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Has Inflation Targeting Become Less Credible? Oil Prices, Global Aggregate Demand and Inflation Expectations during the Global Financial Crisis

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Abstract

Beginning with the global financial crisis (2008) the correlation between crude oil prices and medium-term and forward inflation expectations increased leading to fears of their un-anchoring. Using the first principal component of commodity prices as a measure for global aggregate demand, we decompose nominal oil prices to a global demand factor and remaining factors. Using a Phillips Curve framework we find a structural change after the collapse of Lehman Brothers when inflation expectations reacted more strongly to global aggregate demand conditions embedded in oil prices. Within this framework we cannot reject the hypothesis that expectations remained anchored.[1]

Keywords: Inflation targeting, inflation expectations, monetary policy, oil prices, anchoring, credibility
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1 Introduction

The sharp decline in oil prices beginning in late 2014 sparked a debate about their effect on inflation and the world economy [e.g., Chen et al. (2015); Baumeister and Kilian (2016a,b)]. This decline lowered inflation in the short run and in some cases resulted in negative inflation [IMF (2016)]. More surprisingly, data from the USA, France, UK and Israel show that oil prices have a strong correlation with inflation expectations for the medium-term, as measured by five-year breakeven inflation rates, and more recently with five-years to five-years

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[1]The views presented in this paper do not necessarily represent the views of the Bank of Israel. We would like to thank participants at seminars at the Bank of Israel, the University of Western Ontario and the BIS for their helpful comments.

forward inflation expectations (Figure 1).[2] Before the global financial crisis (GFC), with the exception of the UK, this correlation was weaker and expectations were firmly anchored at two percent.[3] However, from the onset of the GFC the correlation is quite high, suggesting that expectations for the five-year horizon became less anchored with respect to the inflation target. While this phenomenon is more visible in medium-term inflation expectations, since 2014 we can observe a similar pattern with respect to longer term inflation expectations, namely the five-year five-year forward breakeven rates. A concern raised by central bankers was that the increased correlation of breakeven inflation rates with oil prices may indicate an erosion of the anchoring of expectations [e.g., IMF (2016)]. These developments may signal a decline in either the effectiveness, appropriateness or credibility of the inflation targeting monetary regime and questions conclusions reached about the credibility of this regime and its effect on the anchoring of inflation expectations [Gürkaynak et al. (2010); Beechey et al. (2011)].

Our main contribution is to test for un-anchoring of inflation expectations using a structural framework based on a novel *global* Phillips curve. We construct measures of global demand shocks - that we extract from commodity prices, global inflation and monetary policy. Using this approach we find a structural change in the effect of global demand on inflation expectations following the onset of the GFC. However, this does not necessarily imply that expectations became unanchored. In fact, we cannot reject the hypothesis that they remained anchored.

The observed correlation between oil prices and medium-term inflation expectations that alarmed policy makers and motivated this study is puzzling since we do not expect a correlation between (expected) *rates of change* in the CPI in the medium term and *levels* of oil prices. However, Killian, in numerous studies [Barsky and Kilian (2001, 2004); Kilian (2008a, 2009); Kilian and Hicks (2013)]), already showed that *real* oil prices convey information about global economic activity and therefore could be related to inflation.

We extend Killian's approach by focusing on the increase (decrease) in the aggregate price level, and hence inflation expectations, caused by changes to aggregate demand or supply.[4] We begin by identifying the component of oil price changes that is affected by global aggregate demand.[5] We exploit the fact that a large number of commodity contracts are traded in financial markets. While each commodity is affected by idiosyncratic supply and demand shocks, they are also affected by common "global aggregate demand" shocks. Since idiosyncratic changes in the price of one commodity may affect other prices in different directions (depending on substitution and income effects), a factor that can move the prices of all commodities in the same direction is global aggregate demand.[6] We exploit

[2] We show simple correlations to motivate our discussion and relate it to current public debate. Owing to unit roots in the data our formal analysis is carried out in rates of change. Due to data availability we use French breakeven rates as a proxy for Eurozone expected inflation. We also show data for Israel since it has a deep market for indexed bonds and has an inflation target.

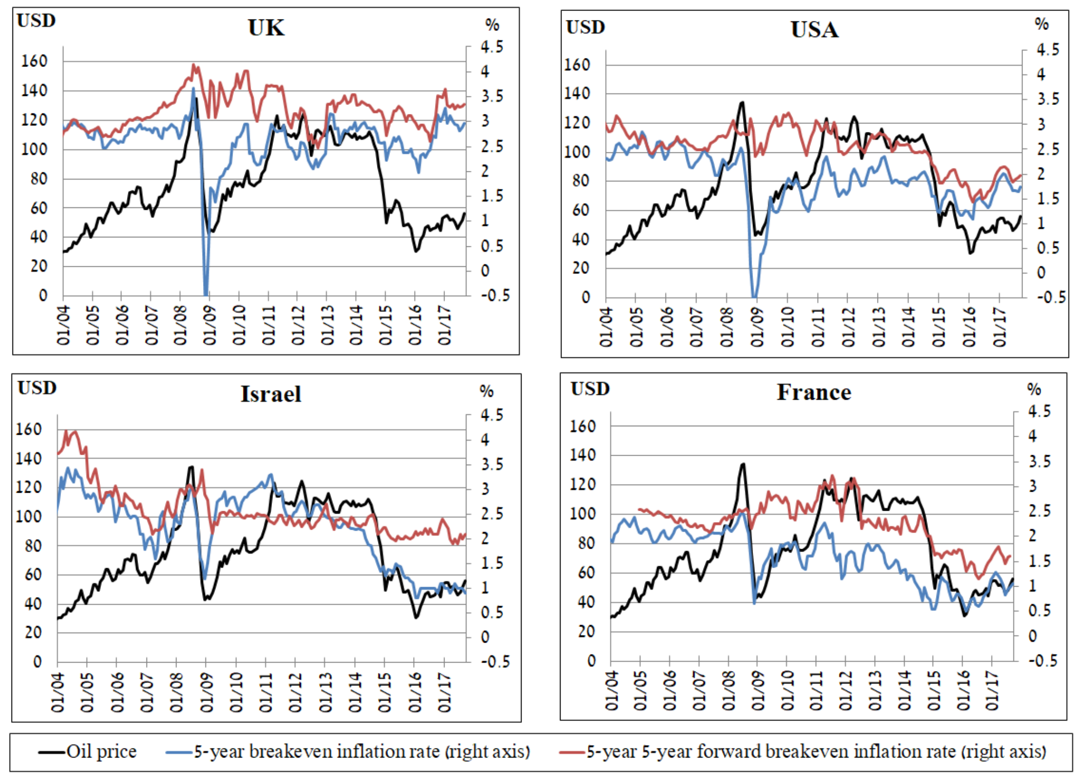
[3] Looking at the period before the crisis, O'Neill et al. (2008) found that there is no long term relationship between inflation expectations and oil prices. Beechey et al. (2011) showed that before the global financial crisis oil prices affected inflation expectations in the USA but not in the Eurozone.

[4] Tawadros (2013) shows, using quantities of oil consumed globally, rather than prices, a pro-cyclically contemporaneous relationship between the demand for crude oil and real output for the OECD.

[5] The decomposition of oil prices into different factors was initially proposed by Kilian (2008a, 2009).

[6] Alquist and Coibion (2014) arrived independently to a similar decomposition. In the same spirit, Perez-

Figure 1: Inflation Expectations and Brent Crude Oil Prices (2004-17)



Correlations		USA	France	UK	Israel
Oil prices and 5Y breakeven rates	2004M01-2008M08	-0.34	0.37	0.46	-0.27
	2008M09-2017M08	0.60	0.65	0.28	0.71
Oil prices and 5Y5Y breakeven rates	2004M01-2008M08	0.03	0.23	0.89	-0.47
	2008M09-2017M08	0.62	0.65	0.08	0.31

Source: Bloomberg and the Bank of Israel.

Note: Correlations were computed for monthly averaged data.

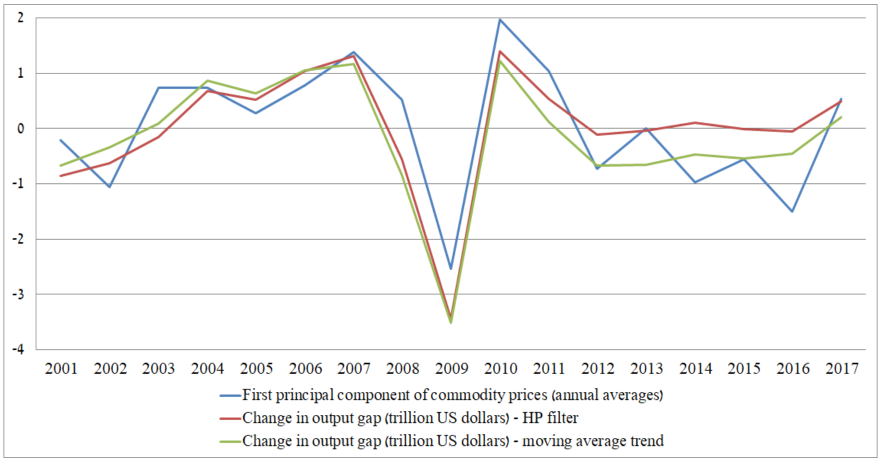
the strong co movement of commodity prices to identify global aggregate demand as their first principal component.[7] The advantage of using a common factor of commodity prices to extract information about global aggregate demand is that these prices are derived from almost perfect markets: they are standardized goods, traded in thick markets, and there is global full-information of their prices.[8] Figure 2 shows that the common factor we extract

Segura and Vigfusson (2016) identified changes in oil prices as demand-induced if they have the same sign as changes in equity and metal prices.

[7] In section 4 we control for the USA Dollar exchange rate that could also contribute to the co movement.

[8] In our sample, the first principal component of commodity price levels captures 65 percent of the total variation in the data. However, to deal with non-stationarity, we construct our proxy from monthly rates of change in prices. While this transformation weakens the correlation, the first principal component still captures 29 percent of the variation in the transformed data and assigns positive loadings to all commodities, meaning that it captures the co-movement of prices. This makes the first component a natural candidate for a measure of global aggregate demand. Byrne et al. (2013) find that this factor is negatively related to

Figure 2: Changes in the Global Output Gap and the First Principal Component of Commodity Prices: 2001-17



Source: OECD, Bloomberg and authors' calculations.

Notes: Both measures of the change in the output gap are constructed as the annual change in detrended global output. In the first measure output is detrended using HP filter and in the second measure using a trend of a ten year moving average growth rate (in the second method the level of the output gap is normalized to equal the HP filter gap in 2005).

from commodity prices is strongly correlated (correlation coefficients higher than 0.8, see section 2.1.2) with measures of the global output gap.

Our measure of global aggregate demand, embedded in oil prices, is largely responsible for the increase in the correlation between them and breakeven inflation expectations. To rule out that the correlation did not increase due to oil specific effects, we also include in our estimation the residual from a regression of the change in oil prices on our measure of global demand. We further instrument the residual with specific variables affecting oil and energy prices idiosyncratically, namely OPEC's strategic behavior and shocks to oil demand caused by the weather. We construct a novel proxy for OPEC's behavior by using a tally of articles from the London Times. We examine articles that mention OPEC and classify them by the sentiment arising from the text. Our proxy is constructed as the net number of articles suggesting OPEC is expanding supply, minus the number of articles indicating supply reduction.[9] We also use temperature variables from five continents to capture shocks to the demand for oil arising from anomalous weather conditions. Using these factors as instruments supports our hypothesis that the increase in the correlation between oil prices and inflation expectations was largely due to changes in the correlation between global aggregate demand and expected inflation.

We find an increased volatility of breakeven expectations due to a structural change in the correlation between them and global demand. To address the question whether our results

real interest rates and positively related to output, supporting our premise that it captures global aggregate demand forces. Below we provide additional evidence to support our choice of this measure.

[9]For a full account of historical oil prices see Kilian and Murphy (2012) and Baumeister and Kilian (2016b).

imply an un-anchoring of inflation expectations, we test for un-anchoring using a structural model with rational expectations. The structural framework, together with our decomposition of oil prices, allows us to identify the channel by which inflation expectations react more strongly to the global demand factor embedded in oil prices. We estimate a reduced form 'global' Phillips curve, taking a similar approach to Ciccareli and Mojon (2010) and Diebold et al. (2008) who used global principal component analysis.[10] We exploit the fact that all advanced economies are part of the monetary regime referred to as 'inflation targeting'. The USA, the ECB and, to some extent, the UK are perceived as the global anchors of this regime and therefore, there is a common factor in medium-long term inflation expectations for these economies. This allows us to compute a global measure of expected inflation using the first principle component of inflation expectations in these economies. Similarly we construct measures of global inflation and global monetary policy. This method removes idiosyncratic shocks to expected inflation and bond markets from which these expectations are extracted (for example the shock of Brexit on the London capital market).

We estimate a reduced form global Phillips curves (with and without assuming a monetary policy rule) using mainly market based five year breakeven expected inflation rate, but also one year ahead expectation based on consumer surveys.[11] We find, again, that the increase in the correlation between oil prices and expected inflation, following the onset of the crisis, is mainly due to the increased effect of global aggregate demand on global inflation expectations. Within the assumptions of the model we used, we can reject the hypothesis of un-anchoring and attribute our findings to an increase in the slope of the global Phillips curve during the period following the onset of the global financial crisis.

The implication of our findings for policy makers is that the increased volatility of medium term inflation expectations does not necessarily imply un-anchoring. Nevertheless, central bankers are concerned that the increased volatility of medium term inflation expectations may cause, over time, a deterioration of the credibility of inflation targeting. In fact, since 2014 we observe a decline in the long term inflation expectations - the five-year to five-year breakeven rates and inflation swaps. This development may indicate en erosion in the public belief in the ability of central banks to bring inflation back to target in the longer run, either because monetary may be less affective around the effective lower bound, or that central bankers may be less willing to use monetary policy tools because of potential macro-prudential concerns. Another possibility, recently raised by Morris and Shin (2018), is that central bankers' communication of perhaps, according to our findings, unjust fears of un-anchoring have led to the decline in long term inflation expectations.

While outside the scope of this paper, we found that there is a possibility that the slope of the global Phillips curve increased after the global financial crisis. Our findings suggest that the volatility of inflation and inflation expectations may increase and that there are fewer frictions in the global economy and particularly in prices. This implies that economists and policy makers should consider the possibility of this scenario and its implications for the monetary rule and the models used to support it.

