SFB 649 Discussion Paper 2015-041

Forecasting the oil price using house prices

Rainer Schulz*
Martin Wersing*

* University of Aberdeen Business School, United Kingdom

This research is published by the CRC 649 "Economic Risk", which is supported by the Deutsche Forschungsgemeinschaft

This research was supported by the Deutsche Forschungsgemeinschaft through the SFB 649 "Economic Risk".

http://sfb649.wiwi.hu-berlin.de
ISSN 1860-5664

SFB 649, Humboldt-Universität zu Berlin
Spandauer Straße 1, D-10178 Berlin

SFB 649 ECONOMIC RISK BERLIN

Forecasting the oil price using house prices

Rainer Schulz and Martin Wersing*

July 30, 2015

*University of Aberdeen Business School, Edward Wright Building, Dunbar Street, Aberdeen AB24 3QY, United Kingdom. Emails: r.schulz@abdn.ac.uk and martin.wersing@abdn.ac.uk.

Abstract

We show that house prices from Aberdeen in the UK improve in- and out-of-sample oil price forecasts. The improvements are of a similar magnitude to those attained using macroeconomic indicators. We explain these forecast improvements with the dominant role of the oil industry in Aberdeen. House prices aggregate the dispersed knowledge of the future oil price that exists in the city. We obtain similar empirical evidence for Houston, another city dominated by the oil industry. Consistent with our explanation, we find that house prices from economically more diversified areas in the UK and the US do not improve oil price forecasts.

Keywords: oil price forecasting, house prices, knowledge spillover

JEL Classification: C53, E32, Q47, R31

1 Introduction

This paper shows that house prices from Aberdeen in the UK improve monthly forecasts of the Brent crude oil price in- and out-of-sample. House prices from Scotland and the UK do not improve oil price forecasts. This rules out that a hidden factor, such as interest rates, drives the empirical result.

The empirical forecasting power of Aberdeen's house prices comes from the role the oil industry plays in the city. Aberdeen is a major oil industry hub and, as such, hosts an agglomeration of major oil corporations and hundreds of oil-related service and subsea engineering firms. Its harbour and airport supply about two hundred production platforms in the North Sea (Hallwood 1988, Newlands 2000, Tiesdell and Allmendinger 2004). The adverse conditions in the North Sea are ideal tests of drilling and installation equipment to be used elsewhere.[1] The drilling experts, sub-sea engineers, geologists, and lawyers living and working in Aberdeen are part of a highly connected global network and travel frequently to other oil regions, such as the Gulf states, Kazakhstan, and Texas. There, they exchange information with colleagues and gain insights into the economic and political conditions in these regions. Aberdeen oil professionals hold pieces of implicit knowledge that could be used for predicting world supply and demand conditions, and eventually, the future oil price.

While oil industry expertise abounds in Aberdeen, it does not explain why this dispersed knowledge should show up in house prices. We see two channels through which this happens. First, individual income and job prospects in Aberdeen depend on the fortunes of the oil industry. Consequentially, the

[1] Stanley Reed: Aberdeen, with a foot on the seafloor, *New York Times*, print edition, July 30, 2013, page B1.

industry and the oil price are discussed over dinner, in bars, on the golf course, in the gym and receive special attention in local newspapers. People in Aberdeen also love talking about house prices. This is not different in the rest of the UK, but only in Aberdeen does the expected oil price feature prominently in such discussions. If an oil price increase is expected, future income will be higher on average and people will be prepared to pay more for a house. The buying decision will be discussed with colleagues and friends, who might also ponder about trading up. Eventually, by acting on the expectation of a higher future oil price, the current house price should increase. Second, if oil executives expect the price of oil to increase in the future, they want to be prepared for increases in production. In a firm without spare workforce capacity, attractive salaries have to be offered to bring additional staff to Aberdeen. Their additional housing demand will have an immediate positive effect on house prices, whereas the expected oil price increase will, if at all, materialize only with a delay.

Our empirical results for monthly UK time series from 1984:7-2013:6 are as follows. First, the Aberdeen real house price Granger-causes the Brent real oil price in a bivariate VAR model. The estimated relationship shows that a higher current house price is followed, on average, by a higher future oil price. This is exactly what should happen when implicit knowledge on future supply and demand conditions in the oil market feed into current house prices. We find no such relationship for real house prices from Scotland and the UK. Relative to univariate forecasts, consideration of the Aberdeen house price improves out-of-sample oil price forecasts for horizons of up to twelve months. The improvements measured with the ratio of mean squared forecast errors are similar in magnitude to those from state-of-the-art econometric forecasts using macroeconomic indicators (Alquist et al. 2013). The house price thus aggregates information on global supply and demand to a similar degree as econometric models.[2]

Second, conducting the same analysis for nominal prices, we find that the Aberdeen house price Granger-causes the Brent oil price in-sample. The current house price is again positively related to the future oil price, as should be if the housing market is influenced by expectations of the future oil price. We find no such relationship for nominal house prices from Scotland and the UK. The ratios of out-of-sample mean squared forecast errors from the Aberdeen VAR relative to those of univariate models are smaller than one, but this time not statistically significant. The evidence is thus weaker for nominal prices than for real prices.

Third, as a robustness check, we conduct the same analysis for Houston, a US city dominated by the oil industry. Using quarterly time series from 1991:1 to 2014:1, we find that the Houston house price Granger-causes the West Texas Intermediate (WTI) oil price. House prices from the West South Central (WSC) census region of the US show no such in-sample power. The Houston house price also improves out-of-sample forecasts relative to forecasts from univariate models, both for real and nominal prices. The forecast improvements are, however, never statistically significant. This lack of statistical power might be due to the shorter sample and the quarterly frequency of the series. The evidence for Houston provides further indication that house price from oil cities condense implicit knowledge on the price of oil. Moreover, different to the UK, new housing supply is price elastic in most parts of the US (Malpezzi and Maclennan 2001). This applies particularly to Houston, a city without zoning ordinances. Our finding shows that the

[2]Economists have not reached a consensus on a model yet (Barsky and Kilian 2004, Kilian 2009).

forecasting relationship holds even if housing supply reacts quickly to house price changes.

In summary, our empirical results show that house prices from cities dominated by the oil industry improve oil price forecasts. We explain this empirical result with the underlying mechanism of information spillovers from dispersed implicit knowledge to house prices.

The remainder of the paper is organised as follows. Section 2 presents a model to motivate the empirical analysis. Section 3 explains our empirical strategy and Section 4 describes the data. Section 5 discusses the empirical results. Section 6 concludes.

2 A simple model

We use a two-period model to motivate the relationship between the current house price and the expected output price in a city dominated by a single industry. When expectations of the output price change, the reservation price schedule for houses shifts, which leads to a change of the current market clearing house price in the same direction.

At the start of period 0, a household buys a house at price p_0; the house is sold at the end of period 1. Household's income y is positively correlated with the price of output. The household maximizes $\mathrm{E}_0[u(c_0, c_1)]$, with $u(\cdot)$ monotone increasing and strictly concave. Consumption is $c_0 = y_0 - p_0 - s_0$ and $c_1 = y_1 + (1+r)s_0$, where $y_1 = \mu_1 + \sigma_1 z_1$ with $\mu_1 \equiv \mathrm{E}_0[y_1]$, $\sigma_1^2 \equiv \mathrm{Var}_0[y_1]$, and $z_1 \sim (0, 1)$. The household forms μ_1 and σ_1 based on information available in period 0.[3] The optimal saving s_0^* is determined through the first order

[3]We assume that both moments exist. The standardization places no additional restric-

condition

$$\mathrm{E}_0\left[\frac{\partial u}{\partial c_0}\right] = (1+r)\mathrm{E}_0\left[\frac{\partial u}{\partial c_1}\right] \ . \tag{1}$$

Instead of living and working in the city, the household could live somewhere else and receive expected utility $\overline{u}$. This determines the reservation price p_0^r the household is prepared to pay for a house in the city

$$\overline{u} = \mathrm{E}_0\left[u\{y_0 - p_0^r - s_0^*, \mu_1 + \sigma_1 z_1 + (1+r)s_0^*\}\right] \ . \tag{2}$$

Differentiating Eq. 2 with respect to μ_1 and using the first order condition Eq. 1 gives

$$\left.\frac{dp_0^r}{d\mu_1}\right|_{\overline{u}} = \frac{1}{1+r} > 0 \ . \tag{3}$$

An expected increase in the future output price leads to higher expected future income and therefore a higher reservation price for a house. As all households work in the same industry, Eq. 3 holds for all of them. However, because the magnitude of the positive correlation between the output price and income can differ between households, the increase of the reservation price will be smaller for some households than for others.

Figure 1 plots the reservation price schedule $p_{0,a}^r$ of ranked reservation prices for I households. The housing stock is $h_0 < I$. Given the schedule, the market clearing house price is $p_{0,a}^*$. At this price, the marginal household is indifferent between living in the city or somewhere else. Households with a reservation price below $p_{0,a}^*$ will not live in the city.

[Figure 1 about here.]

---

tions on the utility function or the distribution of income. The smallest possible realization of z_1 is larger than $-\{(1+r)(y_0 - p_0) + \mu_1\}\sigma_1^{-1}$ and household's lifetime resources are sufficient to purchase the house and consume x in both periods.

The schedule $p^r_{0,b}$ in Figure 1 shows the case where a higher output price is expected. The new market clearing price is $p^*_{0,b}$. Households settling in the city at $p^*_{0,b}$ are not necessarily the same as those settling at $p^*_{0,a}$, because the individual reservation price depends also on how strongly household's future income is related to the output price. Further, the magnitude of the house price increase will be smaller if house supply is elastic, as denoted by the dashed curve in Figure 1. The current market clearing house price p^*_0 and the expected output price will have a positive relationship unless house supply is perfectly elastic.

The essential assumption of the model is that the household are well-informed about μ_1 and therefore the future price of output. In a single-industry city, this assumption is reasonable. A household is confronted on a daily basis with news and discussions on the likely future of the industry. And during the process of purchasing a house, the search for information will be intensified.[4]

3 Empirical implementation

We examine the empirical relationship between the log house price and the log oil price in terms of both in-sample Granger-causality tests and out-of-sample performance assessments. The approaches complement each other.

[4]In Scotland, a valuer is involved in the sales process to provide the market value of the property, which serves as the list price and informs the mortgage underwriting process. Once the property is listed, potential buyers view it and note their interest through their solicitors. If there are sufficient notes of interest, the interested parties are invited to submit their bids and the highest bid in the first price sealed-bid auction wins. In Aberdeen this process takes, on average, 100 days from listing to sale (median is 52 days), see Table A1.

