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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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האם נפגעה אמינותה של מדיניות יעד האינפלציה?

מחירי הנפט, הביקוש העולמי המצרפי והציפיות לאינפלציה במהלך המשבר הפיננסי העולמי

אסנת זהר ונתן זוסמן

תמצית

מאז שפרץ המשבר הפיננסי העולמי (2008) התחזק בעולם המתאם בין מחירי הנפט הגולמי לבין הציפיות לאינפלציה לטווח הבינוני. אנו רואים במרכיב העיקרי הראשון (First Principal Component) של מחירי הסחורות אומדן לביקוש העולמי המצרפי, ומפרקים בעזרתו את מחירי הנפט לגורם של הביקוש העולמי ולגורמים ייחודיים לנפט, לרבות גורמים שקשורים בהיצע הנפט ובמזג האוויר.

בעזרת הפירוק אנו מראים כי מאז שפרץ המשבר הציפיות לאינפלציה לחמש שנים מגיבות בעוצמה לביקוש העולמי המצרפי הגלום במחירי הנפט. ייתכן כי הדבר נובע מכך שבשנים האחרונות קובעי המדיניות המוניטרית שמים דגש רב יותר על מדיניות מקרו-יציבותית. ייתכן גם שהשוק סבור כי מדיניות יעד האינפלציה פחות אגרסיבית כאשר האינפלציה סוטה מהיעד כלפי מטה, או כי היא פחות אפקטיבית בקרבת מחסום הריבית האפקטיבי.

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

Nathan Sussman* Osnat Zohar†

November 2016

Abstract

Following the onset of the global financial crisis (2008) we witness a strengthening of the correlation between crude oil prices and medium-term inflation expectations. Using the first principal component of commodity prices as a measure for global aggregate demand, we decompose oil prices into a global demand factor and idiosyncratic factors that include supply side effects and weather conditions.

The decomposition of oil prices allows us to show that since the crisis, global five-year breakeven inflation rates react quite strongly to global aggregate demand conditions embedded in oil prices. One explanation for this finding is that in recent years monetary authorities put greater emphasis on macro-prudential issues. Alternatively, it may be that market participants perceive inflation targeting as either less aggressive when inflation deviates below target or less effective around the effective lower bound.

Keywords: Inflation targeting, inflation expectations, monetary policy, oil prices, anchoring, credibility
JEL Classification: E52, E58, E31, E32

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1 Introduction

The sharp declines in oil prices starting in late 2014 sparked a debate about their effect on inflation and the world economy [e.g., Chen et al. (2015); Arezki and Blanchard (2015)]. This decline lowered inflation in the short run and in some cases pushed economies that already experienced very low inflation into negative inflation. More surprisingly, data from the US, France, UK and Israel shows that oil prices have a strong correlation with inflation expectations for the medium-term, as measured by five-year breakeven inflation rates (Figure 1).[1] Before the global financial crisis this correlation was weaker and expectations were firmly anchored at the middle of the inflation target range at two percent.[2] However, from the onset of the global crisis 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, in the past two or three years we can observe a similar pattern with respect to longer term inflation expectations, namely the five-year five-year forward breakeven rates. These developments indicate a decline in either the effectiveness or appropriateness or credibility of the inflation targeting monetary regime. In any case it questions conclusions recently reached about the credibility of the inflation target regime and its effect on the anchoring of inflation expectations [Gürkaynak et al. (2010); Beechey et al. (2011)].

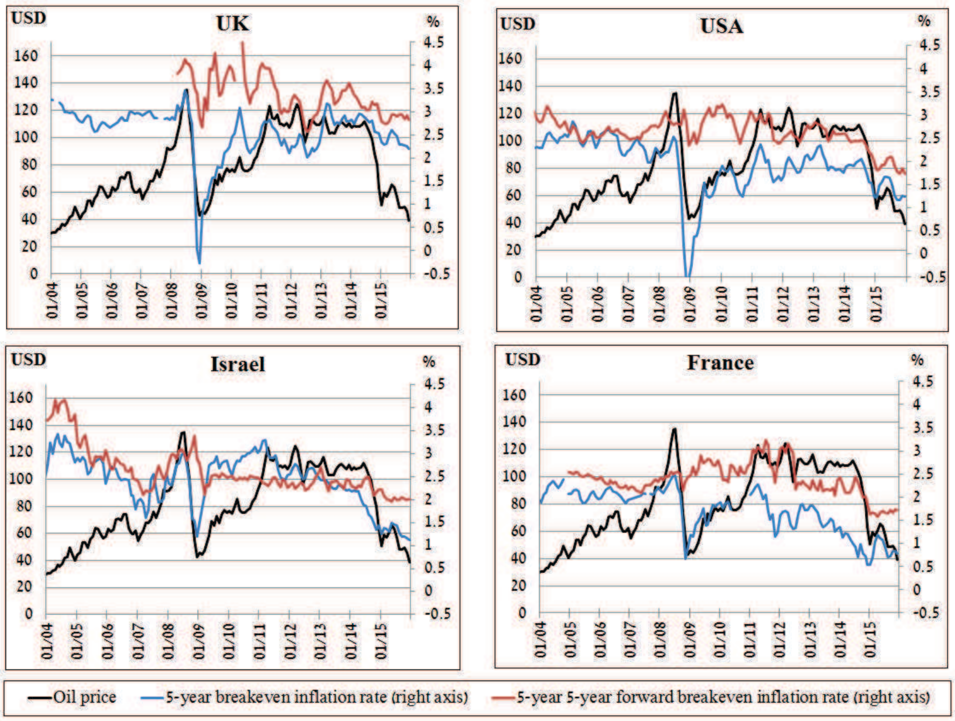
The recent rising correlation between inflation expectations and oil prices rekindles the debates that followed the oil crisis in the 1970s. Whereas demand shocks are positively correlated with inflation, the extent to which monetary policy should accommodate supply shocks has been under debate. Rogoff's (1985) seminal paper, that predates inflation targeting, suggested that it is optimal to accommodate supply shocks to some degree to lower unemployment costs. On the other hand, in Svensson (2000), under one variety of inflation targeting regimes, namely flexible CPI inflation targeting, policy makers should respond symmetrically to demand and supply shocks. More recently, Ireland (2007) showed that the Fed accommodated supply shocks and allowed the de-facto inflation target to change.

There is a consensus that in 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

[1]Owing to data availability we use French breakeven rates as a proxy for Eurozone expected inflation. Since Israel has a deep market for indexed bonds and is an inflation targeter we also include data from Israel.

[2]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 US but not in the Eurozone.

Figure 1: Inflation Expectations and Brent Crude Oil Prices



Correlations		USA	France	UK	Israel
Oil prices and 5Y breakeven rates	2004M01-2008M08	-0.34	0.39	0.35	-0.27
	2008M09-2015M12	0.74	0.51	0.58	0.67
Oil prices and 5Y5Y breakeven rates	2004M01-2008M08	0.03	0.23	-	-0.47
	2008M09-2015M12	0.37	0.41	0.14	0.09

Source: Bloomberg and the Bank of Israel.

Note: Correlations were computed for monthly averaged data.

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) find that by responding more strongly to inflation expectations, monetary policy has stabilized the economy more effectively in the post-1980 period. Blanchard and Gali (2007) and Blanchard and Riggi (2013) find 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) find 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.

At first pass, the correlation between oil prices and medium-term inflation expectations is surprising since we do not expect correlation between (expected) *rates of change* in the CPI and *levels* of oil prices. We resolve this puzzle by showing that oil prices convey information on global activity.[3] We argue that the price of oil reflects, among other thing, the global output gap. If this is the case, then part of the correlation we observe could reflect a link between expected inflation and global output similar to the well-known Phillips Curve that links inflation to the domestic output gap. According to our interpretation, the increasing correlation between oil prices and expected inflation could be explained either by an increase in the correlation between global activity and oil prices or by a rise in the correlation between global activity and inflation expectations. Our hypothesis is that the latter explanation is the dominant one. Of course, the increase in the correlation between oil prices and inflation expectations could also reflect an increase in the correlation between oil-specific shocks and inflation expectations, yet we find almost no evidence for this effect.

To test our hypothesis, we identify the source of the increased correlation between oil prices and expected inflation by decomposing changes in oil prices to two elements: global aggregate demand and idiosyncratic factors. 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), the main factor that can move the prices of all commodities in the same direction is global aggregate demand. In fact, commodity prices are characterized by a strong co-movement and we exploit this fact to construct a proxy for global aggregate demand. Specifically, we identify global aggregate demand as the first principal component of a group of highly traded commodity prices.[4] The residual change in oil prices, unaccounted for by

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

[4]In our sample, the first principal component of commodity price levels captures 64 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 30 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 real interest rates and positively

the first principal component of commodity prices, mainly captures idiosyncratic developments in the market for crude oil. These developments include, among other things, measures taken by OPEC to control supply, changes in production technologies of alternative energy sources, or idiosyncratic demand shifts for crude oil. Our method for extracting information about global aggregate demand conditions from oil prices could be a practical tool for observers of the global economy and policy makers.[5]

We exploit the fact that all economies in our sample pursue essentially the same inflation target to compute a global measure of expected inflation using the first principle component of inflation expectations for the countries in our sample. This removes idiosyncratic shocks to expected inflation and the bond markets from which these expectations are extracted. Combining this measure of global inflation expectations with our identification strategy allows us to show that the increase in the correlation between oil prices and five year expected inflation, following the onset of the crisis, is due to the increase in the correlation between global inflation expectations and global aggregate demand conditions.[6] At the same time, the correlation between idiosyncratic changes in oil prices and inflation expectations remained stable and was mild, suggesting that the perceived degree to which monetary policy accommodates supply shocks is stable in the 2000s.

Given the emphasis on the idiosyncratic factors affecting oil prices in the popular press and amongst policy makers during the second half of 2014 it is possible that our decomposition of the determinants of oil prices differed from those of market observers. Indeed, we are able to demonstrate that, compared with our decomposition, market observers overestimated the effect of oil market specific shocks and underestimated the effect of global economic conditions on oil prices.

To verify our identification strategy and in particular to rule out that our measure of the effect of global aggregate demand conditions is biased, we attempt to directly control for two major variables affecting oil prices, namely OPEC's price behavior that affects the supply of oil and shocks to oil demand caused by the weather. We construct a novel proxy for OPEC's behavior in the market for oil 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

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.