[10]Ciccareli and Mojon (2010) and Diebold et al. (2008) analyzed global inflation and common global factors in bond yields using principal component analysis respectively.

[11]Reis and Watson (2010), estimate Phillips curves for the USA using a measure of 'pure inflation' based on a principle component of consumer goods.

Related Literature

Our findings mainly relate to the literature on the anchoring of inflation expectations. There is a consensus that since the 1980s, and more so in the 2000s, inflation became anchored and monetary policy became more credible. The apparently relatively large effect that oil prices had on inflation and activity in the 1970s and early 1980s was followed by the 'great moderation'. Leading macroeconomists sought to evaluate the contribution of monetary policy to the large impact of oil prices in the 1970s and even more so to the great moderation that ensued in the 1980s. Bernanke et al. (1997) argued that oil prices per-se did not have a large effect on the economy and that monetary policy response exacerbated their effect on the economy. Hooker (2002) did not rule out that the decline of the transmission between oil prices to the economy in the 1980s could have been due to effective monetary policy. Subsequent and influential research was more conclusive: Boivin and Giannoni (2006) found that by responding more strongly to inflation expectations, monetary policy has stabilized the economy more effectively in the post-1980 period. Blanchard and Gali (2010) and Blanchard and Riggi (2013) found that the improvement in the credibility of monetary policy explains a substantial part of the difference between the 2000s and the 1970s. Nakov and Pescatori (2010) found that around half of the reduced volatility of inflation is explained by better monetary policy alone, and that oil related effects explain around a third.

Our paper is related to the ongoing debate about the relevance and slope of the Phillips curve. While there is strong following for the view that "missing inflation" is consistent with the Phillips curve flattening or disappearing altogether [IMF (2013)], recent research has suggested otherwise. Blanchard (2016) shows that while it may have flattened, the Phillips curve is alive for the USA. Recent evidence from the Euro area, [Oinonen and Paloviita (2014), Riggi and Venditti (2015) and Bulligan and Viviano (2017)], is consistent with our findings and points to a steepening of the slope of the Phillips curve in the last decade. Borio and Filardo (2007) show that global economic slack has an increasingly important role in determining inflation since the early 1990's. Finally, Coibion and Gorodnichenko (2015) show that using expectations from survey data for the USA they can demonstrate the persistence of the Phillips curve which is not the case when market data on expectations is used. Moreover, they point to the high elasticity of survey expectations to oil prices. We can reconcile these separate findings using a global version of the Phillips curve, extracting a global aggregate demand factor from commodity prices and using principal component methods to remove country specific and idiosyncratic factors.

This paper also relates to the vast literature that studies the underlying forces in the market for crude oil [Kilian (2008b); Hamilton (2009a,b); Baumeister and Peersman (2013); Kilian and Murphy (2014); Fueki et al. (2018)]. Our approach is similar to the one taken by Kilian (2009) who uses a measure of global economic activity based on freight rates of dry cargo to identify the underlying shocks in the crude oil market. This measure, as well as ours, is designed to capture the main forces that drive the demand for a large group of commodities. Baumeister and Kilian (2016b) use this measure of global activity to examine the decline in oil prices in the second half of 2014. They find that the decline in prices was due to a momentum effect of positive supply shocks in earlier periods as well as unexpected adverse developments in global activity (they also highlight the role of storage demand driven by a shift in expectations). Our analysis of oil prices portrays a similar narrative.

Our decomposition of oil prices exploits the link between these prices and the prices of other commodities, using the first principal component of commodity prices. There is a large literature studying the linkage between prices of oil and other commodities [Baffes (2007); Du et al. (2011); Baumeister and Kilian (2014); Hassler and Sinn (2016); see Serra and Zilberman (2013) for a survey], and it points to several aspects of this linkage. First, prices of crude oil and other commodities are affected by global demand for the aggregate output. Second, crude oil enters the production function of other commodities through the use of various energy-intensive inputs. Third, some commodities can be used to produce substitutes to crude oil (e.g., corn and sugar for ethanol production), linking their demand to occurrences in the energy market. Finally, changes in the price of oil affect disposable income and thus influence the demand for other commodities. Note that out of the four mentioned links between prices of oil and other commodities, only the first two can explain contemporaneous co-movement of prices in a broad and diverse group of commodities such as we use. In accordance with previous studies [Barsky and Kilian (2001); Kilian (2009); Kilian and Murphy (2014)], we provide evidence that the global aggregate demand factor is more dominant in explaining the co-movement of prices, and that the pass-through from oil prices to other commodity prices is limited.

The rest of the paper is organized as follows. Section 2 specifies our methodology for testing the sources of change in oil prices and the anchoring of medium-term inflation expectations; In section 3 we estimate the effect of global demand on inflation expectations using a structural framework. Section 4 provides some robustness checks by examining household inflation expectations and excluding the period around the collapse of Lehman Brothers. Section 5 discusses possible implications for our findings and Section 6 concludes.

2 Accounting for the Change in the Relationship between Oil Prices and Medium-Term Inflation Expectations

The increasing correlation between inflation expectations and oil prices following the onset of the global crisis may be suggestive of a structural change in the anchoring of medium term inflation expectations. Beechey et al. (2011) already noted that using oil price shocks has some advantages in comparing the anchoring of inflation expectations across countries since these are uniform shocks and since advanced economies have similar energy intensities. Extending Gürkaynak et al. (2005), they test for the anchoring of inflation expectations by regressing changes in far-ended inflation expectations on shocks to macroeconomic variables. If inflation is well anchored, these shocks, in particular oil price shocks, should not have a statistically significant effect on medium-term inflation expectations. In this section we employ Beechey's et al. (2011) framework and test the anchoring of medium term inflation expectations. We extend their analysis in two ways: first, we differentiate between changes in oil prices induced by shifts in global aggregate demand and other sources of oil price changes. This refinement is important because, with the exception of the flexible CPI inflation targeting rule [Svensson (2000)], monetary policy reacts differently to supply shocks and to demand shocks. While some degree of accommodation of supply shocks could be viewed as socially optimal [Rogoff (1985)] and could be incorporated in inflation expectations for the medium-term, a perceived accommodation of demand shocks contrasts with inflation targeting and raises questions about the effectiveness or credibility of the monetary regime.[12] Secondly, we extend the empirical investigation to include the period following the onset of the global financial crisis. In this period monetary policy was operating in hitherto uncharted territory of quantitative easing and negative interest rates. We present evidence that medium term inflation expectations became significantly more correlated with changes in oil prices induced by shocks to global output gap.

2.1 Estimating Global Aggregate Demand

To estimate the information on the global output gap embedded in oil prices we use the first principal component of commodity prices. While we refer to alternative methods of assigning demand and supply factors to oil price changes (see Section 1), we suggest that our measure is natural and transparent. We begin by describing the data and the methodology of principal component analysis. Subsequently, we analyze the relation of the estimated factor to global aggregate demand.

2.1.1 Data and Methodology

We use a panel of 20 commodity price indexes that were included in the S&P GSCI index in 2015. The data spans over the period 2000-2017 and includes commodities from five groups: agricultural commodities, livestock, industrial metals, precious metals[13], and energy (the commodities are listed in Table 1).[14] In order to focus on fundamental co-movements of prices, we use monthly averages of commodity prices.[15] One way to capture the co-movement of commodity prices is to take the first principle component of the levels of commodity prices (this factor accounts for 64 percent of the variation in commodity prices).[16] However, we

[12]For non-oil-producing economies changes to oil prices can be considered as supply shocks. Baumeister and Kilian (2016a) show that for the USA oil price shocks are also demand shocks. In a New-Keynesian model, Bodenstein et al. (2012) show that an optimal interest rate rule should attach no weight to oil prices. Under an inflation targeting regime, Mankiw and Reis (2003) argue that monetary policy should put a small weight on stabilizing prices that are subject to large idiosyncratic shocks such as energy prices. Filardo et al. (2014) emphasize the importance of identifying the source of commodity price shocks when conducting monetary policy. Ireland (2007) showed that the Fed accommodated supply shocks and allowed the de-facto inflation target to change.

[13]One of the precious metals included in our data is gold. One might argue that gold has characteristics of a financial asset, and thus its price behaves differently from that of other commodities. However, our results remain essentially unchanged when we exclude gold prices from our analysis.

[14]There are four commodities in the S&P index which we exclude from our sample. One is feeder cattle for which there is not enough available data. Three other commodities which we exclude are heating oil, gasoline, and gas oil. Their prices are highly correlated with prices of crude oil (correlation of over 0.98) and we wish to avoid a strong bias of the principal component towards oil prices. As can be seen in Table 1, we keep three other energy commodities: WTI crude oil, Brent crude oil and natural gas.

[15]In Appendix D.3 we test the sensitivity of our results to data frequency. We repeat our analysis using data at daily and quarterly frequencies, and find that our main results remain qualitatively unchanged.

[16]The first principal component is an estimator of a common factor that drives the prices of all commodities and it is constructed to best explain the variation in the data. In Appendix B we describe the methodology for constructing this estimator.

Table 1: Commodities and Loadings of the First Principal Component $pc_t^{\Delta cmd}$

Chicago Wheat	Kansas Wheat	Corn	Soybeans	Coffee	Sugar	Cocoa	Cotton	Lean Hogs	Live Cattle
0.21	0.22	0.21	0.23	0.21	0.15	0.14	0.19	0.04	0.06

Alumi-num	Copper	Lead	Nickel	Zinc	Gold	Silver	Brent Crude Oil	WTI Crude Oil	Natural Gas
0.31	0.33	0.26	0.26	0.3	0.19	0.25	0.28	0.26	0.07

convert the data to differenced logs of prices in order to avoid issues of non-stationarity. Finally, following the common practice in principal component analysis, all the series are standardized.

In our sample, the first principal component of rates of change in commodity prices, $pc_t^{\Delta cmd}$, explains 29 percent of the variance in the data. The loadings of all variables are positive (Table 1), so the first principal component captures the positive co-movement in *all* commodity prices. This justifies our interpretation of the first principal component as a proxy for global aggregate demand. In Section 4 we perform robustness checks that show that our measure is not driven by the fact that all commodities are quoted in USA Dollars and that the co-movement is not capturing the effect of oil prices on other commodities.

2.1.2 First Principal Component of Commodity Prices and Global Aggregate Demand

As we saw in Figure 2 the annual rates of change of the first principal component , $pc_t^{\Delta cmd}$(the unprocessed principal component based on monthly data is presented in Figure 11 in the Appendix) tracks very well the two measures of the global output gap. In the first measure, output is de-trended using an HP filter and in the second measure we use a trend of a ten year moving average growth rate (in the second method the *level* of the output gap is normalized to equal the HP filter gap in 2005). The correlation between the principal component of commodity prices and the change in output gap is 0.85 using either measure of the output gap.

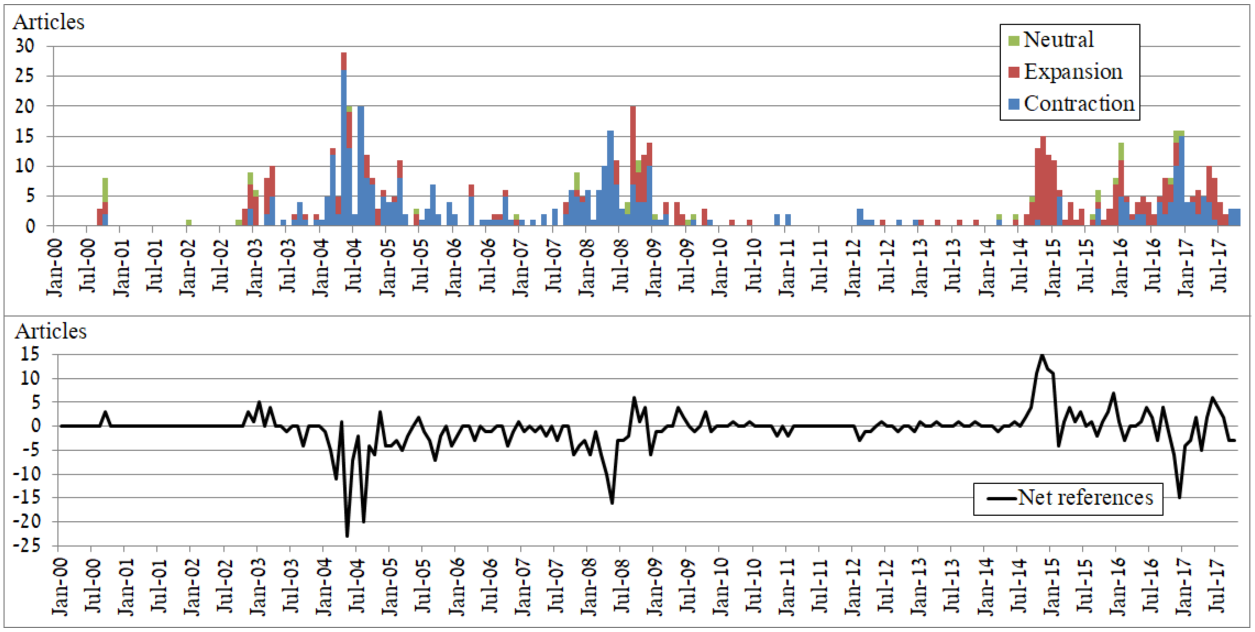
2.2 Idiosyncratic Components of Oil Prices

We derived our measure of global output gap embedded in oil prices using first principal component of commodity prices. We can decompose the change in oil prices into two components:

$$\Delta oil_t = \alpha_0 + \alpha_1 pc_t^{\Delta cmd} + u_t \tag{1}$$

Where $pc_t^{\Delta cmd}$ is the first principal component of commodity prices and the residual u_t captures all remaining remaining variables affecting the change in oil prices. In this section we propose a more detailed specification of oil price decomposition that directly identifies some of the idiosyncratic forces that drive oil prices and show that they are largely orthogonal to our measure of global output gap. Showing that our measure of global demand is not correlated with oil specific factors strengthens our claim that the first principle component

Figure 3: References of OPEC in the London Times, Classified by Type of Operation in the Oil Market (2000-17)



Source: The London Times website (http://www.thetimes.co.uk/tto/search/) and authors' calculations.

of commodity prices can be used to identify the effect of global demand shocks on inflation expectations. We focus on two idiosyncratic components of oil prices, one from the supply side and the second from the demand side. From the supply side, we examine OPEC's efforts to control prices of crude oil. These efforts may vary across time, depending on OPEC members' objectives and their ability to collude to promote these objectives. From the demand side, we focus on the idiosyncratic demand shocks to oil driven by extreme weather conditions. The detailed breakdown of the change in oil prices to global demand, OPEC's behavior and weather conditions is shown in Appendix C.