The in-sample Granger-causality test uses the full sample information and is an asymptotically optimal test for predictability in population. The out-of-sample performance assessment, on the other hand, mimics the data constraints of real-time forecasting and is the relevant setting for the applied econometrician.

We implement the tests assuming that the joint process of the house price and the oil price is governed by the p-th order vector autoregression (VAR)

$$y_t = c + \sum_{i=1}^{p} A_i y_{t-i} + u_t \ . \tag{4}$$

The two-dimensional vector $y_t = [y_{1,t}, y_{2,t}]'$ collects the oil price and the house price at time t ($t = 1, \ldots, T$). The two-dimensional vector $u_t = [u_{1,t}, u_{2,t}]'$ collects white noise innovations. The (2×1) vector c collects the coefficients for the constants and the (4×4) matrix A_i collects the coefficients on the i-th lag of y_t. We model the y_t process as a VAR in levels instead of in first differences to ensure that any long-run relationship between house and oil prices is preserved.

The null hypothesis of Granger non-causality for the house price in the VAR of Eq. 4 is

$$H_0\colon\ a_{12,t-1} = a_{12,t-2} = \ldots = a_{12,t-p} = 0 \ , \tag{5}$$

which is tested against the alternative hypothesis that at least one of these coefficients is different from zero. The series in y_t are likely to be non-stationary, so we adopt the testing procedure developed in Toda and Yamamoto (1995). This procedure avoids pre-testing for cointegration. We estimate the VAR in Eq. 4 first with ordinary least squares and select the lag order p using an information criteria. We then estimate the VAR again with $p+d$ lags, where d is the highest order of integration of the variables in y_t. The Wald-statistic for the first p coefficients of this lag-augmented VAR is then asymptotically χ^2_p distributed with p degrees of freedom.

We examine the out-of-sample performance of the VAR with a pseudo real-time forecast experiment. First, we generate h-period ahead forecasts from fixed origin regressions, where each forecast uses only information available up to $t-h$. We then assess the mean squared forecast errors (MSFEs) produced by the VAR against the MSFEs produced by three different univariate models for the oil price. The first is a random walk without drift (RW), which leads to a no-change forecast, the second model is a random with drift (RWD), and the third model is an ARMA(p,q) (ARMA).[5] The no-change forecast is a popular benchmark, because the oil price conditioned only on its own history follows a random walk without drift (Hamilton 2009). During our evaluation period, the oil price shows an upward trend and both the RWD and the ARMA models allow for the possibility of a non-zero drift. This puts these two models on equal footing with the VAR.

Whereas the ratios of MSFEs will give a clear picture of the performance of the VAR for our sample, we are also interested in whether performance differences are also statistically significant. We use the DM-test of Diebold and Mariano (1995) to assess this. The test is based on the mean loss differential

$$\bar{d}_h \equiv \frac{1}{N}\sum_{t=1}^{N}\left(e^2_{h,t,\mathrm{VAR}} - e^2_{h,t,j}\right) \ , \tag{6}$$

where $e^2_{h,t,\mathrm{VAR}}$ is the time t squared forecast error of the VAR model at forecast horizon h and $e^2_{h,t,j}$ is the time t squared forecast error of model

[5] The RWD forecast is computed as $\widehat{y}_{1,t} = h \cdot \widehat{\mu} + y_{1,t-h}$, where $\widehat{\mu}$ comes from the regression $\Delta y_{1,t} = \mu + \varepsilon_{1,t}$ estimated with ordinary least squares. The ARMA forecast is computed recursively as $\widehat{y}_{1,t} = \widehat{\mu} + \sum_{i=1}^{p}\widehat{\phi}_i(\Delta\widehat{y}_{1,t-i} - \widehat{\mu}) + \sum_{j=1}^{q}\widehat{\theta}_j\varepsilon_{1,t-j} + \widehat{y}_{1,t-1}$, with $\widehat{y}_{t-h} = y_{t-h}$. The coefficients come from $\Delta y_{1,t} = \mu + \sum_{i=1}^{p}\phi_j y_{1,t-j} + \sum_{j=1}^{q}\theta_j\varepsilon_{1,t-j} + \varepsilon_{1,t}$ and are estimated with unconditional Maximum Likelihood.

$j \in \{\text{RW}, \text{RWD}, \text{ARMA}\}$ at forecast horizon h. The null hypothesis is equal forecast accuracy

$$H_0\colon\ \bar{d}_h = 0 \tag{7}$$

against the alternative hypothesis that the VAR produces, on average, smaller forecast errors than the univariate model, $H_1:\ \bar{d}_h < 0$. We compute the statistic for the DM-test with Newey-West standard errors, where we set the number of truncating lags to $h-1$ as suggested by Diebold and Mariano (1995). The DM-test compares squared forecast errors and evaluates the finite sample accuracy of different forecasting models. We regard this as the relevant out-of-sample test for the applied econometrician.[6]

We conduct several robustness checks. First, depending on the application, economists and decision makers will be interested in forecasts of either the real or the nominal oil price. We thus perform our analysis for both real and nominal series. Second, we repeat the whole analysis for both house prices from Scotland and the UK. These areas are not dominated by the oil industry and are economically more diversified, therefore we do not expect that house prices from Scotland or the UK have any forecasting power for the oil price. Using these series allows us also to assess if the forecasting power of the Aberdeen house price is driven by unobserved country-wide factors, such as a forward-looking monetary policy by the Bank of England. Third, we conduct the whole analysis also for house prices from Houston, Texas, another global hub of the oil industry. We examine if the house price helps to

[6] Out-of-sample tests of predictability in population, on the other hand, compare fully specified and possibly nested models by taking the estimation uncertainty into account, for a survey see Clark and McCracken (2013). These tests might reject the null hypothesis of equal predictive ability if the observed mean loss differential is zero or even positive. Optimal population model comparisons are based on full sample information, but not an out-of-sample forecast experiment like ours, see e.g. Diebold (2012).

forecast the WTI oil price. We compare the results with those we obtain if we use the house price of the economically broader WSC census region. Fourth, we conduct the analysis when the Schwarz (SIC) and when the Akaike (AIC) information criterion is used to select the lag order of the VAR.

4 Data

4.1 UK data

The monthly UK data set covers the period 1984:7-2013:6 and consists of the Brent oil price and constant-quality house price indices for Aberdeen, Scotland, and the UK. The Brent oil price series comes from ICIS Pricing via Thompson-Reuters Datastream and is the end of month spot price for Brent crude oil in US Dollars per barrel. We convert the Brent oil price to Pound Sterling using the spot exchange rate as reported by the Bank of England. The constant-quality Aberdeen house price index is computed from residential transactions provided by Aberdeen Solicitor's Property Centre (ASPC). The constant-quality Halifax house price indices for Scotland and the UK come from Lloyds Banking Group. Details on the house price indices are in the Appendix. We generate price series in real terms by deflating with the UK consumer price index (UK CPI) from OECD's revision and real-time data base. We use the revised data for in-sample analysis and the real-time data for out-of-sample analysis. We state whenever real-time data is used.

Table 1 reports summary statistics for the UK data. The average growth rates of houses prices are of similar magnitude in the three areas. The volatility of the house price growth rates is highest in Aberdeen, but still only a fifth of those of the Brent oil price. Even if the Aberdeen house price could improve oil price forecasts, much uncertainty will remain.

[Table 1 about here.]

Figure 2 shows the pattern of house price for the three areas. Whereas house prices in Aberdeen were falling in the first years of our sample period and were mostly below their level in 1984, house prices in Scotland and the UK behaved markedly differently over this period.

[Figure 2 about here.]

Unlike house prices in Scotland and the UK, real house prices fell in Aberdeen in the 1980s and did not grow much in the 1990s. Growth only started to catch up with the other two areas in the 2000s. Figure 3 shows the Aberdeen house price and the Brent oil price. The relationship is close, but the much higher volatility of the Brent oil price is clearly visible.

[Figure 3 about here.]

Table 2 reports the results for unit root tests for the UK price series. The first is the augmented Dickey-Fuller (ADF) test, which assumes under the null that the tested series is a random walk without drift.[7] The second is the KPSS test of Kwiatkowski et al. (1992), which assumes under the null that the tested series is stationary around a constant mean.[8] For robustness, we

[7]We implement the ADF test by running the regression $\Delta y_t = \alpha + \beta y_{t-1} + \sum_{i=1}^{k} \zeta_i \Delta y_{t-i} + \epsilon_t$ and test the one-sided null hypothesis $H_0 : \beta = 0$ against $H_1 : \beta < 0$. We choose the number of lags with the SIC.

[8]The KPSS test uses the Lagrange multiplier statistic $LM^{KPSS} = \left(\sum_{t=1}^{T} \widehat{s}_t^2\right) / \widehat{\sigma}_u^2$, where $\widehat{s}_t = \sum_{i=1}^{T} \widehat{u}_i$. The residual $\widehat{u}_t$ comes from a regression of y_t on a constant, $\widehat{\sigma}_u^2$ is the estimated error variance from this regression.

also considered a linear trend in the test regressions. The test results are not qualitatively different from those in Table 2 and are not reported here.

[Table 2 about here.]

All four series are $I(1)$ non-stationary in levels and stationary in growth rates, both in real and in nominal terms. The house price growth rate regressions need to be augmented with lagged terms to cope with serial correlation. Such correlation has been documented before, see for instance Rosenthal (2006). The oil price growth regression needs no lags to render residuals that behave like white noise. The constant in the regression for the oil price growth rate is statistically insignificant. This fits with the result of Hamilton (2009) that the oil price conditioned only on its own history follows a RW.

4.2 US data

The quarterly US data covers the period 1991:1-2014:2 and consists of the WTI oil price and constant-quality house price indices for Houston and the WSC census region, which consists of Arkansas, Louisiana, Oklahoma, and Texas. The WTI oil price is the end of quarter spot price of WTI crude oil as reported by ICIS pricing via Thompson-Reuters Datastream. The constant-quality house price indices come from the Federal Housing Finance Agency. The indices are based on repeat-sales of single-family houses whose mortgages are bought or securitized by Fannie Mae and Freddie Mac. By construction, these indices are revised each quarter. Real-time data was not available to us. We thus use the revised series in out-of-sample analysis. We generate price series in real terms by deflating prices with the US consumer price index (US CPI) from OECD's revision and real-time data base.

Table 3 reports summary statistics for the US data.

[Table 3 about here.]

The growth rate of Houston house prices is on average higher and more volatile than the growth rate of WSC house prices. Figure 4 shows the pattern of the two house price series.

[Figure 4 about here.]

