Have Inflation Expectations Become Un-anchored? The Role of Oil Prices and Global Aggregate Demand*

Nathan Sussman[a] and Osnat Zohar[b]
[a]Graduate Institute, Geneva, and CEPR
[b]Bank of Israel

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 an idiosyncratic factor. In 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. Within this framework, we find no evidence that expectations became un-anchored.

JEL Codes: E52, E58, E31, E32.

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, 2016b). This decline lowered inflation in the short run and, in some cases, resulted in negative inflation (International Monetary Fund (IMF) 2016). More

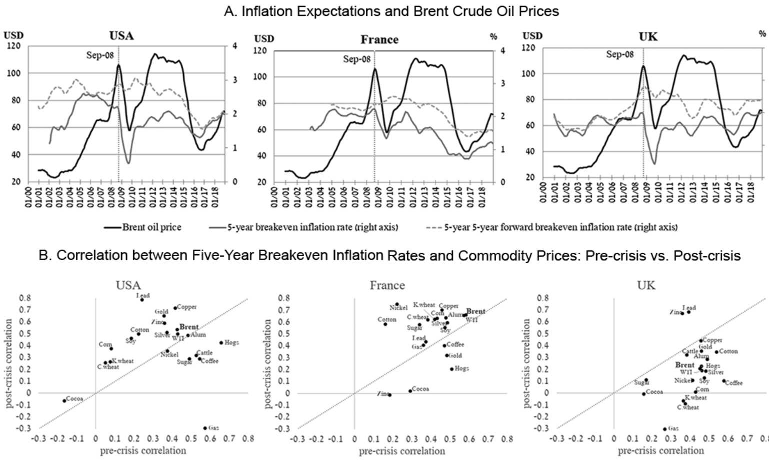
*The views presented in this paper do not necessarily represent the views of the Bank of Israel. Previous versions of this paper appeared under the title "Has Inflation Targeting Become Less Credible? Oil Prices, Global Aggregate Demand and Inflation Expectations during the Global Financial Crisis." We thank Sharon Kozicki and several anonymous reviewers for their insightful comments. We also thank participants at seminars at the Bank of Israel, the University of Western Ontario, and the Bank for International Settlements for their helpful comments. Author e-mails: nathan.sussman@graduateinstitute.ch and osnat.zohar@boi.org.il.

surprisingly, data from the United States and France show 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 (GFC), this correlation was weaker, and expectations were firmly anchored at 2 percent. However, from the onset of the GFC, the correlation is quite high. While this phenomenon is more visible in medium-term inflation expectations, since 2014, we can observe a similar pattern for longer-term inflation expectations, namely the five-year, five-year-forward breakeven rates. At the time, central bankers were concerned that this change might indicate an erosion of the anchoring of expectations (e.g., IMF 2016). Figure 1 also shows five-year breakeven rates in the United Kingdom. Admittedly, they show weaker correlation with oil prices, which even decreased after the crisis. However, our subsequent analysis shows that this is due to idiosyncratic components of U.K. expectations, as the common component of all three economies became more correlated with oil prices (and other commodities) since the GFC.

Our main contribution is to test whether inflation expectations became un-anchored since the GFC using a semi-structural framework based on a global Phillips curve. Because the correlation between oil prices and inflation expectations increased in several large economies, we believe that using a global framework is the proper approach. We hypothesize that oil prices contain information about global economic activity in addition to specific oil-related developments. We separate these two components by noting that global conditions should also affect other commodities. Therefore, we construct a measure of global aggregate demand by extracting a common factor from various commodity prices. We also construct measures of global inflation and monetary rates. Using this approach, we find a structural change in the effect of global demand conditions on global inflation expectations following the onset of the GFC. Controlling for global aggregate demand, we find no change in the impact of oil-market-specific developments on inflation expectations. Furthermore, we find no evidence that expectations became

[1] Due to data availability, we use French breakeven rates as a proxy for euro zone expected inflation.

Figure 1. Inflation Expectations and Commodity Prices (2001–18)



Source: Bloomberg and the Bank of England.
Note: Panel A shows 12-month moving averages of Brent crude oil prices and five-year breakeven inflation rates. Panel B shows correlations between five-year breakeven inflation rates and 20 commodity prices (all computed on monthly data) in the pre-crisis period (x-axis) versus the post-crisis period (y-axis). The figures also depict the 45-degree line to highlight which correlations increased since the crisis and which decreased. The sample for the pre-crisis period begins at 2001:M1 or with the first breakeven inflation data available (see panel A).

more backward-looking. We conclude that expectations remained anchored but react more strongly to global conditions since the GFC.

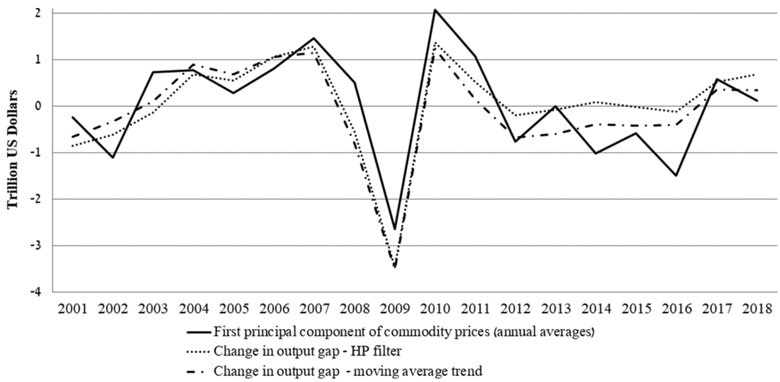
The correlation between oil prices and expected inflation was salient and highly discussed among policymakers in recent years. However, our conjecture that global economic activity was the cause of this increase is strengthened by noting that correlation between prices of other commodities, mainly metals, and expected inflation was even higher (Figure 1B). Thus, what was initially attributed to oil is actually a broader phenomenon that relates to various commodities. At first glance, this phenomenon is puzzling, since we do not expect a correlation between (expected) *rates of change* in the CPI in the medium term and *levels* of commodity prices. However, we argue that commodity prices convey information regarding global aggregate demand, which we expect to be correlated with inflation expectations.

Killian, in numerous studies, already showed that oil prices convey information about global economic activity (Barsky and Kilian 2002, 2004; Kilian 2008, 2009; Kilian and Hicks 2013). We extend Killian's general approach by noticing that various commodities other than oil also convey such information. While each commodity is affected by idiosyncratic supply and demand conditions, they are also affected by common "global aggregate demand" conditions. 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 moves the prices of all commodities in the same direction is global aggregate demand.[2] Exploiting the fact that a large number of commodity contracts are traded in financial markets, we use their first principal component to identify global aggregate demand. The advantage of using these prices is that they are derived from almost perfect markets: they are standardized goods, traded in thick markets, and there is global full information of their prices. Figure 2 shows that the first principal component of commodity price inflation is strongly correlated with changes in measures of the global output gap (correlation coefficients higher than 0.8).

In the first part of the paper, we use this measure in a nonstructural model to examine the increase in the correlation between oil prices and medium-term inflation expectations. A simple regression shows that global aggregate demand is mainly responsible for this increase. The residual change in oil prices, not related to global aggregate demand, has a stable correlation with inflation expectations. To ensure that we correctly identify idiosyncratic changes in oil prices, we instrument the residual with specific variables affecting oil and energy prices idiosyncratically, namely, OPEC's strategic behavior and changes in oil supply and 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

[2] Alquist, Bhattarai, and Coibion (2020) arrived independently at a similar decomposition. In the same spirit, Perez-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.

Figure 2. Changes in the Global Output Gap and the First Principal Component of Commodity Price Inflation (2001–18)



Source: OECD (Economic Outlook No. 104, November 2018), Bloomberg, and authors' calculations.
Note: Both measures of the change in output gap are based on annual world GDP volume to U.S. dollar market prices. We constructed the measures as the annual change in detrended global output. In the first measure, output is detrended using an HP filter, and in the second measure using a trend of a 10-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).

is expanding supply, minus the number of articles indicating supply reduction. We also use temperature variables from five continents to capture changes in the demand and supply for oil arising from abnormal weather conditions.

In the second part of the paper, we address the question of whether our results imply an un-anchoring of inflation expectations. For this purpose, we first have to define un-anchoring. Blanchard (2016) defines un-anchoring as an increase in the backward-looking component of inflation expectations or an increase in their persistence. Beechey, Johannsen, and Levin (2011) define it is an increase in the correlation of inflation expectations with idiosyncratic shocks such as oil prices.

Utilizing our decomposition of oil prices in such a framework allows us to identify the channel by which inflation expectations react more strongly to the global demand factor. We estimate a reduced-form *global* Phillips curve, taking a similar approach to that of Ciccarelli and Mojon (2010) and Diebold, Canlin, and Yue (2008), who used global principal component analysis.[3] We exploit the fact that all advanced economies are part of the monetary regime referred to as "inflation targeting." The United States, the European Central Bank, and, to some extent, the United Kingdom are perceived as the global anchors of this regime. Therefore, there is a common factor of medium-term inflation expectations in these economies, which we estimate using the first principal component of five-year breakeven rates. Similarly, we construct measures of global inflation and global monetary policy. This method removes idiosyncratic components from expected inflation and bond markets from which these expectations are extracted (for example, the shock of Brexit on the London capital market). Another advantage of this approach, as compared with single country estimations or a panel estimation, is that it fits the simpler closed-economy model (nonetheless, we show that our results hold in panel estimation as well).