To estimate the effect of OPEC's policies on crude oil prices, we assembled a novel data series that will serve as a proxy for the cartel's operations. In each month of our sample period, we examine articles published in the London Times that refer to OPEC. We classify each article as either indicating supply expansion by OPEC, supply contraction or as neutral articles. Our proxy is then constructed as the net number of "expansionary articles", meaning the number of articles classified as expansionary, minus the number of articles classified as contractionary (Figure 3). The sign of the proxy captures the objective of the cartel's operations (negative indicating supply contraction, and positive indicating expansion), while the absolute size captures their magnitude.[17]

For the measure of idiosyncratic demand shocks driven by extreme weather conditions,

[17]A potential concern is that OPEC's behavior is endogenous to global aggregate demand and therefore our instrument is not valid. We test for this by regressing our IV on the global demand factor and find that the R squared of this regression is only 0.01 and therefore we can reject the hypothesis that our IV is not valid.

we examine global temperature data. The NCEI[18] provides five monthly data sets, one for each continent, of seasonally adjusted temperature data.[19] The rational of using this data is that weather conditions affect the usage of heating or cooling devices which are usually energy intensive, thus affecting the idiosyncratic demand for oil.[20]

2.3 Estimating the Correlation between Oil Prices and Inflation Expectations

We now turn to examine the sources of the increase in the correlation between oil prices and inflation expectations, exploiting the decomposition of oil prices we performed in the previous section (Equation (1)). The increase in the correlation can be the result of two possible developments; First, it is possible that one of the factors that drives oil prices has become more correlated with inflation expectations. Alternatively, it may be that the magnitude of the correlation did not change but one of the factors became more dominant in determining oil prices in recent years. We claim that the elasticity effect dominates the composition effect. Specifically, we show that from the onset of the crisis, the correlation between the global aggregate demand factor embedded in oil prices and inflation expectations increased.

Since we are interested in the main factors that link oil prices and inflation expectations, we wish to ignore idiosyncratic components of breakeven inflation rates. We exploit the fact that our economies are anchors of the global monetary regime and pursue a similar inflation target. Therefore, we focus on the main factors that drive global inflation expectations. For this purpose we extract, pc_t^{beir}, the first principal component of five-year breakeven inflation rates from the USA, France and the UK (Figure 5). This factor can be viewed as an estimator for global expected inflation at the five-year horizon.[21]

To estimate the source of the correlation between inflation expectations and oil prices we regress Δpc_t^{beir}, the change in the first principal component of five-year breakeven inflation rates, on decomposed oil prices allowing for a different correlation before and after the global

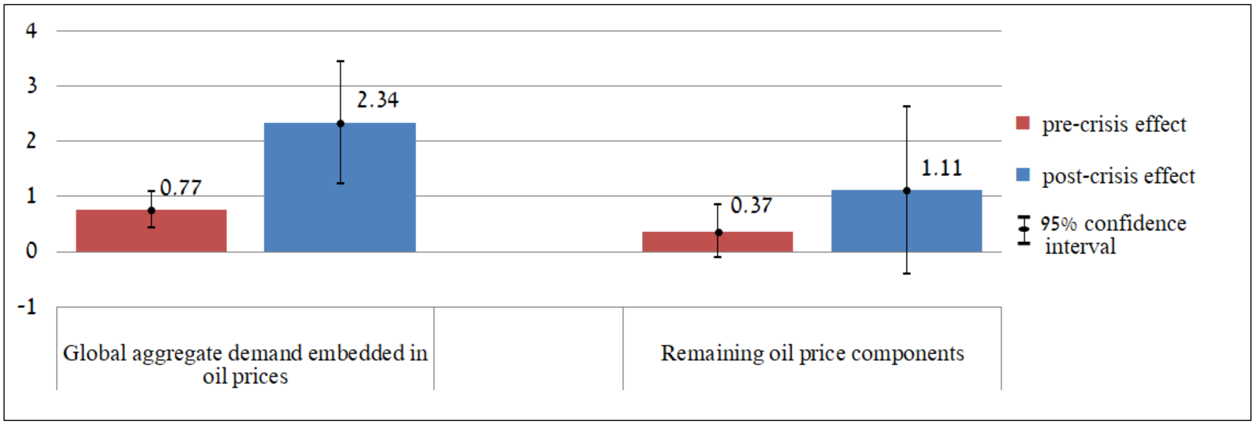
[18]The National Centers for Environmental Information (NCEI) are part of the National Oceanic and Atmospheric Administration (NOAA) in the USA Department of Commerce.

[19]The NCEI refers to these data sets as temperature anomalies and calculates them as follows. For each calendar month and each continent (North America, South America, Europe, Asia and Africa), a long-run average of temperatures is calculated. The anomaly series for a specific continent is then calculated as the deviation of measured temperature from this average.

[20]Anomalous weather can of-course affect the supply of agricultural commodities. However,in contrast to the unique effect on demand for energy, the supply effect could be in both directions, depending on the commodity. When we test for the effect on each agricultural commodity we find that our measure of anomalous weather is negatively correlated with their prices, whereas it is positively related to the price of oil.

[21]The first principal component explains 73 percent of the variance in the panel of breakeven inflation rates. The loadings of the factor are: USA - 0.64, France - 0.56, UK - 0.53. In order to facilitate the interpretation of regression coefficients the factor was multiplied by the coefficient c_1 estimated in a country panel regression $y_i = c_{0,i} + c_1 PC^{beir} + \epsilon_i$ for $i \in \{\text{USA,UK,France}\}$. The analysis in this section can be carried out for the individual countries in our sample with similar results.

Figure 4: Effects of Oil Price Components on the First Principal Component of Breakeven Inflation Rates Before and After the Global Financial Crisis (2003-17)



Notes: The figure depicts 2SLS estimation results of Equations (2). For each variable, the post-crisis partial effect is the coefficient on the variable itself, and the pre-crisis effect is the sum of that coefficient and of the coefficient on the interaction of the variable with the pre-crisis dummy. For example, the partial effect of global aggregate demand is the estimator of $\beta_1 + \beta_2$ for the pre-crisis period, and β_1 for the post-crisis period. Confidence intervals are calculated with Newey-West standard errors. Detailed results appear in Table 9 in the Appendix.

financial crisis:[22] [23]

$$\Delta pc_t^{beir} = \beta_0 + \beta_1(\hat{\alpha}_1 pc_t^{\Delta cmd}) + \beta_2(\hat{\alpha}_1 pc_t^{\Delta cmd}) \times dprecri_t + \beta_3 \hat{u}_t + \beta_4 \hat{u}_t \times dprecri_t + \beta_5 dprecri_t + \epsilon_t \quad (2)$$

Where $\hat{\alpha}_1 pc_t^{\Delta cmd}$ is our estimate for the global aggregate demand factor embedded in oil prices, $\hat{u}_t$ is the remaining component of oil prices (fitted value and residual from Equation (1), respectively) and $dprecri_t$ is a dummy for the pre-crisis period (2004M01-2008M08).

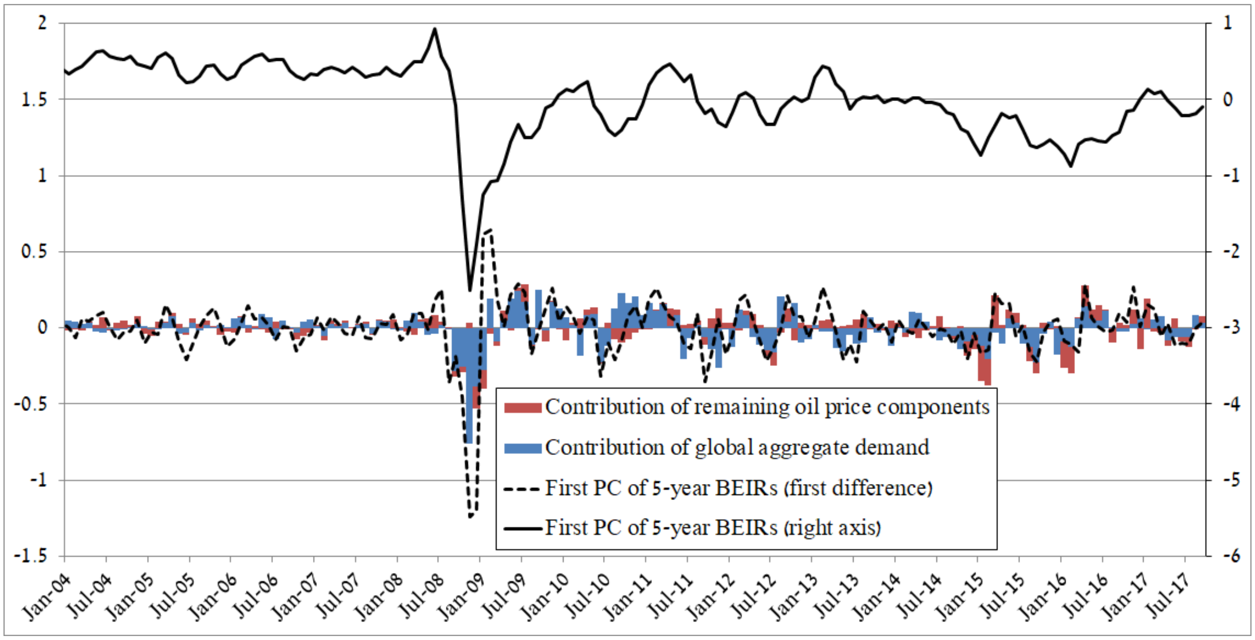
Since the response of global aggregate demand to other shocks is not instantaneous [Kiley (2014); Gertler and Karadi (2015)], it is reasonable to assume that it is exogenous in Equation (2). However, we cannot account for all the determinants of the "remaining components" of oil prices and thus cannot assert that $\hat{u}_t$ is exogenous. We therefore use as instruments the variables derived in section 2.2: the proxy for OPEC's cartelistic behavior and a factor of weather variables, both interacted with the pre-crisis period dummy. Two-stage least square estimation results, which are depicted in Figure 4, shed some light on the observed change in the correlation between changes to inflation expectations for the medium term and changes to oil prices.

Prior to the global crisis, changes in oil prices stemming from either global aggregate demand or other components, had a small and similar effect on inflation expectations. This suggests that even if the composition of factors that drive oil prices has changed, it cannot by

[22] The Bai-Perron test for breaks identifies December 2008 as a break point.

[23] We are interested in modeling the relationship between breakeven inflation rates and levels of oil prices. In Equation (1) we decomposed the differenced log terms of oil prices in order to deal with non-stationarity. Thus, if we are to use this decomposition, we need to examine *changes* in breakeven rates.

Figure 5: First Principal Component of Five-Year Breakeven Inflation Rates and the Contribution of Global Aggregate Demand to its Monthly Change (2003-17)



Notes: The contribution of global aggregate demand to inflation expectations is calculated according to estimation of Equation (2). The contribution of global aggregate demand (in blue) is $(\beta_1 + \beta_2 \times dprecri_{t-i})\hat{\alpha}_1 pc_t^{\Delta cmd}$, and the contribution of the remaining components (in red) is $(\beta_3 + \beta_4 \times dprecri)\hat{u}_{t-i}$.

itself explain the increase in correlation between oil prices and inflation expectations in recent years. In the post-crisis period the picture is very different. We cannot reject the hypothesis that the effect of the remaining components of oil prices on expectations remained stable. However, the effect of global aggregate demand increased significantly. Since we breakdown our sample to pre-crisis and post-crisis according to the timing of the collapse of Lehman Brothers in September 2008, one might argue that the correlations we document are driven by the sharp drops of both inflation expectations and commodity prices in the months that followed the collapse. Though there is no a-priori reason to partition the sample differently, for robustness we estimate Equation (2) controlling for the crisis years 2008-2009. In this exercise we also see a substantial increase in the coefficient of the global aggregate demand factor since the crisis, but not in that of the idiosyncratic component. See section 4.2 for a detailed discussion.

Our results suggest that the information embedded in oil prices regarding global activity has become much more dominant in the formation of inflation expectations, even at the five-year horizon. The contribution of the global aggregate demand factor to the correlation of global inflation expectations over time is depicted in Figure 5 and it seems that in the post-crisis period it accounts for a substantial part of the development in expectations. In the following section we offer an explanation for this change using a rational expectations framework.

3 A Rational Expectations View on the Anchoring of Inflation Expectations

We showed that global medium-term inflation expectations became more correlated with oil prices since the global financial crisis, and this is due to a stronger effect of global aggregate demand on inflation expectations. A possible concern for policymakers is that the increased sensitivity of breakeven inflation rates to oil prices may indicate an erosion in the anchoring of expectations and the credibility of the inflation targeting regime, especially since monetary policy has been operating in formerly uncharted territories of quantitative easing and negative interest rates [e.g., IMF (2016)].

To address the question whether inflation expectations became un-anchored, we turn to examine the increased correlation between oil prices and five-year breakeven inflation rates in a context of a structural model with rational expectations. The structural framework, together with our decomposition of oil prices, allows us to identify channels through which inflation expectations react more strongly to the global demand factor embedded in oil prices. We are able to show that this change can be attributed to the increase in the slope of the Phillips curve. Furthermore, we find no evidence that expectations became more adaptive since the criss, meaning that they have so far remained forward-looking. These results hold for market expectations for a five-year horizon as well as for household expectations for a twelve-month horizon. We conclude that the increased responsiveness of inflation expectations to the global aggregate demand factor embedded in oil prices does not indicate un-anchoring of expectations as formulated in Beechey et al. (2011) or Blanchard (2016).At the same time we find that although the coefficient of idiosyncratic oil price changes on breakeven inflation rates increased, the increase is not statistically significant. Moreover, unlike Coibion and Gorodnichenko (2015), we do not find, controlling for the information on global aggregate demand embedded in oil prices, that their effect on household survey-based expectations increased; it actually (insignificantly) declined.

