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Can the change in the composition of the US GDP explain the Great Moderation? A test via oil price shocks

Can the change in the composition of the US GDP explain the Great Moderation? A test via oil price shocks

Alessandro Maravalle*

The paper investigates whether the growing GDP share of the services sector can contribute to explain the great moderation in the US. We identify and analyze three oil price shocks and use a SVAR analysis to measure their economic impact on the US economy at both the aggregate and the sectoral level. We find mixed support for the explanation of the great moderation in terms of shrinking oil shock volatilities and observe that increases (decreases) in oil shock volatilities are contrasted by a weakening (strengthening) in their transmission mechanism. Across sectors, services are the least affected by any oil shock. As the contribution of services to the GDP volatility increases over time, we conclude that a composition effect contributed to moderate the conditional volatility to oil shocks of the US GDP.

JEL: Q43, E32, C32
Keywords: oil price shocks; great moderation; services; structural change.

1 Introduction

Over the last decades the US economy experienced a smooth change in its production structure away from good producing industries and towards services producing industries. In addition to it, business cycle fluctuations in the services sector have been far less volatile than those of the goods sectors over the period 1957-2011. These facts arise the question of whether the change in the output composition and the evidence of different cyclical behavior across sectors might have brought about a modification of the transmission mechanism of the shocks

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to the US economy that (partially) explains the great moderation. In the paper we address this question by focusing on oil price shocks.

This paper is related to the strand of the literature that analyze the great moderation, the decrease in macroeconomic volatility observed since the 1980s in US macroeconomic variables (i.e., Kim and Nelson 1999, Kahn et al. 2002, Boivin and Giannoni 2006). The debate over the source(s) of the great moderation mainly focuses on two explanations. The first one sees it as the result of a change in the transmission mechanism of shocks to the economy, which in turn may be attributed to different causes like the adoption of better technology or better policies, with a special focus on monetary policy (i.e. Bernanke, Gertler and Watson 1997, Ahmed et al. 2004, Herrera and Pesavento 2009, Justiniano and Primiceri 2008). The second approach, instead, interprets the great moderation as largely due to the reduction in the size of the shocks hitting the economy in the last two decades, and is often labeled as the good luck hypothesis (i.e. Sims and Zha 2006, Blanchard and Simon 2001, Stock and Watson 2002). Both possibilities are taken into account in the paper.

The paper is also related to that part of the oil literature that studies the weakening of the economic impact of oil price shocks to the US economy (i.e., Ferderer 1996, Barsky and Kilian 2004, Hooker 2006). The proposed explanations have mainly considered a non-linear relationship between oil and the macroeconomy (Hamilton 2003, Lee et al. 1995), the adoption of a less oil-intensive technology and/or improved flexibility in the labor markets (Blanchard and Galí 2010), the adoption of a better monetary policy (Bernanke, Gertler and Watson 1997, Bohi 1991), the increased rigidity in the demand for oil (Baumeister and Peersman 2008), and changes in the composition of the shocks driving the price of oil (Kilian 2009). Our contribution to this literature is to consider the growing GDP share of the services sector in the US as an additional factor for the explanation of the weakening impact of oil price shocks.

There are several reason for choosing oil price shocks to analyze the potential link between the dynamic of the composition of the US GDP and the great moderation. First, the evidence collected at the business cycle level tell us little about changes in the composition and distribution of the shocks hitting the economy over time. Thus, we need to focus on a specific shocks to disentangle the changes in the variance of the shocks from modifications of their transmission mechanism. This is necessary because, potentially, a shrinking (increase) in the size of a shock (lower variance) might go along with an amplification (weakening) of its transmission mechanism. Thus, observing either one of the two factors in isolation might not deliver an accurate picture of the underlying causes of the great moderation.[1] Second, the fact that in recent times the impact of oil shocks on the US economy has decreased makes oil price shocks an ideal candidate to investigate whether the structural change in the US GDP composition played any role in it. Third, recent developments in the oil literature provide us with an accurate identification methodology for oil price shocks (Kilian 2009) that allows us to distinguish across three different sources: oil supply shocks, global demand shocks and oil demand shocks. Such a distinction is fundamental as the economic effect of oil price shocks strictly depend on the underlying source. Fourth, given the international nature of the oil market, oil price shocks are common across countries (in the absence of significant country-specific exchange rate shocks), rendering the present analysis extendable to other countries.

