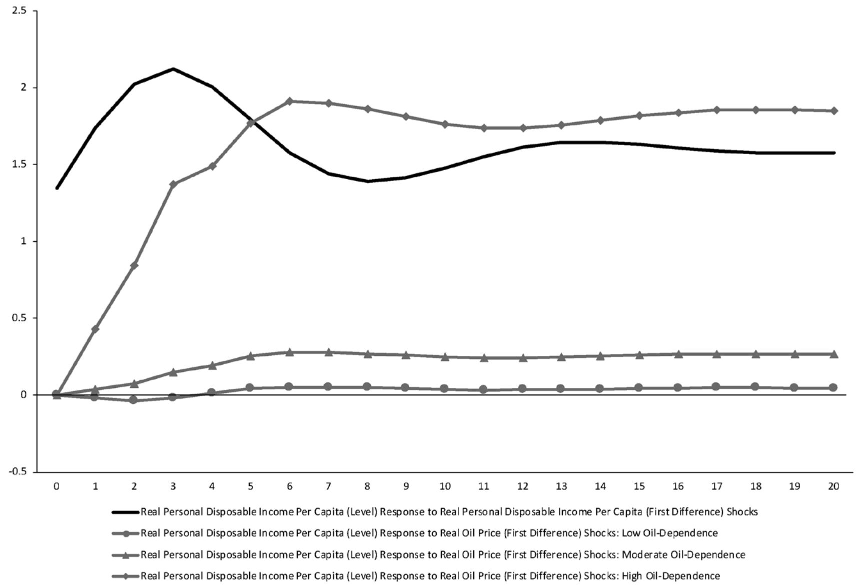


Notes: The IRFs reported are computed for the benchmark pVARX model by blocks given by (1) and (2). The estimates are based on the full sample 1975:Q1–2016:Q2 whose estimates are reported in Table 3 and Table 4. The confidence intervals for the IRFs are estimated using 500 Monte Carlo simulation and bootstrap resampling methods.

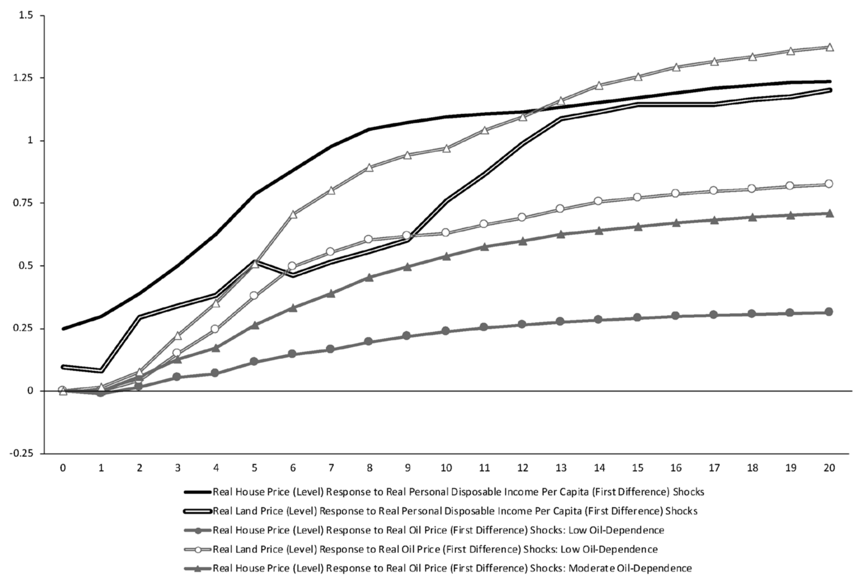
Hence, the questions are: (a) how do exogenous shocks to real oil prices and to personal disposable income per capita propagate into local housing markets?; and (b) has the relationship between real oil prices and real house prices remained stable as shale oil upended the oil and gas industry in the 2000s? Figures 4.A and 4.B provide us with a broad overview of the propagation mechanism of (non-oil) discretionary real income shocks and real oil price shocks across Texas.

Figure 4: Real personal disposable income per capita shocks vs. real oil price shocks

A. Real personal disposable income per capita response to real income shocks and to real oil price shocks



B. Real house prices and real rural land prices response to real income shocks and to real oil price shocks



Notes: The propagation dynamics reported in this figure are based on the estimated benchmark pVARX model by blocks given in (1)-(2) and its corresponding cumulative IRFs. The estimates are from the full sample as given in Table 3 and Table 4. Panel A reports the point-estimate of the cumulative IRF of real personal disposable income per capita in response to exogenous real income shocks and to real oil price shocks propagated into the local housing block under the benchmark estimates for equation (1). Panel B similarly reports the cumulative IRFs on real house prices and real rural land prices propagated in response to real income shocks and real oil price shocks.