3.1 Rational Expectations with Optimal Policy Rule

To examine the change in the correlation between changes in medium term global inflation expectations and changes to global output gap and other determinants of oil prices, we introduce a framework of how expectations are formed. We consider the semi-structural model of Orphanides and Williams (2004) which was also used in Beechey et al. (2011) to examine the anchoring of inflation expectations. The model consists of a Phillips curve and an IS curve as follows:

$$\pi_{t+1} = \phi\pi_{t+1/t} + (1-\phi)\pi_t + \alpha y_{t+1} + e_{t+1} \tag{3}$$

$$y_{t+1} = -\xi(r_t - r^*) + u_{t+1} \tag{4}$$

Where π_t is the annual rate of inflation at time t, $\pi_{t+1/t}$ is the one-period ahead expected inflation, y_t is the output gap, r_t is the real interest rate, r^* is the long-run real rate, e_t is a cost-push shock and u_t is a demand shock. The model is closed with the following policy rule that minimizes a weighted average of the variances of the output gap and of deviation of inflation from a target π^*:

$$r_t - r^* = \frac{\theta}{\xi}(\pi_t - \pi^*) \tag{5}$$

In this model, rational expectations for inflation take the following form:

$$\pi_{t+1/t} = \frac{1}{1-\phi}\big[(1-\phi)\pi_t + \alpha E_t(y_{t+1})\big] = \\ \frac{\alpha\theta}{1-\phi}\pi^* + \frac{1-\phi-\alpha\theta}{1-\phi}\big[\phi\pi_{t/t-1} + (1-\phi)\pi_{t-1} + \alpha y_t + e_t\big] \tag{6}$$

Since we wish to employ our decomposition of oil prices that identifies *changes* in the output gap (see Section 2.1.2) we convert this equation to a difference equation:

$$\Delta\pi_{t+1/t} = \frac{1-\phi-\alpha\theta}{1-\phi}\big[\phi\Delta\pi_{t/t-1} + (1-\phi)\Delta\pi_{t-1} + \alpha\Delta y_t + \Delta e_t\big] \tag{7}$$

In accordance with this specification, we estimate the following regression model, using our proposed decomposition of oil prices to account for changes in the output gap and cost-push shocks and allowing for a structural change after the global financial crisis:

$$\Delta pc_t^{beir} = \beta_0 + \beta_1\Delta pc_{t-1}^{beir} + \beta_2\Delta pc_{t-1}^{beir} \times dprecri_t + \beta_3\Delta pc_{t-1}^{\pi} + \beta_4\Delta pc_{t-1}^{\pi} \times dprecri_t + \\ \beta_5(\hat{\alpha}_1 pc_t^{\Delta cmd}) + \beta_6(\hat{\alpha}_1 pc_t^{\Delta cmd}) \times dprecri_t + \beta_7\hat{u}_t + \beta_8\hat{u}_t \times dprecri_t + \beta_9 dprecri_t + \epsilon_t^{beir} \tag{8}$$

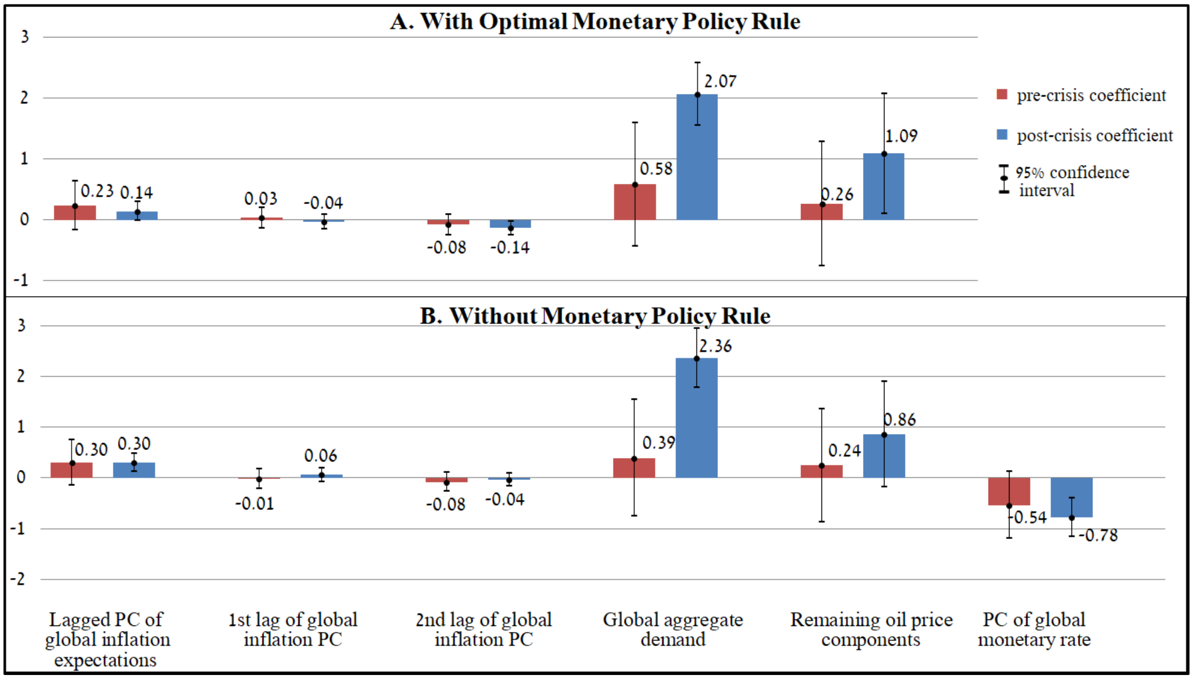
Where pc_t^{beir} and pc_t^{π} are the first principle components of five-year inflation expectations and annual inflation, respectively, rescaled to match the data.[24] $\hat{\alpha}_1 pc_t^{\Delta cmd}$ is our estimate for the global aggregate demand factor embedded in oil prices and $\hat{u}_t$ is the remaining component of oil prices (fitted value and residual from Equation (1), respectively).

As explained in Section 2.3, we assume that the response of global aggregate demand to other shocks is not instantaneous and therefore assume $pc_t^{\Delta cmd}$ is exogenous in Equation (8). Since we cannot assert that $\hat{u}_t$ is exogenous, we use the instruments derived in Section 2.2 to capture exogenous changes in oil prices. Two-stage least square estimation results are depicted in Panel A in Figure 6 (detailed results appear in Table 3 in the Appendix).

Our results indicate that the only coefficient that significantly changed after the crisis is that of global aggregate demand. Other than that variable, no other determinant of inflation expectations has a different effect since the onset of the crisis. Specifically, the adaptive component of expectations is low and stable in our sample. There was also no significant change in the response of expectations to changes in oil prices unrelated to global aggregate demand. Examining the structural specification of inflation expectations (7) we find that an increase in the coefficient on the output gap with stability of the other coefficients is necessarily due to an increase in α, the perceived slope of the Phillips curve, while the adaptive coefficient $1-\phi$ remained stable. The analysis we perform in the following section provides additional evidence for this conclusion.

[24] In order to facilitate the interpretation and comparison of regression coefficients, the first principal components were multiplied by coefficients c^{beir} and c^{π} from a country panel regression $y_i = c_{0,i} + c^y PC^y + \epsilon_i$ for $y \in \{beir, \pi\}$ and $i \in \{\text{USA,UK,France}\}$.

Figure 6: Determinants of the Monthly Change in the First Principal Component of Breakeven Inflation Rates - Partial Effects Before and After the Global Financial Crisis (2004-17)



Notes: Panels A and B depict 2SLS estimation results of Equations (8) and (11), respectively. For each variable, the post-crisis partial effects is the coefficients on the variable itself, and the pre-crisis effect is the sum of that coefficient and of the coefficient on the interaction of the variable with the pre-crisis dummy. For example, the partial effect of lagged inflation expectations is the estimator of $\beta_1 + \beta_2$ for the pre-crisis period, and β_1 for the post-crisis period. Detailed results appear in Table 3 in the Appendix.

The fact that expectations did not become more adaptive or more responsive to oil-specific price changes since the crisis implies that they have so far remained anchored and that the concerns for the credibility of inflation targeting were premature. Instead, our results point to a perceived structural change in the Philips curve that made inflation expectations more responsive to global aggregate demand and thus more correlated with oil prices which contain information regarding global output.

While we do not directly estimate the Phillips curve and therefore cannot take a stand on whether the slope has indeed changed or was it merely *perceived* by the public to have changed, some recent papers find evidence of structural change in the Phillips curve in recent years. Riggi and Venditti (2015) show an increase in the sensitivity of inflation to the output gap in the Euro area since the sovereign debt crisis and offer two structural explanations for this change.[25] First, lower nominal rigidities, and second, a fall in the number of firms in the economy that lowers the elasticity of demand. For the USA economy, Stella and Stock (2012)

[25]Similar results for the Euro area were also obtained by Oinonen and Paloviita (2014) and by Larkin (2014).

find evidence of a stronger inflation-unemployment relationship since the global financial crisis. We believe that a fruitful direction for future research will be to use our measure for the global output gap, namely the first principal component of commodity prices, to test for changes in the Phillips curve in a global perspective.

3.2 Rational Expectations without Specifying the Policy Rule

Monetary policy has operated since the global financial crisis in an environment of interest rates approaching the 'effective lower bound' and saw an extended use of unconventional policies. We, therefore, consider an alternative specification of rational inflation expectations which is agnostic to the monetary policy rule. In Section 3.1 we used the Phillips curve and the IS curve (Equations (3) and (4), respectively) as well as an optimal monetary rate rule (5) to formulate rational inflation expectations. However, using only (3) and (4), we can construct an alternative formulation of expectations which does not assume any structure of the monetary policy rate:

$$\pi_{t+1/t} = \frac{1}{1-\phi}\big[(1-\phi)\pi_t + \alpha E_t(y_{t+1})\big] = \phi\pi_{t/t-1} + (1-\phi)\pi_{t-1} + \alpha y_t - \frac{\xi\alpha}{1-\phi}(r_t - r^*) + e_t \quad (9)$$

and in first differences:

$$\Delta\pi_{t+1/t} = \phi\Delta\pi_{t/t-1} + (1-\phi)\Delta\pi_{t-1} + \alpha\Delta y_t - \frac{\xi\alpha}{1-\phi}\Delta r_t + \Delta e_t \quad (10)$$

We estimate the following model which adds to (8) a measure of the change in the global monetary rate, $pc_t^{\Delta i}$ - the first principal component of the change in the monetary interest rate in the USA, UK and the Euro area:[26]

$$\begin{aligned}\Delta pc_t^{beir} = \beta_0 + \beta_1\Delta pc_{t-1}^{beir} + \beta_2\Delta pc_{t-1}^{beir} \times dprecri_t + \beta_3\Delta pc_{t-1}^{\pi} + \beta_4\Delta pc_{t-1}^{\pi} \times dprecri_t +\\ \beta_5(\hat{\alpha}_1 pc_t^{\Delta cmd}) + \beta_6(\hat{\alpha}_1 pc_t^{\Delta cmd}) \times dprecri_t + \beta_7 pc_t^{\Delta i} + \beta_8 pc_t^{\Delta i} \times dprecri_t +\\ + \beta_9\hat{u}_t + \beta_{10}\hat{u}_t \times dprecri_t + \beta_{11} dprecri_t + \epsilon_t^{beir} \quad (11)\end{aligned}$$

Following our discussion in the previous section, it is reasonable to assume that global demand is exogenous in (11). However, the monetary interest rate is clearly endogeneous and we also treat $\hat{u}_t$ as such. We thus estimate (11) using the lag of $pc_t^{\Delta i}$ as an instrument for the monetary rate, and the instruments detailed in Section 2.3 for $\hat{u}_t$.

Two-stage least-square estimation results of model (11) are depicted in Panel B of Figure 6 and they portray a similar picture to the one portrayed by the estimation of Equation (8), namely that the effect of global aggregate demand on medium-term inflation expectations increased substantially since the global financial crisis while the effect of the other components remained stable. Examining the structural specification (10) confirms that these results may only be explained by a perceived rise in the slope of the Phillips curve, α, while the parameter of inflation adaptiveness, $1-\phi$, remains unchanged. We conclude that there was no change in the anchoring of inflation expectations after the crisis, but rather a perceived structural change that made inflation expectations more sensitive to global aggregate demand.

[26] Note that in the structural model the real interest rate is used. Since the measurement of the real interest rate is subject to some debate we decompose the real interest, using the Fisher identity to the nominal yield and inflation (expectations) and estimate the equation using the nominal policy rate. The interpretation fo the coefficient on inflation is adjusted accordingly.

4 Robustness

In this section we perform four main robustness checks to our results. The first is to use household expectations instead of expectations derived from financial markets. The second is to show that our results are not driven by the financial turmoil around the collapse of Lehman Brothers. In the third and final sections we consider two possible reservations regarding our interpretation of the first principle component of commodity prices as reflecting changes in global aggregate demand: The direct effect of oil prices on other commodities and the effect of the USA Dollar exchange rate. Additional robustness checks are deferred to the appendix.

4.1 Household Inflation Expectations

So far, our analysis of inflation expectations focused on five-year breakeven inflation rates. While this measure is closely monitored by policymakers and is readily available for a substantial set of countries, it has some shortfalls [Coibion and Gorodnichenko (2015)]. First, it is affected by financial factors such as risk and liquidity premiums. Second, one might argue that a five-year horizon is too long to consider in a context of a Phillips curve which is constructed to capture the effect of nominal rigidities. Therefore, in a way of robustness test, we repeat the analysis preformed in the two previous sections using household surveys, a measure of one-year inflation expectations that is commonly used in the literature examining the Phillips curve.

Data availability only allows us to use quarterly data, however, we are able to extend our sample to 2000Q1-2017Q3. We extract the first principal component of household surveys for the USA, UK and Euro area, pc_t^{sur}.[27] Following the convention in the Phillips curve literature and more recently Coibion and Gorodnichenko (2015), we estimate the two models of rational expectations in levels (Equations (6) and (9))[28] . For this purpose we first decompose the *log level* of oil prices

$$oil_t = \gamma_0 + \gamma_1 pc_t^{cmd} + v_t$$

where pc_t^{cmd} is the first principal component of levels of commodity prices (in log terms). This factor serves as an estimate of the global output gap so we interpret the fitted value of the regression, $\hat{\gamma}_1 pc_t^{cmd}$, as the component of oil prices driven by the level of global aggregate activity. The change in the residual, $\Delta\hat{v}_t$, is a proxy for cost-push shocks. Using these measures we estimate the following two models of rational inflation expectations, one without

[27] Our data sources: For the USA, a quarterly average of expectations from the Michigan Survey of Consumers; For the UK, the Bank of England Inflation Attitude Survey which is preformed quarterly; For the Euro area, a quarterly average of the OECD Consumer Opinion Survey regarding future tendency of consumer prices. The first two surveys ask respondents for a point estimate of expected inflation, while the latter asks about the *tendency* of prices. Although the two types of surveys are not directly comparable, we claim that the first principal component of the three measures captures the main common factor of expected inflation due to the fact that two of the three measures are point estimates of inflation. The first principal component explains 62% percent of the variation in the data and gives weights of 0.61, 0.62 and 0.49 for the USA, UK and Euro area, respectively.