[5]Several studies identify global demand shocks that drive oil prices [e.g., Kilian (2009); Peersman and Van Robays (2012); Cashin et al. (2014)]. The appeal of our method stems from the fact that our proxy of global aggregate demand is transparent, readily calculated and can supplement "nowcast" estimates at monthly (or higher) frequencies to monitor global activity on a regular basis.

[6]The term "correlation" in this context refers to the partial correlation arising from a simple linear regression model. Since our model is not structural we are cautious in interpreting the estimated coefficients as causal effects.

proxy is constructed as the net number of "expansionary articles", meaning the number of articles suggesting OPEC is expanding supply, minus the number of articles indicating supply reduction. This measure explains a substantial part of the idiosyncratic component of oil prices, especially during the 2014 drop in prices. We also use temperature variables from five continents to capture the demand for oil arising from weather conditions around the world. Adding the two measures of idiosyncratic forces to our basic model of oil price decomposition, leaves the estimated effect of global aggregate demand essentially unchanged. This suggests that the estimated effect of global aggregate demand in the basic model is unbiased and strengthens our conclusion that the change in the correlation behavior of oil prices and inflation expectations was indeed due to changes to global economic activity.

We conclude that contrary to the conclusions in the literature on the contribution of inflation targeting to the anchoring of inflation expectations [Beechey et al. (2011)], our findings suggest that the public belief in the ability of monetary authorities worldwide to stabilize inflation at the medium-term horizon has deteriorated. Moreover, data we present in Figure 1 suggests that monetary policy credibility as measured by the more stringent five year for five years forward inflation expectations has eroded in the last couple of years following its erosion for the short to medium terms.[7] This could be due to A. greater emphasis put by monetary authorities on macro-prudential issues as opposed to stabilizing inflation [Galí (2014)]. B. Asymmetric behavior of central banks with respect to negative deviations from the inflation target. C. Public perception about the effectiveness of monetary policy around the effective lower bound.

This paper also relates to the vast literature that studies the underlying forces in the market for crude oil [Kilian (2008); Hamilton (2009a,b); Baumeister and Peersman (2013); Kilian and Murphy (2014)]. 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 (2016) 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. 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

[7] In Appendix B we provide a more rigorous analysis of the correlation between oil prices and five-year five-year forward breakeven inflation rates.

other commodities [Baffes (2007); Du et al. (2011); 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 [Baumeister and Kilian (2012); Alquist et al. (2013); Baumeister and Kilian (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; Section 3 examines the idiosyncratic component of oil prices; Section 4 discusses the 2014 drop in oil prices and how it was percived by the market; Section 5 discusses possible explanations for the increased correlation between oil prices and inflation expectations; Section 6 concludes.

2 Methodology for Testing the Changes to Oil Prices and Anchoring of Medium-Term Inflation Expectations

Our motivation is the increasing correlation between inflation expectations and oil prices following the onset of the global crisis. Beechey et al. (2011) already noted that using oil price shocks has some advantage in comparing the anchoring of inflation expectations across countries since these are uniform shocks and since advanced economies have similar energy intensities. Indeed, the financial press and observers of the international economy seem to justify Beechey's et al. (2011) assessment.

Beechey et al. (2011), extending Gürkaynak et al. (2005), test for the anchoring of inflation expectations by regressing changes in expected inflation on shocks to macroeconomic variables. If inflation is well anchored these shocks should not have a statistically significant effect on medium-term inflation expectations. This holds in particular for shocks to oil prices. Ultimately we will test for this relationship and compare the period before the global financial crisis to the period that followed. Our contribution is twofold: A. we extend Beechey's et al (2011) analysis by breaking shocks to oil prices into two components - shocks to global aggregate demand and shocks that are specific to oil prices. This refinement is important because, with the exception of the flexible CPI inflation targeting rule [Svensson (2000)], monetary policy reacts differentially to supply shocks; 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. However, a perceived accommodation of demand shocks contrasts with inflation targeting and raises questions about the effectiveness or credibility of the monetary regime. B. We extend the empirical investigation to the period following the onset of the global financial crisis where monetary policy is operating in hitherto uncharted territory.

2.1 Oil Prices and Inflation Expectations

Before we proceed it is useful to show in a more rigorous way 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.[8] For each country i we estimate the following regression:

$$\begin{aligned} beir_{i,t} = \delta_{0_i} + \delta_{1_i} oil_t + \delta_{2_i} oil_t \times dprecri_t + \delta_{3_i} dprecri_t \\ + \delta_{4_i} dleh_{i,t} + \delta_{5_i} ex_{i,t-1} + \delta_{6_i} ex_{i,t-1} \times dprecri_t + \epsilon_{i,t} \quad (1) \end{aligned}$$

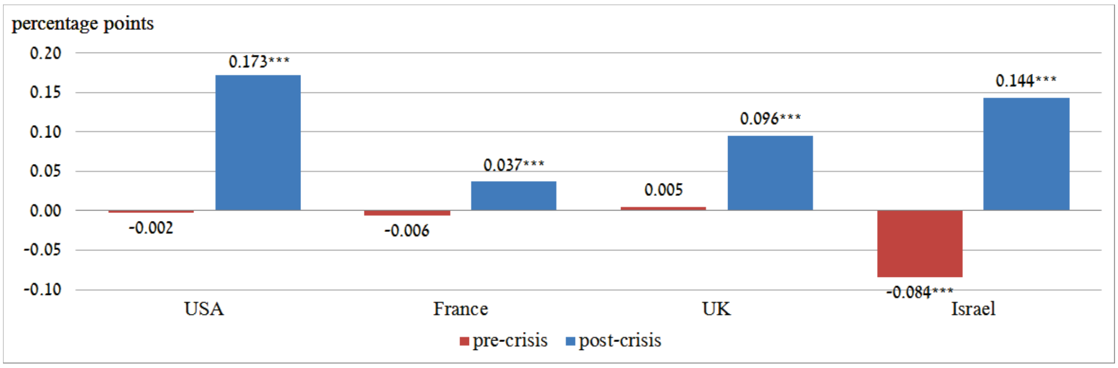
Where oil_t is the log price of Brent crude oil, $dprecri_t$ is a dummy for the pre-crisis period (2004M01-2008M08), $dleh_{i,t}$ is a dummy variable that equals one circa September 2008 (indicating known liquidity problems in country i's government bonds market), and $ex_{i,t}$ is the log term of country i's exchange rate versus the USD.[9]

Figure 2 depicts the estimated correlation between oil prices and five-year breakeven inflation rates (detailed estimation results are reported in Table 8 in the Appendix). 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. In fact, in all countries but

[8] Due to availability of five-year breakeven inflation rates data, we preform all analysis involving expected inflation for the period 2004M01-2015M12. In the following section where we decompose oil prices, we extended the sample period to 2000M01-2015M12.

[9] For the USA regression we use the DXY index. We examine an alternative specification for the USA regression without the exchange rate and the qualitative results carry through. See Table 8 in the Appendix for more details.

Figure 2: Partial Effect of a 10% Increase in Oil Prices on Five-Year Breakeven Inflation Rates



Notes: Asterisks represent significance levels (*** $p < 1\%$, ** $p < 5\%$, * $p < 10\%$). The figure is based on estimation results of Equation (1) (detailed results appear in Table 8 in the Appendix). 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 $\log(1.1)(\delta_{1_i} + \delta_{2_i} dprecri_t)$.

Israel we cannot reject the hypothesis that prior to the global crisis, oil prices and breakeven rates were uncorrelated. In Israel it seems that prior to the crisis oil prices were negatively correlated with inflation expectations, but since the crisis the correlation is positive.

2.2 Estimating Global Aggregate Demand

In order to estimate the information on the global output gap embedded in oil prices we present an estimator for global aggregate demand in the form of 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 more 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.

2.2.1 Data and Methodology

We use a panel of 20 commodity prices that were included in the S&P GSCI index in 2015. The data spans over the period 2000-2015 and includes prices of commodities from five groups: agricultural commodities, livestock, industrial metals, precious metals[10], and energy (the set of commodities is specified in Table

[10]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

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

Chicago Wheat	Kansas Wheat	Corn	Soy-beans	Coffee	Sugar	Cocoa	Cotton	Lean Hogs	Live Cattle
0.22	0.23	0.21	0.23	0.20	0.15	0.14	0.19	0.04	0.07

Alumi-num	Copper	Lead	Nickel	Zinc	Gold	Silver	Brent Crude Oil	WTI Crude Oil	Natural Gas
0.30	0.33	0.26	0.26	0.29	0.20	0.26	0.28	0.27	0.08

1).[11] In order to focus on fundamental co-movements of prices, we use monthly averages of commodity prices.[12] The natural 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).[13] However, we 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 30 percent of the variance in the data. The loadings of all variables are positive (Table 1), so the first principal component captures the co-movement in commodity prices. This fact justifies our interpretation of the first principal component as a proxy for global aggregate demand.

2.2.2 First Principal Component of Commodity Prices and Global Aggregate Demand

Figure 3 presents the twelve-month moving average of the first principal component of rates of change in commodity prices, $pc_t^{\Delta cmd}$(the unprocessed principal component is presented in Figure 12 in the Appendix). Examining the evolution of this factor over time shows that it tracks very well global economic activity.

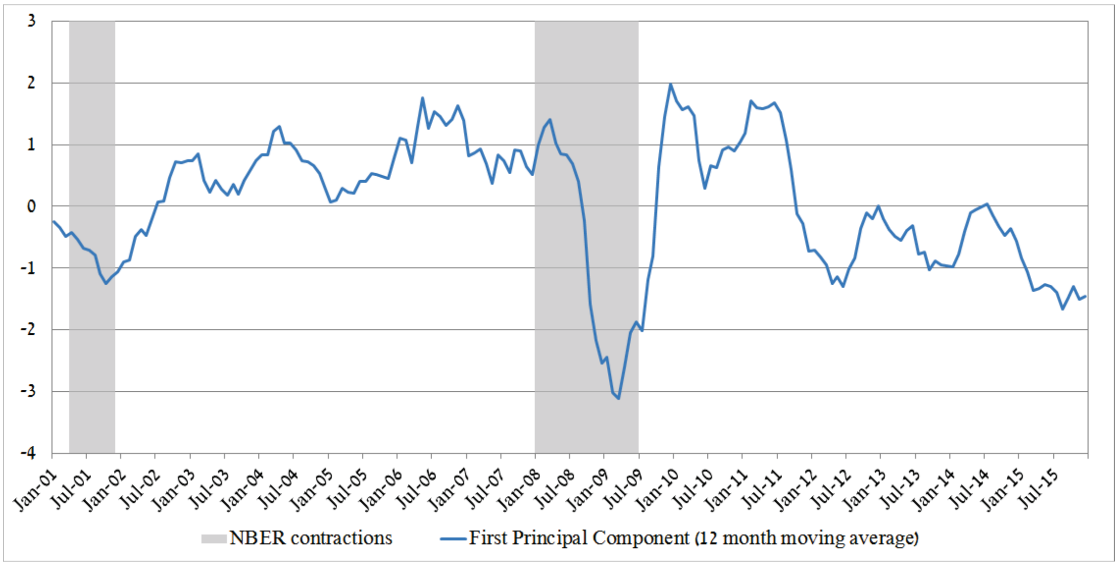
commodities. However, our results remains essentially unchanged when we exclude gold prices from our analysis.