We label the median of the distribution of the share of pre-existing crude oil reserves across Texas MSAs (which comes at an average of 0.8 percent over the full sample) as low oil-dependence, the upper quartile of the distribution (at an average of 3.0 percent) as moderate oil-dependence, and the 90-percentile of the distribution (at an average of 18.7 percent) as high oil-dependence. As can be seen from Figure 4.A, the point-estimate response of real personal disposable income per capita to a real oil price shock is rather modest for local MSAs of low or moderate oil-dependence. For the most oil-dependent areas, in turn, the estimated real oil price shock shifts real income upward over the medium term (3–5 years) by approximately the same order of magnitude as the estimated exogenous (non-oil) real income shock (albeit its impact is more gradual during the first year).

The evidence in Figure 4.A suggests the income effects of real oil price shocks display strongly non-linear features. Indeed, real income effects boosting housing demand are shown to be modest in most local areas except those around which most of the pre-existing proved crude oil reserves in the state are concentrated. The impact of an exogenous real oil price shock on the long-term real interest rate is quite limited, although not trivial (increasing long-term real rates by about 17 basis points over the medium term). The implication of all of this is that real oil price shocks operate on the demand-side of the local housing market predominantly through their impact on personal disposable income per capita—most heavily in local areas strongly tied to oil—and less so through the concurring small increases of the long-term real interest rate which induce only a modest tightening of financial conditions.

Figure 4.B shows that exogenous (non-oil) real income shocks tend to pull up real house prices and adjacent real rural land prices—more gradually for real rural land prices than for real house prices earlier on, but by a similar magnitude over the medium term (3–5 years). Interestingly, the impact of real oil price shocks on real rural land prices, and to a lesser extent on real house prices, is quite significant even in local areas of low or moderate oil-dependence and comparable in magnitude with the response triggered by an exogenous (non-oil) real income shock. We recognize that the strength of their response to real oil price shocks is partly a matter of scale—real oil price shocks are an order of magnitude larger than personal disposable income per capita shocks (as seen in Figure 3).

We interpret the evidence in Figure 4.B as suggesting that real rural land prices are partly being pulled up by rising real house prices as the housing demand shifts in response to real oil price shocks (particularly so in those local areas more dependent on oil activity where the effects of real oil price shocks on incomes can be quite large, as seen in Figure 4.A). The model also suggests that real oil price shocks play an important role on the supply-side of housing as well and, in doing so, influence the demand of rural land for urban development and drive rural land prices up.

At this point, we should recall that the rural land price data available to us do not identify if mineral rights are included in the land transactions or not. Though mineral severance is quite common in Texas, it is by no means ubiquitous. The price for rural land ought to be higher when mineral rights are included since the owner of the mineral rights can lease the drilling rights to oil companies receiving royalty payments in return (Brown, et al., 2016; Brown, et al., 2019).[16] We expect the issue with mineral rights, though, to have only a limited impact on our model estimates because our benchmark already incorporates what effectively constitutes a proxy for mineral rights values—the interaction between oil price changes and the share of pre-existing proved crude oil reserves (a measure of the value of the adjacent oil wealth underground).

16. Not having ownership of the mineral resources underground has been shown to drag house prices down given that drilling can damage roads and crop land, and cause water, air, and noise pollution (Boslett, et al., 2019).

Indeed, the interaction between real oil prices and pre-existing crude oil reserves takes account of the mineral-rights-value-channel's influence on the housing supply separately from that of real rural land prices. Our findings therefore support the view that the effects of real oil price shocks matter for urban development and partly contribute to the strong response in real rural land prices seen in Figure 4.B. Moreover, the evidence shows clear structural differences in the propagation of real (non-oil) income shocks and real oil price shocks into real rural land prices and real house prices. Accordingly, in oil-producing regions like Texas, we would argue that it would be an error to confound real oil price shocks as discretionary real income shocks.