[28] All the variables in the quarterly regression are stationary using the Engle-Granger test.

the monetary rate and one with the monetary rate:

$$pc_t^{sur} = \beta_0 + \beta_1 pc_{t-1}^{sur} + \beta_2 pc_{t-1}^{sur} \times dprecri_t + \beta_3 pc_{t-1}^{\pi} + \beta_4 pc_{t-1}^{\pi} \times dprecri_t + \beta_5(\hat{\gamma}_1 pc_t^{cmd}) + \beta_6(\hat{\gamma}_1 pc_t^{cmd}) \times dprecri_t + \beta_7 \Delta\hat{v}_t + \beta_8 \Delta\hat{v}_t \times dprecri_t + \beta_9 dprecri_t + \epsilon_t \quad (12)$$

$$pc_t^{sur} = \beta_0 + \beta_1 pc_{t-1}^{sur} + \beta_2 pc_{t-1}^{sur} \times dprecri_t + \beta_3 pc_{t-1}^{\pi} + \beta_4 pc_{t-1}^{\pi} \times dprecri_t + \beta_5(\hat{\gamma}_1 pc_t^{cmd}) + \beta_6(\hat{\gamma}_1 pc_t^{cmd}) \times dprecri_t + \beta_7 pc_t^{i} + \beta_8 pc_t^{i} \times dprecri_t + + \beta_9 \Delta\hat{v}_t + \beta_{10} \Delta\hat{v}_t \times dprecri_t + \beta_{11} dprecri_t + \epsilon_t \quad (13)$$

2SLS estimation results of these models are depicted in Figure 7 (detailed results are reported in Table 4 in the Appendix). Both specifications indicate, as found in Coibion and Gorodnichenko (2015), that the effect of oil prices on consumers' expectations is significant and has increased. However, the increase can be attributed to the effect of global aggregate demand embedded in oil prices, while the effect of all other variables remained stable. This means that similarly to breakeven inflation rates, household expectations have not become more adaptive since the crisis but are consistent with a perceived increase in the slope of the Phillips curve.

Coibion and Gorodnichenko (2015) find that incorporating household expectations in the estimation of a standard Phillips curve for the USA resolves the puzzle of the "missing disinflation" in the aftermath of the global financial crisis. This is due to the rise in household expectations at that period which they attribute to a rise in oil prices. Our results can be interpreted as indicating that it is not the rise in oil prices themselves that affected household expectations at the aftermath of the crisis, but rather the information regarding the global output gap that is embedded in them.

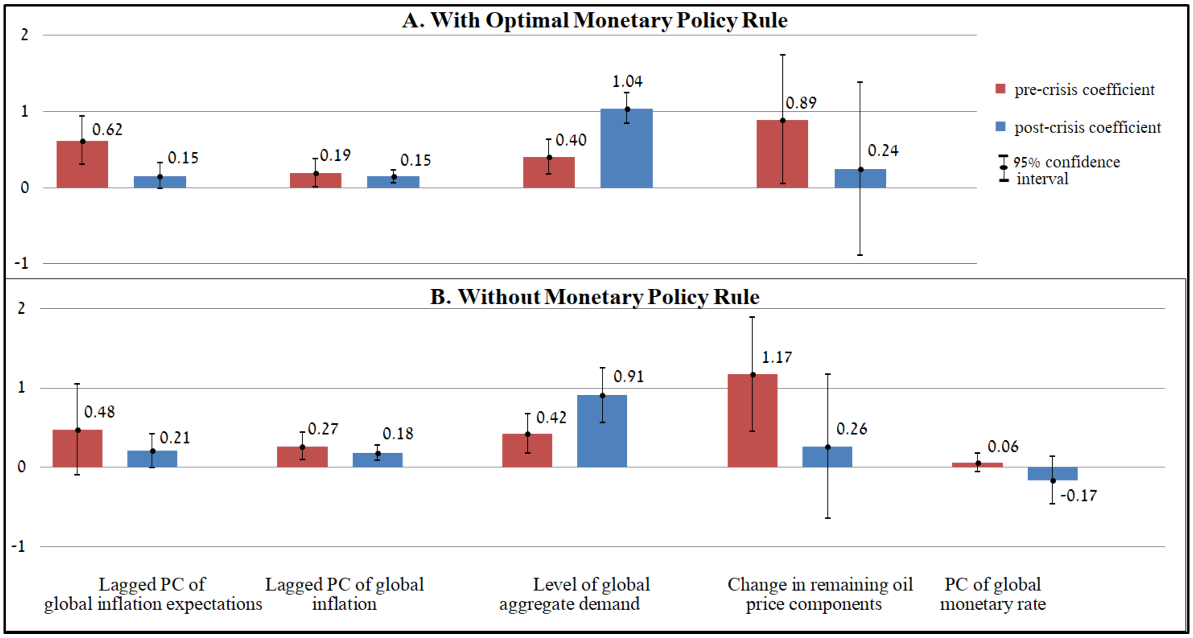
4.2 Excluding the Period of the Financial Turmoil Around the Collapse of Lehman Brothers

In Section 2.3 we showed that since September 2008 global aggregate demand conditions embedded in oil prices have a stronger effect on medium-term inflation expectations. One might argue that the strong effect stems from a short period following the collapse of Lehman Brothers and does not reflect the later period. Nevertheless, in this section we show that while the months following Lehman's collapse contributed to our identification, they do not fully account for our main results. Namely, we find that even if we disregard a wide period around Lehman's collapse, the effect of global aggregate demand conditions on inflation expectations increased in the post-crisis period relative to the pre-crisis period. On the other hand, the effect of the remaining component of oil remained unchanged.

We consider a model which is based on Equation (2) but instead of a single breakpoint in the sample, we partition the sample to three periods: 2003M03-2007M12 (pre-crisis), 2008M01-2009M12 and 2010M01-2017M08 (post-crisis).

$$\Delta pc_t^{beir} = \beta_0 + \beta_1(\hat{\alpha}_1 pc_t^{\Delta cmd}) + \beta_2(\hat{\alpha}_1 pc_t^{\Delta cmd}) \times d_t^{03-07} + \beta_3(\hat{\alpha}_1 pc_t^{\Delta cmd}) \times d_t^{08-09} + \beta_4 \hat{u}_t + \beta_5 \hat{u}_t \times d_t^{03-07} + \beta_6 \hat{u}_t \times d_t^{08-09} + \beta_7 dprecri_t + \epsilon_t \quad (14)$$

Figure 7: Determinants of Household Inflation Expectations - Partial Effects Before and After the Global Financial Crisis (2004-17)

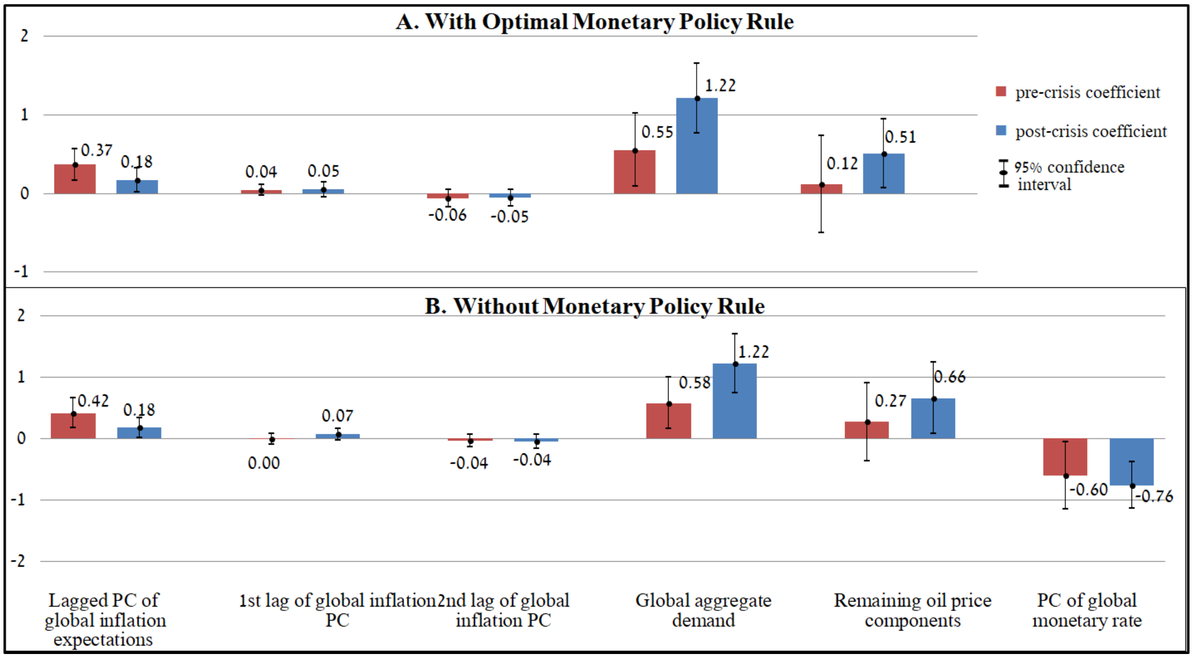


Notes: Panels A and B depict 2SLS estimation results of Equations (12) and (13), respectively, for the period 2000Q1-2017Q3. For each variable, the post-crisis partial effects is the coefficients on the variable itself, and the pre-crisis effect is the sum of that coefficient and of the coefficient on the interaction of the variable with the pre-crisis dummy. For example, the partial effect of lagged inflation expectations is the estimator of $\beta_1 + \beta_2$ for the pre-crisis period, and β_1 for the post-crisis period. Confidence intervals are calculated with Newey-West standard errors. Detailed estimation results appear in Table 4 in the Appendix.

Where d^{03-07} and d^{08-09} are dummy variables for 2003M03-2007M12 and 2008M01-2009M12, respectively. We can then compare the coefficient of pre-2007 to those of post 2010, disregarding an extensive period around the collapse of Lehman Brothers. The results of this exercise are compared to our baseline results in Table 5. In both models the coefficient of the global aggregate demand factor increases significantly after the crisis, while the coefficient of the remaining components is stable (the difference between the periods is insignificant).

Next we repeat the same exercise on our structural equations and estimate variants of Equations (8) and (11) that include interactions with the dummies d^{03-07} and d^{08-09} instead of $dprecrisis$. Our main results, shown in figure 8, are that the impact of changes in global output gap on changes in breakeven expectations increased significantly, whereas the effect of idiosyncratic changes to oil prices did not significantly change. Admittedly, the significance of the difference between the two periods is lower than in our benchmark regressions, however, it is significant at the 5 percent level.

Figure 8: Determinants of the Monthly Change in the First Principal Component of Breakeven Inflation Rates - Partial Effects Before and After the Global Financial Crisis Excluding 2008 and 2009 (2003-17)



Notes: Panels A and B depict 2SLS estimation results of variants of Equations (8) and (11) that include interactions with the dummies d^{03-07} and d^{08-09} instead of $dprecrisis$. The figure compares coefficients of the period 2003M03-2007M12 (pre-crisis) to those of the period 2009M01-2017M08 (post-crisis). Confidence intervals were calculated with Newey-West standard errors. Detailed results are available from the authors upon request.

4.3 The direct effect of oil prices on the other commodities

We consider the possibility that the co-movement in commodity prices captured by $pc_t^{\Delta cmd}$ may be related to energy prices since manufacturing of all commodities requires some use of energy. If this effect is significant, $pc_t^{\Delta cmd}$ may be capturing the evolution of energy prices rather than global aggregate demand. However, we argue that energy prices have only a modest effect on other commodity prices, so they do not dominate the first principal component.

First, we note that the energy component contained in agriculture and metal industries is small. To illustrate this point, we examine data from the USA Department of Commerce regarding six industries that best match the S&P non-energy commodities.[29] In each of these six industries we calculate the value of energy-intensive inputs, as a share of total output in that industry. As specified in Table 2, the share of total output that can be associated with energy-intensive inputs is lower than 17 percent in all six industries. This is consistent with

[29]The data was extracted from the 2007 input-output use table. Industry classifications are based on the Bureau of Economic Analysis (BEA) classifications.

Table 2: Value of Energy-Intensive Inputs as a Share of Total Output in Non-Energy Industries

Intermediate industries / Final product industries	Petroleum (1)	Transportation (2)	Electric power & natural gas (3)	Chemical products of petroleum & gas (4)	Support activities of mining (5)	**Total**
Oilseed farming	4.21%	1.99%	0.69%	-	-	**6.89%**
Grain farming	9.78%	4.24%	2.11%	-	-	**16.13%**
Other crop farming	6.24%	1.34%	1.55%	-	-	**9.13%**
Beef cattle ranching & farming	5.74%	4.15%	0.76%	-	-	**10.65%**
Iron, gold, silver & other metal ore mining	8.99%	1.25%	4.09%	1.14%	1.26%	**16.73%**
Copper, nickel, lead & zinc mining	3.76%	1.23%	3.21%	0.51%	1.06%	**9.77%**

Source: USA Department of Commerce (2007 input-output use table) and authors calculations. (1) Includes petroleum refineries and other petroleum and coal products manufacturing. (2) Includes the following forms of transportation: air, rail, water, truck and pipeline. (3) Includes natural gas distribution, and electric power generation, transmission and distribution. (4) Includes petrochemical manufacturing and industrial gas manufacturing. (5) Includes drilling oil and gas wells, and other support activities for mining.

the findings of Baffes (2007) which reports pass-through rates of 0.11-0.19 from oil prices to prices of metals and agricultural commodities.

Second, we perform a Granger Causality test between $pc_t^{\Delta cmd}$ and the monthly rate of change in the S&P *energy* index.[30] The test indicates that we cannot reject the hypothesis that the energy index does not Granger cause $pc_t^{\Delta cmd}$ (F-statistic of 0.70). This means that given past information regarding the first principal component, energy prices have no significant contribution to forecasting $pc_t^{\Delta cmd}$. The result supports our argument that energy prices have a limited effect on $pc_t^{\Delta cmd}$.

Interestingly, a Granger Causality test for the other direction shows that $pc_t^{\Delta cmd}$ Granger causes the monthly rate of change in the energy index (F-statistic of 4.51 for the null hypothesis that $pc_t^{\Delta cmd}$ does not Granger cause the monthly rate of change in the energy index).