[11] 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 gasoil. 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.

[12] In Appendix C.4 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.

[13] 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 A we describe the methodology for constructing this estimator.

Figure 3: Twelve-Month Moving Average of the First Principal Component of Rates of Change in Commodity Prices



Source: National Bureau of Economic Research, Bloomberg and authors' calculations.
Notes: The first principal component, $pc_t^{\Delta cmd}$, was constructed from monthly rates of change of commodity prices. The graph depicts rolling twelve-month averages of $pc_t^{\Delta cmd}$.

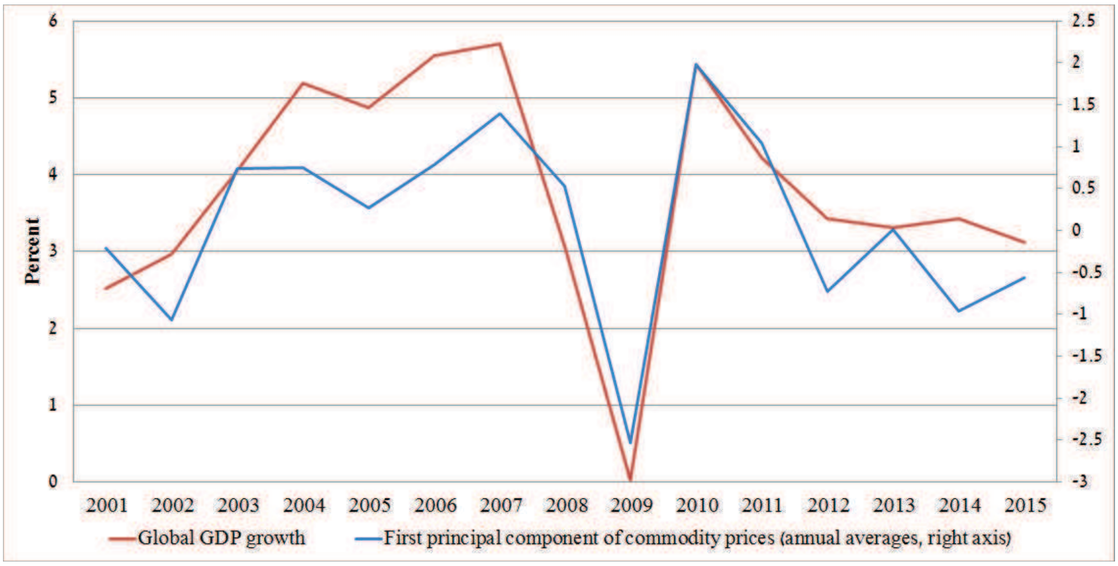
For example, the two NBER contractions associated with the collapse of the dot-com bubble and the 2008 financial crisis are well depicted by a prominent decline in $pc_t^{\Delta cmd}$. The factor shows another sharp decline starting in mid-2011, around the break of the European debt crisis. Since then, the factor shows no significant improvement, and we certainly do not see any sign of returning to pre-2008 conditions.

Another indication that $pc_t^{\Delta cmd}$ tracks global activity well is its relation with global GDP. Figure 4 shows annual averages of $pc_t^{\Delta cmd}$ together with annual rates of change in global output. The correlation between the two series is 0.87.

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. We examine data from the US Department of Commerce

Figure 4: Global Output and the First Principal Component of Commodity Prices



Source: International Monetary Fund, Bloomberg and authors' calculations.

regarding six industries that best match the S&P non-energy commodities.[14] 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 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.[15] 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

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

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

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: US 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.

change in the energy index). 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 and WTI crude oil (F-statistics of 4.89 and 5.11, respectively). In the following section we examine the effect of global aggregate demand on oil prices more thoroughly.

2.3 Decomposing Oil Prices

We use the estimator of global aggregate demand constructed in Section 2.2 to evaluate monthly changes in oil prices during our sample period. Specifically, we wish to distinguish between changes in oil prices that arise from global aggregate demand shifts and changes that are caused by idiosyncratic factors (e.g., idiosyncratic demand, supply control by OPEC, developments in alternative energy sources, and geopolitical concerns). Consider the following model:

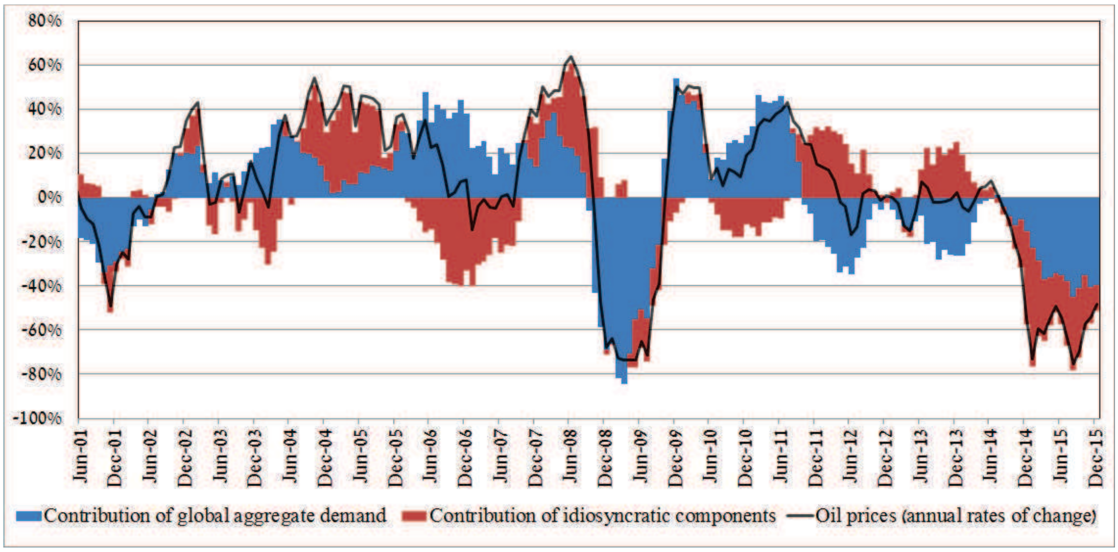
$$\Delta oil_t = \alpha_0 + \alpha_1 pc_t^{\Delta cmd} + u_t \tag{2}$$

Where Δoil_t is the differenced log of Brent crude oil prices in USD terms, $pc_t^{\Delta cmd}$ is the first principal component of the differenced log of commodity prices, and u_t is the residual. The fitted value of this equation captures the part of oil price fluctuations that are caused by changes in global aggregate demand. The residual captures idiosyncratic changes in the price of oil (in Section 3 we propose direct identification for some of the idiosyncratic components of oil prices). Least squares estimation results of Equation (2) are summarized in Table 4 in the Appendix.[16]

Figure 5 depicts *annual* rates of change in oil prices in monthly frequency, with the contributions of the global aggregate demand factor and the idiosyncratic factor. Specifically, the figure presents the twelve-month moving sum of both sides of Equation (2). We see that the surge in oil prices in 2007-08 was to a large extent caused by an increase in global aggregate demand. As pointed out by Hamilton (2009a), this is mainly due to substantial growth in China, which at that time was the third biggest importer of oil and a dominant player in world markets. Likewise, from the break of the global financial crisis until mid-2011, oil prices were mainly driven by global aggregate demand. However, in the two years that followed, moderations in global aggregate demand were offset by idiosyncratic changes in prices of oil so that prices remained stable. This is suggestive of price smoothing by the oil cartel.

[16]In Appendix C.1 we examine alternative specifications of Equation (2). We examine different lag structures, estimate this equation with the first principal component of *non-energy* commodity prices, and use deflated prices of both oil and commodity prices. In all specifications, the estimation results of the decomposition of oil prices, as well as subsequent analysis, remain essentially unchanged.

Figure 5: Contributions of Global Aggregate Demand and Idiosyncratic Components to the Annual Rates of Change in Oil Prices



Notes: The decomposition of oil prices was estimated for monthly rates of change (Equation (2)). 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 (2).

Looking at the latest data points, we see that the sharp decline in oil prices in late 2014 was initiated by idiosyncratic changes in oil prices but was then intensified by a decline in global aggregate demand. The common view is that the idiosyncratic side of the decline was due to expansions of shale oil output in the US, as well as decreasing geopolitical concerns regarding supply disruptions. These effects were boosted by a decline in global aggregate demand which sustained until the end of our sample. In contrast to previous periods, the downward pressure on prices was not mitigated by the oil cartel. In November 2014 OPEC switched to a policy of maintaining market share, which effectively meant relinquishing price stabilization. Since then oil prices were much more sensitive to fundamental forces.[17]

We explore these narratives in Section 3 where we provide a more detailed analysis of the idiosyncratic component of oil prices.

[17] An elaborate discussion regarding the sharp decline in oil prices in 2014 appears in Chen et al. (2015).

2.4 Explaining the Link 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 Section 2.3. In view of this decomposition, the increase in correlation has two possible explanations. First, it is possible that one of the factors that drive oil prices has a greater effect on inflation expectations since the crisis. Alternatively, it may be that the magnitude of the effects did not change but one of the factors became more dominant in determining oil prices in recent years. We claim that the former explanation is the dominant one. Specifically we show that from the onset of the crisis the global aggregate demand factor that is embedded in oil prices affects inflation expectation much more than in the past.