In the early 1990s, the Houston real house price was decreasing, whereas it increased in the WSC census region. From 1998 onwards, the Houston house price caught up quickly with prices in the WSC census region. The financial crisis in 2008 had a lesser effect on the Houston house price, which also recovered much quicker than the WSC house price. Figure 5 shows the relationship between the Houston house and the WTI oil price. The relationship seems overall close, but the much higher volatility of the WTI oil price is also clearly visible.

[Figure 5 about here.]

Table 4 reports results from unit root tests for the two US house price series and the WTI oil price.

[Table 4 about here.]

The three real price series are $I(1)$ non-stationary in levels and stationary in growth rates. This also applies to the nominal WTI oil price. The regressions for the growth rate of the WTI oil price need no lags and have both an insignificant constant. The WTI oil price conditioned only on its own history follows a RW, a result we also obtained for the Brent oil price. For the two nominal house price series, the ADF and KPSS tests are in disagreement. The ADF tests do not reject the null hypothesis of non-stationary nominal growth rates, whereas the KPSS test indicates stationary growth rates. The ADF test results are also at odds with the result for the growth real house prices. We explain this outcome with the low power of the ADF test given the relatively small number of observations. Inclusion of a linear trend in the test regressions does not alter the qualitative test results.

5 Empirical results

We set the maximal possible lag order for the VARs to twelve for the monthly UK data and to four for the quarterly US data. In line with the unit root test results, we set $d = 1$ in the lag-augmented VARs.[9]

5.1 Results for the UK

In-sample: Table 5 reports results of Granger-causality tests for house prices from the UK and the Brent oil price. For each area, test results are given for two lag-augmented VAR$(p + 1)$s. The first VAR uses the lag order p selected with the SIC, the second the lag order selected with the AIC.

[Table 5 about here.]

[9]For US nominal house prices, the ADF tests above indicated $d = 2$. The corresponding lag-augmented VAR does not give qualitatively different results from those reported below.

In all four specifications of the Aberdeen VARs, lags of the house price help to predict the Brent oil price. The P-values of the respective Wald-statistics are 0.035 ($p = 1$) and 0.029 ($p = 4$) for real prices and 0.040 ($p = 1$) and 0.038 ($p = 4$) for nominal prices. No such relationship exists in the opposite direction: lags of the Brent oil price do not help to predict the Aberdeen house price. This holds both for real and nominal prices.

We reasoned above that the Aberdeen house price should not only help to predict the Brent oil price, but should also move in the same direction. Such a positive relationship is present, as the estimated coefficients in Tables 6 and 7 show.

[Table 6 about here.]

[Table 7 about here.]

The estimated coefficient is $\hat{a}_{12,t-1} = 0.546$ (standard error 0.259) for the lagged real house price in the VAR(1) specification and significantly, see Table 6. In the VAR(4) specification $\hat{a}_{12,t-1} = 0.556$ (standard error 0.264) and the remaining coefficients for lags of the real house price are not statistically significant. Table 7 reports results for VARs estimated with nominal prices. The signs and magnitudes of the estimated coefficients are similar to those already discussed. This confirms our expectation: In all four VAR specifications, the current Aberdeen house price has a positive predictive link with the future Brent oil price.

The Granger-causality tests for Scotland and the UK are reported in Table 5. There is no indication that house prices from these areas have predictive power for the Brent oil price. This result holds both for real and nominal prices. There is some statistical evidence that the Brent nominal oil price might help to predict the Scottish nominal house price ($p = 2$) and the UK house nominal price ($p = 6$). The predictive relationship is positive for Scotland and negative for the UK (not reported). This finding is not implausible, given that the oil-producing Scottish economy should benefit from a high oil price, whereas the effects for the UK overall should be mixed. In both instances, however, the finding depends on p and thus is not robust.

In summary, the in-sample analysis confirms that the Aberdeen house price condenses implicit knowledge on the future Brent oil price. No such relationship exists for house prices from broader and economically more diversified areas. This rules out that house prices have forecasting power in general, as it would be the case if they simply reflected the effects of forward-looking monetary policy. There is some weak evidence that the Brent nominal oil price helps to predict nominal house prices in the broader areas. Such a relationship is absent in Aberdeen. This strengthens the argument that implicit oil industry knowledge exists in Aberdeen and that it is reflected in the house price. Such knowledge is not present in the less specialized areas and people there might not fully anticipate Brent oil price's effect on area's economy and the housing market.

Out-of-sample: For each month in $\tau \in \{2001{:}1, \ldots, 2013{:}6\}$, we fit the four models to monthly real-time data from 1984:7 to $t(\tau, h)$. The fitted models are then used to forecast the Brent oil price $h \in \{1, \ldots, 12\}$ periods ahead. The last period in the estimation sample for τ depends on the forecast horizon h. For instance, $t(2001{:}1, 12)$ is 2000:1 and $t(2001{:}1, 6)$ is 2000:7. This set-up ensures that we obtain 150 forecasts per model and horizon h in our validation sample. The forecast error $e_{h,t,j}$ from model

$j \in \{\text{VAR}, \text{RW}, \text{RWD}, \text{ARMA}\}$ is the difference between the realized Brent oil price in t and its forecast based on information from period $t - h$.

We find the lag-order of the bivariate VARs with the SIC using the data from 1984:7-2000:1. Coefficients of lagged oil prices are set to zero in the house price equation of a VAR if not statistically significant over this period. These restrictions reduce estimation uncertainty.[10] Below we only report results for fixed origin estimation windows. We also computed forecasts with rolling regressions that keep the estimation window size fixed. The rolling regressions produce slightly less accurate forecasts.

Figure 6 plots forecasts of the Brent real oil price growth for different forecast horizons $h \in \{3, 6, 9, 12\}$. The Aberdeen VAR forecasts track the realized oil price growth rates much better than forecasts from the RW (represented by the horizontal zero line), the RWD, and the ARMA models. Even for the VAR forecasts, however, the unpredicted variation of the realized growth rate is considerable. Given the high oil price volatility, this is no surprise.

[Figure 6 about here.]

Table 8 compares the out-of-sample performance of Brent real oil price forecasts from the VAR with those of the three benchmark models. Performance is assessed with MSFE-ratios, where a ratio below one implies that the VAR forecasts are more accurate then those of the respective benchmark model. P-values for the DM-statistic are reported to assess if any performance differences are statistically significant and not caused by chance.

[10] As for the full sample, we find unidirectional Granger-causality from the Aberdeen house price to the Brent oil price. We find no causality in neither direction for the other two house price series.

[Table 8 about here.]

Relative to the no-change forecasts of the RW model, the Aberdeen VAR has lower MSFEs at all forecast horizons. The reductions range from 2.6 percent ($h = 1$) to 11.8 percent ($h = 12$). These improvements are of similar magnitude to those achievable when indicators of real global activity are used to forecast oil prices, see Alquist et al. (2013, Table 8.8).[11]

The null of equal forecast performance can be rejected at the 10% significance level for horizons of two to six months, but not for other horizons. Given the high volatility of the Brent oil price, the DM-test has low power. Compared with RWD and ARMA, the Aberdeen VAR has lower MSFEs for all horizons except the first, for which the ARMA model performs slightly better. The superior performance is statistically significant in most cases. The RW is the best univariate model for the oil price and the Aberdeen VAR outperforms this benchmark. The VAR performs even better when compared with RWD and ARMA, which are likely to be misspecified for the oil price. This aspect makes it easier to reject the null of equal forecast performance despite the high oil price volatility, see Table 8.

Tables 9 and 10 report results from VARs that use real house prices from Scotland and the UK.

[Table 9 about here.]

[Table 10 about here.]

Relative to the RW forecasts, consideration of real house prices from Scotland or the UK does not systematically improve forecasts. In both cases,

[11] The monthly out-of-sample WTI oil price forecasts are for 1991:12-2009:8.

MSFE-ratios are predominantly above one. A few MSFE-ratios are below one, mainly for the Scotland VAR. The P-values for the null of equal forecast performance are always larger than 10%. When the RWD and the ARMA are used as benchmark models, the relative MSFE ratios are mostly below one, but never as small as the corresponding ones for the Aberdeen VAR reported in Table 8. Further, even though RWD and ARMA are likely to be misspecified, the null of equal forecast performance can never be rejected.

The analysis for real prices shows that the Aberdeen real house price improves forecasts of the Brent real oil price at all horizons in the validation sample. House prices from Scotland and the UK do not do this. While the DM-tests cannot always be rejected for forecasts from the Aberdeen VAR, the tests can never be rejected for forecasts of VARs fitted with the other two house price series. This holds irrespectively of benchmark model and horizon.

Forecasts of the Brent nominal oil price growth behave very similar to the ones reported already in Figure 6 and are not shown here. Table 11 shows that the forecast performance of the Aberdeen VAR is weaker for nominal than real prices. All but one MSFE-ratio in the validation sample are smaller than one, but all DM-tests are now all statistically insignificant.

[Table 11 about here.]

While not statistically significant, the performance of the Aberdeen VAR for nominal prices is much better than those of the Scotland VAR and the UK VAR. Tables 12 and 13 show that these produce MSFE-ratios predominantly larger than one. Different from the forecasts of the Aberdeen VAR, none of these two models is able to beat the RW benchmark in the validation sample.

[Table 12 about here.]

[Table 13 about here.]

In summary, an econometrician who had to forecast the Brent oil price based on real-time information over the validation sample from 2001:1-2013:6 would have benefited from using the Aberdeen VAR instead of the widely accepted RW. This holds both for forecast of real and nominal oil prices and for all forecast horizons considered. While this is true with hindsight, the direct statistical significance of forecasting superiority is mixed. For real prices, there is evidence that the good performance of the Aberdeen VAR is not simply the result of luck. For nominal prices, Aberdeen VAR forecasts of the Brent nominal oil price are systematically superior to RW forecasts, whereas forecasts of the Scotland VAR and the UK VAR are all inferior. While it seems unlikely that this is a chance outcome, the DM-test does not have enough power to establish significance.

5.2 Results for the US

In-sample: Table 14 reports Granger-causality test results for the two US housing markets.

[Table 14 about here.]

For real prices, there is strong statistical evidence that the Houston house price Granger-causes the WTI oil price unidirectionally. This holds for both VAR specifications. The relevant estimated coefficients of the VARs (not reported) show that the current Houston house price is, as expected, positively correlated with the future WTI oil price. WSC house prices do not Granger-cause the WTI oil price, but are Granger-caused by it. Our explanation is that oil plays an important role for the economically more diversified WSC region, but different from Houston, the role is not important enough to be reflected in house prices. The empirical evidence is less clear for nominal prices. Houston house prices Granger-cause the oil price, but in the VAR(4) specification only at the 10% significance level (P-value is 0.057). At this significance level, we cannot reject Granger-causality of the oil price for the Houston house price, making the relationship bidirectional. We detect no Granger-casualty relationship between the WSC house price and the WTI oil price.[12]

Out-of-sample: For each quarter in $\tau \in \{2001{:}1, \ldots, 2014{:}2\}$, we fit the four models to quarterly real-time data from 1991:1 to $t(\tau, h)$. The fitted models are then used to forecast the WTI oil price $h \in \{1, \ldots, 4\}$ periods ahead. We obtain 54 forecasts per model and horizon h in our validation sample.