[30] The S&P energy index includes contracts on WTI crude oil, Brent crude oil, heating oil, gasoline, gasoil and natural gas.

This result suggests that energy prices are highly influenced by global aggregate demand. An even stronger result is obtained when we test the hypothesis that $pc_t^{\Delta cmd}$ does not Granger cause the monthly rate of change in the prices of Brent crude oil (F-statistics of 4.89).

4.4 Controlling for the USA Dollar exchange rate

Since all commodities are denominated in USA Dollars it may be argued that our measure of global demand extracted from the first principle component of all commodities might reflect changes in the USA Dollar exchange rate. While it is reasonable to assume that changes in the USA Dollar exchange rate are endogenous to shocks to global demand we nevertheless control for the exchange rate in our baseline regression. In this robustness we also subject the data to the previous robustness check and exclude the period around the Lehman Brothers' crisis.

We regress the following two stage regression:

$$\hat{\alpha}_1 pc_t^{\Delta cmd} = \alpha_0 + \alpha_1 \Delta log DXY_t + v_t \tag{15}$$

Where the the first stage is:

$$\Delta log DXY_t = \beta_0 + \beta_1 \Delta log DXY_{t-1} + \epsilon_t$$

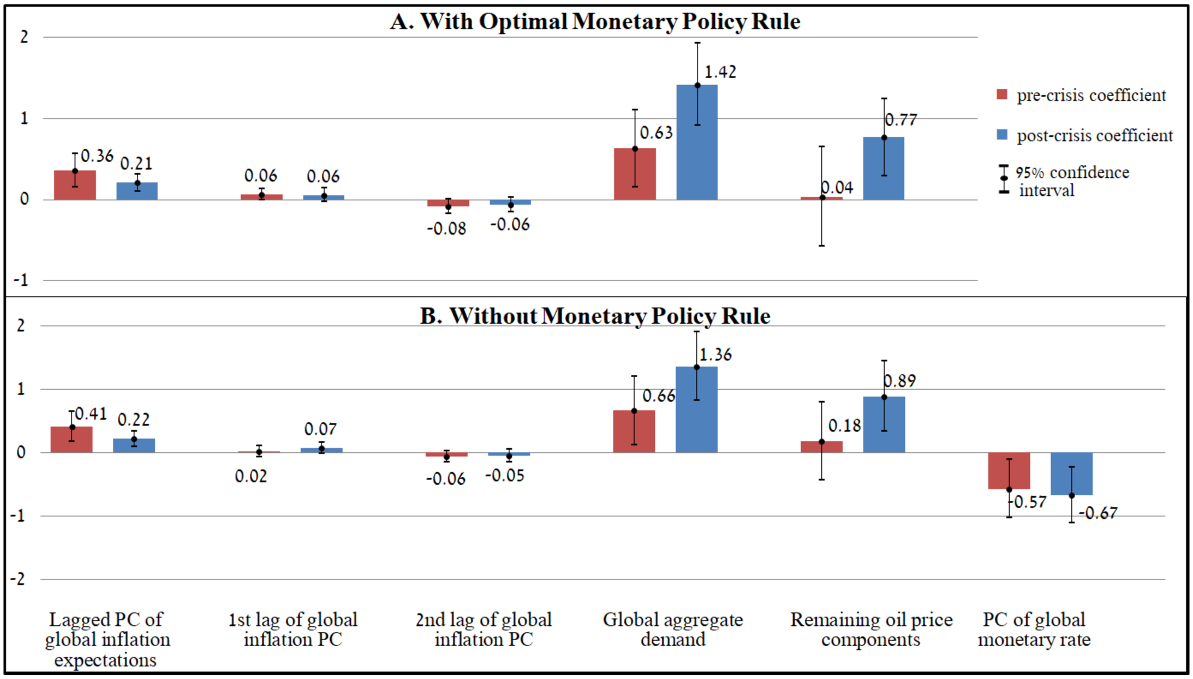
Where $\hat{\alpha}_1 pc_t^{\Delta cmd}$ is our measure for global demand and the independent variable is the change in the log of the Dollar trade weighted exchange rate (DXY). We take the residuals $\hat{v}_t$ from equation (15) above as an adjusted measure of global aggregate demand and re-estimate Equation (14) and the two structural equations, controlling the years 2008-2009 (as in Section 4.2). The results of equation (14) are reported in table 5 in the appendix and the results of the structural equations are depicted in figure 9.

Controlling for the exchange rate, we still find a significant increase in the effect of global aggregate demand on global inflation expectations after the crisis (the results are actually slightly more robust with respect to the estimation in the preceding exercise of controlling for the crisis years). However, this model also shows a marginally significant increase in the effect of the idiosyncratic component of oil prices.

5 Discussion: Implications of the Increased Correlation Between Oil Prices and Inflation Expectations

Our results show that inflation expectations for the medium-term are affected by oil prices and that this effect increased since the GFC. Decomposing oil prices, we showed that their reaction to oil specific shocks is small and remained stable, consistent with the accepted practice to look through supply shocks [Rogoff (1985); Ireland (2007)]. However, our results also show that inflation expectations react more to global aggregate demand shocks than previously. Since central bankers view the stability of medium and long term inflation expectations - anchoring - as indicators of the credibility of inflation targeting, our result could indicate an erosion of that credibility. In particular, the results may suggest that the

Figure 9: Determinants of the Monthly Change in the First Principal Component of Breakeven Inflation Rates - Partial Effects Before and After the Global Financial Crisis Excluding 2008 and 2009 and Controlling for the USA Dollar Trade Weighted Exchange Rate.



Notes: Panels A and B depict 2SLS estimation results of variants of Equations (8) and (11) that include interactions with the dummies d^{03-07} and d^{08-09} instead of *dprecrisis*, and that use residuals from Equation (15) as an estimator of global demand. The figure compares coefficients of the period 2003M03-2007M12 (pre-crisis) to those of the period 2009M01-2017M08 (post-crisis). Confidence intervals are calculated with Newey-West standard errors. Detailed results are available from the authors upon request.

public perceives that monetary authorities either look through demand shocks or may have changed their policy rules. These perceptions could lead to un-anchoring of expectations.

Embedded in a structural New Keynesian model with rational expectations, the same results suggest that, so far, expectations have not become un-anchored. The increasing correlation between inflation expectations and demand shocks is consistent with a structural change in the slope of the Phillips curve. Under an optimal policy rule, an increase in the slope of the Phillips curve (even if it is only a perceived rise), given a Taylor type monetary rule, should call for a weaker response of the monetary rate to deviations of inflation from target. In terms of the model presented in Section 3.1, this means that policymakers should reduce θ.[31]

[31] Following the derivation of the optimal policy rule in Orphanides and Williams (2004), a rise in α should be followed by a decline in θ such that $\frac{1-\phi-\alpha\theta}{1-\phi}$, the coefficient that premultiplies the explanatory variables in (7), will decrease (if only the perceived α rises then the data generating process of inflation, which depends on a weighted average of the perceived and the true α, still becomes more sensitive to the output gap and the

It is useful to clarify what exactly is meant by un-anchoring. In the context of a reduced form New Keynesian model (Phillips curve) un-anchoring could be related to changes in the degree of backward looking behavior or persistence of past expectations. Our finding for the global Phillips curve, similar to those of Blanchard (2016) for the USA economy show no such change (for financial market data and household survey data). Another approach is to test whether expectations react more to idiosyncratic shocks. Our results indicate, in the spirit of Beechey et al. (2011) that we cannot reject the hypothesis that this did not happen in the case of global five year breakeven rates. Our findings, however, are consistent with a steepening of the Phillips curve which means that for a given demand shock, inflation volatility increases. Increasing inflation volatility also means that rational agents' inflation expectations for the short and medium term become less stable.

The implications of our results are that care should be taken by monetary authorities in interpreting the correlation between oil prices and inflation expectations. In particular, the assessment by policy makers [IMF (2016)] of un-anchoring may lead to policy actions, including forward guidance, that may actually contribute to un-anchoring of longer term forward inflation expectations. While this is beyond the scope of this paper, beginning in 2014 we witness a sharp decline five-year to five-year forward inflation expectations. What could explain this change? We offer two possible, mutually non-exclusive, explanations. The first is that monetary policy had been operating since 2008 in a new environment where interest rates have reached the "effective lower bound".[32] At the same time unconventional monetary tools such as quantitative easing and forward guidance are employed. Our findings suggest that the public may perceive these measures as less effective in restoring inflation to its target. Moreover, according to Morris and Shin (2018), this could have been amplified by non-conventional monetary tools. Central bank communications that tied future policy to long term forward expectations could have led to a vicious circle of declining long term expectations.

The second explanation relates to a perceived change in monetary policy objectives. Before the global financial crisis monetary authorities followed, or were expected to follow, a Taylor rule that puts a large weight on meeting the inflation target and a lower weight on stabilizing output. At that period inflation expectations were firmly anchored at the two percent level. However, the financial crisis of 2008 stressed the importance of financial stability in maintaining output growth and price stability. Consequently, several central banks adopted "leaning against the wind" approaches in recent years [ECB (2010); Svensson (2014); Filardo and Rungcharoenkitkul (2016)]. While the effectiveness of using the central bank rate to achieve macro-prudential goals, and particularly to contain asset price bubbles, has been under debate [Galí (2014); Galí and Gambetti (2015)], and is considered by some to be a blunt tool in dealing with financial stability issues [Bernanke (2010); Blanchard et al. (2010)], nevertheless, monetary authorities became more attentive to financial conditions in recent years. It could be that the public interpreted this as a decline in the commitment to uphold the inflation target in the medium term. A variant of this explanation is that

theoretical result carries through). Our empirical results that show that only the parameter α increased are consistent with an offsetting decline such that $\frac{1-\phi-\alpha\theta}{1-\phi}$ did not change. Note, however, that the reduced form estimation does not allow us to estimate ξ the elasticity of output with respect to changes in the interest rate.

[32] We use the term "zero lower bound" to refer to the effective lower bound of nominal interest rates.

when inflation deviates below the target, the public believes that monetary authorities will be less aggressive in attempting to move it back into the target zone, i.e., that the weight on inflation in the Taylor rule is asymmetric with respect to positive and negative deviations from the target.

6 Conclusions

We used the first principal component of a variety of commodity prices to decompose the changes in oil prices to those emanating from a global demand factor and those that arise due to oil specific ones. We use this decomposition to analyze the increase in the correlation between oil prices and inflation expectations following the onset of the global financial crisis and find that it is mainly due to a stronger effect of global aggregate demand embedded in oil prices on expected inflation.

We compute global inflation and monetary regime variables using principal component method and estimate a global Phillips curve. We cannot reject the hypothesis that expectations remained anchored. Instead, our structural estimation suggests that the increased volatility of inflation expectations with respect to global demand factors can be explained by an increase in the perceived slope of the Phillips curve. Our findings have implications for monetary policy.

The high degree of covariation in major global macroeconomic aggregates allows to extract global factors using principle component analysis. While we used this methodology to focus on the global factors themselves, policy makers in advanced small open economies can use it to identify domestic factors that they can hope to control and hone their policies accordingly. Specifically, the principal component we use as a proxy for global aggregate demand can be readily employed to monitor in real time global aggregate demand conditions. Moreover, this factor can be useful for macroeconomic empirical research that uses higher temporal frequency data, either as a proxy or as an instrument. For example, the proxy can be used to infer the contribution of global aggregate demand shocks on monthly, country specific, price level data. Another example is to use the variable as an instrument in research that uses the CPI which is usually determined simultaneously with the left hand variable in question. Finally, one can use our proxy to revisit some of the studies on monetary policy and oil prices since the 1970s.

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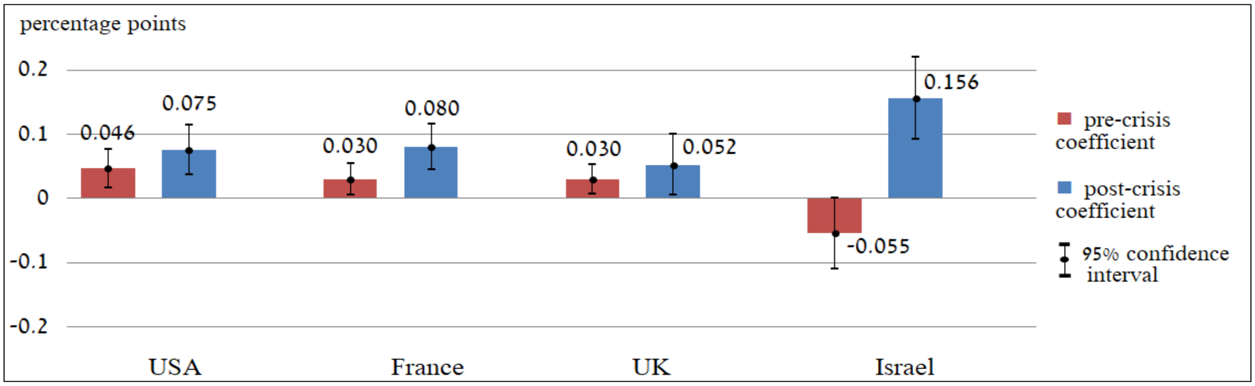
Figure 10: Partial Correlation between a 10% Increase in Oil Prices and Five-Year Breakeven Inflation Rates (2000-17)



Notes: The figure is based on estimation results of Equation (16) (detailed results appear in Table 6. Sample for USA begins in 2002M09 and for France in 2003M02). Since this is a linear-log model, the estimated effect of a 10% increase in oil prices on country i's five-year breakeven inflation rate is $\log(1.1)(\delta_{1_i} + \delta_{2_i} dprecri_t)$. Confidence intervals are based on Newey-West standard errors.

Appendix

A Oil Prices and Inflation Expectations

In this section we show more rigorously the observed relationship between oil prices and expected inflation (Figure 1). We estimate country-specific regressions of five-year breakeven inflation rates, $beir_{i,t}$, on oil prices, allowing for a different effect before and after the global crisis.[33] For each country i we estimate the following regression:

$$beir_{i,t} = \delta_{0_i} + \delta_{1_i} oil_{i,t} + \delta_{2_i} oil_{i,t} \times dprecri_t + \delta_{3_i} dprecri_t + \delta_{4_i} dleh_{i,t} + \epsilon_{i,t} \quad (16)$$

Where $oil_{i,t}$ is the log price of Brent crude oil in domestic currency[34], $dprecri_t$ is a dummy for the pre-crisis period (2004M01-2008M08), $dleh_{i,t}$ is a dummy variable that equals one circa September 2008 (indicating known liquidity problems in country i's government bonds market).