Since we are interested in the main factors that link oil prices and inflation expectations, we wish to ignore idiosyncratic components embedded in breakeven inflation rates. Therefore, we focus on the main factors that drive global inflation expectations. For this purpose we extract the first principal component of five-year breakeven inflation rates from the US, France, UK and Israel (Figure 7). This factor can be viewed as an estimator for global expected inflation at the five-year horizon.[18,19]

To examine the effects of oil prices on inflation expectations we should first set a framework of how expectations are formed. We consider the semi-structural model used in Beechey et al. (2011), who build on Orphanides and Williams (2004). The model consists of a Phillips curve and an IS curve as follows:

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

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

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 function that reacts to deviations of inflation from a target π^*:

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

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

[18] The first principal component explains 71 percent of the variance in the panel of breakeven inflation rates. The loadings of the factor are: USA - 0.55, France - 0.52, UK - 0.47, Israel - 0.46.

[19] The analysis in this section can be carried out for the individual countries in our sample with similar results.

$$\pi_{t+1/t} = \frac{\alpha\theta}{1-\phi}\pi^* + \frac{1-\phi-\alpha\theta}{1-\phi}\left[\phi\pi_{t/t-1} + (1-\phi)\pi_{t-1} + \alpha y_t + e_t\right]$$

Meaning that inflation expectations are formed based on the inflation target, an adaptive component, the current output gap and current cost-push shocks. We use our proposed decomposition of oil prices to account for the output gap and cost-push shocks and estimate the following regression model, expressed in first differences and allowing for a structural change after the global financial crisis.[20,21]

$$\begin{aligned}\Delta pc_t^{beir} = \beta_0 + \beta_1 \Delta pc_{t-1}^{beir} + \beta_2(\hat{\alpha}_1 pc_t^{\Delta cmd}) + \beta_3(\hat{\alpha}_1 pc_t^{\Delta cmd}) \times dprecri_t \\ + \beta_4 \hat{u}_t + \beta_5 \hat{u}_t \times dprecri_t + \beta_6 dprecri_t + \epsilon_t^{beir} \quad (3)\end{aligned}$$

Where pc_t^{beir} is the first principle component of five-year inflation expectations, $\hat{\alpha}_1 pc_t^{\Delta cmd}$ is our estimate for the global aggregate demand factor embedded in oil price, and $\hat{u}_t$ is the idiosyncratic component (fitted value and residual from Equation (2), respectively).

The contemporaneous effects of global aggregate demand and the idiosyncratic component of oil prices on Δpc_t^{beir} are summarized in Figure 6 (detailed estimation results are specified in Table 7 in the Appendix). Note that the absolute size of the coefficients is irrelevant since pc_t^{beir} has a somewhat arbitrary scale.[22] The estimation results shed some light on our previous and more naïve analysis. Prior to the global crisis, changes in oil prices stemming from either global aggregate demand or idiosyncratic changes, have 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 itself explain the increase in correlation between oil prices and inflation expectations in recent years.[23]

In the post-crisis period the picture is very different. While the effect of the idiosyncratic component remained essentially unchanged (the difference relative

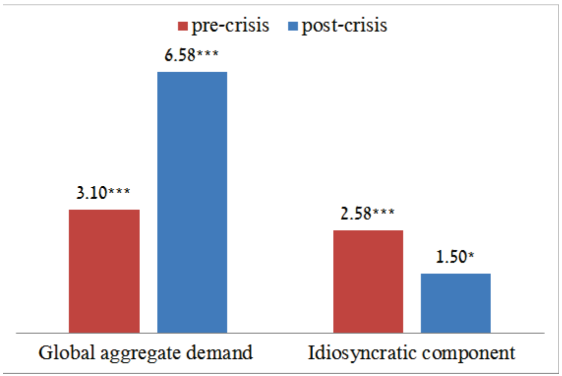
[20]We are interested in modeling the relation between breakeven inflation rates and levels of oil prices. In Equation (2) we decomposed the differenced log terms of oil prices in order to deal with non-stationarity. Thus, if we are to use this decomposition, we need to examine *changes* in breakeven rates.

[21]When adding an interaction of Δpc_{t-1}^{beir} and the dummy variable to Equation (3), the coefficient turns out to be insignificant and the other coefficients remain essentially unchanged, thus we focus on the more parsimonious specification of (3) with no structural change to the autoregressive coefficient.

[22]The first principal component is unique up to rescaling. We chose the first principal component that corresponds to a normalized loading vector. See Appendix A for more details.

[23]Testing the stability of the coefficients in Equation (2) supports the hypothesis that there was no structural change in the effect of global aggregate demand on oil prices.

Figure 6: Effects of Global Aggregate Demand and Idiosyncratic Component of Oil Prices on the Monthly Change in the First Principal Component of Breakeven Inflation Rates



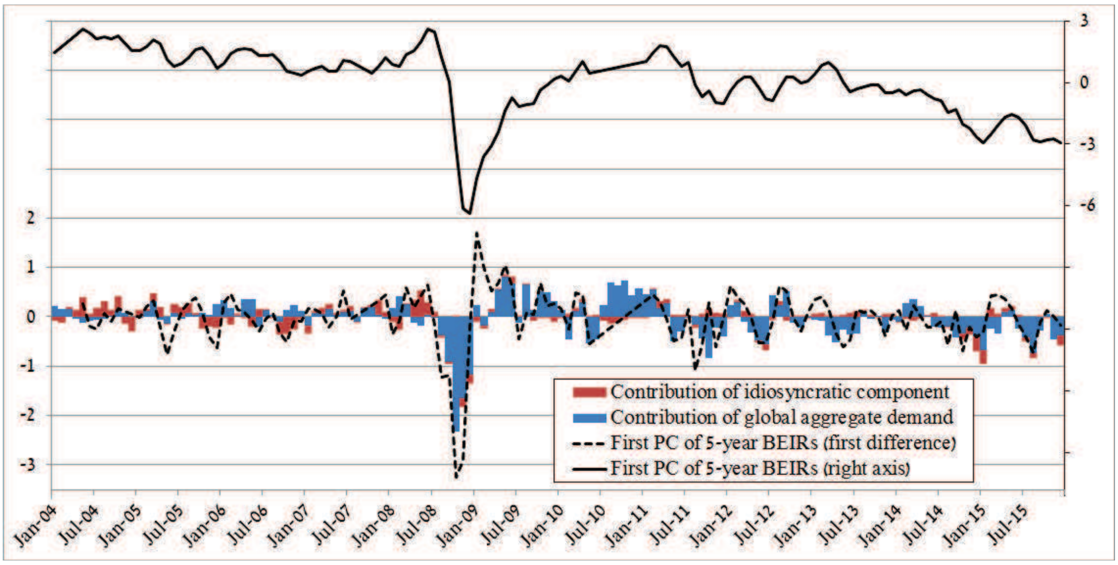
Notes: The figure presents estimation results of Equation (3). The effect of global aggregate demand (or idiosyncratic component) is given by the estimator of $\beta_1 + \beta_2$ (or $\beta_3 + \beta_4$) for the pre-crisis period, and β_1 (or β_3) for the post-crisis period.

to the pre-crisis coefficient is statistically insignificant), the effect of global aggregate demand more than doubled.[24] This suggests 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. We conclude that the tightening relationship between oil prices and inflation expectations reflects a tightening relationship between shocks to global aggregate demand and medium-term inflation expectations.

To better understand the magnitude of global aggregate demand and idiosyncratic changes in oil price in the formation of global inflation expectation, we examine their estimated contributions in Figure 7. It seems that in the post-crisis period global aggregate demand explains a substantial part of the development in global expected inflation.

[24]It is worth noting that we breakdown our sample to pre-crisis and post-crisis according to 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 (3) for two separate periods, 2004M01-2007M12 and 2010M01-2015M12, disregarding an extensive period around the collapse of Lehman Brothers. 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 Appendix C.3 for an elaborate discussion.

Figure 7: First Principal Component of Five-Year Breakeven Inflation Rates and the Contributions of Global Aggregate Demand and Idiosyncratic Component of Oil Prices to its Monthly Change



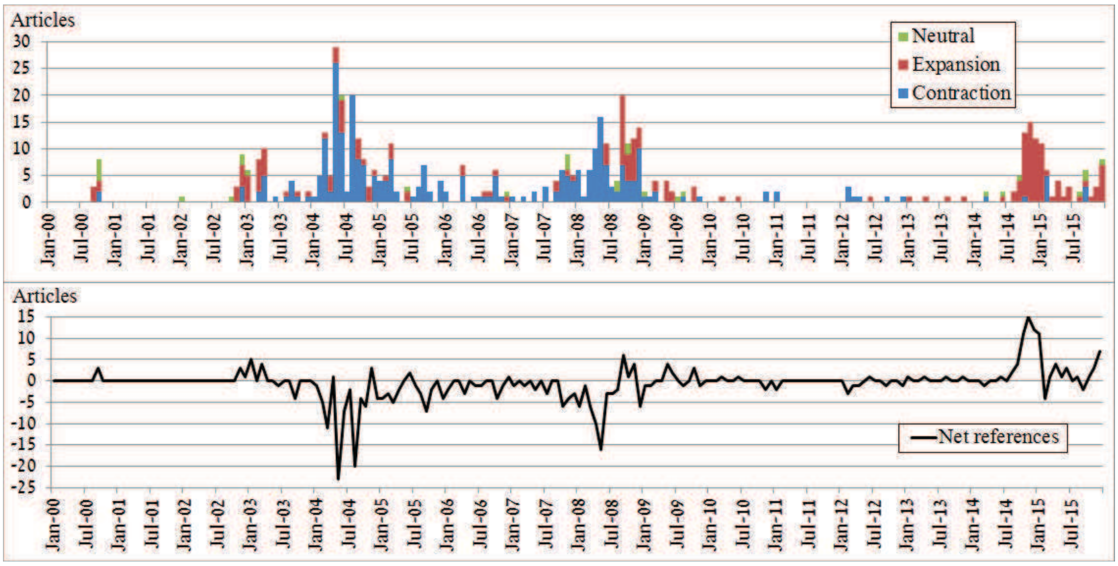
Notes: The contributions are calculated according to a transformation of Equation (3): $\Delta pc_t^{beir} = \sum_{i=1}^{\infty} \beta_1^i \left[\beta_0 + \beta_6 dprecri_{t-i} + (\beta_2 + \beta_3 dprecri_{t-i})\hat{\alpha}_1 pc_{t-i}^{\Delta cmd} + (\beta_4 + \beta_5 dprecri_{t-i})\hat{u}_{t-i} + \epsilon_{t-i}^{beir}\right]$. The contribution of global aggregate demand (in blue) is $\sum_{i=1}^{\infty} \beta_1^i (\beta_2 + \beta_3 dprecri_{t-i})\hat{\alpha}_1 pc_{t-i}^{\Delta cmd}$, and the contribution of the idiosyncratic component (in red) is $\sum_{i=1}^{\infty} \beta_1^i (\beta_4 + \beta_5 dprecri_{t-i})\hat{u}_{t-i}$.