Figure 7 plots forecasts of the WTI real oil price growth for the four different horizons and models. The forecasted growth rate from the Houston VAR tracks the real oil price growth quite well, but the unexplained variation is still substantial.

[Figure 7 about here.]

The MSFE-ratios in Panel A of 15 show that the Houston VAR produces performs better than the three benchmark models at all forecast horizons.

[12] We conducted the analysis also for $I(2)$ nominal house prices, as was indicated by the ADF tests. The qualitative results of the Granger-causality tests are unchanged.

[Table 15 about here.]

Given the small sample size, none of these differences is statistically different from zero.

Forecasts of the nominal oil price growth rate behave very similar to forecasts of the real growth rates and we omit the plot. All MSFE-ratios in Panel B of Table 15 are below one for all benchmark models and forecast horizons. Table 16 shows that this is not the case for the WSC VAR.

[Table 16 about here.]

With hindsight, an econometrician would have benefited from using the Houston VAR for forecasts of the WTI oil price. This result applies to real and nominal prices.

6 Conclusion

House prices in a city dominated by the oil industry should be related to the oil price. One view of this relationship is that residents are surprised by oil price changes and adjust their housing consumption once the oil price change is reflected in their income. House prices will then follow suit. We take the opposite view. The oil industry is far too important to be ignored by city's residents. Information relevant for the future oil price, while dispersed, is abundant. Through anticipation and social interaction, this information filters into the current house price.

The empirical analysis supports our view. House prices from Aberdeen improve forecasts of the Brent oil price relative to standard benchmark models, both in-sample and out-of-sample. No forecasting relationship exists in the opposite direction from the current oil price to the future house price. House prices from economically more diversified and geographically larger regions in the UK do not improve the oil price forecasts. We also obtained similar results from our analysis of house prices from Houston, another oil city. Our realistic out-of-sample forecast exercise shows that an econometric forecaster would have benefited from the consideration of oil city house prices over all considered time horizons. This result has practical relevance, even though the forecast improvements were not always statistically significant.

Future use of Aberdeen house prices for oil price forecasting depends on the industry's development. Oil production in the North Sea is expensive compared with new production technologies such as hydraulic fracturing and shale extraction. It may thus happen that the oil industry loses its importance for Aberdeen's economy. But other oil cities abound.

Acknowledgments

We are grateful for helpful comments from Marc Gronwald, Alex Kemp, Helmut Lütkepohl, Liang Peng, Verity Watson, Julian Williams, Jürgen Wolters, Jin Xin and from seminar participants at the Freie Universität Berlin, Humboldt-Universität zu Berlin, University of Aberdeen Petroleum Markets Workshop 2015, and Scottish Economic Society Conference 2015. The usual disclaimer applies. Financial support by the Deutsche Forschungsgemeinschaft through the CRC 649 "Economic Risk" is gratefully acknowledged.

Appendix (for online publication)

A.1 Aberdeen house price index

We compute the constant-quality house price index for Aberdeen based on the hedonic regression model

$$\begin{aligned}\ln p_i = & \gamma_0 + \sum_{t=1}^{T} I_t(i)\,\gamma_t + \sum_{l=1}^{L} I_l(i)\,\beta_l + \sum_{j=1}^{J-1} I_j(i)\,\beta_j \\ & + \sum_{j=1}^{J}\sum_{k=1}^{K} I_j(i)\,x_{k,i}\beta_{j,k} + u_i\end{aligned} \tag{A1}$$

with the transaction price p_i of house i. $I_t(i)$ are binary indicator variables that become one if house i was sold in period t and zero otherwise. $I_l(i)$ are binary indicator variables that becomes one if house i is located in area l, $l \in \{1, 2, \ldots, 155\}$, and zero otherwise. The areas are classified by the ASPC. $I_j(i)$ are binary indicator variables that become one if property i is of type j, $j \in \{\text{detached}, \text{non-detached}, \text{flat}\}$. x_k is the k'th characteristic of the building. The constant-quality (log) house price index is then $\widehat{\gamma}_t$, which is the least square estimate of time-dummy coefficient in period t.

Eq. A1 is fitted to the full sample (1984:7-2013:6) for the index used in the in-sample analysis. It is fitted to samples 1984:7 to $t(\tau, h)$ for the real-time out-of-sample analysis with $\tau \in \{2001{:}1, \ldots, 2013{:}6\}$ and $h \in \{1, \ldots, 12\}$.

Table A1 reports summary statistics for the full transaction data set. According to the ASPC, their data covers about 95 percent of all residential property sales in Aberdeen. For each property, we observe the building type, the number of rooms, and various discrete characteristics, such as the presence of a garage or garden.

[Table A1 about here.]

Table A2 presents ordinary least square estimates for Eq. A1 fitted to the full data set. To allow for non-linearities, the number of rooms, bathrooms, and ensuites enter the regression through binary indicators.

[Table A2 about here.]

The $\bar{R}^2 = 0.927$ indicates a very good regression fit. Most of the estimated coefficients are statistically significant at the usual levels. Signs and magnitudes of the coefficients are plausible. For instance, non-detached houses and flats sell at a rebate of about 6 to 27 percent compared with non-detached houses. Larger dwellings, as measured by the number of rooms, increase the expected sales price.

A.2 Halifax house price indices

We use the seasonally-unadjusted Halifax house price indices, which are real-time series. The index for Scotland has a quarterly frequency and we use the regression model

$$y_q = C_D X_m \beta + C_D u_m = X_q \beta + u_q \tag{A2}$$

of Chow and Lin (1971) to compute a monthly series. The $(n \times 1)$ vector y_q contains the Halifax house price index for Scotland, which has quarterly observations. The $(m \times 2)$ matrix X_m contains a constant and the monthly Halifax house price index for the UK. We expect the latter to be closely related to the unobserved monthly Scottish series. The $(n \times m)$ matrix

$$C_D = \frac{1}{3}\begin{bmatrix} 1 & 1 & 1 & 0 & & & & \cdots & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 & 0 & \cdots & 0 \\ & & & & & & & \cdots & \\ 0 & \cdots & & & & 0 & 1 & 1 & 1 \end{bmatrix}$$

converts the monthly UK index into a quarterly series. We assume that the error term u_m, and hence u_q, is homoscedastic and serially uncorrelated. Estimating Eq. A2 with ordinary least squares gives $\widehat{\beta}$ and the corresponding residual vector $\widehat{u}_q$. The monthly house price series for Scotland is then computed as

$$\widehat{y}_m = X_m\widehat{\beta} + C'_D\widehat{u}_q \; . \tag{A3}$$

References

Alquist, R., Kilian, L. and Vigfusson, R. J.: 2013, Forecasting the price of oil, *in* G. Elliot and A. Timmermann (eds), *Handbook of Economic Forecasting*, Vol. 2A, North-Holland, Amsterdam, pp. 427–507.

Barsky, R. B. and Kilian, L.: 2004, Oil and the macroeconomy since the 1970s, *Journal of Economic Perspectives* **18**, 115–134.

Chow, G. C. and Lin, A.-L.: 1971, Best linear unbiased interpolation, distribution, and extrapolation of time series by related series, *Review of Economics and Statistics* **53**, 372–375.

Clark, T. and McCracken, M.: 2013, Advances in forecast evaluation, *in* G. Elliot and A. Timmermann (eds), *Handbook of Economic Forecasting*, Vol. 2B, North-Holland, Amsterdam, pp. 1107–1201.

Diebold, F. X.: 2012, Comparing predictive accuracy, twenty years later: A personal perspective on the use and abuse of Diebold-Mariano tests, NBER Working Paper No 18391, National Bureau of Economic Research, Cambridge, MA.

Diebold, F. X. and Mariano, R. S.: 1995, Comparing predictive accuracy, *Journal of Business and Economic Statistics* **13**, 253–263.

Fuller, W. A.: 1996, *Introduction to Statistical Time Series*, second edn, Wiley, New York, NY.

Hallwood, C. P.: 1988, Host regions and the globalization of the offshore oil supply industry: The case of Aberdeen, *International Regional Science Review* **11**, 155–166.

Hamilton, J. D.: 2009, Understanding crude oil prices, *Energy Journal* **30**, 179–206.

Kilian, L.: 2009, Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market, *American Economic Review* **99**, 1053–1069.

Kwiatkowski, D., Phillips, P., Schmidt, P., and Shin, Y.: 1992, Testing the null hypothesis of stationarity against the alternative of a unit root. How sure are we that economic time series have a unit root?, *Journal of Econometrics* **54**, 159–178.

Malpezzi, S. and Maclennan, D.: 2001, The long-run price elasticity of supply of new residential construction in the United States and the United Kingdom, *Journal of Housing Economics* **10**, 278–306.

Newlands, D.: 2000, The oil economy, *in* W. H. Fraser and C. H. Lee (eds), *Aberdeen 1800-2000. A new history*, Tuckwell Press, East Linton, pp. 126–152.

Rosenthal, L.: 2006, Efficiency and seasonality in the UK housing market, 1991–2001, *Oxford Bulletin of Economics and Statistics* **68**, 289–317.

Tiesdell, S. and Allmendinger, P.: 2004, City profile: Aberdeen, *Cities* **21**, 167–179.

Toda, H. Y. and Yamamoto, T.: 1995, Statistical inference in vector autoregressions with possibly integrated processes, *Journal of Econometrics* **66**, 225–250.