Figure 10 depicts the estimated correlation between oil prices and five-year breakeven inflation rates (detailed estimation results are reported in Table 6). Similarly to the correlations reported in Figure 1, the regression results show a strengthening correlation between oil prices and medium-term inflation expectations after the onset of the global crisis.

[33] Due to availability of five-year breakeven inflation rates data, we perform all analysis involving expected inflation for the period 2004M01-2017M08.

[34] Similar results are obtained when regressing the dollar price of Brent oil and controlling for the exchange rate.

B Methodology for Constructing the First Principal Component

In Section 2.1 we presented our estimator of global aggregate demand - the first principal component of commodity prices. We now briefly discuss the methodology for constructing this factor (see Stock and Watson (2011) for more details).

The first principal component is a factor that best explains the total variation in the data. For a data set of N variables over T periods, let $X_t \in \mathbb{R}^N$ denote the column vector of variables in period $t \in \{1, ..., T\}$. In our case there are $N = 20$ commodities and X_t is the vector of monthly changes in prices. The first principal component is the factor $(f_1, ..., f_T) \in \mathbb{R}^T$ that, together with a loading vector $\Lambda \in \mathbb{R}^N$, solves the least square problem,

$$\min_{f_1,..,f_T,\Lambda} \frac{1}{NT} \sum_{t=1}^{T} (X_t - \Lambda f_t)'(X_t - \Lambda f_t)$$
$$s.t. \quad ||\Lambda|| = 1$$

The factor that solves this problem is a linear combination of the variables constructed as follows. Denote the sample variance matrix by $\hat{\Sigma} \equiv T^{-1} \sum_{t=1}^{T} X_t X_t'$ and let $\hat{\Lambda}$ be the normalized eigenvector of $\hat{\Sigma}$ associated with the largest eigenvalue. The first principal component estimator is then given by $\hat{f}_t = \hat{\Lambda}' X_t$ and the loading vector is $\hat{\Lambda}$.

The first principal component of the monthly rate of change of the 20 commodity prices is depicted in Figure 11.

C Decomposing Oil Prices

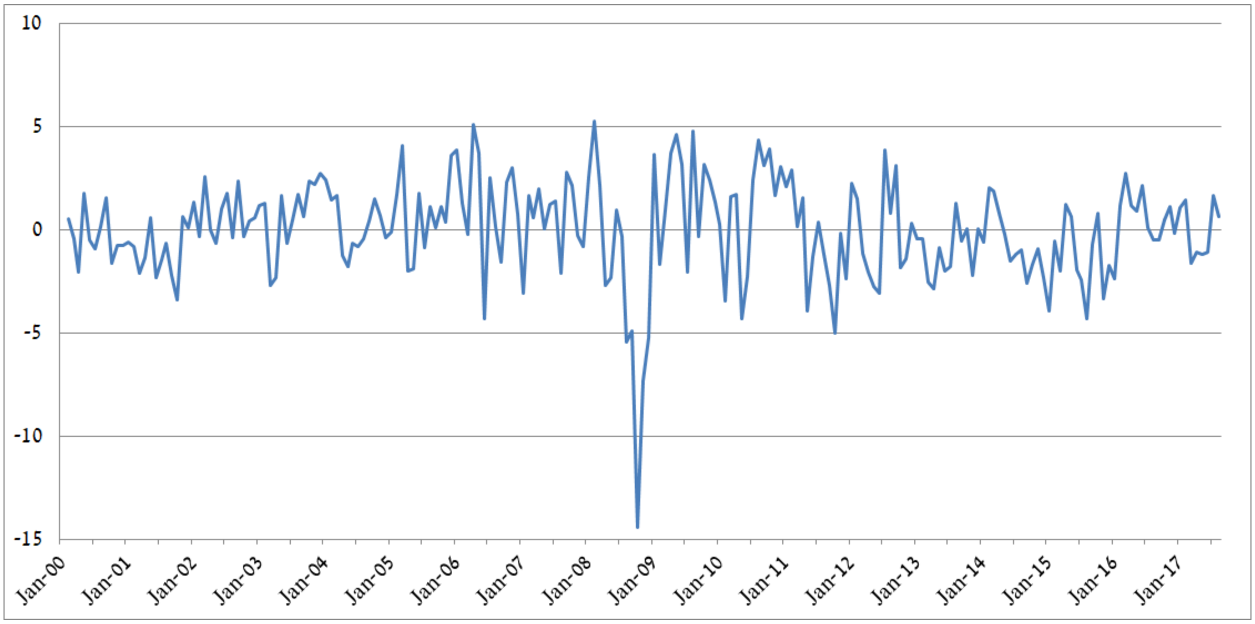
Recall from equation (1) that the basic decomposition of oil prices is $\Delta oil_t = \alpha_0 + \alpha_1 pc_t^{\Delta cmd} + u_t$, where $pc_t^{\Delta cmd}$ is the first principal component of commodity prices and the residual u_t captures all remaining remaining (orthogonal) variables affecting the change in oil prices. In the detailed decomposition (section 2.2) we added the proxy for OPEC's operation and weather variables:

$$\Delta oil_t = \alpha_0 + \alpha_1 pc_t^{\Delta cmd} + \alpha_2 opecref_t + \vec{\Gamma}_1 \cdot \vec{w}_t + \sum_{s=2}^{4} \vec{\Gamma}_s \cdot \vec{w}_t \, d_{s,t} + \sum_{s=2}^{4} \varphi_s d_{s,t} + u_t \tag{17}$$

Where $opecref_t$ is the OPEC "net references" proxy, $\vec{w}_t$ is a vector of the temperatures measured in the five continents, $\vec{\Gamma}_s$, $s = 1, .., 4$ are vectors of coefficients, and $d_{s,t}$ is a dummy variable for the season of the year.[35]

[35] We use the following partition of the year to seasons: Dec-Feb, Mar-May, Jun-Aug, Sep-Nov. In Appendix D.2 we provide robustness test for this specification using dummy variables for calendar months instead of seasons.

Figure 11: First Principal Component of Commodity Prices (2000-17) ($pc_t^{\Delta cmd}$)



Notes: The first principal component was calculated for monthly rates of change in prices of various commodities. See Section 2.1.1 for more details.

The least square estimator of the coefficient of $pc_t^{\Delta cmd}$ in Equation (17) is 0.022 (s.e. 0.0018), compared to an estimator of 0.023 (s.e. 0.018) in Equation (1).[36]

Figure 12 depicts the contribution of all elements in Equation (17) to the annual rate of change in oil prices. We see that the proxy for OPEC's operation explains a substantial portion of the price changes in several periods (admittedly, the weather component has less explanatory power). For example, we see that expansionary operations of OPEC since mid-2014 contributed considerably to the decline in prices. This is in line with our previous knowledge regarding the decreased ability of OPEC to collude in that period.

D Alternative Specifications

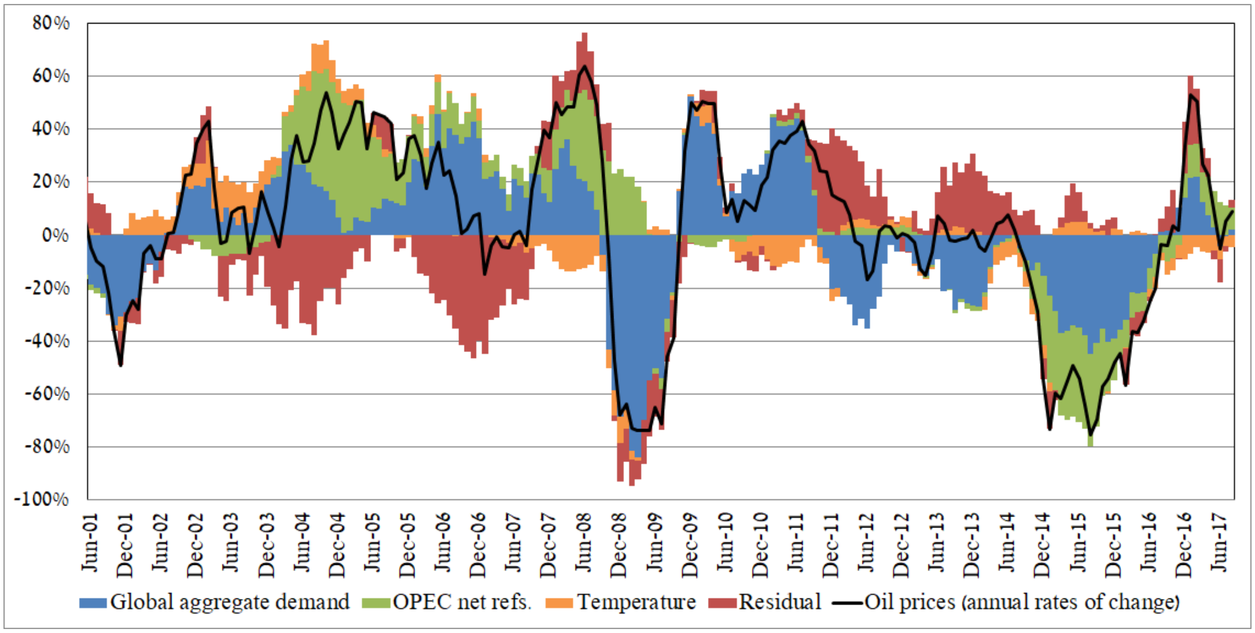
D.1 Basic Oil Price Decomposition

In this section we explore alternative specification for the decomposition of oil prices. Recall that the baseline specification, as presented in Equation (1), is:

$$\Delta oil_t = \alpha_0 + \alpha_1 pc_t^{\Delta cmd} + u_t$$

[36]Full estimation results of Equation (17) are compared to those of Equation (1) and several other specifications in Appendix D.2. The comparison reveals that the coefficient of $pc_t^{\Delta cmd}$ is robust at around 0.022. A possible concern we referred to is that OPEC is reacting to global aggregate demand. We test for the correlation coefficient of OPEC net references and our measure of global demand and find it to very low: -0.1. For robustness we estimate our two stage regression with the residual of a regression of OPEC references on our measure of global demand and the results are unchanged.

Figure 12: Detailed Decomposition of Annual Rates of Change in Oil Prices (2001-17)



Notes: The graph depicts annual rates of change in oil prices, together with the cumulative contribution of global aggregate demand and idiosyncratic elements, i.e., the twelve-month moving sum of the right-hand-side elements in Equation (17).

The OLS estimation results of the baseline model and several other specifications are summarized in Table 7. We examine different lag structures of the equation (columns (2)-(3)) and the use of the first principal component of *non-energy* commodities instead of $pc_t^{\Delta cmd}$ (columns (4)-(5)). We find that the estimate for the coefficient of the first principal component is robust at around 0.02.

In column (6) of Table 7 we present estimation results for real prices. We repeat the procedure specified in section 2.1 with all prices divided by USA core CPI. This means that we extract the first principal component of *real* commodity prices, $pc_t^{\Delta rcmd}$, and use it to decompose *real* oil prices. In the final column of Table 7 we perform another robustness check and use the real prices of oil prices and a principal component of real prices of commodities excluding energy and gold, $pc_t^{\Delta rneng}$, we also control for financial uncertainty by including the log of the VIX.

The final step in our analysis requires using the decomposition of oil prices to estimate the effect of global aggregate demand and other changes in oil prices on global expected inflation (Equation (2)). With either one of the decompositions specified in Table 7, the estimated coefficients in the final step are not significantly different from the ones in our baseline model, so we waive the presentation of the detailed results.

D.2 Detailed Oil Price Decomposition

This section specifies estimation results of the detailed decomposition of oil prices and the contribution of idiosyncratic components (Section 2.2). The first two columns of Table 8 present estimation results of the basic model (Equation (1)) and the detailed model (Equation (17)) of oil price decomposition. Comparing the two columns, we see that the coefficient of $pc_t^{\Delta cmd}$ is estimated at around 0.02 in both models, indicating that the variables added in the second model are orthogonal to $pc_t^{\Delta cmd}$.

For a robustness check, we present an alternative model in the third column of Table 8. It is similar to the detailed specification from the second column, except for a different specification of the weather variables. Recall that in Equation (17) we use the temperature data from five continents, interacted with dummy variables for the seasons of the year. In the third column of Table 8, we estimate a model with dummy variables for *calendar months*:

$$\Delta oil_t = \alpha_0 + \alpha_1 pc_t^{\Delta cmd} + \alpha_2 opecref_t + \vec{\Lambda}_1 \cdot \vec{w}_t + \sum_{m=2}^{12} d_{m,t}\,\vec{\Lambda}_m \cdot \vec{w}_t + \sum_{m=2}^{12} \rho_m d_{m,t} + u_t'' \quad (18)$$

Where $\vec{w}_t$ is the vector of the temperatures in the five continents, $\vec{\Lambda}_m$, $m = 1, ..., 12$ are vectors of coefficients, and $d_{m,t}$ is a dummy variable for the calendar month m. As seen in Table 8, the estimated coefficients of $pc_t^{\Delta cmd}$ and $opecref_t$ are essentially the same as those estimated in columns 1-2.

A leading topic in the public discussion regarding the 2014 oil price decline was technological developments in the production of shale oil. As shale oil is a substitute for crude oil, technology developments in its manufacturing are expected to lower prices of crude oil. To test this effect, we examined references of shale oil in the London Times (Figure 13).[37] There are not much references of shale oil prior to 2009 (45 references in the period 2000M01-2008M12, relative to 1317 in 2009M1-2017M08), and since 2014 the series of shale oil references, $shaleref_t$, is correlated with $opecref_t$ (partially by construction since some articles mention both OPEC and shale oil). Thus it is not surprising that shale oil references do not contribute to the estimation of oil price changes (forth column of Table 8).