3 The Idiosyncratic Component of Oil Prices

We derived our measure of global aggregate demand in a natural and transparent way without imposing any model or making any additional assumptions. However, it still possible that our measure captures some oil specific factors that may affect all commodities. If this would be the case then our measure could be biased. In a way of a robustness test we extend the analysis of the price of oil and break down its idiosyncratic component. So far we have proposed direct identification only for the global aggregate demand component and attributed the residual to idiosyncratic forces (Equation (2)). We now propose a more detailed specification of oil price decomposition that directly identifies some of the idiosyncratic forces. We show that the identified idiosyncratic components are essentially orthogonal to our estimator of global aggregate demand, which supports our original identification strategy.

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,

Figure 8: References of OPEC in the London Times, Classified by Type of Operation in the Oil Market



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

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.

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 8). 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.

For the measure of idiosyncratic demand shocks driven by extreme weather conditions, we examine global temperature data. The NCEI[25] provides five monthly data sets, one for each continent, of seasonally adjusted temperature data.[26] The

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

[26]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

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.

Recall that the basic decomposition of oil prices was $\Delta oil_t = \alpha_0 + \alpha_1 pc_t^{\Delta cmd} + u_t$ (Equation (2)), where $pc_t^{\Delta cmd}$ is the first principal component of commodity prices and the residual u_t is the idiosyncratic component of oil prices. In the detailed decomposition we add the proxy for OPEC's operation and weather variables:

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

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.[27]

The least square estimator of the coefficient of $pc_t^{\Delta cmd}$ in Equation (4) is 0.022 (s.e. 0.0018), compared to an estimator of 0.023 (s.e. 0.018) in Equation (2).[28] This indicates that the idiosyncratic components we identify are orthogonal to $pc_t^{\Delta cmd}$, suggesting that our basic model, despite its simplicity, provides an unbiased estimator of the main global forces that drive oil prices.

Figure 9 depicts the contribution of all elements in Equation (4) to the annual rate of change in oil prices. Comparing with Figure 5, 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.

4 Was the 2014 Drop in Oil Prices Misinterpreted at the Time?

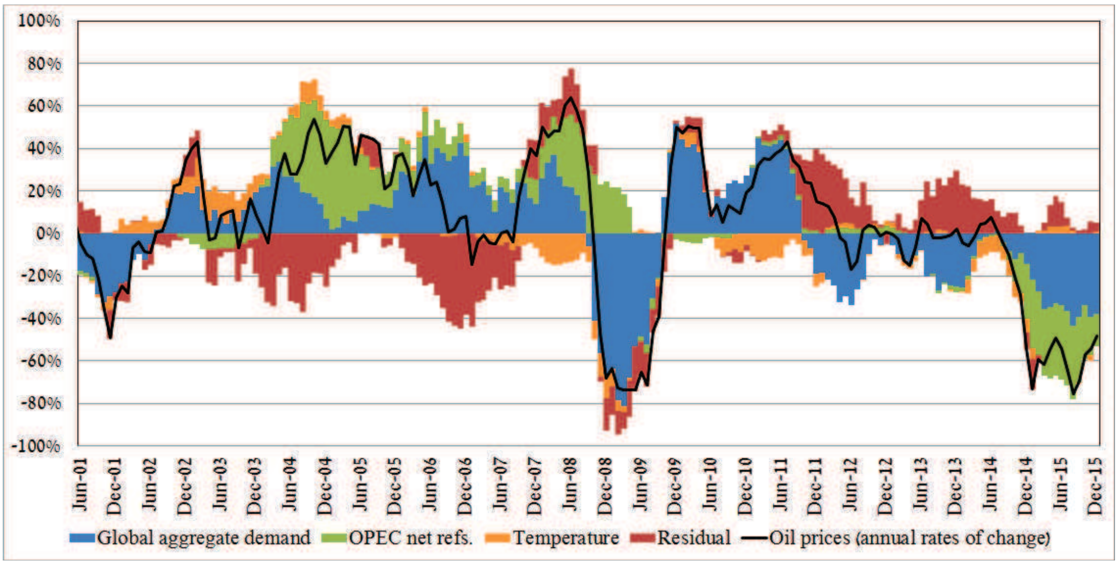
In the second half of 2014 crude oil prices fell by more than fifty percent. At the time, the economic press and policymakers emphasized the role of oil-specific

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.

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

[28] Full estimation results of Equation (4) are compared to those of Equation (2) and several other specifications in Appendix C.2. The comparison reveals that the coefficient of $pc_t^{\Delta cmd}$ is robust at around 0.022. The results of the second stage (i.e., the regression of Δpc_t^{beir} on decomposed oil prices) appear in Table 9.

Figure 9: Detailed Decomposition of Annual Rates of Change in Oil Prices



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 (4).

developments in the drop in prices. Specifically, a lively discussion was conducted regarding the increasing production of shale oil in the US, as apparent in the spike in references of "shale oil" in the London Times in the second half of 2014 (Figure 13). Together with the weakening collusion among OPEC members at the time, the effects of shale oil production were perceived as highly influencing the price of crude oil. At the same time, global economic forecasts published by international institutions indicated expected recovery of global trade and output even though they were later revised downwards.

However, our decomposition of oil prices (Section 2.3), as well as recent research [Baumeister and Kilian (2016)], indicate that while oil-specific factors contributed to the drop in prices, adverse developments in global aggregate demand also played a significant role. It is thus possible that market participants misinterpreted the sources of the drop in oil prices in 2014, and put too much weight on the idiosyncratic factors that pushed prices downwards.

When analyzing the evolution of global inflation expectations we assumed that market participants form rational expectations based on full information and full understanding of contemporaneous conditions (Section 2.4). While agents have access to contemporaneous oil prices, it is not clear that they are able to accurately assess in real time the forces that drive these prices. This is especially true since data on global output arrives in a lag and is prone to revisions. While the data we use to evaluate global aggregate conditions, namely prices of various commodities, was readily available, our methodology was not and at the time it may have been disregarded due to other sources of information such as international institutions' assessments and the press which focused on the supply side of the oil market.

To test the hypothesis that market participants may have misinterpreted the sources of the large oil price drop, we conduct an exercise using our model for testing the effect of decomposed oil prices on medium-term global expected inflation (Equation (3)):

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

In Section 2.4 we estimated this equation for the period 2004M01-2015M12. Let $\hat{\epsilon}_t^{beir}$ denote the estimated residuals from this regression. For the purpose of our exercise, we estimate this equation for the period ending in 2014M06, just before the sharp drop in oil prices. The estimated coefficients are presented in Table 9 in the Appendix and we denote them by $\hat{\beta}_i^{2014}$ for $i = 0, ..., 6$. Compared to the regression on the entire sample, the coefficients of the global demand factor $(\hat{\alpha}_1 pc_t^{\Delta cmd})$ and the idiosyncratic component $(\hat{u}_t)$ seem to have a slightly larger effect on inflation expectations in the post-crisis period.

How can we interpret the difference in the estimation results? If we assume that participants have relatively good assessments of current global aggregate demand conditions, then Equation (3) accurately represents the effect of oil prices on the formation of global medium-term inflation expectations. If this is the case, we can conclude that what changed since the 2014 drop in oil prices is the public perception of the response of monetary policy to idiosyncratic developments in oil prices. Alternatively, it may be that in real time market participants did not fully account for the role of global aggregate demand in the drop in oil prices in the second half of 2014.

To evaluate in what way and to what extent market participants may have misinterpreted the developments in oil prices in that period we conduct the following exercise. We assume that until 2014M06 the public had a relatively good understanding of real-time global aggregate conditions.[29] Furthermore, we assume that in the last year and a half of our sample (2014M07-2015M12) the formation of inflation expectations remained as it was in earlier periods, given oil prices (which were available in real-time) and the market's perception of global conditions. Under these assumptions we ask what is the implied decomposition of oil prices that

[29] This assumption means that up to 2014 the market's assessment of global conditions in real time, whatever learning process it was generated from, was on average in line with actual developments. The result of our exercise will show that this learning process did not perform as well in late 2014 and led to a bias in the market's assessments.

explains the evolution of breakeven inflation rates we observe since 2014M07? Specifically, for each $t = 2014M07, ..., 2015M12$ we calculate a "perceived" global demand factor, $pglobdem_t$ that solves:

$$\Delta pc_t^{beir} = \hat{\beta}_0^{2014} + \hat{\beta}_1^{2014} \Delta pc_{t-1}^{beir} + \hat{\beta}_2^{2014} pglobdem_t + \hat{\beta}_4^{2014} (\Delta oil_t - pglobdem_t) + \hat{\epsilon}_t^{beir}$$

In Figure 10 we compare $pglobdem_t$ to the global aggregate demand factor we extracted in our baseline model ($\hat{\alpha}_1 pc_t^{\Delta cmd}$ from Equation (3)). Under the assumptions of this exercise, it seems that in late-2014 market participants put too much weight on the idiosyncratic developments that pushed oil prices downwards and were overly optimistic regarding global aggregate conditions. In fact, during the second half of 2014 the market misinterpreted almost a fifth of the decline in oil prices - 10 percent out the 55 percent decline in oil price were mistakenly attributed to oil-specific developments instead of global conditions. Had the market been more attentive to adverse global developments (manifested, for example, in the decline of various commodity prices), a different understanding of the oil market in late 2014 may have emerged, resulting in an even sharper decline in inflation expectations in that period.[30] However, the bias was short-lived and almost disappeared in the beginning of 2015. Since then it seems that the notion that oil prices convey information about global aggregate demand increased and public perception is more in-line with actual developments.