4.2 The Shale Revolution

Arguably one of the most significant breakthroughs over the past 15 years was the technological advancement that made extraction of gas and then oil from shale rock formations commercially viable (Wang and Krupnick, 2015). Prior to that, drilling had targeted primarily reservoir rock, typically sandstones, to which oil and gas had migrated from the shale rock where it was formed from organic matter deposited millions of years ago. Improvements in multi-stage drilling and "fracking"—injecting a mixture of water, sand, and chemicals underground at high pressure to open small cracks to release the oil and gas—made it viable to tap shale rock for gas, which had been expanding since the early 2000s. By 2009, it had become cost-effective to begin extraction of shale oil as well. Horizontal drilling—sinking a well straight down, then sideways—exposed a much greater area of resource-bearing rock. The latest automated rigs are able to drill long lateral sections in horizontal wells, moving to new well sites faster. As a result, drilling and completing wells continues to become more cost effective to operate.

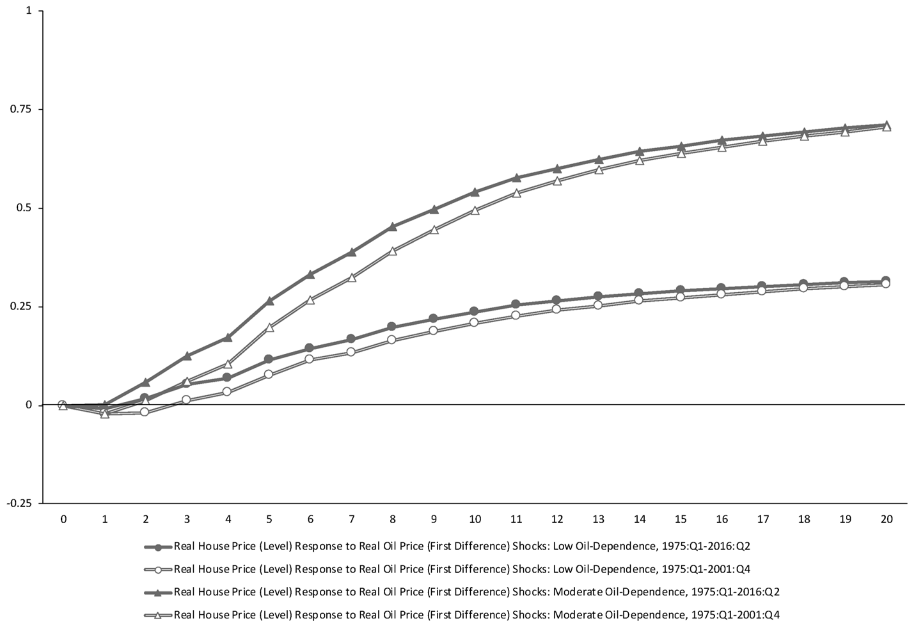
The large amounts of shale oil uncovered during the shale revolution period have turned on its head the conventional wisdom that U.S. oil production was inexorably on a declining path, and world oil production was nearing its peak. Even after the dramatic fall in oil prices of late 2014, the oil and gas industry continues to adapt and thrive under shifting conditions. In a turnaround with few parallels in the history of the industry, U.S. crude oil production bounced back from a post-WWII bottom of 4.76 million barrels (bbl) on average daily in 2008:Q3 to 10.50 million ten years later. Of the additional 5.74 million barrels gained by 2018:Q2, 3.18 million (55.40 percent of the total U.S. gains) are accounted for by Texas production (excluding offshore) alone—mostly shale oil coming from the Eagle Ford shale (Western Gulf basin of Southern Texas) and the Permian Basin (Western Texas).

We interpret the impact of the shale revolution as a structural break that has ushered in a new era where global oil supply appears to be more elastic in response to real oil price fluctuations. The hypothesis here is that new technologies have made it possible to tap into shale oil in a cost-efficient way, expanding oil supply significantly in oil-producing areas of Texas and, therefore, accentuating the impact of real oil price shocks on real personal diposable income per capita and/or on real rural land prices. We adopt a sample splitting approach to assess changes in the propagation of real oil price shocks over time. We plot in Figure 5 the response of real house prices to real oil price shocks over the full sample (1975:Q1–2016:Q2) and over the subsample period excluding the shale revolution (1975:Q1–2001:Q4).[17]

We have already discussed the limited effect of the shale revolution on the characteristics of the model and the estimates reported elsewhere (particularly in Table 3 and Table 4). As can be seen in Figure 5, the impact on real house prices and real rural land prices is somewhat more accen-

17. We find similar results, available upon request, if we only exclude the shale oil boom years (1975:Q1–2008:Q4).

Figure 5: Real house price (level) response to a real oil price (first difference) shock



Notes: The propagation dynamics reported in this figure are based on the estimated benchmark pVARX model by blocks given in (1)-(2) and its corresponding cumulative IRFs. The estimates are from the full sample and the subsample that excludes the shale revolution period (1975:Q1-2001:Q4) as given in Table 3 and Table 4. Similar to Figure 4.B, this figure reports the cumulative IRFs on real house prices and real rural land prices propagated in response to real oil price shocks.

tuated in the short term while differences tend to dissipate over the medium term (3–5 years). In the end, however, the estimated propagation path for real house prices and even for real rural land prices is fairly similar with or without including the shale revolution period.