In the Philips-curve framework, we find, again, an increase in the effect of global aggregate demand on global inflation expectations after the GFC. Within the assumptions of the model we used, we can reject the hypothesis of un-anchoring, i.e., we do not find evidence that expectations became more backward-looking or that they react more to idiosyncratic oil-price changes. Instead, we attribute our findings to an increase in the slope of the global Phillips curve following the GFC. This finding is consistent with a growing effect of global conditions on country-specific inflation expectations.

Our approach and findings relate to a growing strand of literature, which argues that globalization changed the evolution of inflation in recent years (Borio and Filardo 2007; Ihrig et al. 2010; Auer, Borio, and Filardo 2017; Berganza, Borrallo, and del Río 2018; Forbes 2019). As global integration gathered momentum, global factors have had an increasingly important role in determining inflation. This literature supports our approach of estimating a global Phillips curve to test for the un-anchoring of inflation expectations. It is also

[3]Ciccarelli and Mojon (2010) and Diebold, Canlin, and Yue (2008) analyzed global inflation and common global factors in bond yields using principal component analysis, respectively.

consistent with our finding that the role of global economic slack has become more dominant in determining inflation expectations.

For policymakers, our findings imply that the increased effect of global conditions on medium-term inflation expectations does not necessarily imply the un-anchoring of expectations. We find that there is a possibility that the slope of the global Phillips curve increased after the global financial crisis, which suggests that there are fewer frictions in the global economy and particularly in prices. 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, has affected inflation expectations.

The rest of the paper is organized as follows. Section 2 specifies our methodology for testing the sources of change in oil prices and their effect on medium-term inflation expectations. In Section 3, we test the un-anchoring of inflation expectations in a semi-structural framework. Section 4 discusses alternative interpretations of the first principal component of commodity prices, Section 5 provides some robustness checks, Section 6 discusses possible implications for our findings, and Section 7 concludes.

2. The Change in the Correlation between Oil Prices and Medium-Term Inflation Expectations

Figure 1 shows that the correlation between oil prices and five-year breakeven inflation rates increased since the financial crisis in two major economies—the United States and the euro area—suggesting that this is a global phenomenon. In this section, we seek to understand the origins of this change better.

Since we explore a global phenomenon in expectations, we wish to focus on the common factor that drives breakeven inflation rates. We exploit the fact that our economies are anchors of the global monetary regime and pursue a similar inflation target to extract pc_t^{beir}, the first principal component of five-year breakeven inflation rates from the United States, France, and the United Kingdom. Due to data limitations, we extract this factor for the period 2003:M2–2018:M12. This factor can be viewed as an estimator for the global component of expected inflation at the five-year horizon.[4]

Following the country-specific evidence, Table 1 shows that the global factor of medium-term expectations became significantly more correlated with oil prices after the financial crisis (due to considerations of stationarity, we perform this analysis in first differences). Furthermore, we observe that this phenomenon is not unique to oil prices but widespread across different commodities, suggesting that it originates from a more fundamental source. Indeed, in what follows, we show that global expectations became more correlated with oil prices due to a greater effect of global aggregate demand on expectations.

2.1 Estimating Global Aggregate Demand

To identify changes in global aggregate demand, we estimate the first principal component of commodity prices. We use a panel of 20 commodity prices from the 2015 S&P GSCI Spot index (Table 2).[5] The data span the period 2000–18,[6] and to focus on fundamental comovements of prices, we use monthly averages of commodity prices.[7] We convert the data to differenced logs of prices to avoid issues of

[4]The first principal component explains 71 percent of the variance in the panel of breakeven inflation rates. The loadings of the factor are United States—0.66, France—0.52, United Kingdom—0.55. To facilitate the interpretation of regression coefficients, the factor is multiplied by the coefficient c_1 estimated in a country panel regression $y_i = c_{0,i} + c_1 PC^{beir} + \epsilon_i$ for $i \in \{\text{US,UK,France}\}$.

[5]It should be noted that the S&P GSCI Spot index tracks the price of the nearby futures contracts, not returns available to investors. 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 that 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 2, we keep three other energy commodities: WTI crude oil, Brent crude oil, and natural gas.

[6]We begin our analysis in 2000 to match available data of inflation expectations. For the analysis of market-based expectations, we are compelled to use a shorter sample starting in 2003, due to data availability of French breakeven rates. However, household expectations are available from 2000.

[7]In the online appendix (available at http://www.ijcb.org), we test the sensitivity of our results to the data frequency. We repeat our analysis using data at daily and quarterly frequencies, and find that our main results remain qualitatively unchanged.

Table 1. Change in Correlation between Global Medium-Term Inflation Expectations and Different Commodity Prices (dep. var. Δpc_t^{beir}, 2003–18)

cmd_t	Chicago Wheat	Kansas Wheat	Corn	Soybeans	Coffee	Sugar	Cocoa	Cotton	Lean Hogs	Live Cattle
Const.	0.003	0.004	0.003	0.004	0.002	0.001	0.000	0.003	−0.001	−0.002
	(0.013)	(0.011)	(0.013)	(0.012)	(0.014)	(0.012)	(0.014)	(0.010)	(0.020)	(0.016)
$100\Delta log(cmd_t)$	0.010	0.011	0.011*	0.015**	0.007	0.006**	0.017	0.017**	0.003	0.009
	(0.007)	(0.008)	(0.006)	(0.007)	(0.005)	(0.003)	(0.012)	(0.008)	(0.003)	(0.009)
$100\Delta log(cmd_t) \times D_t^{pre}$	−0.008	−0.007	−0.008	−0.013**	−0.006	−0.006	−0.012	−0.013	−0.004	−0.005
	(0.007)	(0.008)	(0.005)	(0.006)	(0.005)	(0.004)	(0.008)	(0.008)	(0.004)	(0.010)
Obs.	178	178	178	178	178	178	178	178	178	178
Adj. R-sq.	0.06	0.07	0.09	0.13	0.03	0.03	0.16	0.23	0.00	0.01
F-stat.	6.91	7.92	10.01	13.92	3.43	3.72	17.84	27.65	1.23	2.29
cmd_t	**Aluminum**	**Copper**	**Lead**	**Nickel**	**Zinc**	**Gold**	**Silver**	**Brent Crude Oil**	**WTI Crude Oil**	**Natural Gas**
Const.	0.001	0.003	0.001	0.004	−0.004	−0.005	−0.000	0.001	0.001	−0.002
	(0.013)	(0.010)	(0.009)	(0.008)	(0.010)	(0.020)	(0.013)	(0.012)	(0.012)	(0.015)
$100\Delta log(cmd_t)$	0.015**	0.020***	0.013***	0.014**	0.018***	0.015	0.013*	0.015***	0.013***	0.001
	(0.007)	(0.006)	(0.003)	(0.007)	(0.006)	(0.014)	(0.007)	(0.004)	(0.004)	(0.002)
$100\Delta log(cmd_t) \times D_t^{pre}$	−0.010	−0.018***	−0.014***	−0.014**	−0.017**	−0.012	−0.010	−0.009**	−0.007**	0.001
	(0.007)	(0.005)	(0.004)	(0.007)	(0.007)	(0.013)	(0.007)	(0.004)	(0.003)	(0.002)
Obs.	178	178	178	178	178	178	178	178	178	178
Adj. R-sq.	0.11	0.31	0.13	0.23	0.22	0.04	0.13	0.33	0.27	−0.00
F-stat.	11.54	40.18	14.20	27.52	25.99	4.66	14.10	44.54	33.13	0.85

Note: The table shows estimation results of ordinary least squares (OLS) regressions: $\Delta(pc_t^{beir}) = \beta_0 + \beta_1 100\Delta log(cmd_t) + \beta_2 100\Delta log(cmd_t) \times D_t^{pre} + \epsilon_t$, where cmd_t is the S&P index for the respective commodity and D_t^{pre} is a dummy for the pre-crisis period (2003:M2–2008:M8). Newey-West standard errors are reported in parentheses (*** $p < 1\%$, ** $p < 5\%$, * $p < 10\%$).

Table 2. Commodities and Loadings of the First Principal Component $pc_t^{\Delta cmd}$

Chicago Wheat	**Kansas Wheat**	**Corn**	**Soybeans**	**Coffee**
0.21	0.22	0.21	0.23	0.21
Sugar	**Cocoa**	**Cotton**	**Lean Hogs**	**Live Cattle**
0.15	0.13	0.19	0.05	0.05
Aluminum	**Copper**	**Lead**	**Nickel**	**Zinc**
0.31	0.33	0.26	0.27	0.30
Gold	**Silver**	**Brent Crude Oil**	**WTI Crude Oil**	**Natural Gas**
0.20	0.26	0.27	0.26	0.07

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 28 percent of the variance in the data.

The loadings of all variables are positive (Table 2). Therefore, the first principal component captures the positive co-movement in all commodity prices, which implies that it mainly captures changes in global aggregate demand. Byrne, Fazio, and Fiess (2013) find that this factor is negatively related to real interest rates and positively related to output. Similarly, Figure 2 shows that the annual averages of $pc_t^{\Delta cmd}$ tracks very well changes in the two measures of the global output gap. In the first measure, GDP is detrended using an HP filter, and in the second measure, we use a trend of a 10-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 price inflation and the change in the output gap is above 0.8, using either measure.