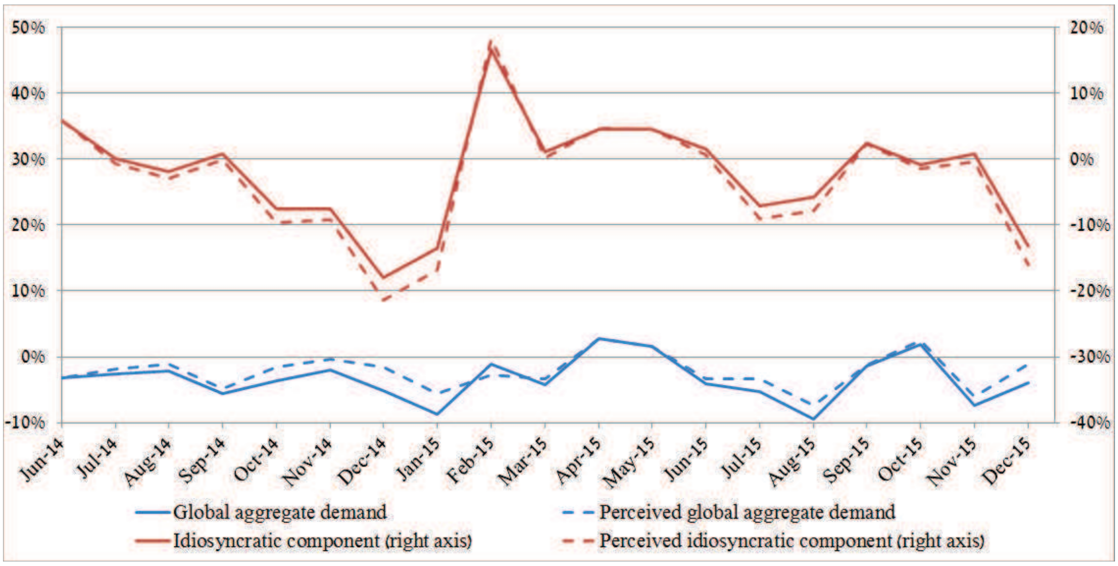
To better understand the sources of the possible misinterpretation we regress Δpc_t^{beir} on decomposed oil prices with weather variables and the proxy for OPEC's operations (Table 9). We find that prior to mid-2014 OPEC's operations had a large effect on global inflation expectations, yet this effect decreased in the following period. This suggests that prior to 2014 market participants put a high weight on OPEC's operation relative to other forces that drive oil prices (such as technological advances or global aggregate conditions). In retrospect, the market may have overestimated the ability of OPEC to mitigate the effect of global aggregate shocks on oil prices.

5 Discussion: Possible Explanations for the Increased Correlation Between Oil Prices and Inflation Expectations

Our analysis shows that inflation expectations for the medium-term are affected by oil prices, suggesting that for the five-year horizon these expectations are not

[30] This is due to the fact that even in the pre-2014 sample global aggregate demand affected inflation expectations more than the idiosyncratic factors did (Table 9).

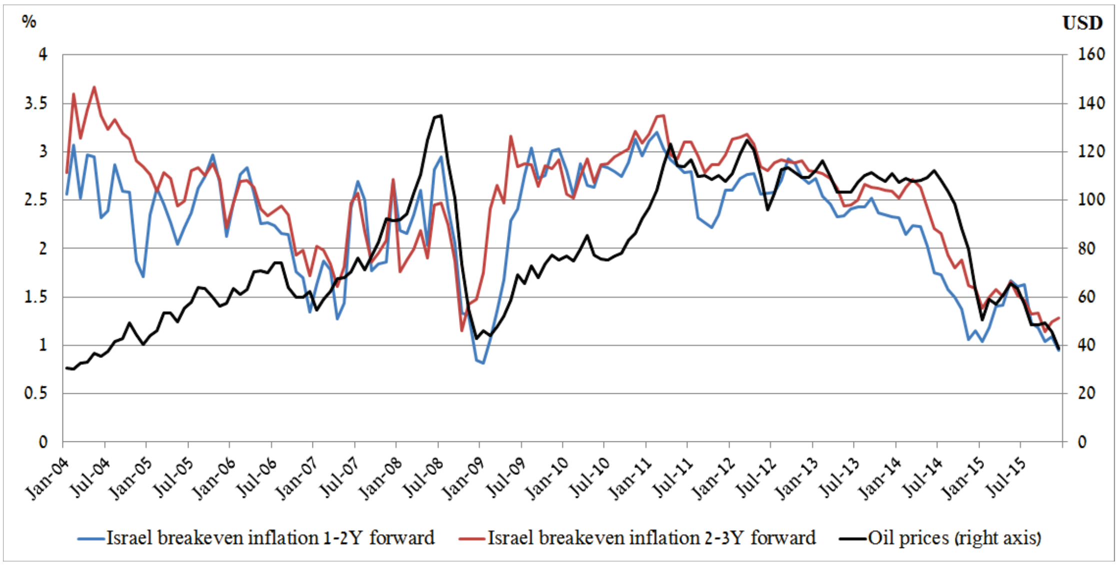
Figure 10: The Factors that Drive Monthly Changes in Oil Prices Since Mid-2014 - How they were Perceived in Real Time and How they are Evaluated in Retrospect



Notes: The solid lines depict the factors estimated in our oil price decomposition (Equation (2)). The dashed lines depict the implied decomposition of oil prices that explains the evolution of global medium-term inflation expectations if they were formed in the same way as in the period prior to June 2014 (see Section 4 for more details).

fully anchored. We also saw that inflation expectations for the medium-term became less anchored following the onset of the global financial crisis in 2008. Our breakdown of oil prices into a global aggregate demand factor and oil specific factors allows to infer that during the entire sample period monetary policy was perceived by market participants to be weakly accommodative with respect to oil specific shocks [Rogoff (1985); Ireland (2007)]. We also found that from 2008 monetary policy was perceived to accommodate low inflation associated with global aggregate demand shocks. Our results were obtained using the five-year breakeven inflation rate that could be heavily influenced by low inflation expectations for the immediate term to which monetary policy cannot effectively respond. However, this reasoning should also apply to the period before 2008 and therefore we can argue that the public changed its perception regarding the degree of accommodation to low inflation in the medium term. Moreover, data for Israel that has, for historical reasons, a thick market for inflation indexed bonds for shorter maturities show that forward inflation rates for one to two years or two to three years have also fallen below the inflation target (Figure 11). Finally we document a recent decline in the five-year for five years forward rate. This development is consistent with a reversal of findings reported in earlier research [Gürkaynak et al. (2010);

Figure 11: Oil Prices and Forward Inflation Expectations in Israel



Source: Bloomberg and the Bank of Israel.

Notes: Breakeven inflation 1-2Y (2-3Y) forward is the one-year breakeven inflation one year ahead (two years ahead).

Blanchard and Gali (2007); Blanchard and Riggi (2013); Beechey et al. (2011)].

What could explain this change? We offer two possible, mutually non-exclusive, explanations. The first is a change in monetary policy. 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)]. 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. At the very least it made inflation expectations more sensitive to global activity. A variant of this explanation is that 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.

The second explanation is that monetary policy had been operating since 2008 in a new environment where interest rates have reached the zero (effective) lower bound,[31] 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. Alternatively, the public may perceive that monetary policy has exhausted it tools. Unfortunately, in the absence of positive shocks to prices, these expectations can be self-fulfilling. It is beyond the scope of this paper and perhaps even too early to test the relative importance of these possible explanations.

6 Conclusion

We use the first principal component of various commodity prices to analyze the fundamental forces that drive oil prices. We associate changes in oil prices that are explained by the first principal component with changes in global aggregate demand, and the residual is associated with idiosyncratic forces. We use this distinction to examine the increase in correlation between medium-term expected inflation and prices of oil. We find that global aggregate demand factors manifested in oil prices have increased effects on expected inflation since the global financial crisis, and explain a substantial part of their developments. The effects of idiosyncratic forces have remained small throughout our sample period. This phenomenon may reflect changes in monetary policy objectives, namely putting less emphasis on stabilizing inflation, or the struggle to stabilize inflation when interest rates are approaching the zero lower bound.

Our methodology can be readily applied to monitor in real time global aggregate demand conditions. Moreover, the principal component we use as a proxy for global aggregate demand 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.

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

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A Methodology for Constructing the First Principal Component

In Section 2.2 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,

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

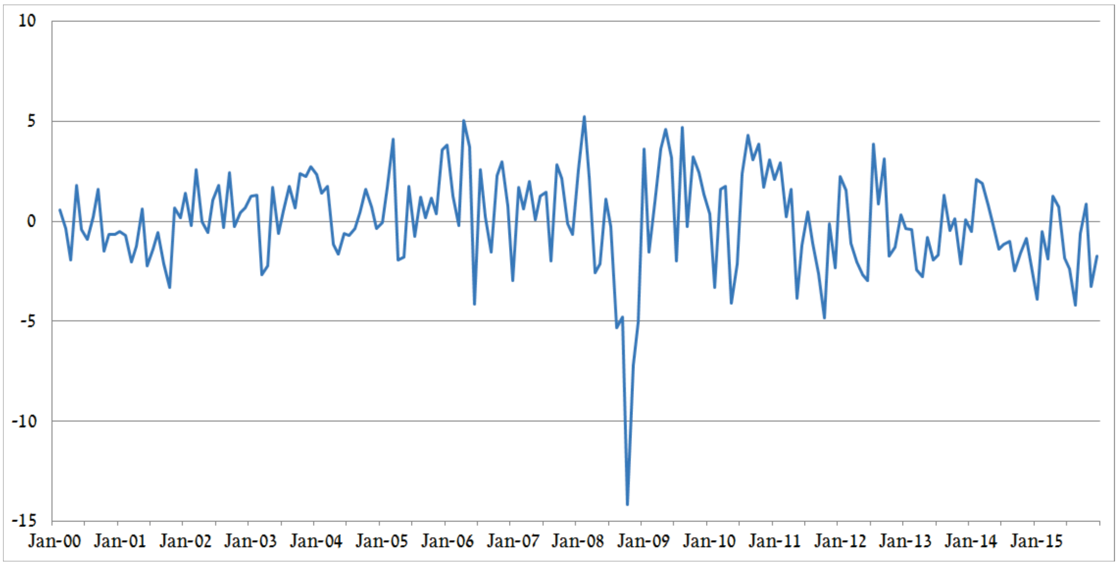
The factor that solves this problem is a linear combination of the variables constructed as follows. Denote the sample variance matrix by $\hat{\Sigma} \equiv T^{-1} \sum_{t=1}^{T} X_t X_t'$ and let $\hat{\Lambda}$ be the normalized eigenvector of $\hat{\Sigma}$ associated with the largest eigenvalue. 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 12.