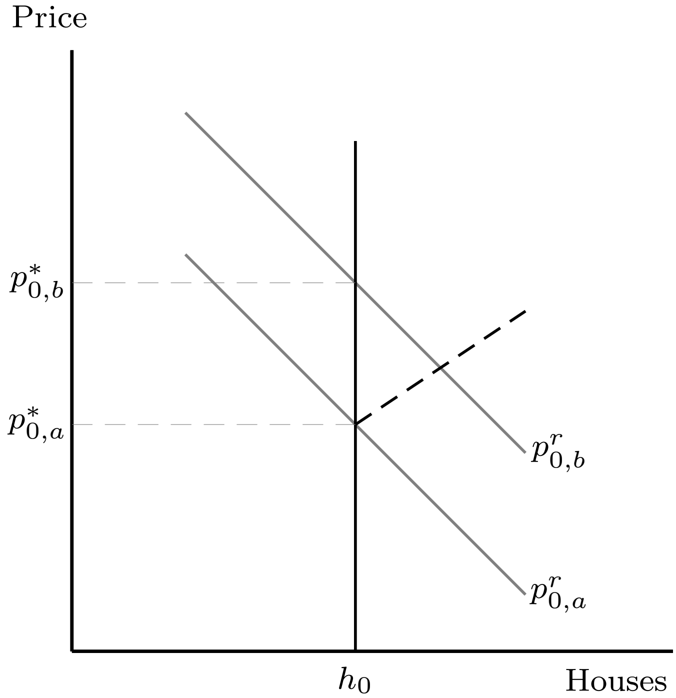

Figure 1: Market outcome in spatial equilibrium. Shows house demand, house supply, and market clearing price.

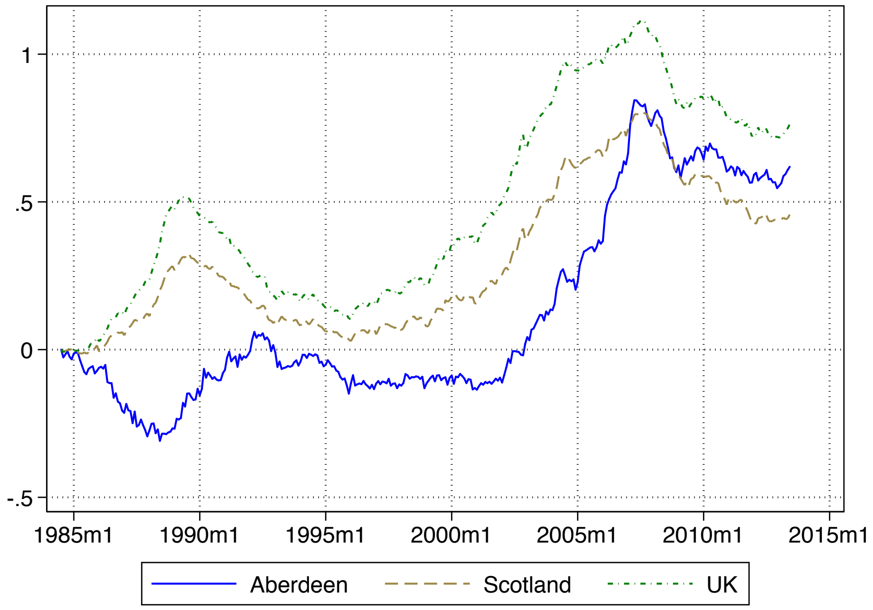

Figure 2: UK house prices by area. Prices are in real terms and in log scale. All series are normalised to 1984:7=0.

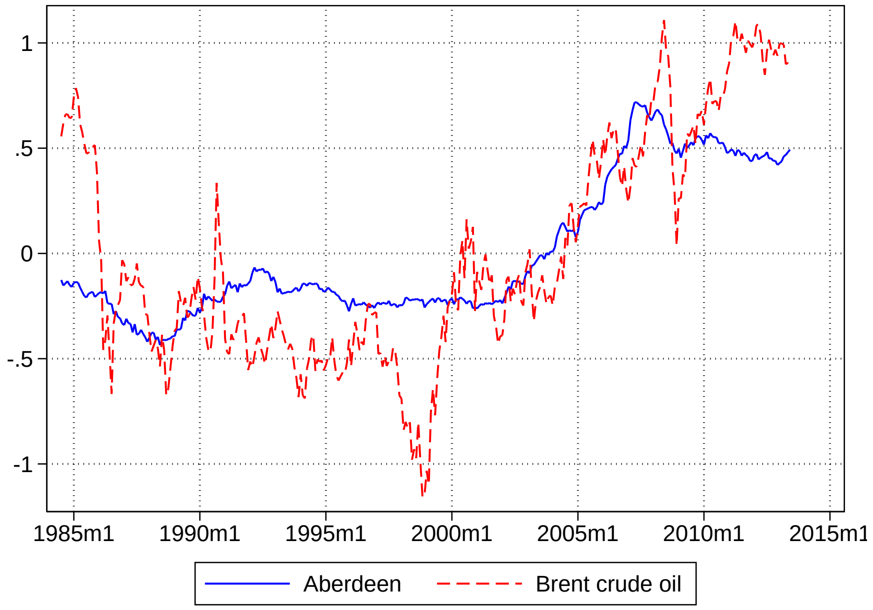

Figure 3: Aberdeen house price and Brent oil price. Prices are in real terms and in log scale. All series are normalised with their respective average.

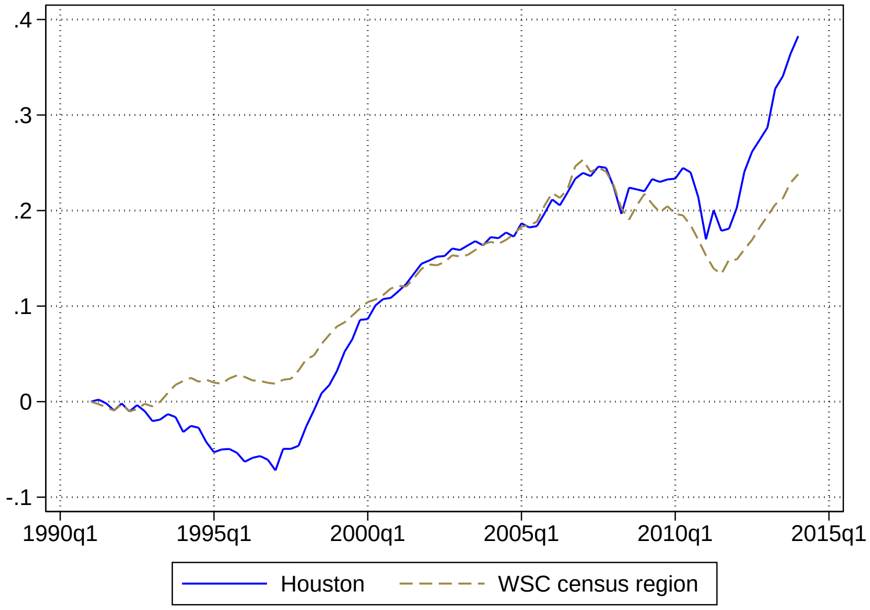

Figure 4: US house prices by area. Prices are in real terms and in log scale. All series are normalised to 1991:1=0.

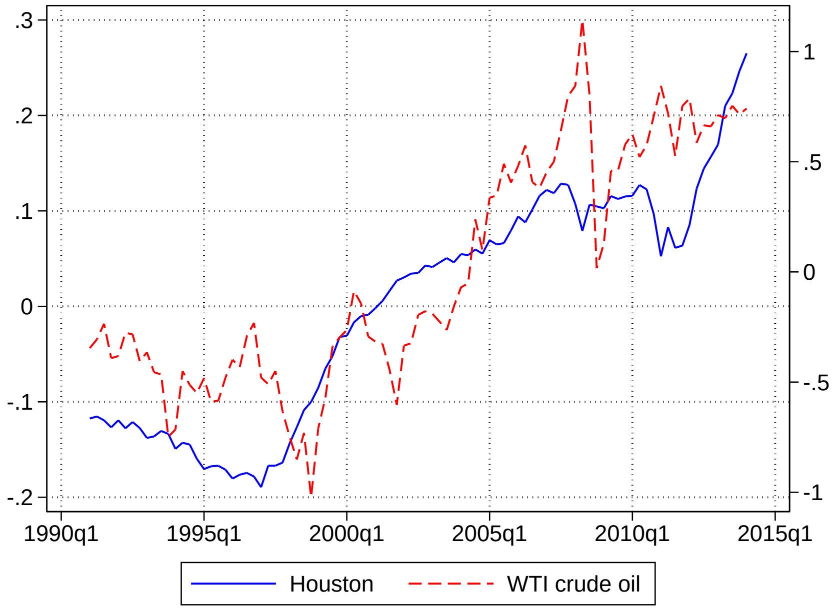

Figure 5: Houston house price and WTI oil price. Prices are in real terms and in log scale. All series are normalised with their respective average.

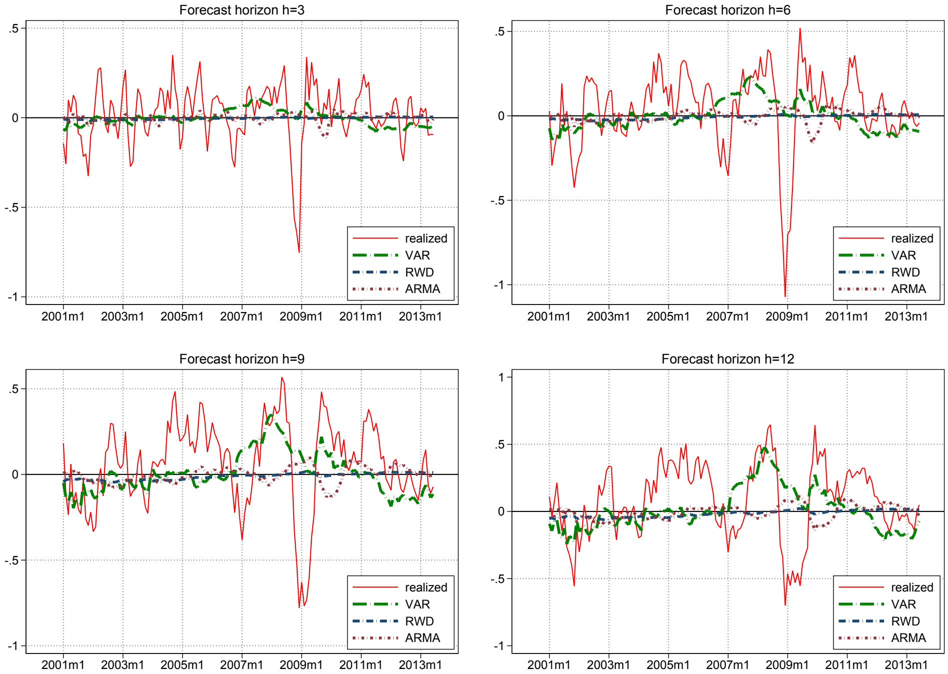

Figure 6: Forecasts of Brent real oil price growth. VAR models uses the Aberdeen real house price.