Since all commodities are denominated in U.S. dollars, the first principal component of commodity price inflation may be affected by changes in the U.S. dollar exchange rate. We address this issue in the following subsection. Other components that may be embedded

Table 3. Decomposition of Oil Prices (dep. var. $\Delta log(oil_t)$, 2000:M1–2018:M12)

	Baseline	No DXY
Const.	0.004	0.004
	(0.005)	(0.005)
$pc_t^{\Delta cmd}$	0.024***	0.023***
	(0.003)	(0.002)
$\Delta log(dxy_t)$	0.234	
	(0.274)	
Obs.	227	227
Adj. R-sq.	0.42	0.42
F-stat.	82.06	163.43

Note: The table shows OLS estimation results of Equation (1). Newey-West standard errors are reported in parentheses (*** $p < 1\%$, ** $p < 5\%$, * $p < 10\%$).

in this factor, and alternative interpretations of it, are discussed in Section 4.

2.2 Decomposing Oil Prices

Using our measure of global aggregate demand, we decompose the change in oil prices into two components: a global demand factor and an idiosyncratic factor. We also control for the U.S. exchange rate since we are concerned that it might be correlated with both $pc_t^{\Delta cmd}$ and oil prices. Specifically, we estimate the following regression:

$$\Delta log(oil_t) = \alpha_0 + \alpha_1 pc_t^{\Delta cmd} + \alpha_2 \Delta log(dxy_t) + u_t, \tag{1}$$

where oil_t is the dollar price of a Brent crude oil barrel, and dxy_t is the dollar trade-weighted exchange rate (DXY). Table 3 shows estimation results of Equation (1). We use these results in our subsequent analysis to construct estimators of the two main factors that drive oil prices:

(i) Global aggregate demand factor (rescaled by $\hat{\alpha}_1$ to match the scaling of the residual): $globdem_t \equiv \hat{\alpha}_1 pc^{\Delta cmd}$.

(ii) Idiosyncratic factor: $idio_t \equiv \hat{u}_t$.

Table 3 also reports estimation results without controlling for the DXY index. Comparing the two specifications indicates that the coefficient of the global demand factor is not sensitive to the inclusion of the U.S. dollar exchange rate. However, since we are also interested in the residual of Equation (1) to capture idiosyncratic changes in oil prices, we choose to control for the exchange rate in our baseline estimation.[8] Finally, note that in our sample, global demand conditions explain 42 percent of the variation in oil prices, similarly to the magnitude found by Caldara, Cavallo, and Iacoviello (2019).

2.2.1 Idiosyncratic Components of Oil Prices

Next, we propose direct identification of some of the idiosyncratic forces that drive oil prices. The factors we estimate in this section explain a substantial portion of the variation in $idio_t$, and we use them as instruments in our subsequent analysis.

We focus on two idiosyncratic factors of oil prices. First, we examine OPEC's efforts to control the price of crude oil by managing its supply. These efforts may vary across time, depending on OPEC members' objectives and their ability to collude to promote these objectives. Second, we identify oil-price changes driven by extreme weather conditions. These conditions affect both the demand and the supply of crude oil. From the demand side, extreme weather conditions affect the demand for byproducts of crude oil, such as heating oil. From the supply side, severe weather conditions may disrupt the production of crude oil.

To estimate the effect of OPEC's policies on crude oil prices, we assemble a novel data series that serves as a proxy for the cartel's operations. In each month of our sample, we examine articles published in the *London Times* that refer to OPEC. We classify each

[8] A possible concern is that the exchange rate is correlated with our global demand factor and might bias our estimates of the factor's effect on inflation expectations. However, we find that including the exchange rate in our subsequent analysis of inflation expectations (Equation (2)) yields insignificant coefficients before and after the GFC, and does not affect our main qualitative results.

article as either indicating supply expansion by OPEC, supply contraction, or as neutral articles.[9] Our proxy is a net measure: the number of articles indicating expansion, minus the number of articles indicating contraction (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.[10] For the measure of idiosyncratic changes driven by extreme weather conditions, we examine global temperature data. Specifically, we use five variables, one for each continent, of seasonally adjusted temperature data.[11]

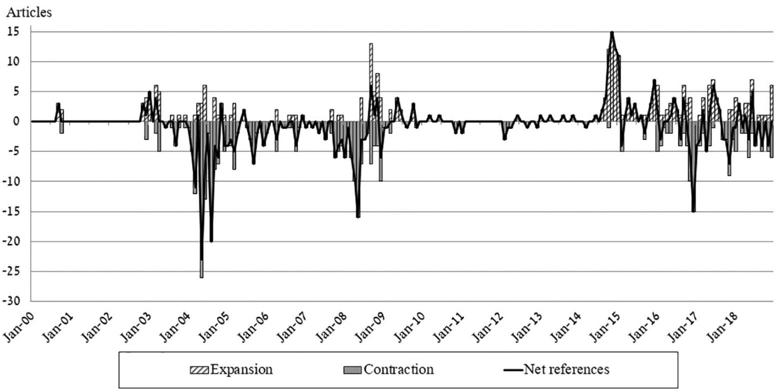
The F-statistic of the regression of $idio_t$ on OPEC's behavior and weather conditions is 33.66, meaning that they are strong instruments. Furthermore, in the online appendix, we report the results of a detailed breakdown of the change in oil prices using these variables. It yields a coefficient of $pc_t^{\Delta cmd}$ which is almost identical to our baseline model. Thus, these factors are primarily orthogonal to $pc_t^{\Delta cmd}$, supporting our claim that the first principal component of commodity price inflation is a valid measure for global aggregate demand.

[9] In a similar approach to Baker, Bloom, and Davis (2016), we search the digital archives of the *London Times* to assemble articles containing the word "OPEC." We then manually evaluate the text sentiment and classify each observation as indicating supply expansion or contraction. Nine percent of all articles show no clear sentiment and are classified as neutral. The series that counts them shows a 20 percent correlation with each of the other two series, indicating that it is not biased. Caldara, Cavallo, and Iacoviello (2019) estimate oil supply shocks in a structural VAR model. The series of shocks is positively correlated with our OPEC proxy, and adding it as an instrument to our baseline equations leaves the results essentially unchanged.

[10] A potential concern is that OPEC's behavior is endogenous to global aggregate demand and, therefore, our instrument is not valid. However, the endogeneity concern is mostly relieved since we control for global aggregate demand. Admittedly, our measure is not perfect, and there may be a component of global aggregate demand that we do not capture but that still affects both OPEC's operations and inflation expectations. Since $globdem_t$ tracks changes in measures of the output gap well (Figure 2), we believe that this missing component is not substantial and so does not significantly impair the validity of the instrument.

[11] Source of the data: National Centers for Environmental Information (NCEI). The NCEI calculates temperature anomalies as the deviation of monthly temperatures from their long-run average.

Figure 3. References of OPEC in the *London Times,* Classified by Type of Operation in the Oil Market (2000–18)



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

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 (Equation (1)). The increase in the correlation can be the result of two possible developments. First, one of the factors that drives oil prices may have become more correlated with inflation expectations. Alternatively, it may be that the elasticities 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 global aggregate demand and inflation expectations has increased.

Our motivation is the relationship between breakeven inflation rates and levels of oil prices. In Equation (1), we decomposed the differenced log terms of oil prices to deal with non-stationarity. Thus, if we are to use this decomposition, we need to examine *changes* in breakeven rates. Specifically, 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 effect before and after the global financial crisis:

$$\Delta pc_t^{beir} = \beta_0 + \beta_1 globdem_t + \beta_2 globdem_t \times D_t^{pre} + \beta_3 idio_t \\ + \beta_4 idio_t \times D_t^{pre} + \beta_5 D_t^{pre} + \epsilon_t, \quad (2)$$

where D_t^{pre} is a dummy for the pre-crisis period (2003:M2–2008:M8).

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 idiosyncratic components of oil prices and thus cannot assert that $idio_t$ is exogenous. We, therefore, use as instruments the variables derived in Section 2.2.1: the proxy for OPEC's behavior and a factor of weather variables, both interacted with the pre-crisis period dummy (in Section 5.7 we address the concern of the endogeneity of $globdem_t$ directly and provide instruments for this variable as well). Two-stage least-squares (2SLS) estimation results (Table 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.

Before the global crisis, changes in oil prices stemming from either global aggregate demand or the idiosyncratic component had a small and similar (non-significantly different) effect on inflation expectations. Thus, 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. This conclusion is supported by a Bai-Perron test that does not identify any breakpoints in Equation (1) at conventional significance levels. In the post-crisis period, the picture is different. We cannot reject the hypothesis that the effect of the idiosyncratic component of oil prices on expectations remained stable. However, the effect of global aggregate demand increased significantly.

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. In the following section, we explain this change using a rational expectations framework. In Section 5, we provide some alternative specifications as robustness tests for these results.

Table 4. Determinants of Global Five-Year Breakeven Inflation Rates (dep. var.: Δpc_t^{beir})

	Basic	Model with the Optimal Policy Rule	Model without a Policy Rule
Equation →	**(2)**	**(8)**	**(11)**
Const.	0.017	0.012	0.011
	(0.014)	(0.012)	(0.015)
$globdem_t$	2.223***	1.996***	2.266***
	(0.513)	(0.540)	(0.714)
$globdem_t \times D_t^{pre}$	−1.525***	−1.318**	−1.709**
	(0.487)	(0.545)	(0.731)
$idio_t$	0.983	0.976	0.936
	(0.685)	(0.733)	(0.801)
$idio_t \times D_t^{pre}$	−0.646	−0.778	−0.688
	(0.747)	(0.794)	(0.851)
D_t^{pre}	−0.022	−0.020	0.006
	(0.019)	(0.017)	(0.024)
Δpc_{t-1}^{beir}		0.151	0.291**
		(0.105)	(0.119)
$\Delta pc_{t-1}^{beir} \times D_t^{pre}$		0.080	0.001
		(0.170)	(0.188)
Δpc_{t-1}^{π}		−0.108	0.041
		(0.128)	(0.060)
$\Delta pc_{t-1}^{\pi} \times D_t^{pre}$		0.138	−0.056
		(0.136)	(0.079)
$pc_t^{\Delta i}$			−0.797***
			(0.280)
$pc_t^{\Delta i} \times D_t^{pre}$			0.270
			(0.375)
Obs.	177	173	173
Adj. R-sq.	0.40	0.41	0.31
F-stat.	23.60	13.99	11.63

Note: The table reports 2SLS estimation results. The instruments used in the first and second models are the net measure of OPEC references in the *London Times* and a component of weather variables (see Section 2.2.1). In the third 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 parentheses (*** $p < 1\%$, ** $p < 5\%$, * $p < 10\%$).