B Long-Term Inflation Expectations and Oil Prices

In the body of the paper we showed that five-year inflation expectations became much more correlated with the global aggregate demand factor embedded in oil

Figure 12: First Principal Component of Commodity Prices ($pc_t^{\Delta cmd}$)



Notes: The first principal component was calculated for monthly rates of change in prices of various commodities. See Section 2.2.1 for more details.

prices since the global financial crisis. We discussed the implications of this phenomenon on the credibility of inflation targeting in recent years. However, the most prominent indicator of the credibility of the inflation target regime is the anchoring of long-term inflation expectations. Examining five-year five-year forward expectations (Figure 1), we see that while they remained anchored around the two percent level for a longer period, they too show gradual descent toward the end of our sample period.

In this section we examine the anchoring of long-term expectations and their correlation with the global aggregate demand and oil prices. We find some evidence of an increase in the correlation between long-term expectations and the global aggregate demand factor embedded in oil prices. However, relative to our findings regarding expectations for the five-year horizon, the increase occurs in a later period (around the peak of the European debt crisis), and the evidence is less robust. This may indicate that what started in the aftermath of the global crisis in medium-term inflation expectations, gradually trickles down to long-term expectations.

To test this hypothesis, we begin with a naïve analysis using decomposed *levels* of oil prices. We construct the first principal component of levels of commodity prices (in log terms), pc_t^{cmd}, and use it to decompose log levels of oil prices:

$$oil_t = \gamma_0 + \gamma_1 pc_t^{cmd} + u_t^{cmd} \tag{5}$$

We then construct a proxy of global long-term inflation expectations, pc_t^{55beir} - the first principal component of five-year five-year forward breakeven rates from the USA, France and Israel.[32] Finally, we regress global expected inflation on decomposed oil prices:

$$pc_t^{55beir} = \beta_0 + \beta_1 pc_{t-1}^{55beir} \beta_2(\hat{\gamma}_1 pc_t^{cmd}) + \beta_3 \hat{u}_t^{cmd} + \epsilon_t^{55beir} \tag{6}$$

Test of the stability of the coefficients in Equation (6) indicates a breaking point at 2011M09 - the peak of the European debt crisis.[33] We thus add to (6) a dummy variable, $dEDC_t$, that equals one in the period 2004M01-2011M08, and zero otherwise.

$$\begin{aligned} pc_t^{55beir} = \beta_0 + \beta_1 pc_{t-1}^{55beir} \beta_2(\hat{\gamma}_1 pc_t^{cmd}) + \beta_3(\hat{\gamma}_1 pc_t^{cmd}) \times dEDC_t \\ + \beta_4 \hat{u}_t^{cmd} + \beta_5 \hat{u}_t^{cmd} \times dEDC_t + \beta_6 dEDC_t + \epsilon_t^{55beir} \end{aligned} \tag{7}$$

Estimation results of (5) and (7) are detailed in the first column of Table 3. They indicate that since the end of 2011, global long-term inflation expectations are more correlated with global aggregate demand and with the idiosyncratic component of oil prices, even though the change is statistically insignificant.

Admittedly, these results do not hold when we conduct a more statistically appropriate analysis using first differences, i.e., when repeating the analysis of Section 2.4 using five-year five-year forward breakeven rates. Stability tests on a version of Equation (6) with first differences indicate no breakpoint in the equation at any conventional significance levels, but this may be due to the fact that the suspected "structural change" is relatively recent and is manifested only in a small number of observations. If we push the breakpoint one year further to 2012M09, we find weak evidence of an increase in the correlation between the change in long-term expectations and both components of oil prices. It might be too early to determine whether long-term global expectations became unanchored, but we believe that the preliminary evidence we do find justifies further research in this direction.

C Alternative Specifications

C.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 (2), is:

[32]Due to the short available sample of five-year five-year breakeven rates in the UK, we disregard this series in the analysis in this section.

[33]A Bai-Perron test for one versus no breakpoints of the coefficients in (6) indicates a breakpoint at 2011M09 which is significant at the 0.01 level (Scaled F-statistic of 298.67 and Bai-Perron critical value of 18.26).

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

The OLS estimation results of the baseline model and several other specifications are summarized in Table 4. 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 the final column of Table 4 we present estimation results for real prices. We repeat the procedure specified in Sections 2.2-2.3 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.

The final step in our analysis requires using the decomposition of oil prices to estimate the effect of global aggregate demand and idiosyncratic changes in oil prices on global expected inflation (Equation (3)). With either one of the decompositions specified in Table 4, 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.

C.2 Detailed Oil Price Decomposition

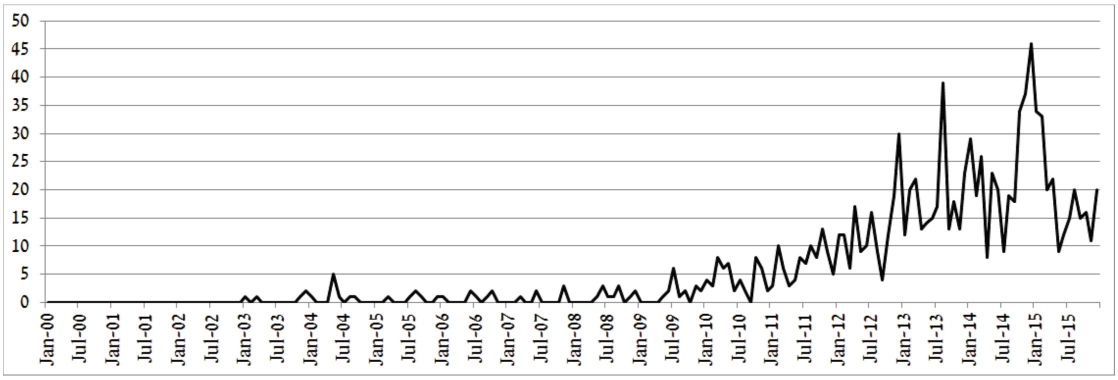
This section specifies estimation results of the detailed decomposition of oil prices and their idiosyncratic component (Section 3). The first two columns of Table 5 present estimation results of the basic model (Equation (2)) and the detailed model (Equation (4)) of oil price decomposition. Comparing 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 5. It is similar to the detailed specification from the second column, except for a different specification of the weather variables. Recall that in Equation (4) we use the temperature data from five continents, interacted with dummy variables for the seasons of the year. In the third column of Table 5, we estimate a model with dummy variables for *calendar months*:

$$\Delta oil_t = \alpha_0 + \alpha_1 pc_t^{\Delta cmd} + \alpha_2 opecref_t + \vec{\Lambda}_1 \cdot \vec{w}_t + \sum_{m=2}^{12} d_{m,t}\, \vec{\Lambda}_m \cdot \vec{w}_t + \sum_{m=2}^{12} \rho_m d_{m,t} + u_t'' \tag{8}$$

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

Figure 13: References of Shale Oil in the London Times



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.

month m. As seen in Table 5, 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).[34] There are not much references of shale oil prior to 2009 (45 references in the period 2000M01-2008M12, relative to 1045 in 2009M1-2015M12), 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 5).

C.3 Sensitivity to the 2008 Global Financial Crisis

In Section 2.4 we showed that since September 2008 global aggregate demand conditions embedded in oil prices are highly correlated with medium-term inflation expectations. One might argue that the strong correlation stems from a short period following the collapse of Lehman Brothers and does not reflect the later period. 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,

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

the correlation between global aggregate demand conditions and inflation expectations increased in the post-crisis period relative to the pre-crisis period. On the other hand, correlation between the idiosyncratic component of oil and expected inflation remained unchanged.

Consider the following model, which is a simple version of Equation (3):

$$\Delta pc_t^{beir} = \beta_0 + \beta_1 \Delta pc_{t-1}^{beir} + \beta_2(\hat{\alpha}_1 pc_t^{\Delta cmd}) + \beta_3 \hat{u}_t + \epsilon_t^{beir} \tag{9}$$

We estimate this model on two separate periods - 2004M01-2007M12 and 2010M01-2015M12 - disregarding an extensive period around the collapse of Lehman Brothers. The results of this exercise are compared to our baseline results in Table 6. In both models the coefficient of the global aggregate demand factor is similar to that of the idiosyncratic component in the pre-crisis period. In the post-crisis period the coefficient of the aggregate demand doubles, while the coefficient of the idiosyncratic component remains low.

C.4 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 (2) and (3), respectively) are summarized in Table 7. In Panel A we observe that $pc_t^{\Delta cmd}$ has a positive and statistically significant coefficient in all three frequencies, and it explains 36-44 percent of the one-period percentage change in oil prices (R-squared is 0.36-0.44). 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 idiosyncratic component (captured by the residual from panel A, $\hat{u}_t$) remains low throughout the sample period.

D Tables

Table 3: Oil Prices and Five-Year Five-Year Forward Global Inflation Expectations

	Levels	First Difference
A. Decomposition of Oil Prices		
Dependent var.	oil_t	Δoil_t
const.	6.20***	0.0025
	(0.11)	(0.0043)
pc_t^{cmd}	0.14***	-
	(0.0028)	
$pc_t^{\Delta cmd}$	-	0.023***
		(0.0018)
R^2	0.93	0.46
DW	0.18	1.49
B. Decomposition of Long-Term Inflation Expectations		
Dependent var.	pc_t^{55beir}	Δpc_t^{55beir}
const.	-0.83***	-0.0085
	(0.30)	(0.088)
pc_{t-1}^{55beir}	0.70***	-
	(0.051)	
Δpc_{t-1}^{55beir}	-	0.037
		(0.085)
$globdem_t$	0.96*	2.53
	(0.56)	(2.16)
$globdem_t \times dEDC_t$	-0.25	-0.90
	(0.57)	(2.28)
$idio_t$	1.91***	2.065
	(0.59)	(1.28)
$idio_t \times dEDC_t$	-1.04	-1.44
	(0.69)	(1.59)
$dEDC_t$	0.84***	-0.027
	(0.32)	(0.10)
R^2	0.91	0.08
DW	1.74	2.12

Notes: Standard errors are reported in parenthesis. Asterisks represent significance levels (*** $p < 1\%$, ** $p < 5\%$, * $p < 10\%$). In Panel B: $globdem_t$ and $idio_t$ are the fitted value and the residual from panel A, respectively.