4.3 Real Oil Price Shock Spillovers

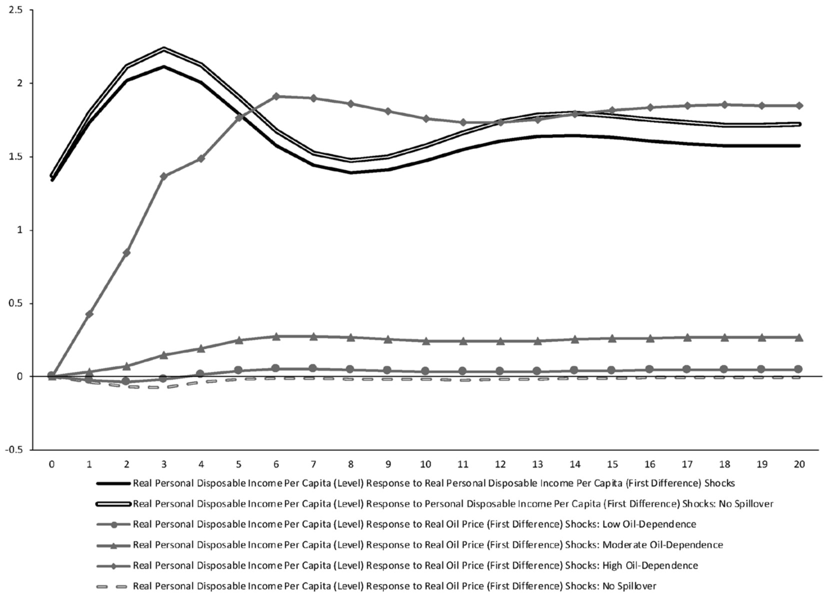
Real oil price shocks and long-term real interest rates are exogenous common factors in the local housing market block in (2). Our premise is that ignoring spillovers from real oil prices can bias our inferences about the role that housing demand determinants such as personal disposable income per capita play in the housing market. We explore that hypothesis in Figure 6 where we compare the point-estimate propagation of exogenous (non-oil) real income and real oil price shocks over the full sample (1975:Q1–2016:Q2) for two alternative specifications: our estimated benchmark model in (1)–(2) against an alternative specification that imposes zero-restrictions on the matrices $B_1, B_2, \ldots, B_q$ omitting real oil price spillovers (where we retain the lag q equal to 6).

The implications of the zero-restrictions on the $\left\{B_i\right\}_{i=1}^{6}$ matrices are quite stark in Figures 6.A and 6.B—omitting the spillovers of real oil prices means real oil price shocks get woven into real income shock. The consequence of this is twofold: (a) we omit the important role played by real oil price shocks on real house prices; and (b) the empirical inferences we draw about real income shocks (no longer orthogonal to real oil prices) are accordingly biased.

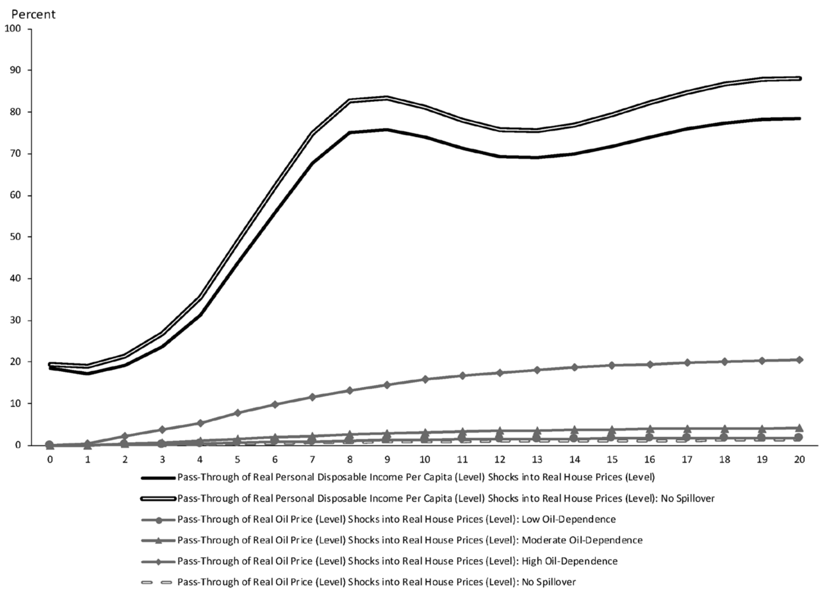
First, we observe that omitting the spillovers from real oil prices in (2) amplifies somewhat the response of personal disposable income per capita to the estimated real income shocks (Figure 6.A).