3. A Rational Expectations View on the Anchoring of Inflation Expectations

A possible concern for policymakers was that the increased sensitivity of breakeven inflation rates to oil prices might indicate an erosion in the anchoring of expectations. Concerns grew over the fact that monetary policy has been operating in formerly uncharted territories of quantitative easing and negative interest rates (IMF 2016).

To address the question of whether inflation expectations became un-anchored, we turn to examine the increased correlation between oil prices and five-year breakeven inflation rates in the context of a semi-structural model with rational expectations. This framework, together with our decomposition of oil prices, further supports our results from the previous section. Furthermore, it provides structural interpretations of the changes we identify. We show that the increased effect of global aggregate demand is attributed to the increase in the slope of the Phillips curve, and not to the un-anchoring of expectations.

Beechey, Johannsen, and Levin (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, Sack, and Swanson (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.

We employ Beechey, Johannsen, and Levin's (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 idiosyncratic changes in oil prices. This refinement is essential because, except for 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 may be socially optimal (Rogoff 1985), a perceived accommodation of demand shocks contrasts with inflation targeting and raises questions about the effectiveness or credibility of the monetary regime. 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 the hitherto uncharted territory of quantitative easing and negative interest rates.

Blanchard (2016) defines un-anchoring as an increase in the backward-looking component of inflation expectations or an increase in their persistence. In what follows, we show that the increased responsiveness of inflation expectations to global aggregate demand does not indicate un-anchoring of expectations as formulated in Beechey, Johannsen, and Levin (2011) or Blanchard (2016).

3.1 Rational Expectations with Optimal Policy Rule

To test for un-anchoring, we introduce a framework of how inflation expectations are formed. Since we focus on *global* inflation expectations, we use a closed-economy model. Specifically, we consider the semi-structural model of Orphanides and Williams (2004), which was also used in Beechey, Johannsen, and Levin (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 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:

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

Since we wish to employ our decomposition of oil prices that identifies *changes* in the output gap, we take the first difference of Equation (6), which yields

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

Under 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:

$$\begin{aligned}\Delta pc_t^{beir} &= \beta_0 + \beta_1\Delta pc_{t-1}^{beir} + \beta_2\Delta pc_{t-1}^{beir} \times D_t^{pre} + \beta_3\Delta pc_{t-1}^{\pi} \\ &\quad + \beta_4\Delta pc_{t-1}^{\pi} \times D_t^{pre} + \beta_5 globdem_t + \beta_6 globdem_t \times D_t^{pre} \\ &\quad + \beta_7 idio_t + \beta_8 idio_t \times D_t^{pre} + \beta_9 D_t^{pre} + \epsilon_t^{beir}, \end{aligned} \quad (8)$$

where pc_t^{beir} and pc_t^{π} are the first principal components of five-year inflation expectations and annual inflation, respectively.[12]

As explained in Section 2.3, we assume that the response of global aggregate demand to other shocks is not instantaneous at the monthly frequency and therefore assume that $pc_t^{\Delta cmd}$ is exogenous in Equation (8). Since we cannot assert that $idio_t$ is exogenous, we use the instruments derived in Section 2.2.1 to capture exogenous changes in oil prices.

Two-stage least-squares estimations of Equation (8) are reported in Table 4. They indicate that the only coefficient that significantly changed after the crisis is that of the global demand factor. Other than that variable, no other determinant of inflation expectations

[12] All factors used in this section are depicted in the online appendix. 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 $i \in \{$US,UK,France$\}$.

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 semi-structural specification of inflation expectations (7), we find that an increase in the coefficient on output gap changes with the 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.[13] The analysis we perform in the following section provides additional evidence for this conclusion.

Another possibility ruled out by our estimation is that the inflation target perceived by the public has changed. While the theoretical model assumes a constant inflation target, any change in the public's perception of it should be reflected in the intercept of Equation (8). Since we do not find any significant change in the intercept, we conclude that the announced inflation target has remained credible.

The fact that expectations did not become more adaptive or more responsive to oil-specific price changes since the crisis, and that the announced target has remained credible, implies that expectations have so far remained anchored. Instead, our results point to a structural change in the Philips curve. This change 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 merely *perceived* by the public to have changed, some 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

[13]The fact that the coefficients of lagged changes in inflation and inflation expectations remained stable implies that ϕ and $\alpha\theta$ did not change. Thus, an increase in the coefficient of output gap changes necessarily implies that α increased, together with an offsetting decrease in the monetary policy parameter θ. Note that under an optimal policy rule, a rise in the slope of the Phillips curve should make policymakers less responsive to deviations of inflation from target, meaning that θ should, in fact, decrease.

debt crisis.[14] Stella and Stock (2013) find evidence of a stronger inflation-unemployment relationship in the United States since the global financial crisis. Alternatively, it may be that curves of individual countries have not changed with respect to *local* output gaps but have become more sensitive to the *global* output gap (Forbes 2019).

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 "zero lower bound" (ZLB) and saw an extended use of unconventional policies. While it is not clear that the ZLB affected the transmission of shocks (Debortoli, Galí, and Gambetti 2020), we nonetheless 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 (3) and the IS curve (4) 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:[15]

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

and in first differences:

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

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

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

[15] In Section 5.6 we take a different approach and estimate Equation (8) using shadow rates instead of monetary rates.

component of the change in the monetary interest rate in the United States, the United Kingdom, and the euro area:[16]

$$\Delta pc_t^{beir} = \beta_0 + \beta_1 \Delta pc_{t-1}^{beir} + \beta_2 \Delta pc_{t-1}^{beir} \times D_t^{pre} + \beta_3 \Delta pc_{t-1}^{\pi} + \beta_4 \Delta pc_{t-1}^{\pi} \times D_t^{pre} + \beta_5 globdem_t + \beta_6 globdem_t \times D_t^{pre} + \beta_7 pc_t^{\Delta i} + \beta_8 pc_t^{\Delta i} \times D_t^{pre} + \beta_9 idio_t + \beta_{10} idio_t \times D_t^{pre} + \beta_{11} D_t^{pre} + \epsilon_t^{beir}. \tag{11}$$

Following the discussion in the previous section, it is reasonable to assume that the global demand factor is exogenous in (11). However, the monetary interest rate is endogenous, and we also treat $idio_t$ as such. We thus estimate Equation (11) using the lag of $pc_t^{\Delta i}$ as an instrument for the monetary rate, and the instruments detailed in Section 2.2.1 for $idio_t$.

Two-stage least-squares estimation results of Equation (11) are reported in Table 4. Similarly to Equation (8), we find that the effect of global aggregate demand on medium-term inflation expectations increased significantly since the global financial crisis. In contrast, the effect of the idiosyncratic component remained stable. Examining the semi-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.

4. Alternative Interpretations of the First Principal Component of Commodity Prices

Our estimation uses the first principal component of commodity price inflation as a proxy for global aggregate demand. Section 2.1

[16] Note that in the semi-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 rate using the Fisher identity to the nominal yield and inflation (expectations), and estimate the equation using the nominal policy rate. The interpretation for the coefficient on inflation is adjusted accordingly.

showed that this component is highly correlated with changes in measures of the output gap. In this section, we discuss other elements that might be captured in this factor. We argue that their magnitude is small so that the first principal component is a valid proxy for global aggregate demand. (Recall that our baseline estimation already addresses the issue that all commodities are denominated in U.S. dollars by controlling for the DXY index.)

4.1 The Direct Effect of Oil Prices on Other Commodities

The literature points to several mechanisms that link oil prices to the prices of other commodities (Baffes 2007; Du, Cindy, and Hayes 2011; Baumeister and Kilian 2014; Hassler and Sinn 2016; see Serra and Zilberman 2013 for a survey). 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 are used to produce substitutes for crude oil (e.g., corn and sugar for ethanol production), linking their demand to developments in the energy market. Finally, changes in the price of oil affect disposable income and thus influence the demand for other commodities.

The first principal component of commodity price inflation captures a positive co-movement in the data (the loadings on all commodities are positive). Out of the four mechanisms above, only the first two can generate such a co-movement, namely, global aggregate demand and energy-intensive inputs in the production of other commodities. If the second mechanism 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, following previous studies (Barsky and Kilian 2002; Kilian 2009; Kilian and Murphy 2014), we note that the pass-through from oil prices to other commodity prices is modest. Specifically, we show that the energy component contained in the agriculture and metal industries is small. We do so by examining data from the U.S. Department of Commerce regarding six industries that best match the S&P non-energy commodities.[17] In each of these six industries, we calculate the value of energy-intensive inputs as a share of total output in that industry. We find that the share of total output that can be associated with energy-intensive inputs is lower than 17 percent in all six industries (results appear in the online appendix). The finding is consistent with Baffes (2007), who 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. The test indicates that we cannot reject the hypothesis that the energy index does not Granger-cause $pc_t^{\Delta cmd}$ (F-statistic of 0.73). Namely, given past information regarding the first principal component, energy prices have no significant contribution to forecasting $pc_t^{\Delta cmd}$. However, 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 5.27 for the null hypothesis that $pc_t^{\Delta cmd}$ does not Granger-cause the monthly rate of change in the energy index).[18] These results suggest global aggregate demand profoundly influences energy prices, but the reverse effect is modest.