Table 4: Alternative Specifications of Basic Oil Price Decomposition (Dependent Variable: Δoil_t)

	(1) Baseline	(2)	(3)	(4)	(5)	(6) Real Prices
const.	0.0025	0.0016	0.0023	0.0025	0.00138	0.00077
	(0.0043)	(0.0042)	(0.0044)	(0.0051)	(0.0049)	(0.0044)
Δoil_{t-1}	-	0.20***	-	-	0.25***	-
		(0.054)			(0.061)	
$pc_t^{\Delta cmd}$	0.023***	0.021***	0.021***	-	-	-
	(0.0018)	(0.0018)	(0.0019)			
$pc_{t-1}^{\Delta cmd}$	-	-	0.0032*	-	-	-
			(0.0019)			
$pc_t^{\Delta ne}$	-	-	-	0.018***	0.017***	-
				(0.0022)	(0.0021)	
$pc_t^{\Delta rcmd}$	-	-	-	-	-	0.021***
						(0.0019)
R^2	0.46	0.49	0.47	0.26	0.33	0.40
DW	1.49	1.87	1.51	1.47	1.97	1.47

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

Table 5: Different Specifications of Idiosyncratic Component of Oil Prices (Dependent Variable: Δoil_t)

	Basic (Eq. (2))	Detailed (Eq.(4))	Detailed 2 (Eq. (8))	Detailed 3
const.	0.0025 (0.0043)	-0.54 (0.029)	-0.071 (0.079)	0.019 (0.029)
$pc_t^{\Delta cmd}$	0.023*** (0.0018)	0.022*** (0.0018)	0.021*** (0.0022)	0.022*** (0.0018)
$opecref_t$	-	-0.0059*** (0.0012)	-0.0066*** (0.0014)	-0.0062*** (0.0013)
$shaleref_t$	-	-	-	0.00037 (0.00052)
Temperature vars.	-	✓	✓	✓
Season dummy vars.	-	✓	-	✓
Month dummy vars.	-	-	✓	-
R^2	0.46	0.60	0.73	0.61
Adj. R^2	0.45	0.55	0.57	0.54
DW	1.49	1.77	1.67	1.79

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

Table 6: Sensitivity of Main Results to the Period of the Global Financial Crisis (Dependent Variable: Δpc_t^{beir})

		Baseline	Separate Regressions
Pre-crisis	Global aggregate demand ($\hat{\alpha}_1 pc_t^{\Delta cmd}$)	3.10***	1.89* (1.046)
	Idiosyncratic component ($\hat{u}_t$)	2.58***	1.56* (0.82)
Post-crisis	Global aggregate demand ($\hat{\alpha}_1 pc_t^{\Delta cmd}$)	6.58*** (0.75)	3.91*** (0.92)
	Idiosyncratic component ($\hat{u}_t$)	1.50* (0.80)	2.39*** (0.68)

Notes: Standard errors are reported in parenthesis. Asterisks represent significance levels (*** $p < 1\%$, ** $p < 5\%$, * $p < 10\%$). $\hat{\alpha}_1 pc_t^{\Delta cmd}$ and $\hat{u}_t$ are the fitted value and residual of Equation (2), respectively.

The table shows the main results of two models which differ in the definition of the pre-crisis and post-crisis periods as well as in the methods of estimation. The baseline model is a regression of Equation (3) on the entire sample (2004M01-2015M12). Recall that in this model we included a dummy variable for the pre-crisis period which was defined as 2004M01-2008M08. For this model significance levels for the pre-crisis coefficients are the result of Wald tests. In the separate regressions model we estimated the equation $\Delta pc_t^{beir} = \beta_0 + \beta_1 \Delta pc_{t-1}^{beir} + \beta_2(\hat{\alpha}_1 pc_t^{\Delta cmd}) + \beta_3 \hat{u}_t + \epsilon_t^{beir}$ (Equation (9)) twice, on two different samples: 2004M01-2007M12 and 2010M01-2015M12.

Table 7: Estimation Results for Alternative Frequencies

Frequency: Monthly (Baseline)		Daily	Quarterly
A: Decomposition of Oil Prices (Dependent variable: Δoil_t)			
const.	0.0025	0.00011	0.0093
	(0.00044)	(0.00028)	(0.015)
$pc_t^{\Delta cmd}$	0.023***	0.0057***	0.32***
	(0.0018)	(0.00012)	(0.0055)
R^2	0.46	0.44	0.36
DW	1.49	2.10	1.88
Obs.	191	2917	63
B: Decomposition of Inflation Expectations (Dependent variable: Δpc_t^{beir})			
const.	0.065	0.0022	0.26*
	(0.044)	(0.0031)	(0.13)
Δpc_{t-1}^{beir}	0.25***	0.27***	-0.23**
	(0.067)	(0.029)	(0.079)
$\hat{\alpha}_1 pc_t^{\Delta cmd}$	6.58***	2.076***	11.18***
	(0.75)	(0.22)	(1.27)
$\hat{\alpha}_1 pc_t^{\Delta cmd} \times$	-3.47**	-0.79*	-8.29*
$dprecri_t$	(1.41)	(0.43)	(4.38)
$\hat{u}_t$	1.50*	1.039***	4.63***
	(0.80)	(0.19)	(1.34)
$\hat{u}_t \times$	1.078	-0.16	-2.97
$dprecri_t$	(1.23)	(0.32)	(2.39)
$dprecri_t$	-0.15**	-0.011	-0.53*
	(0.075)	(0.0055)	(0.27)
R^2	0.61	0.23	0.81
DW	1.84	2.17	2.01
Obs.	123	821	37

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.

Table 8: Estimation Results of Equation (1)
(Dependent Variable: $beir_{i,t}$)

	USA (1)	USA (2)	France	UK	Israel (1)	Israel (2)
const.	-22.29***	-7.29***	-1.78**	-456***	-12.97***	-4.94***
	(3.18)	(0.64)	(0.71)	(0.85)	(2.79)	(1.095)
oil_t	1.81***	1.36***	0.39***	1.00***	1.51***	1.10***
	(0.13)	(0.098)	(0.12)	(0.14)	(0.21)	(0.17)
oil_t $\times$	-1.84***	-1.55***	-0.45**	-0.95***	-2.39***	-1.60***
$dprecri_t$	(0.20)	(0.14)	(0.20)	(0.23)	(0.34)	(0.24)
$dprecri_t$	18.86***	10.89***	4.06***	6.43	23.89***	10.69***
	(5.28)	(0.97)	(1.13)	(1.28)	(4.10)	(1.54)
$dleh_t$	-1.02***	-1.19	-0.40**	-1.99***	-0.14	-0.34
	(0.15)	(0.16)	(0.20)	(0.38)	(0.27)	(0.27)
ex_{t-1}	2.72***	-	-2.43***	-0.71	4.06***	-
	(0.57)		(0.46)	(0.99)	(1.31)	
$ex_{t-1}\times$	-1.37	-	1.59*	-0.36	-5.97***	-
$dprecri_t$	(0.97)		(0.84)	(1.60)	(1.69)	
R^2	0.83	0.80	0.70	0.59	0.39	0.33
DW	0.56	0.49	0.29	0.49	0.17	0.15

Notes: Standard errors are reported in parenthesis. Asterisks represent significance levels (*** $p < 1\%$, ** $p < 5\%$, * $p < 10\%$). For the USA and Israel we estimated two alternative specifications: (1) baseline regression with exchange rates (DXY index for the USA); (2) with no exchange rate.

Table 9: Regression of Five-Year Global Inflation Expectations on Decomposed Oil Prices - Up to Mid-2014 and the Entire Sample (Dependent Variable: Δpc_t^{beir})

Sample period	2004M01-2015M12		2004M01-2014M06	
	Baseline	Detailed Decomp. of Oil Prices	Baseline	Detailed Decomp. of Oil Prices
const.	0.065	0.061	0.035	0.055
	(0.044))	(0.059)	(0.051)	(0.063)
Δpc_{t-1}^{beir}	0.25***	0.27***	0.24***	0.23***
	(0.067)	(0.070)	(0.075)	(0.072)
$\hat{\alpha}_1 pc_t^{\Delta cmd}$	6.58***	6.80***	7.042***	7.17***
	(0.75)	(0.80)	(0.82)	(0.82)
$\hat{\alpha}_1 pc_t^{\Delta cmd} \times dprecri_t$	-3.47**	-3.84**	-3.96***	-4.25***
	(1.41)	(1.49)	(1.48)	(1.49)
$\hat{\alpha}_2 opecref_t$	-	3.01	-	20.47***
		(2.33)		(5.62)
$\hat{\alpha}_2 opecref_t \times dprecri_t$	-	-0.21	-	-17.56***
		(3.37)		(6.08)
Temperature	-	-0.77	-	0.68
		(2.20)		(2.37)
Temperature $\times dprecri_t$	-	1.23	-	-0.21
		(3.47)		(3.53)
$\hat{u}_t$	1.50*	1.33	2.16*	2.87**
	(0.80)	(0.93)	(1.23)	(1.23)
$\hat{u}_t \times dprecri_t$	1.078	1.73	0.42	0.20
	(1.23)	(1.58)	(1.56)	(1.75)
$dprecri_t$	-0.15**	-0.13	-0.12	-0.13
	(0.75)	(0.10)	(0.081)	(0.10)
R^2	0.61	0.62	0.63	0.67
DW	1.84	1.90	1.83	2.10

Notes: Standard errors are reported in parenthesis. Asterisks represent significance levels (*** $p < 1\%$, ** $p < 5\%$, * $p < 10\%$). The baseline model (first and third columns) is based on the decomposition of oil prices given by Equation (2), and the detailed decomposition model (second and forth columns) is based on the decomposition in Equation (4). $\hat{\alpha}_i$, $i = 1, 2$ are the estimated coefficients from these regressions and $\hat{u}_t$ is the residual. In the detailed decomposition model the "Temperature" variable is the sum of the fitted values of temperature variables in Equation (4), i.e, Temperature$= \hat{\Gamma}_1 \cdot \vec{w}_t + \sum_{s=2}^{4} \hat{\Gamma}_s \cdot \vec{w}_t\, d_{s,t} + \sum_{s=2}^{4} \hat{\varphi}_s d_{s,t}$