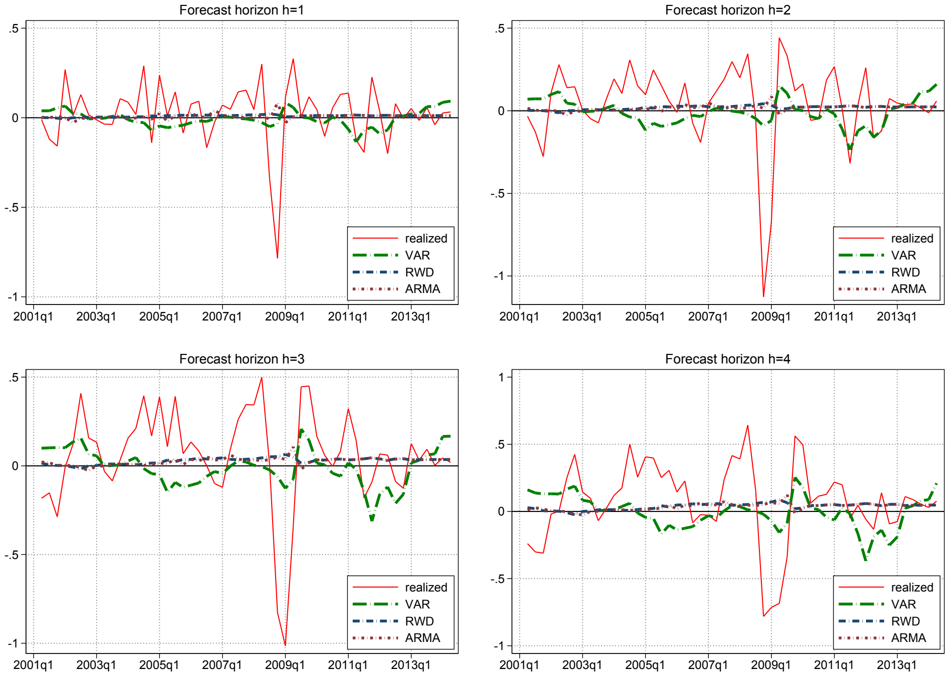

Figure 7: Forecasts of WTI real oil price growth. VAR models use the Houston real house price.

Table 1: Summary statistics for UK data. Data cover the period 1984m7-2013m6, number of observations per series is 347. Table reports summary statistics for monthly growth rates. All figures are in percent. Observations used for the computation of the statistics in Panel A are nominal observations deflated with the UK CPI.

	Mean	Median	Std. Dev.
Panel A. Real			
House price			
Aberdeen	0.178	0.203	2.120
Scotland	0.132	0.103	1.191
UK	0.220	0.225	1.382
Brent oil price	0.098	0.490	10.495
Panel B. Nominal			
House price			
Aberdeen	0.425	0.333	2.210
Scotland	0.379	0.347	1.012
UK	0.467	0.453	1.136
Brent oil price	0.347	0.715	10.467
Panel C. Inflation			
UK CPI	0.247	0.285	0.430

Table 2: Unit root and stationarity test for UK data. Reports results for ADF and KPSS test. t_{β}^{ADF} statistic is for the null hypothesis of a unit root. Critical values are published in Fuller (1996, Ch. 10A). k is number of lags in ADF test regression. LM^{KPSS} statistic is for the null hypothesis of stationarity. Critical values are published in Kwiatkowski et al. (1992, Table 1). **significant at 1%-level *significant at 5%-level.

	k	t_{β}^{ADF}	LM^{KPSS}
Panel A. Real prices			
Aberdeen house price			
Level	3	-0.164	4.998**
Growth rate	2	-8.032**	0.379
Scottish house price			
Level	3	-1.166	4.561**
Growth rate	2	-7.494**	0.320
UK house price			
Level	4	-1.326	4.876**
Growth rate	3	-4.946**	0.333
Brent oil price			
Level	0	-1.563	3.318**
Growth rate	0	-18.373**	0.196
Panel B. Nominal prices			
Aberdeen house price			
Level	3	0.111	6.047**
Growth rate	2	-7.987**	0.220
Scottish house price			
Level	1	-1.785	6.174**
Growth rate	0	-13.224**	0.376
UK house price			
Level	4	-1.458	6.108**
Growth rate	3	-5.766**	0.397
Brent oil price			
Level	0	-0.834	5.019**
Growth rate	0	-18.455**	0.159

Table 3: Summary statistics for US data. Data cover the period 1991q1-2014q1, number of observations per series is 92. Table reports summary statistics for quarterly growth rates. All figures are in percent. Observations used for the computation of the statistics in Panel A are nominal observations deflated with the US CPI.

	Mean	Median	Std. Dev.
Panel A. Real prices			
House price			
Houston	0.416	0.367	1.339
WSC	0.259	0.397	0.828
WTI oil price	1.182	2.969	15.996
Panel B. Nominal prices			
House price			
Houston	1.021	1.041	1.388
WSC	0.864	0.952	0.667
WTI oil price	1.814	4.074	16.145
Panel C. Inflation			
US CPI	0.605	0.597	0.594

Table 4: Unit root and stationarity test for US data. Reports results for ADF and KPSS test. t_{β}^{ADF} statistic is for the null hypothesis of a unit root. Critical values are published in Fuller (1996, Ch. 10A). k is number of lags in ADF test regression. LM^{KPSS} statistic is for the null hypothesis of stationarity. Critical values are published in Kwiatkowski et al. (1992, Table 1). **significant at 1%-level *significant at 5%-level.

	k	t_{β}^{ADF}	LM^{KPSS}
Panel A. Real prices			
Houston house price			
Level	1	0.936	2.223**
Growth rate	0	-7.651**	0.290
WSC house price			
Level	3	-1.140	2.140**
Growth rate	2	-3.417*	0.107
WTI oil price			
Level	0	-1.178	2.054**
Growth rate	0	-9.584**	0.075
Panel B. Nominal prices			
Houston house price			
Level	4	0.436	2.422**
Growth rate	3	-1.973	0.237
WSC house price			
Level	2	-0.705	0.362**
Growth rate	1	-2.530	0.123
WTI oil price			
Level	0	-0.827	2.251**
Growth rate	0	-9.539**	0.230

Table 5: Granger-causality tests for the UK. Reports results for Wald-test in lag-augmented VAR(p+1). For each area, two VARs are fitted: the first uses the lag order selected with the SIC, the second uses the lag order selected with the AIC. The λ_W statistics is for the null hypothesis of Granger non-causality. P-value is calculated from χ^2_p-distribution with p degrees of freedom.

Area	Equation	Predictor	p	λ_W	P-value
		Panel A. Real prices			
Aberdeen	Brent oil price	House price	1	4.430	0.035
			4	10.792	0.029
	House price	Brent oil price	1	0.089	0.766
			4	4.837	0.304
Scotland	Brent oil price	House price	2	0.623	0.430
			3	1.008	0.799
	House price	Brent oil price	2	0.951	0.329
			3	5.317	0.150
UK	Brent oil price	House price	2	0.785	0.675
			6	4.366	0.627
	House price	Brent oil price	2	4.010	0.135
			6	10.424	0.108
		Panel B. Nominal prices			
Aberdeen	Brent oil price	House price	1	4.237	0.040
			4	10.176	0.038
	House price	Brent oil price	1	0.205	0.651
			4	4.644	0.326
Scotland	Brent oil price	House price	2	0.194	0.908
			3	0.374	0.945
	House price	Brent oil price	2	4.950	0.084
			3	5.76	0.124
UK	Brent oil price	House price	2	0.280	0.869
			6	4.971	0.548
	House price	Brent oil price	2	2.459	0.292
			6	12.957	0.044

Table 6: VAR for real Aberdeen house and Brent oil price. Reports OLS estimates of VAR from Eq. 4, VAR augmented during estimation with $d = 1$ lag. Coefficients on augmented lags are not reported. Standard errors are in square brackets. B-statistic is for null hypothesis that residuals are white noise. P-value is calculated from $\mathrm{CDF}(B) = \sum_{j=-\infty}^{\infty}(-1)^j e^{-2B^2 j^2}$.

	VAR(1)		VAR(4)	
Equation:	Oil price	House price	Oil price	House price
Oil price$_{t-1}$	0.972	-0.001	0.974	-0.010
	[0.054]	[0.004]	[0.054]	[0.011]
Oil price$_{t-2}$			-0.014	0.018
			[0.075]	[0.015]
Oil price$_{t-3}$			0.051	-0.024
			[0.074]	[0.015]
Oil price$_{t-4}$			-0.145	0.028
			[0.074]	[0.015]
House price$_{t-1}$	0.546	1.001	0.556	1.008
	[0.259]	[0.006]	[0.264]	[0.054]
House price$_{t-2}$			-0.209	0.102
			[0.370]	[0.075]
House price$_{t-3}$			-0.869	0.081
			[0.370]	[0.075]
House price$_{t-4}$			0.693	-0.235
			[0.371]	[0.076]
Constant	0.123	0.005	0.137	0.003
	[0.038]	[0.008]	[0.040]	[0.008]
RMSE	0.103	0.021	0.102	0.021
B-stat.	0.763	1.298	0.605	0.673
P-value	0.605	0.069	0.858	0.756
Observations		346		343

Table 7: VAR for nominal Aberdeen house and Brent oil price. Reports OLS estimates of VAR from Eq. 4, VAR augmented during estimation with $d = 1$ lag. Coefficients on augmented lags are not reported. Standard errors are in square brackets. B-statistic is for null hypothesis that residuals are white noise. P-value is calculated from $\mathrm{CDF}(B) = \sum_{j=-\infty}^{\infty}(-1)^j e^{-2B^2j^2}$.

	VAR(1)		VAR(4)	
Equation:	Oil price	House price	Oil price	House price
Oil price$_{t-1}$	0.979	0.005	0.983	-0.002
	[0.053]	[0.011]	[0.054]	[0.011]
Oil price$_{t-2}$			-0.030	0.011
			[0.075]	[0.015]
Oil price$_{t-3}$			0.057	-0.028
			[0.074]	[0.015]
Oil price$_{t-4}$			-0.137	0.028
			[0.075]	[0.015]
House price$_{t-1}$	0.541	1.030	0.532	1.026
	[0.263]	[0.054]	[0.268]	[0.054]
House price$_{t-2}$			-0.249	0.103
			[0.379]	[0.076]
House price$_{t-3}$			-0.816	0.046
			[0.378]	[0.076]
House price$_{t-4}$			0.784	-0.233
			[0.379]	[0.076]
Constant	0.126	0.005	0.139	0.002
	[0.038]	[0.008]	[0.040]	[0.008]
RMSE	0.103	0.021	0.103	0.021
B-stat.	0.755	1.365	0.606	0.672
P-value	0.619	0.048	0.856	0.758
Observations		346		343

Table 8: Performance of Aberdeen VAR forecasts, real prices. Reports MSFE for Brent real oil price forecasts from VAR(1) relative to MSFEs of forecasts from three benchmark models. Per h, number of forecasts is 150. P-value is for null hypothesis $H_0\colon\ \bar{d}_h = 0$ against one-sided alternative $H_1\colon\ \bar{d}_h < 0$. P-value comes from the standard normal distribution.