4.2 Other Interpretations

One concern is that the first principal component might be capturing productivity shocks. The effect of a positive productivity shock is to reduce the aggregate global price level; nevertheless, it could have a positive income effect (that dominates the substitution effect) on commodity prices. If these shocks are prominent in our sample, then $pc_t^{\Delta cmd}$ might be capturing deflationary effects. While it is common wisdom that global productivity shocks did not cause the lead-up boom and the following global recession in 2008, we nevertheless verify that the principal component we extract is positively correlated with global inflation. Furthermore, in all our specifications, this factor has a positive effect on inflation expectations. These findings

[17] We extract the data from the 2007 input-output use table. Industry classifications follow those of the Bureau of Economic Analysis (BEA).

[18] We obtain an even stronger result 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 6.78).

indicate that aggregate demand shocks, rather than productivity shocks, dominate this factor.

Another concern is that the first principal component of commodity price inflation is affected by the role of commodities as a hedge against inflation and, therefore, will be endogenous to expected inflation in our subsequent analysis. However, Batten, Ciner, and Lucey (2010) report that gold, which is the commodity that historically served as a hedge against inflation, responds mainly to monetary factors, whereas other precious metals respond to financial variables. At the same time, Blose (2010) finds that the price of gold is not correlated with inflation expectations. In our analysis, the loading of gold in the first principal component is slightly lower than the average loadings of all commodities and is much lower than that of oil or other metals (Table 2). Moreover, a Granger causality test reveals that inflation expectations are Granger-caused by the common factor representing global demand, but reverse causation cannot be established. Nevertheless, in Section 5.7, we directly address the possibility that *globdem* is endogenous in our analysis.

5. Robustness

5.1 Household Inflation Expectations

So far, our analysis of inflation expectations focused on five-year breakeven inflation rates. While policymakers closely monitor this measure, and even though it 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 the context of a Phillips curve, which captures the effect of nominal rigidities. Therefore, in the way of a robustness test, we repeat our analysis using household surveys of one-year inflation expectations. This measure is commonly used in the literature examining the Phillips curve.

Data limitations only allow us to use quarterly data. However, we can extend our sample to 2000:Q1–2018:Q4. We extract the first principal component of household surveys for the United States, the

United Kingdom, and the euro area, pc_t^{sur}.[19] 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)). For this purpose, we first decompose the *log level* of oil prices:

$$log(oil_t) = \gamma_0 + \gamma_1 pc_t^{cmd} + \gamma_2 log(dxy_t) + v_t,$$

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 $\hat{\gamma}_1 pc_t^{cmd}$ 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 the monetary rate and one with the monetary rate:

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

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

Two-stage least-squares estimation results of these models are reported in Table 5. Similarly to breakeven inflation rates, the first

[19] Our data sources: For the United States, a quarterly average of expectations from the Michigan Survey of Consumers; for the United Kingdom, the Bank of England's quarterly Inflation Attitude Survey; for the euro area, a quarterly average of the OECD Consumer Opinion Survey regarding the 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 since two of the three measures are point estimates of inflation. The first principal component explains 64 percent of the variation in the data and gives weights of 0.60, 0.62, and 0.51 for the United States, the United Kingdom, and the euro area, respectively.

Table 5. Determinants of Global Household Inflation Expectations (dep. var.: pc_t^{sur}, 2000:Q1–2018:Q4)

	Model with Optimal Policy Rule	Model without a Policy Rule
Const.	-0.279^{***}	-0.566^{***}
	(0.062)	(0.207)
pc_{t-1}^{sur}	0.087	0.148
	(0.119)	(0.165)
$pc_{t-1}^{sur} \times D_t^{pre}$	0.400^{**}	0.097
	(0.194)	(0.201)
pc_{t-1}^{π}	0.167^{***}	0.220^{***}
	(0.054)	(0.065)
$pc_{t-1}^{\pi} \times D_t^{pre}$	0.041	0.108
	(0.122)	(0.139)
$\hat{\gamma}_1 pc_t^{cmd}$	1.047^{***}	0.868^{***}
	(0.171)	(0.283)
$\hat{\gamma}_1 pc_t^{cmd} \times D_t^{pre}$	-0.570^{***}	-0.368
	(0.209)	(0.305)
$\Delta \hat{v}_t$	1.210^{**}	1.114^{**}
	(0.475)	(0.499)
$\Delta \hat{v}_t \times D_t^{pre}$	-0.236	0.306
	(0.681)	(0.706)
D_t^{pre}	0.392^{***}	0.463^{**}
	(0.077)	(0.226)
pc_t^i		-0.248
		(0.190)
$pc_t^i \times D_t^{pre}$		0.354^{*}
		(0.193)
Obs.	75	75
Adj. R-sq.	0.87	0.88
F-stat.	56.03	50.88

Note: The table shows 2SLS estimation results of Equations (12) in the first column and (13) in the second column. 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 2.2.1). 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 parentheses (*** $p < 1\%$, ** $p < 5\%$, * $p < 10\%$).

specification indicates that the effect of global aggregate demand on household expectations has increased since the crisis. In contrast, the effect of the idiosyncratic component remained stable. Coibion and Gorodnichenko (2015) find that household inflation expectations were highly sensitive to oil prices in the aftermath of the crisis. We can refine their findings by showing that expectations became relatively more sensitive to information about the global output gap, which is embedded in oil prices. Admittedly, the results do not hold in the second specification. We do not observe any significant change in the effect of global aggregate demand in this model. In any case, similarly to breakeven inflation rates, household expectations have not become more adaptive or more responsive to idiosyncratic changes in oil prices.

5.2 Inflation Swaps

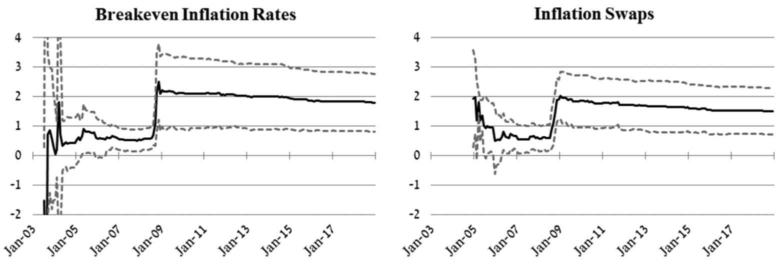
Breakeven inflation rates are not perfect measures of inflation expectations since they include compensation for risk and illiquidity. For this reason, policymakers also track zero-coupon inflation swaps. Like breakeven rates, inflation swaps also entail a risk premium.[20] However, they are free from the liquidity premium, which might be significant during financial turmoils such as the GFC. It should be noted that imbalances in demand for inflation payments versus its supply affect swap quotes, generally biasing them upwards. While there is no reason to prefer one measure over the other, for robustness, we test the effect of oil prices and global aggregate demand on five-year inflation swaps. Unfortunately, inflation swap data is available only from 2004, which shortens our pre-crisis sample.

We regress changes in the first principal component of inflation swaps on decomposed oil prices, as specified in Equation (2).[21] The results portray a similar image to the one we document for breakeven inflation rates. Namely, global aggregate demand has a stronger

[20] We test whether the change in market expectations reflects changes in uncertainty and risk aversion manifested in risk premiums by adding the VIX index (with interaction with D^{pre}) to Equation (2). Its coefficient is insignificant at any conventional level, and we find no evidence that its effect changed after the crisis. Furthermore, the coefficients of *globdem* and *idio* remain essentially unchanged.

[21] The first principal component of these measures captures 59 percent of their common variation. The loadings of the factor are as follows: United States—0.71, euro area—0.61, United Kingdom—0.35.

Figure 4. Stability of the Effect of Global Aggregate Demand on the First Principal Component of Breakeven Inflation Rates and Inflation Swaps (2004–18)



Note: The figure depicts the coefficient of global aggregate demand in a rolling 2SLS estimation of Equation (2) with an expanding window. In the left panel, the dependent variable is the change in the first principal component of breakeven rates, and in the right panel, it is the first principal component of inflation swaps. The solid line is the estimated coefficient and dashed lines represent ±2 Newey-West standard errors.

effect on inflation swaps since the crisis, while the effect of oil-specific factors remains stable. However, the results are more sensitive to the breakpoint. With the breakpoint of the crash of Lehman Brothers (2008:M9), the change in the global demand coefficient is significant only at the 10 percent level and not at the 5 percent level. Moving the breakpoint one month earlier (2008:M8) generates results that are significant at the 5 percent level (Figure 4).

Indeed, when we examine the evolution of the global demand coefficient in Equation (2) in a recursive regression with an expanding window, we find that the change in inflation swaps was smaller and more gradual than in breakeven rates (Figure 4). Therefore, the results in the structural models (8) and (11) are less robust (in the online appendix we present detailed results of these estimations and compare them with the results with breakeven inflation rates using the same sample and the earlier breakpoint).