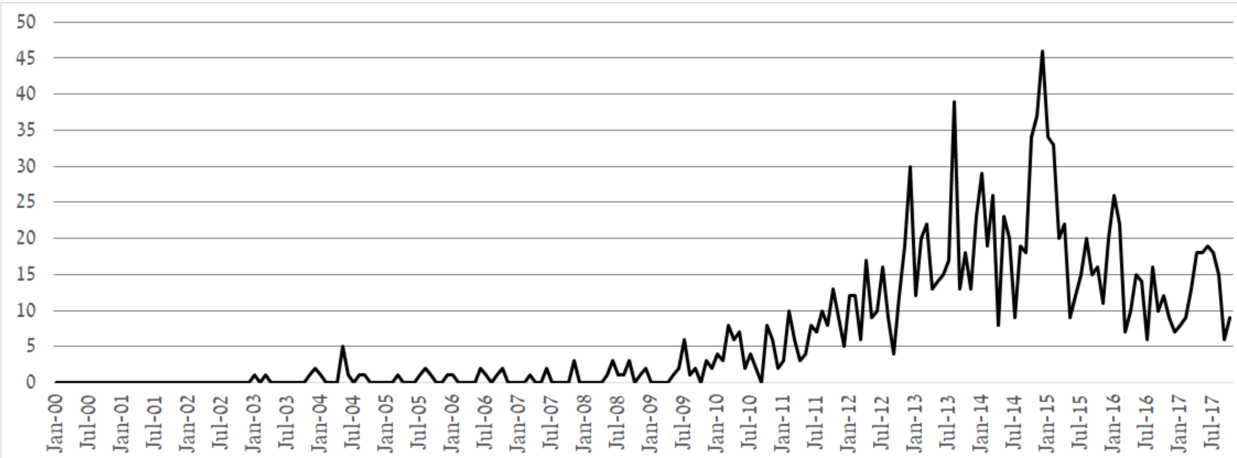
D.3 Alternative Data Frequencies

In this section, we test the sensitivity of our results to data frequency. In the baseline estimation we used monthly averages of daily data. This frequency conversion was used for the estimation of the first principal component, the decomposition of oil prices, and the analysis of breakeven inflation rates. We now repeat all the steps of our analysis using higher frequency (daily) data, as well as lower frequency (quarterly) data.

The estimation results of oil price decomposition and breakeven inflation rates analysis (Equations (1) and (2), respectively) are summarized in Table 9. In Panel A we observe that $pc_t^{\Delta cmd}$ has a positive and statistically significant coefficient in all three frequencies, and it explains 44-57 percent of the one-period percentage change in oil prices. In Panel B we observe that in all three frequencies the effect of the global aggregate demand factor embedded in oil prices (captured by the fitted value of Panel A, $\hat{\alpha}_1 pc_t^{\Delta cmd}$) is higher in the post-crisis period. The effect of the remaining component (captured by the residual from panel A, $\hat{u}_t$) is low throughout the sample period.

[37]We considered articles that mentioned the words "shale" and "oil" anywhere in the text, not necessarily adjacent.

Figure 13: References of Shale Oil in the London Times(2000-17)



Source: The London Times website (http://www.thetimes.co.uk/tto/search/)
Notes: The series is constructed of the number of articles in the London Times in that mention the words "shale" and "oil" somewhere in the text, not necessarily adjacent.

Tables

Table 3: Determinants of Global Inflation Expectations - 2SLS Estimation Results of Two Structural Models (Dependent Variable: Δpc_t^{beir})

	Model with Opimal Policy Rule	Model without a Policy Rule
const.	0.01	-0.002
	(0.014)	(0.016)
Δpc_{t-1}^{beir}	0.14*	0.3***
	(0.079)	(0.092)
$\Delta pc_{t-1}^{beir} \times dprecri_t$	0.09	0.002
	(0.221)	(0.248)
Δpc_{t-1}^{π}	-0.04	0.06
	(0.06)	(0.07)
$\Delta pc_{t-1}^{\pi} \times dprecri_t$	0.07	-0.08
	(0.106)	(0.121)
Δpc_{t-2}^{π}	-0.14**	-0.04
	(0.055)	(0.065)
$\Delta pc_{t-2}^{\pi} \times dprecri_t$	0.06	-0.041
	(0.102)	(0.114)
$\hat{\alpha}_1 pc_t^{\Delta cmd}$	2.07***	2.36***
	(0.263)	(0.296)
$\hat{\alpha}_1 pc_t^{\Delta cmd} \times dprecri_t$	-1.485**	-1.97***
	(0.579)	(0.654)
$pc_t^{\Delta i}$	-	-0.78***
		(0.191)
$pc_t^{\Delta i} \times dprecri_t$	-	0.24
		(0.386)
$\hat{u}_t$	1.09**	0.86
	(0.501)	(0.532)
$\hat{u}_t \times dprecri_t$	-0.83	-0.61
	(0.725)	(0.777)
$dprecri_t$	-0.01	0.02
	(0.026)	(0.033)
Adj. R^2	0.42	0.32
DW	1.91	2.00
Prob. J-stat.	0.41	0.78

Notes: The table shows 2SLS estimation results of Equations (8) in the first column and (11) in the second column for the period 2003M04-2017M08. The instruments used in the first model are the net measure of OPEC references in the London Times and a component of weather variables (see Section 2.2). In the second model we also use the lag of the principal component of monetary rates. All the instruments are interacted with the pre-crisis dummy. Standard errors are reported in parenthesis. Asterisks represent significance levels (*** $p < 1\%$, ** $p < 5\%$, * $p < 10\%$).

Table 4: Determinants of Global Household Inflation Expectations - 2SLS Estimation Results of Two Structural Models (Dependent Variable: pc_t^{sur})

	Model with Opimal Policy Rule	Model without a Policy Rule
const.	-0.31***	-0.51***
	(0.056)	(0.187)
pc_{t-1}^{sur}	0.15***	0.21*
	(0.084)	(0.106)
$pc_{t-1}^{sur} \times dprecri_t$	0.46	0.27
	(0.186)	(0.269)
pc_{t-1}^{π}	0.15	0.18***
	(0.043)	(0.048)
$pc_{t-1}^{\pi} \times dprecri_t$	0.05	0.08
	(0.104)	(0.1)
$\hat{\gamma}_1 pc_t^{cmd}$	1.04***	0.908***
	(0.101)	(0.172)
$\hat{\gamma}_1 pc_t^{cmd} \times dprecri_t$	-0.63**	-0.49**
	(0.157)	(0.189)
pc_t^{i}	-	-0.17
		(0.149)
$pc_t^{i} \times dprecri_t$	-	0.23
		(0.14)
$\hat{v}_t$	0.24	0.26
	(0.376)	(0.453)
$\hat{v}_t \times dprecri_t$	0.65	0.91
	(0.569)	(0.546)
$dprecri_t$	0.4***	0.48**
	(0.072)	(0.238)
Adj. R^2	0.91	0.91
DW	1.68	1.68
Prob. J-stat.	0.31	0.22

Notes: The table shows 2SLS estimation results of Equations (12) in the first column and (13) in the second column for the period 2000Q1-2017Q3. The instruments used in the first model are the net measure of OPEC references in the London Times and a component of weather variables (see Section 2.2). In the second model we also use the lag of the principal component of monetary rates. All the instruments are interacted with the pre-crisis dummy. Newey-West standard errors are reported in parenthesis. Asterisks represent significance levels (*** $p < 1\%$, ** $p < 5\%$, * $p < 10\%$).

Table 5: Sensitivity of Main Results to the Period of the Global Financial Crisis (Dependent Variable: Δpc_t^{beir})

		Baseline	Excluding the Collapse of Lehman Brothers	Controlling for DXY
Pre-Crisis Period		2003M03-2008M08	2003M03-2007M12	2003M03-2007M13
Post-Crisis Period		2008M09-2017M08	2010M01-2017M08	2010M01-2017M09
Pre-Crisis Coef.	Global aggregate demand ($\hat{\alpha}_1 pc_t^{\Delta cmd}$)	0.77*** (0.17)	0.62** (0.18)	0.57* (0.26)
	Remaining component ($\hat{u}_t$)	0.37 (0.25)	0.26 (0.32)	0.17 (0.32)
Post-Crisis Coef.	Global aggregate demand ($\hat{\alpha}_1 pc_t^{\Delta cmd}$)	2.33*** (0.24)	1.37*** (0.22)	1.58*** (0.23)
	Remaining component ($\hat{u}_t$)	1.27** (0.53)	0.64*** (0.22)	0.96*** (0.25)

Notes: The table shows 2SLS estimation of variants of Equation (2) which differ in the definitions of the pre and post crisis periods. In the first column (baseline model) they are defined according to a single breakpoint - the collapse of Lehman Brothers. In the second and third columns Equation (2) is estimated with two dummy variables that partition the sample to three periods: 2003M03-2007M12 (pre-crisis), 2008M01-2009M12 and 2010M01-2017M08 (post-crisis). The model in the third column also controls for the USA Dollar trade weighted exchange rate (15).

Newey-West Standard errors are reported in parenthesis. Asterisks represent significance levels (*** $p < 1\%$, ** $p < 5\%$, * $p < 10\%$).

Table 6: Estimation Results of Equation (16)
(Dependent Variable: $beir_{i,t}$)

	USA	France	UK	Israel
const.	-1.79*	-2.1***	0.4	-7.16***
	(0.95)	(0.77)	(1.02)	(0.95)
$oil_{i,t}$	0.79***	0.84***	0.55**	1.63***
	(0.21)	(0.19)	(0.25)	(0.17)
$oil_{i,t} \times dprecri_t$	-0.3	-0.52**	-0.23	-2.21***
	(0.26)	(0.23)	(0.28)	(0.34)
$dprecri_t$	2.12*	2.97***	1.29	13.04***
	(1.14)	(0.92)	(1.1)	(1.9)
$dleh_{i,t}$	-1.27***	0.13	-1.63***	-0.16
	(0.38)	(0.17)	(0.47)	(0.11)
Adj. R^2	0.59	0.64	0.33	0.43

Notes: Newey-West standard errors are reported in parenthesis. Asterisks represent significance levels (*** $p < 1\%$, ** $p < 5\%$, * $p < 10\%$).

Table 7: Alternative Specifications of Basic Oil Price Decomposition
(Dependent Variable: Δoil_t)

	(1) Baseline	(2)	(3)	(4)	(5)	(6) Real Prices	(7) Real Prices
const.	0.004	0.003	0.003	0.004	0.003	0.002	0.006
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)
Δoil_{t-1}	-	0.178***	-	-	0.235***	-	-
		(0.052)			(0.059)		
$pc_t^{\Delta cmd}$	0.023***	0.021***	0.021***	-	-	-	-
	(0.002)	(0.002)	(0.002)				
$pc_{t-1}^{\Delta cmd}$	-	-	0.003*	-	-	-	-
			(0.002)				
$pc_t^{\Delta ne}$	-	-	-	0.018***	0.017***	-	-
				(0.002)	(0.002)		
$pc_t^{\Delta rcmd}$	-	-	-	-	-	0.022***	-
						(0.002)	
$pc_t^{\Delta rneng}$	-	-	-	-	-	-	0.016***
							(0.002)
$logVIX_t$	-	-	-	-	-	-	-0.021
							(0.014)
Adj. R^2	0.44	0.47	0.44	0.24	0.30	0.40	0.21
DW	1.58	1.94	1.61	1.55	2.02	1.55	1.53

Notes: In columns (1)-(5) the dependent variable is the differenced log of nominal oil price, in columns (6) and (7) the dependent variable is the differenced log of real oil price (oil prices divided by USA CPI). Standard errors are reported in parenthesis. Asterisks represent significance levels (*** $p < 1\%$, ** $p < 5\%$, * $p < 10\%$). Sample: 2000M03-2017M08.

Table 8: Different Specifications of Idiosyncratic Components of Oil Prices (Dependent Variable: Δoil_t)

	Basic (Eq. (1))	Detailed (Eq.(17))	Detailed 2 (Eq. (18))	Detailed 3
const.	0.004 (0.004)	0.018 (0.029)	0.067 (0.060)	0.018 (0.029)
$pc_t^{\Delta cmd}$	0.023*** (0.002)	0.022*** (0.002)	0.020*** (0.002)	0.021*** (0.002)
$opecref_t$	-	-0.006*** (0.001)	-0.007*** (0.001)	-0.006*** (0.0001)
$shaleref_t$	-	-	-	0.00003 (0.00096)
Temperature vars.	-	✓	✓	✓
Season dummy vars.	-	✓	-	✓
Month dummy vars.	-	-	✓	-
Adj. R^2	0.44	0.52	0.51	0.53
DW	1.58	1.79	1.62	1.78

Notes: Standard errors are reported in parenthesis. Asterisks represent significance levels (*** $p < 1\%$, ** $p < 5\%$, * $p < 10\%$). Sample: 2000M09-2017M08

Table 9: Estimation Results for Alternative Frequencies

Frequency:	Monthly (Baseline)	Daily	Quarterly
Estimation method:	2SLS	OLS	2SLS
A. Decomposition of Oil Prices (Dependent variable: Δoil_t)			
const.	0.0036	0.0001	0.01
	(0.004)	(0.0003)	(0.012)
$pc_t^{\Delta cmd}$	0.023***	0.0057***	0.042***
	(0.002)	(0.0001)	(0.004)
Adj. R^2	0.44	0.45	0.57
DW	1.58	2.10	1.94
Obs.	211	2917	70
B. Decomposition of Inflation Expectations (Dependent variable: Δpc_t^{beir})			
const.	0.01	-0.0002	0.049
	(0.01)	(0.0005)	(0.045)
$\hat{\alpha}_1 pc_t^{\Delta cmd}$	2.33***	0.69***	2.69***
	(0.24)	(0.04)	(0.34)
$\hat{\alpha}_1 pc_t^{\Delta cmd} \times dprecri_t$	-1.53***	-0.34***	-0.86
	(0.49)	(0.08)	(1.23)
$\hat{u}_t$	1.27**	0.36***	1.42
	(0.53)	(0.03)	(1)
$\hat{u}_t \times dprecri_t$	-0.81	-0.1*	-0.28
	(0.72)	(0.06)	(1.36)
$dprecri_t$	-0.02	-0.0002	-0.13
	(0.03)	(0.001)	(0.1)
Adj. R^2	0.39	0.17	0.55
DW	1.72	1.43	2.07
Prob. J-Stat.	1.08	-	0.88
Obs.	174	2712	58

Notes: Standard errors are reported in parenthesis. Asterisks represent significance levels (*** $p < 1\%$, ** $p < 5\%$, * $p < 10\%$). In Panel B: $\hat{\alpha}_1 pc_t^{\Delta cmd}$ and $\hat{u}_t$ are the fitted value and residual estimated in Panel A, respectively. For the monthly and quarterly frequencies, estimation in Panel B is 2SLS with instrument variables for $\hat{u}_t$ as reported in Section 2.3 (the instruments are not available at a daily frequency so the model was estimated with OLS).

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