	Benchmark:					
	RW		RWD		ARMA	
h	Ratio	P-value	Ratio	P-value	Ratio	P-value
1	0.974	0.139	0.967	0.084	1.007	0.598
2	0.944	0.053	0.933	0.025	0.949	0.108
3	0.923	0.032	0.908	0.012	0.914	0.044
4	0.909	0.039	0.889	0.015	0.883	0.027
5	0.900	0.061	0.876	0.024	0.853	0.020
6	0.900	0.099	0.871	0.044	0.833	0.025
7	0.892	0.125	0.859	0.057	0.808	0.029
8	0.889	0.164	0.851	0.082	0.785	0.035
9	0.894	0.215	0.848	0.114	0.771	0.048
10	0.893	0.241	0.840	0.130	0.758	0.057
11	0.891	0.256	0.832	0.138	0.745	0.058
12	0.882	0.239	0.817	0.117	0.738	0.054

Table 9: Performance of Scotland VAR forecasts, real prices. Reports MSFE for Brent real oil price forecasts from VAR(2) relative to MSFEs of forecasts from three benchmark models. Per h, number of forecasts is 150. P-value is for null hypothesis $H_0\colon\ \bar{d}_h = 0$ against one-sided alternative $H_1\colon\ \bar{d}_h < 0$. P-value comes from the standard normal distribution.

	Benchmark:					
	RW		RWD		ARMA	
h	Ratio	P-value	Ratio	P-value	Ratio	P-value
1	1.021	0.786	1.013	0.689	1.056	0.954
2	1.009	0.575	0.996	0.469	1.014	0.595
3	0.995	0.467	0.978	0.372	0.985	0.430
4	0.992	0.463	0.970	0.366	0.964	0.370
5	0.988	0.453	0.962	0.360	0.937	0.307
6	0.994	0.480	0.962	0.377	0.920	0.282
7	0.992	0.477	0.956	0.368	0.899	0.252
8	1.002	0.506	0.959	0.390	0.885	0.243
9	1.018	0.543	0.965	0.417	0.878	0.253
10	1.028	0.561	0.967	0.428	0.873	0.262
11	1.036	0.571	0.967	0.435	0.866	0.266
12	1.025	0.547	0.950	0.405	0.858	0.258

Table 10: Performance of UK VAR forecasts, real prices. Reports MSFE for Brent real oil price forecasts from VAR(2) relative to MSFEs of forecasts from three benchmark models. Per h, number of forecasts is 150. P-value is for null hypothesis $H_0: \bar{d}_h = 0$ against one-sided alternative $H_1: \bar{d}_h < 0$. P-value comes from the standard normal distribution.

	Benchmark:					
	RW		RWD		ARMA	
h	Ratio	P-value	Ratio	P-value	Ratio	P-value
1	1.022	0.821	1.014	0.720	1.057	0.967
2	1.009	0.589	0.997	0.470	1.015	0.604
3	0.999	0.492	0.982	0.385	0.989	0.447
4	0.997	0.483	0.975	0.378	0.968	0.380
5	0.996	0.482	0.970	0.377	0.944	0.321
6	1.004	0.514	0.972	0.398	0.929	0.295
7	1.006	0.520	0.968	0.395	0.911	0.265
8	1.016	0.551	0.972	0.415	0.897	0.249
9	1.032	0.591	0.979	0.441	0.890	0.255
10	1.046	0.617	0.983	0.457	0.887	0.265
11	1.059	0.638	0.988	0.472	0.885	0.272
12	1.051	0.618	0.974	0.441	0.880	0.265

Table 11: Performance of Aberdeen VAR forecasts, nominal prices. Reports MSFE for Brent nominal oil price forecasts from VAR(1) relative to MSFEs of forecasts from three benchmark models. Per h, number of forecasts is 150. P-value is for null hypothesis $H_0: \bar{d}_h = 0$ against one-sided alternative $H_1: \bar{d}_h < 0$. P-value comes from the standard normal distribution.

	Benchmark:					
	RW		RWD		ARMA	
h	Ratio	P-value	Ratio	P-value	Ratio	P-value
1	0.996	0.428	0.995	0.414	1.038	0.875
2	0.977	0.250	0.975	0.242	0.991	0.423
3	0.964	0.188	0.961	0.185	0.964	0.279
4	0.956	0.190	0.953	0.188	0.943	0.219
5	0.949	0.200	0.946	0.195	0.917	0.162
6	0.956	0.263	0.953	0.253	0.905	0.160
7	0.953	0.283	0.951	0.267	0.887	0.149
8	0.958	0.334	0.957	0.321	0.874	0.154
9	0.973	0.409	0.974	0.405	0.876	0.191
10	0.981	0.445	0.984	0.449	0.876	0.221
11	0.988	0.469	0.994	0.483	0.877	0.240
12	0.980	0.447	0.985	0.457	0.876	0.242

Table 12: Performance of Scotland VAR forecasts, nominal prices. Reports MSFE for Brent nominal oil price forecasts from VAR(2) relative to MSFEs of forecasts from three benchmark models. Per h, number of forecasts is 150. P-value is for null hypothesis $H_0: \bar{d}_h = 0$ against one-sided alternative $H_1: \bar{d}_h < 0$. P-value comes from the standard normal distribution.

	Benchmark:					
	RW		RWD		ARMA	
h	Ratio	P-value	Ratio	P-value	Ratio	P-value
1	1.037	0.912	1.036	0.887	1.081	0.984
2	1.028	0.748	1.023	0.706	1.042	0.750
3	1.021	0.639	1.018	0.603	1.022	0.596
4	1.027	0.640	1.024	0.605	1.013	0.544
5	1.028	0.622	1.024	0.590	0.992	0.476
6	1.045	0.674	1.041	0.637	0.989	0.469
7	1.050	0.681	1.048	0.645	0.977	0.442
8	1.069	0.722	1.067	0.686	0.975	0.444
9	1.101	0.783	1.102	0.748	0.991	0.480
10	1.130	0.820	1.133	0.788	1.009	0.518
11	1.153	0.842	1.160	0.816	1.023	0.543
12	1.152	0.835	1.156	0.810	1.029	0.555

Table 13: Performance of UK VAR forecasts, nominal prices. Reports MSFE for Brent nominal oil price forecasts from VAR(2) relative to MSFEs of forecasts from three benchmark models. Per h, number of forecasts is 150. P-value is for null hypothesis $H_0: \bar{d}_h = 0$ against one-sided alternative $H_1: \bar{d}_h < 0$. P-value comes from the standard normal distribution.

	Benchmark:					
	RW		RWD		ARMA	
h	Ratio	P-value	Ratio	P-value	Ratio	P-value
1	1.037	0.912	1.036	0.887	1.081	0.984
2	1.028	0.748	1.042	0.750	1.042	0.750
3	1.021	0.639	1.018	0.603	1.022	0.596
4	1.027	0.640	1.024	0.605	1.013	0.544
5	1.028	0.622	1.024	0.590	0.992	0.476
6	1.045	0.674	1.041	0.637	0.989	0.469
7	1.050	0.681	1.048	0.645	0.977	0.442
8	1.069	0.722	1.067	0.686	0.975	0.440
9	1.101	0.783	1.102	0.748	0.991	0.480
10	1.130	0.820	1.133	0.788	1.009	0.518
11	1.153	0.842	1.160	0.816	1.023	0.543
12	1.152	0.835	1.158	0.810	1.029	0.555

Table 14: Granger-causality tests for the US. Reports results for Wald-test in lag-augmented VAR(p+1). For each area, two VARs are fitted: the first uses the lag order selected with the SIC, the second uses the lag order selected with the AIC. The λ_W statistics is for the null hypothesis of Granger non-causality. P-value is calculated from χ^2_p-distribution with p degrees of freedom.

Area	Equation	Predictor	p	λ_W	P-value
		Panel A. Real prices			
Houston:	WTI oil price	House price	1	4.904	0.027
			3	15.001	0.002
	House price	WTI oil price	1	0.010	0.922
			3	0.211	0.976
WSC:	WTI oil price	House price	2	4.048	0.132
			4	7.259	0.123
	House price	WTI oil price	2	19.229	0.000
			4	18.252	0.001
		Panel B. Nominal prices			
Houston:	WTI oil price	House price	2	9.850	0.007
			4	9.177	0.057
	House price	WTI oil price	2	5.889	0.053
			4	7.952	0.093
WSC:	WTI oil price	House price	3	1.873	0.599
			4	3.191	0.526
	House price	WTI oil price	3	1.363	0.714
			4	2.064	0.724

Table 15: Performance of Houston VAR forecasts. Reports MSFE for WTI oil price forecasts from VAR(1) relative to MSFEs of forecasts from three benchmark models. Per h, number of forecasts is 54. P-value is for null hypothesis $H_0: \bar{d}_h = 0$ against one-sided alternative $H_1: \bar{d}_h < 0$. P-value comes from the standard normal distribution.

	Benchmark:					
	RW		RWD		ARMA	
h	Ratio	P-value	Ratio	P-value	Ratio	P-value
	Panel A. Real prices					
1	0.967	0.310	0.961	0.319	0.906	0.227
2	0.922	0.229	0.908	0.253	0.888	0.217
3	0.951	0.359	0.932	0.348	0.925	0.332
4	0.978	0.445	0.957	0.414	0.952	0.404
	Panel B. Nominal prices					
1	0.972	0.205	0.973	0.276	0.919	0.176
2	0.952	0.197	0.952	0.239	0.929	0.189
3	0.952	0.263	0.956	0.311	0.945	0.281
4	0.937	0.261	0.955	0.348	0.946	0.327

Table 16: Performance of WSC VAR forecasts. Reports MSFE for WTI oil price forecasts from VAR(1) relative to MSFEs of forecasts from three benchmark models. Per h, number of forecasts is 54. P-value is for null hypothesis $H_0: \ \bar{d}_h = 0$ against one-sided alternative $H_1: \ \bar{d}_h < 0$. P-value comes from the standard normal distribution.