5.3 Excluding the Period around the Collapse of Lehman Brothers

In Section 2.3, we show that since September 2008, global aggregate demand conditions have a more substantial 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. 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 remove an extensive period around Lehman's collapse, the effect of global aggregate demand 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: 2003:M3–2007:M12 (pre-crisis), 2008:M1–2009:M12, and 2010:M1–2018:M12 (post-crisis):

$$\begin{aligned}\Delta pc_t^{beir} = {} & \beta_0 + \beta_1 globdem_t + \beta_2 globdem_t \times D_t^{03-07} + \beta_3 globdem_t \\ & \times D_t^{08-09} + \beta_4 idio_t + \beta_5 idio_t \times D_t^{03-07} + \beta_6 idio_t \\ & \times D_t^{08-09} + \beta_7 D_t^{03-07} + \beta_8 D_t^{08-09} + \epsilon_t, \end{aligned} \tag{14}$$

where D^{03-07} and D^{08-09} are dummy variables for 2003:M3–2007:M12 and 2008:M1–2009:M12, respectively. We can then compare the coefficient of pre-2007 with those of post-2010, ignoring an extensive period around the collapse of Lehman Brothers. 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 D^{pre}. We find that the impact of changes in global aggregate demand on changes in breakeven expectations increased significantly. However, the effect of idiosyncratic changes to oil prices did not significantly change (Table 6).

5.4 Sensitivity to the First Principal Component of Commodity Prices

A critical factor in our analysis is the first principal component of commodity price inflation, which is an estimated factor. In this section, we address two concerns regarding the use of this measure. First, we account for the fact that it is a generated regressor in our

Table 6. Sensitivity of Main Results to the Period of the Global Financial Crisis (dep. var.: Δpc_t^{beir}, 2003–18)

	Basic	Structural with Monetary Rule	Structural without Monetary Rule
Const.	0.007	0.006	0.035
	(0.010)	(0.009)	(0.023)
$globdem_t$	1.276***	1.185***	1.195***
	(0.185)	(0.206)	(0.271)
$globdem_t \times D_t^{03-07}$	−0.737***	−0.512*	−0.488
	(0.261)	(0.269)	(0.321)
$idio_t$	0.590***	0.531**	0.640**
	(0.214)	(0.218)	(0.295)
$idio_t \times D_t^{03-07}$	−0.403	−0.493	−0.325
	(0.458)	(0.432)	(0.455)
D_t^{03-07}	−0.009	−0.013	−0.006
	(0.017)	(0.015)	(0.033)
$globdem_t \times D_t^{08-09}$	1.453***	1.555*	2.514**
	(0.536)	(0.894)	(1.207)
$idio_t \times D_t^{08-09}$	0.859	1.005	2.761
	(0.827)	(1.355)	(2.281)
D_t^{08-09}	0.001	−0.013	−0.257**
	(0.057)	(0.046)	(0.127)
Control for Lagged Inflation and Expectations		√	√
Control for Monetary Rates			√
Obs.	177	173	173
Adj. R-sq.	0.42	0.44	0.17
F-stat.	16.57	10.78	7.07

Note: The table shows 2SLS estimation of variants of Equations (2), (8), and (11) which are estimated with two dummy variables (instead of one, D_t^{pre}) that partition the sample to three periods: 2003:M3–2007:M12 (pre-crisis), 2008:M1–2009:M12, and 2020:M1–2018:M12 (post-crisis). Newey-West standard errors are reported in parentheses (*** $p < 1\%$, ** $p < 5\%$, * $p < 10\%$).

Table 7. Bootstrap Results for Oil-Price Decomposition Accounting for $pc^{\Delta cmd}$ Being a Generated Regressor

	Constant	$pc_t^{\Delta cmd}$	$\Delta log(dxy)$
OLS Estimator	0.004	0.024	0.233
Bootstrap Median	0.006	0.024	0.235
90% Bootstrap Confidence Interval	[−0.007, 0.017]	[0.017, 0.029]	[−0.282, 0.703]

Note: The table presents bootstrap results based on Gospodinov and Ng (2013) for Equation (1): $\Delta log(oil_t) = \alpha_0 + \alpha_1 pc_t^{\Delta cmd} + \alpha_2 \Delta log(dxy_t) + u_t$.

analysis. Second, we acknowledge that the estimator is affected by the set of commodities available to us and provide a robustness test that captures the sensitivity of our main results to the choice of commodities.

Gospodinov and Ng (2013) propose a bootstrap method for a model that employs principal components as generated regressors. Their procedure entails resampling blocks of observations (with replacement), which means that the bootstrap samples do not preserve period ordering. Since most of our analysis depends on differentiating pre and post-crisis effects, we can apply their methodology only to our oil-price decomposition equation (1). Table 7 presents the results of this bootstrap procedure and shows that the bootstrap median estimators are very close to the ordinary least squares estimators. Furthermore, the constant in the equation is not significant, while the confidence band for the $pc_t^{\Delta cmd}$ coefficient is quite narrow.

Next, we perform a bootstrap procedure to account for the uncertainty originating from the sample of commodities used to estimate the first principal component $pc_t^{\Delta cmd}$. In the spirit of Politis and Romano (1994), we draw subsamples without replacement from our set of 20 commodities. Each subsample consists of 15 commodities, and we perform our main estimations on this subset of commodities, i.e., we extract the first principal component of prices and estimate Equations (1), (2), (8), and (11). Table 8 reports bootstrap estimation results for the semi-structural Equations (8) and (11). We still observe a significant increase in the global aggregate demand coefficient. However, we also observe some increase in the effect of the idiosyncratic component of oil prices.

Table 8. Results from a Subsampling Bootstrap Procedure (dep. var. Δpc_t^{beir}, 2003–18)

	With Rule	**Without Rule**
Reference Equation →	**(8)**	**(11)**
Const.	0.011**	0.010**
	[0.009, 0.015]	[0.007, 0.014]
$globdem_t$	2.016**	2.262**
	[1.729, 2.744]	[2.003, 3.007]
$globdem_t \times D_t^{pre}$	−1.325**	−1.674**
	[–2.001, –0.995]	[–2.456, –1.417]
$idio_t$	1.005**	0.953**
	[–0.954, –0.636]	[0.729, 1.196]
$idio_t \times D_t^{pre}$	−0.811**	−0.713**
	[–0.954, –0.636]	[–0.917, –0.5]
D_t^{pre}	−0.019**	0.007**
	[–0.024, –0.013]	[0, 0.013]
Δpc_{t-1}^{beir}	0.155**	0.297**
	[0.124, 0.181]	[0.266, 0.328]
$\Delta pc_{t-1}^{beir} \times D_t^{pre}$	0.080**	−0.002
	[0.037, 0.128]	[–0.046, 0.038]
Δpc_{t-1}^{π}	−0.110**	0.040**
	[–0.121, –0.092]	[0.029, 0.05]
$\Delta pc_{t-1}^{\pi} \times D_t^{pre}$	0.136**	−0.057**
	[0.113, 0.158]	[–0.071, –0.042]
$pc_t^{\Delta i}$		−0.803**
		[–0.838, –0.747]
$pc_t^{\Delta i} \times D_t^{pre}$		−0.713**
		[–0.917, –0.5]

Note: The table shows 2SLS estimation results of Equations (8) and (11) from a bootstrap procedure. Point estimates are median results, and the intervals in square brackets represent 95 percent coverage of the bootstrap results (** $p < 5\%$). The bootstrap procedure was conducted as follows: in each iteration a subset of 15 commodities was drawn without replacement from the set of 20 commodities available in our data set. The first principal component of inflation in these commodity prices was extracted and used to decompose oil prices (Equation (1)). Finally, Equations (8) and (11) were estimated. The procedure was repeated 15,000 times, which approximately equals $\binom{20}{15}$.

5.5 Dealing with Low Dimensionality in the Cross-Section

In the baseline specifications, we estimated a global Philips curve using data from the United States, the United Kingdom, and the euro area. To capture common factors in these three major economies, we extracted the first principal components of breakeven inflation, actual inflation, and monetary rates. Admittedly, principal component analysis is more appropriate when the dimension of the cross-section is large. However, we are limited to the number of countries with thick and long-established markets of inflation-indexed bonds. Thus, in this section, we propose three alternatives for capturing the global changes in inflation expectations: first, a panel estimation; second, capturing common factors using GDP-weighted averages; and third, expanding the cross-section in inflation and monetary rates.