Figure 6: Real personal disposable income per capita shocks vs. real oil price shocks with and without oil spillovers

A. Real personal disposable income per capita response to real income shocks and to real oil price shocks



B. Pass-through of real income shocks and real oil price shocks into real house prices



Notes: The propagation dynamics reported in this figure are based on the estimated benchmark pVARX model by blocks given in (1) and (2) and its corresponding cumulative IRFs using the full sample. The estimates are given in Table 3 and Table 4. Panel A reports the point-estimate of the cumulative IRF of real personal disposable income per capita in response to exogenous real income shocks and to real oil price shocks propagated into the housing block under the benchmark and under the alternative where we preclude any spillovers from real oil prices. Panel B reports the ratio of the cumulative IRF of the real house price relative to either the cumulative response of real personal disposable income per capita to real income shocks and relative to the cumulative response of real oil prices to real oil price shocks for the benchmark model and the alternative without spillovers.

Second, omitting the spillovers from real oil prices also accentuates the pass-through of the estimated real income shocks into real house prices (Figure 6.B). This upward bias in the pass-through is apparent in the short term, but it strengthens over the medium term (3–5 years ahead). We find similar results when looking at the pass-through of real income shocks into real rural land prices.

Third, the pass-through of real oil price shocks into real house prices in the benchmark model reaches about 21 percent after 20 quarters but only among the most oil-dependent areas while less than 5 percent for low and moderate oil dependence areas (Figure 6.B). The pass-through into real rural land prices and into real house prices is somewhat more robust reaching 31 and 8 percent, respectively. In turn, the omission of spillovers from real oil prices increases the estimated pass-through into real house prices particularly over the medium term (from 78 to 88 percent after 20 quarters). Simultaneously, this also boosts the real personal disposable income per capita pass-through on real rural land prices (from 76 to 92 percent after 20 quarters).

In summary, confounding real oil price shocks and real income shocks by omitting spillovers from real oil prices muddies the waters and significantly biases our understanding of discretionary real income shocks—notably it over-estimates the pass-through of real income shocks into real house prices and real rural land prices.

5. CONCLUDING REMARKS

Texas is the leading oil-producing state in the U.S. and one of the largest oil producers in the world. With a novel dataset of Texas metropolitan statistical areas' (MSAs') housing and rural land market data over the period spanning from 1975:Q1 to 2016:Q2, we investigate the dynamic relationship between real house prices and real oil price shocks controlling for other MSA-specific or common factors—personal disposable income per capita, real rural land prices, real long-term interest rates, and pre-existing crude oil reserves underground.

We adopt a block-partitioned panel VAR framework to investigate the dynamic relationship. We also implement a block-recursive Cholesky decomposition to identify exogenous real oil price shocks as well as exogenous non-oil-related real income shocks. Exploiting the significant regional heterogeneity across Texas MSAs in our dataset, we find empirical support for the view that spillovers from real oil prices play a significant role in local house prices, particularly among the most oil-sensitive MSAs. We find that the response of real house prices (and to a larger extent of real rural land prices) is comparable in magnitude to that of real income shocks even among many MSAs with varying degrees of oil-dependence.

We argue that in oil-producing areas, real oil price shocks are quite distinct from (non-oil) discretionary real income shocks. We show that empirical inferences on real income shocks can be significantly biased if the model does not include real oil price fluctuations due to the significant role played by spillovers from real oil prices in oil-producing areas. To be more precise, omitting the spillovers tends to erroneously suggest that real income shocks induce a larger increase in real personal disposable income per capita over the medium term (3–5 years) while increasing their estimated pass-through into real house prices (and more so into real rural land prices) by a sizeable margin.

Finally, we also consider explicitly the stability of these empirical relationships in light of the historic turnaround that the oil and gas industry in the U.S. (and in particular in Texas) has experienced since the shale revolution ignited in the early 2000s. Interestingly, we only find rather weak evidence that the shale revolution has empirically altered the dynamic relationship between real oil prices and real house prices whether we include the years of the shale revolution or not.

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