	Benchmark:					
	RW		RWD		ARMA	
h	Ratio	P-value	Ratio	P-value	Ratio	P-value
	Panel A. Real prices					
1	1.175	0.998	1.167	0.997	1.101	0.874
2	1.303	0.998	1.284	0.999	1.257	0.997
3	1.436	0.998	1.407	0.997	1.396	0.996
4	1.561	0.997	1.527	0.992	1.519	0.992
	Panel B. Nominal prices					
1	1.084	0.690	1.086	0.670	1.025	0.544
2	1.106	0.673	1.107	0.648	1.079	0.611
3	1.199	0.755	1.205	0.729	1.192	0.718
4	1.265	0.787	1.287	0.776	1.275	0.767

Table A1: Summary statistics for residential transactions in Aberdeen. Transactions took place between 1984:7-2013:6. Number of observations is 127,628. Sales price is in real (year 2010) pound sterling. Asking price is only observed for 127,581 observations. Time on market is the number of days between first listing and date of transaction. Number of rooms is total number of public rooms and bedrooms.

	Mean	Median	Std. Dev.
Sales price ('000)	106.509	82.704	83.840
Sales price/Asking price	1.085	1.040	0.219
Time on market	100.375	52.000	143.351
Number of rooms	3.691	3.000	1.606
Number of bathrooms	0.936	1.000	0.321
Number of ensuites	0.271	0.000	0.494
Building type			
Detached	0.164		
Non-detached	0.315		
Flat	0.521		
Property has			
Central heating	0.601		
Double glazing	0.632		
Garage	0.237		
Garden	0.463		

Table A2: Hedonic regression results. Reports ordinary least square estimates of Eq. A1 using all transactions from Aberdeen. Monthly time dummies, area dummies, and constant are not reported. Standard errors are corrected for heteroscedasticity and intra-area correlation of residuals. **significant at 1%-level *significant at 5%-level.

Dependent variable: ln house price		
	Coef.	Std. Err.
Detached		
2 rooms	-0.339	0.026**
4 rooms	0.208	0.012**
5 rooms	0.305	0.012**
6 rooms	0.419	0.014**
7 rooms	0.529	0.017**
8 rooms	0.647	0.017**
9 rooms	0.787	0.022**
10 rooms	0.866	0.040**
0 bathrooms	-0.111	0.013**
2 bathrooms	0.162	0.012**
3 bathrooms	0.319	0.042**
1 ensuites	0.125	0.012**
2 ensuites	0.215	0.016**
3 ensuites	0.261	0.030**
No garden	0.030	0.021
No garage	-0.077	0.010**
Central heating	0.061	0.011**
Double glazing	-0.062	0.014**
Non-detached		
Type dummy	-0.057	0.021**
2 rooms	-0.313	0.015**
4 rooms	0.120	0.010**
5 rooms	0.214	0.009**
6 rooms	0.347	0.015**
7 rooms	0.502	0.023**
8 rooms	0.635	0.020**

Continued on next page

Table A2: Continued

9 rooms	0.764		0.018^{**}
10 rooms	0.794		0.024^{**}
0 bathrooms	-0.105		0.010^{**}
2 bathrooms	0.143		0.012^{**}
3 bathrooms	0.180		0.046^{**}
1 ensuites	0.101		0.006^{**}
2 ensuites	0.204		0.016^{**}
3 ensuites	0.270		0.049^{**}
No garden	-0.042		0.017^{*}
No garage	-0.072		0.009^{**}
Central heating	0.059		0.007^{**}
Double glazing	-0.025		0.014
Flat			
Type dummy	-0.273		0.026^{**}
1 rooms	-0.635		0.015^{**}
2 rooms	-0.328		0.011^{**}
4 rooms	0.173		0.011^{**}
5 rooms	0.331		0.014^{**}
6 rooms	0.418		0.022^{**}
7 rooms	0.442		0.024^{**}
8 rooms	0.437		0.038^{**}
0 bathrooms	-0.263		0.013^{**}
2 bathrooms	0.174		0.020^{**}
1 ensuites	0.203		0.012^{**}
2 ensuites	0.355		0.029^{**}
3 ensuites	0.730		0.018^{**}
No garden	-0.039		0.017^{*}
No garage	-0.096		0.011^{**}
Central heating	0.110		0.008^{**}
Double glazing	0.023		0.010^{*}
No of observations	127,628	$\bar{R}^2$	0.932

SFB 649 Discussion Paper Series 2015

For a complete list of Discussion Papers published by the SFB 649, please visit http://sfb649.wiwi.hu-berlin.de.

001 "Pricing Kernel Modeling" by Denis Belomestny, Shujie Ma and Wolfgang Karl Härdle, January 2015.
002 "Estimating the Value of Urban Green Space: A hedonic Pricing Analysis of the Housing Market in Cologne, Germany" by Jens Kolbe and Henry Wüstemann, January 2015.
003 "Identifying Berlin's land value map using Adaptive Weights Smoothing" by Jens Kolbe, Rainer Schulz, Martin Wersing and Axel Werwatz, January 2015.
004 "Efficiency of Wind Power Production and its Determinants" by Simone Pieralli, Matthias Ritter and Martin Odening, January 2015.
005 "Distillation of News Flow into Analysis of Stock Reactions" by Junni L. Zhang, Wolfgang K. Härdle, Cathy Y. Chen and Elisabeth Bommes, January 2015.
006 "Cognitive Bubbles" by Ciril Bosch-Rosay, Thomas Meissnerz and Antoni Bosch-Domènech, February 2015.
007 "Stochastic Population Analysis: A Functional Data Approach" by Lei Fang and Wolfgang K. Härdle, February 2015.
008 "Nonparametric change-point analysis of volatility" by Markus Bibinger, Moritz Jirak and Mathias Vetter, February 2015.
009 "From Galloping Inflation to Price Stability in Steps: Israel 1985–2013" by Rafi Melnick and till Strohsal, February 2015.
010 "Estimation of NAIRU with Inflation Expectation Data" by Wei Cui, Wolfgang K. Härdle and Weining Wang, February 2015.
011 "Competitors In Merger Control: Shall They Be Merely Heard Or Also Listened To?" by Thomas Giebe and Miyu Lee, February 2015.
012 "The Impact of Credit Default Swap Trading on Loan Syndication" by Daniel Streitz, March 2015.
013 "Pitfalls and Perils of Financial Innovation: The Use of CDS by Corporate Bond Funds" by Tim Adam and Andre Guettler, March 2015.
014 "Generalized Exogenous Processes in DSGE: A Bayesian Approach" by Alexander Meyer-Gohde and Daniel Neuhoff, March 2015.
015 "Structural Vector Autoregressions with Heteroskedasticy" by Helmut Lütkepohl and Aleksei Netšunajev, March 2015.
016 "Testing Missing at Random using Instrumental Variables" by Christoph Breunig, March 2015.
017 "Loss Potential and Disclosures Related to Credit Derivatives – A Cross-Country Comparison of Corporate Bond Funds under U.S. and German Regulation" by Dominika Paula Gałkiewicz, March 2015.
018 "Manager Characteristics and Credit Derivative Use by U.S. Corporate Bond Funds" by Dominika Paula Gałkiewicz, March 2015.
019 "Measuring Connectedness of Euro Area Sovereign Risk" by Rebekka Gätjen Melanie Schienle, April 2015.
020 "Is There an Asymmetric Impact of Housing on Output?" by Tsung-Hsien Michael Lee and Wenjuan Chen, April 2015.
021 "Characterizing the Financial Cycle: Evidence from a Frequency Domain Analysis" by Till Strohsal, Christian R. Proaño and Jürgen Wolters, April 2015.

SFB 649, Spandauer Straße 1, D-10178 Berlin
http://sfb649.wiwi.hu-berlin.de

This research was supported by the Deutsche Forschungsgemeinschaft through the SFB 649 "Economic Risk".

SFB 649 Discussion Paper Series 2015

For a complete list of Discussion Papers published by the SFB 649, please visit http://sfb649.wiwi.hu-berlin.de.

022 "Risk Related Brain Regions Detected with 3D Image FPCA" by Ying Chen, Wolfgang K. Härdle, He Qiang and Piotr Majer, April 2015.
023 "An Adaptive Approach to Forecasting Three Key Macroeconomic Variables for Transitional China" by Linlin Niu, Xiu Xu and Ying Chen, April 2015.
024 "How Do Financial Cycles Interact? Evidence from the US and the UK" by Till Strohsal, Christian R. Proaño, Jürgen Wolters, April 2015.
025 "Employment Polarization and Immigrant Employment Opportunities" by Hanna Wielandt, April 2015.
026 "Forecasting volatility of wind power production" by Zhiwei Shen and Matthias Ritter, May 2015.
027 "The Information Content of Monetary Statistics for the Great Recession: Evidence from Germany" by Wenjuan Chen and Dieter Nautz, May 2015.
028 "The Time-Varying Degree of Inflation Expectations Anchoring" by Till Strohsal, Rafi Melnick and Dieter Nautz, May 2015.
029 "Change point and trend analyses of annual expectile curves of tropical storms" by P.Burdejova, W.K.Härdle, P.Kokoszka and Q.Xiong, May 2015.
030 "Testing for Identification in SVAR-GARCH Models" by Helmut Luetkepohl and George Milunovich, June 2015.
031 "Simultaneous likelihood-based bootstrap confidence sets for a large number of models" by Mayya Zhilova, June 2015.
032 "Government Bond Liquidity and Sovereign-Bank Interlinkages" by Sören Radde, Cristina Checherita-Westphal and Wei Cui, July 2015.
033 "Not Working at Work: Loafing, Unemployment and Labor Productivity" by Michael C. Burda, Katie Genadek and Daniel S. Hamermesh, July 2015.
034 "Factorisable Sparse Tail Event Curves" by Shih-Kang Chao, Wolfgang K. Härdle and Ming Yuan, July 2015.
035 "Price discovery in the markets for credit risk: A Markov switching approach" by Thomas Dimpfl and Franziska J. Peter, July 2015.
036 "Crowdfunding, demand uncertainty, and moral hazard - a mechanism design approach" by Roland Strausz, July 2015.
037 ""Buy-It-Now" or "Sell-It-Now" auctions : Effects of changing bargaining power in sequential trading mechanism" by Tim Grebe, Radosveta Ivanova-Stenzel and Sabine Kröger, August 2015.
038 "Conditional Systemic Risk with Penalized Copula" by Ostap Okhrin, Alexander Ristig, Jeffrey Sheen and Stefan Trück, August 2015.
039 "Dynamics of Real Per Capita GDP" by Daniel Neuhoff, August 2015.
040 "The Role of Shadow Banking in the Monetary Transmission Mechanism and the Business Cycle" by Falk Mazelis, August 2015.
041 "Forecasting the oil price using house prices" by Rainer Schulz and Martin Wersing, August 2015.

SFB 649, Spandauer Straße 1, D-10178 Berlin
http://sfb649.wiwi.hu-berlin.de

This research was supported by the Deutsche Forschungsgemeinschaft through the SFB 649 "Economic Risk".