5.5.1 Panel Estimation

One of the merits of focusing on global factors is that we can incorporate them into a closed-economy model. While this model is less appropriate at the individual country level, for robustness, we estimate it in a panel regression model as well. Specifically, we estimate the following three models, referring to Equations (2), (8) and (11), respectively:

$$\begin{aligned}\Delta beir_{i,t} = {}& \beta_{0,i} + \beta_1 globdem_t + \beta_2 globdem_t \times D_t^{pre} + \beta_3 idio_t \\ & + \beta_4 idio_t \times D_t^{pre} + \beta_5 D_t^{pre} + \epsilon_{i,t},\end{aligned} \tag{15}$$

$$\begin{aligned}\Delta beir_{i,t} = {}& \beta_{0,i} + \beta_{1,i}\Delta beir_{i,t-1} + \beta_{2,i}\Delta beir_{i,t-1} \times D_t^{pre} \\ & + \beta_{3,i}\Delta\pi_{i,t-1} + \beta_{4,i}\Delta\pi_{i,t-1} \times D_t^{pre} + \beta_{5,i}\Delta\pi_{i,t-2} \\ & + \beta_{6,i}\Delta\pi_{i,t-2} \times D_t^{pre} + \beta_7 globdem_t + \beta_8 globdem_t \\ & \times D_t^{pre} + \beta_9 idio_t + \beta_{10} idio_t \times D_t^{pre} + \beta_{11} D_t^{pre} + \epsilon_{i,t}^{beir},\end{aligned} \tag{16}$$

$$\begin{aligned}\Delta beir_{i,t} = {}& \beta_{0,i} + \beta_{1,i}\Delta beir_{i,t-1} + \beta_{2,i}\Delta beir_{i,t-1} \times D_t^{pre} \\ & + \beta_{3,i}\Delta\pi_{i,t-1} + \beta_{4,i}\Delta\pi_{i,t-1} \times D_t^{pre} + \beta_{5,i}\Delta\pi_{i,t-2} \\ & + \beta_{6,i}\Delta\pi_{i,t-2} \times D_t^{pre} + \beta_7 globdem_t + \beta_8 globdem_t\end{aligned}$$

$$\times D_t^{pre} + \beta_{9,i}\Delta\iota_{i,t} + \beta_{i,10}\Delta\iota_{i,t} \times D_t^{pre} + +\beta_{11} idio_t$$
$$+ \beta_{12} idio_t \times D_t^{pre} + \beta_{i,13} D_t^{pre} + \epsilon_{i,t}^{beir}, \quad (17)$$

where $i = US, UK, EURO$, and $\Delta beir_{i,t}$, $\Delta\pi_{i,t}$, and $\Delta\iota_{i,t}$ are country i's change in five-year breakeven inflation rates, change in annual inflation, and change in the monetary rate, respectively. Note that in Equations (16) and (17), we also included the second lag of inflation since it improves the explanatory power of both models. Two-stage least-squares estimation results are reported in the online appendix. Our main result holds in all three equations. Namely, we record a significant increase in the effect of global aggregate demand after the crisis. However, we also observe a significant increase in the effect of the idiosyncratic component.

5.5.2 GDP-Weighted Averages as Estimators of Global Components

In our baseline estimation, we used principal components to estimate common factors in breakeven rates, actual inflation, and monetary rates. The first principal component is essentially a weighted average of the relevant series, where the weights maximize the total variation of the data explained by this factor (Stock and Watson 2011). We now repeat our analysis using alternative weights. Specifically, we estimate Equations (2), (8), and (11) using *GDP-weighted averages* of breakeven rates, actual inflation, and monetary rates, instead of the principal components used in the baseline estimation.

The weighted averages in all three cases (breakeven rates, inflation, and monetary rates) are almost perfectly correlated with their first principal component counterparts (correlation above 0.97 in all cases). Thus, it is not surprising that our main results hold in this specification. Namely, the effect of the global demand factor significantly increased after the global financial crisis, while the effect of the oil-specific factor did not significantly change (the results are reported in the online appendix).

5.5.3 Expanding the Cross-Section of Past Inflation and Monetary Rates

The limitation in the number of countries in our sample is due to data availability of five-year breakeven inflation rates. However, data on inflation and monetary rates, which we use as explanatory variables in the structural models, are highly available. Thus, we can alleviate the concern of a small sample of countries, at least in regards to these variables, by extracting the first principal components from a larger set of countries. Specifically, we repeat the estimation of Equations (8) and (11), this time using first principal components pc^{π} and $pc^{\Delta i}$ extracted from a set of 13 advanced economies with (explicit or implicit) inflation-targeting central banks (the full set of countries is specified in the online appendix). The factors estimated with the 13-country sample are highly correlated with those based on the 3-country sample (correlation of 0.93 for annual inflation and 0.86 for changes in monetary rates). This is probably due to the high effect of the major three economies in our baseline sample on other economies, at least for monetary conditions. It is thus not surprising that our main results hold in this estimation. Namely, the effect of global aggregate demand on inflation expectations increased after the crisis. The effect of the idiosyncratic component does not have a significant effect on expectations in either period (the results are reported in the online appendix).

5.6 Accounting for Unconventional Monetary Policy

In the years following the GFC, monetary rates approached the effective lower bound, and led policymakers to employ unconventional tools such as asset purchasing and forward guidance. In Section 3.2, we addressed this issue by estimating a semi-structural model that is agnostic to the monetary rate rule, relaxing the assumption that the rate was freely set to stabilize inflation and output. In this section, we address the issue of unconventional monetary policy directly.

We estimate Equation (11) but replace the first principal component of monetary rates with that of shadow rates as estimated by Wu and Xia (2016, 2017) for the United States, the euro area, and the United Kingdom.[22] Results are reported in the online appendix. As in previous specifications, we find a significant increase in the effect

[22]The first principal component explains 46 percent of the variance in the data, and the loadings are as follows: United States—0.38, euro area—0.59, United Kingdom—0.72.

of global aggregate demand on global inflation expectations after the crisis. However, this specification has an inferior explanatory power.

5.7 Endogeneity of Global Aggregate Demand

In all the estimations so far, we treated *globdem* as an exogenous variable, resting on results that show that the response of global aggregate demand to other shocks is not instantaneous (Kiley 2014; Gertler and Karadi 2015). The case is even stronger since we estimate our models at a monthly frequency. Nonetheless, it may be the case that we mismeasure global aggregate demand, and the measurement error is correlated with the residuals in our models. To tackle this issue, we follow Lewbel (2012), who proposes the use of heteroskedastic residuals to obtain identification in such models.

First, we regress $globdem_t$ on the other explanatory variables in Equation (8) (2SLS estimation with instruments for $idio_t$ and $idio_t \times D_t^{pre}$). Second, we use the residuals from this equation, interacted with the exogenous variables, as instruments for $globdem_t$ and $globdem_t \times D_t^{pre}$ in 2SLS estimation of Equations (8) and (11). Admittedly, this model shows a poor fit to the data (the adjusted R-squared is negative), probably because the heteroskedasticity in the first stage is weak. However, the coefficients of $globdem_t$ and $globdem_t \times D_t^{pre}$ are significant and indicate a higher effect of global aggregate demand on expectations in the post-crisis period (the results are reported in the online appendix).

6. Policy Implications

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 show that their reaction to oil-specific components is small and stable, consistent with the accepted practice of central banks to "look through" supply shocks (Rogoff 1985; Ireland 2007). However, our results also show that inflation expectations react more to global aggregate demand conditions than previously, which is consistent with a structural change in the slope of the global Phillips curve.

While this result does not indicate that expectations became unanchored, it does have implications for monetary policy. 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.

Another implication of our finding is that for a given demand shock, inflation volatility increases. Table 9 shows that aggregate demand contributes more to the volatility of global inflation and inflation expectations since the GFC, which is consistent with a steepening Phillips curve. In the case of expectations, this was the leading cause of the increase in their volatility after the crisis (inflation seems to be affected by other factors which are less volatile after the crisis). As highlighted by Adrian and Duarte (2018), the increasing volatility of inflation and inflation expectations may still require the attention of policymakers.

All in all, our results imply that monetary authorities should be careful in interpreting the correlation between oil prices and inflation expectations. In particular, the assessment of un-anchoring (IMF 2016) may lead to policy actions, including forward guidance, which may contribute to the un-anchoring of longer-term inflation expectations, as Morris and Shin (2018) argue.

7. 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 on expected inflation.

We compute global inflation and monetary regime variables using principal component analysis and estimate a global Phillips curve. We cannot reject the hypothesis that expectations remained anchored. Instead, we find that the increased sensitivity of inflation expectations to global aggregate demand is due to an increase in the perceived slope of the Phillips curve. These results could suggest that monetary policy remained credible during the GFC, but we leave this issue for future research.

Table 9. Variance Decomposition of the Change in Global Inflation and Global Inflation Expectations, Before and After the GFC

A. Change in Global Inflation (Δpc_t^{π})				
Period		Δpc_t^{π}	$globdem_t$	**Resid.**
2003–07	OLS Coefficient		1.15*	
			(0.66)	
	Variance	0.068	0.002	0.065
	Var. Decomp.		4.3%	95.7%
2010–18	OLS Coefficient		1.40***	
			(0.45)	
	Variance	0.047	0.002	0.042
	Var. Decomp.		10.2%	89.8%
B. Change in Global Inflation Expectations (Δpc_t^{beir})				
Period		Δpc_t^{beir}	$globdem_t$	**Resid.**
2003–07	OLS Coefficient		0.99**	
			(0.42)	
	Variance	0.034	0.002	0.032
	Var. Decomp		6.7%	93.3%
2010–18	OLS Coefficient		2.76***	
			(0.39)	
	Variance	0.063	0.002	0.047
	Var. Decomp.		25.0%	75.0%

Note: Panel A shows estimation results of the regression $\Delta pc_t^{\pi} = \beta_0 + \beta_1 globdem_t + \epsilon_t$. The contribution of global aggregate demand to the total variation of Δpc_t^{π} is the R-squared of the regression, and the contribution of the residual is its complement $\frac{Var(\epsilon_t)}{Var(\Delta pc_t^{\pi})} = 1 - R^2$. Panel B shows results from a similar estimation with Δpc_t^{beir} as a dependent variable. Newey-West standard errors are reported in parentheses (*** $p < 1\%$, ** $p < 5\%$, * $p < 10\%$).

The high degree of covariation in primary global macroeconomic aggregates allows us to extract global factors using principal component analysis. While we used this methodology to focus on the global factors themselves, policymakers 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 deployed to monitor in real-time global conditions. Moreover, this variable 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 may help infer the contribution of global aggregate demand conditions 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.

References

Adrian, T., and F. Duarte. 2018. "Financial Vulnerability and Monetary Policy." CEPR Working Paper No. 12680.

Alquist, R., S. Bhattarai, and O. Coibion. 2020. "Commodity-Price Comovement and Global Economic Activity." *Journal of Monetary Economics* 112 (June): 41–56.

Auer, R., C. Borio, and A. J. Filardo. 2017. "The Globalisation of Inflation: The Growing Importance of Global Value Chains." CEPR Discussion Paper No. 11905.

Baffes, J. 2007. "Oil Spills on Other Commodities." *Resources Policy* 32 (3): 126–34.

Baker, S. R., N. Bloom, and S. J. Davis. 2016. "Measuring Economic Policy Uncertainty." *Quarterly Journal of Economics* 131 (4): 1593–1636.

Barsky, R. B., and L. Kilian. 2002. "Do We Really Know that Oil Caused the Great Stagflation? A Monetary Alternative." In *NBER Macroeconomics Annual 2001,* Vol. 16, ed. B. S. Bernanke and K. Rogoff, 137–83 (chapter 3). MIT Press.

———. 2004. "Oil and the Macroeconomy Since the 1970s." *Journal of Economic Perspectives* 18 (4): 115–34.

Batten, J. A., C. Ciner, and B. M. Lucey. 2010. "The Macroeconomic Determinants of Volatility in Precious Metals Markets." *Resources Policy* 35 (2): 65–71.

Baumeister, C., and L. Kilian. 2014. "Do Oil Price Increases Cause Higher Food Prices?" *Economic Policy* 29 (80): 691–747.

———. 2016a. “Lower Oil Prices and the U.S. Economy: Is This Time Different?” *Brookings Papers on Economic Activity* 2016 (2, Fall): 287–357.

———. 2016b. “Understanding the Decline in the Price of Oil Since June 2014.” *Journal of the Association of Environmental and Resource Economists* 3 (1): 131–58.

Beechey, M. J., B. K. Johannsen, and A. T. Levin. 2011. “Are Long-run Inflation Expectations Anchored More Firmly in the Euro Area than in the United States?” *American Economic Journal: Macroeconomics* 3 (2): 104–29.

Berganza, J. C., F. Borrallo, and P. del Río. 2018. “Determinants and Implications of Low Global Inflation Rates.” In *International Macroeconomics in the Wake of the Global Financial Crisis*, ed. L. Ferrara, I. Hernando, and D. Marconi, 183–216. Springer.

Blanchard, O. 2016. “The Phillips Curve: Back to the 60’s?” *American Economic Review* 106 (5): 31–34.

Blose, L. E. 2010. “Gold Prices, Cost of Carry, and Expected Inflation.” *Journal of Economics and Business* 62 (1): 35–47.

Borio, C., and A. Filardo. 2007. “Globalisation and Inflation: New Cross-country Evidence on the Global Determinants of Domestic Inflation.” BIS Working Paper No. 227.

Byrne, J. P., G. Fazio, and N. Fiess. 2013. “Primary Commodity Prices: Co-movements, Common Factors and Fundamentals.” *Journal of Development Economics* 101 (March): 16–26.

Caldara, D., M. Cavallo, and M. Iacoviello. 2019. “Oil Price Elasticities and Oil Price Fluctuations.” *Journal of Monetary Economics* 103 (May): 1–20.

Chen, D. C., X. Gong, E. Raju Huidrom, J. Z. Vashakmadze, and T. Zhao. 2015. “Understanding the Plunge in Oil Prices: Sources and Implications.” In *Global Economic Prospects, January 2015: Having Fiscal Space and Using It,* 155–68 (chapter 4). Washington, D.C.: The World Bank.

Ciccarelli, M., and B. Mojon. 2010. “Global Inflation.” *Review of Economics and Statistics* 92 (3): 524–25.

Coibion, O., and Y. Gorodnichenko 2015. “Is the Phillips Curve Alive and Well after All? Inflation Expectations and the Missing Disinflation.” *American Economic Journal: Macroeconomics* 7 (1): 197–232.

Debortoli, D., J. Galí, and L. Gambetti. 2020. "On the Empirical (Ir)relevance of the Zero Lower Bound Constraint." In *NBER Macroeconomics Annual 2019,* Vol. 34, ed. M. S. Eichenbaum, E. Hurst, and J. A. Parker, 141–70 (chapter 3). Chicago: University of Chicago Press.

Diebold, F. X., L. Canlin, and V. Z. Yue. 2008. "Global Yield Curve Dynamics and Interactions: A Dynamic Nelson–Siegal Approach." *Journal of Econometrics* 146 (2): 351–63.

Du, X., L. Y. Cindy, and D. J. Hayes. 2011. "Speculation and Volatility Spillover in the Crude Oil and Agricultural Commodity Markets: A Bayesian Analysis." *Energy Economics* 33 (3): 497–503.

Forbes, K. J. 2019. "Has Globalization Changed the Inflation Process?" BIS Working Paper No. 791.

Gertler, M., and P. Karadi. 2015. "Monetary Policy Surprises, Credit Costs, and Economic Activity." *American Economic Journal: Macroeconomics* 7 (1): 44–76.

Gospodinov, N., and S. Ng. 2013. "Commodity Prices, Convenience Yields, and Inflation." *Review of Economics and Statistics* 95 (1): 206–19.

Gürkaynak, R. S., B. Sack, and E. Swanson. 2005. "The Sensitivity of Long-Term Interest Rates to Economic News: Evidence and Implications for Macroeconomic Models." *American Economic Review* 95 (1): 425–36.

Hassler, J., and H.-W. Sinn. 2016. "The Fossil Episode." *Journal of Monetary Economics* 83 (October): 14–26.

Ihrig, J., S. B. Kamin, D. Lindner, and J. Marquez. 2010. "Some Simple Tests of the Globalization and Inflation Hypothesis." *International Finance* 13 (3): 343–75.

International Monetary Fund. 2016. "Global Disinflation in an Era of Constrained Monetary Policy." In *World Economic Outlook: Subdued Demand—Symptoms and Remedies,* 121–70 (chapter 3).

Ireland, P. N. 2007. "Changes in the Federal Reserve's Inflation Target: Causes and Consequences." *Journal of Money, Credit and Banking* 39 (8): 1851–82.

Kiley, M. T. 2014. "The Aggregate Demand Effects of Short- and Long-term Interest Rates." *International Journal of Central Banking* 10 (4, December): 69–104.

Kilian, L. 2008. "The Economic Effects of Energy Price Shocks." *Journal of Economic Literature* 46 (4): 871–909.

———. 2009. "Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market." *American Economic Review* 99 (3): 1053–69.

Kilian, L., and B. Hicks. 2013. "Did Unexpectedly Strong Economic Growth Cause the Oil Price Shock of 2003–2008?" *Journal of Forecasting* 32 (5): 385–94.

Kilian, L., and D. P. Murphy. 2014. "The Role of Inventories and Speculative Trading in the Global Market for Crude Oil." *Journal of Applied Econometrics* 29 (3): 454–78.

Larkin, J. 2014. "Examining the Sensitivity of Inflation to the Output Gap across Euro Area Member States." *Quarterly Bulletin* (Central Bank of Ireland) (Q2): 50–51.

Lewbel, A. 2012. "Using Heteroscedasticity to Identify and Estimate Mismeasured and Endogenous Regressor Models." *Journal of Business and Economic Statistics* 30 (1): 67–80.

Morris, S., and H. S. Shin. 2018. "Central Bank Forward Guidance and the Signal Value of Market Prices." *AEA Papers and Proceedings* 108 (May): 572–77.

Oinonen, S., and M. Paloviita. 2014. "Updating the Euro Area Phillips Curve: The Slope Has Increased." Research Discussion Paper No. 31, Bank of Finland.

Orphanides, A., and J. Williams. 2004. "Imperfect Knowledge, Inflation Expectations, and Monetary Policy." In *The Inflation-Targeting Debate,* ed. B. S. Bernanke and M. Woodford, 201–46 (chapter 3). Chicago: University of Chicago Press.

Perez-Segura, A., and R. J. Vigfusson. 2016. "The Relationship between Oil Prices and Inflation Compensation." IFDP Notes (April 6), Board of Governors of the Federal Reserve System.

Politis, D. N., and J. P. Romano. 1994. "The Stationary Bootstrap." *Journal of the American Statistical Association* 89 (428): 1303–13.

Riggi, M., and F. Venditti. 2015. "Failing to Forecast Low Inflation and Phillips Curve Instability: A Euro-Area Perspective." *International Finance* 18 (1): 47–68.

Rogoff, K. 1985. "The Optimal Degree of Commitment to an Intermediate Monetary Target." *Quarterly Journal of Economics* 100 (4): 1169–89.

Serra, T., and D. Zilberman. 2013. "Biofuel-related Price Transmission Literature: A Review." *Energy Economics* 37 (May): 141–51.

Stella, A., and J. H. Stock. 2013. "A State-dependent Model for Inflation Forecasting." International Finance Discussion Paper No. 1062, Board of Governors of the Federal Reserve System.

Stock, J. H., and M. W. Watson. 2011. "Dynamic Factor Models." In *Oxford Handbook of Economic Forecasting,* ed. M. P. Clements and D. F. Hendry, 35–59 (chapter 2). Oxford University Press.

Svensson, L. E. 2000. "Open-economy Inflation Targeting." *Journal of International Economics* 50 (1): 155–83.

Wu, J. C., and F. D. Xia. 2016. "Measuring the Macroeconomic Impact of Monetary Policy at the Zero Lower Bound." *Journal of Money, Credit and Banking* 48 (2–3): 253–91.

———. 2017. "Time-varying Lower Bound of Interest Rates in Europe." Chicago Booth Research Paper No. 17-06.