The choice of focusing on a specific shocks to analyze the source of the great moderation is not new in the literature. Chang-Kim et al. (2008) analyze the role played by aggregate demand and aggregate supply shocks by adopting a Blanchard Quah decomposition within a bayesian VAR. Monetary policy shocks have been the focus of several monetary VARs aimed to evaluate the role played by the monetary policy in the great moderation, with controversial results (i.e. Primiceri 2005, Leduc and Sill 2003, Hamilton and Herrera 2004). More specifically, Herrera and Pesavento (2009) and Pescatori and Novak (2010) both used oil price shocks in analyses of the great moderation. Herrera and Pesavento 2009 estimate a SVAR with oil price shocks to evaluate the role of changes in the transmission mechanism of monetary policy in the explanation of the great moderation. Novak and Pescatori, by estimating a DSGE model, find that changes in the variance of oil shocks explain a third of the US inflation volatility reduction but only a small share of that of the GDP.

There is little literature that investigates the link between changes in the composition of the GDP and the great moderation. McConnell and Perez-Quiroz (1999), by performing a sectoral analysis on the sources of the great moderation, dismiss a role for the services sector on the ground that they do not find a structural break around the mid 1980s in the growth contribution of the services sector to the GDP. Even if this result would fit well with the evidence of a smooth rise of the GDP share of services, we actually find evidence of a break

[1] For example, Balke et al. 2010, estimating a DSGE model, find that in recent years the US economy experienced improvements in efficiency together with increases in the demand for oil. This suggests both a strengthening of the transmission mechanism of oil demand shocks and a reduction in their size due to energy efficiency

in the output growth of the services sector in the mid 1980s by applying the multiple structural break by Bai and Perron (1999, 2003). Most importantly, we consider that in general the lack of a break does not preclude the possibility for the change in the composition of the GDP to play a role in the great moderation. To this purpose we adopt a different methodology based on investigating changes in the transmission mechanism at the sectoral level rather than relying only on the presence of structural break in the output growth at the sectoral level. Herrera et al. (2010) also consider the economic impact of oil price shocks at the sectoral level through an impulse response analysis. However, their scope is limited to (sectors of) the industrial production and their main interest is to verify if the response of the industrial production to oil price shocks is nonlinear.

Our methodology is based on Kilian (2009). In a first stage we disentangle oil price shocks into oil supply shocks, global demand shocks and oil demand shocks. Next, we apply the multiple break test by Perron and Wada (1999, 2003) to the estimated shocks to check for breaks in their unconditional variances. Accordingly, for each oil price shock we split the sample into subperiods of low and high variance. In a second stage we adopt an impulse response analysis to measure the impact of the three oil price shocks on the output growth of the services sector, the goods sector and the GDP, considering both the entire sample and the subperiods. The estimation over the entire sample provides information over cross-sector differences in the propagation mechanism of each oil price shock. The estimation over the subperiods allows for a counterfactual analysis which tells us how much of the across-period change in the macroeconomic impact of a oil price shock is due to either the change in the volatility of the shock (good luck) and/or how much is due to a modification of the transmission mechanism of the shock to the economy. A direct comparison of the results across sectors and periods allow us to evaluate the contribution of the change in the GDP composition to the change in the conditional GDP volatility to oil price shocks. To control for changes in technological changes we follow Nordhaus (2008) and scale oil shocks for their economic importance.

Our main results are the following. First, we find mixed evidence in favor of the good luck hypothesis, as long as oil price shocks are concerned. Though the unconditional variance of oil supply shocks appears to dwindle over time (break in the mid 1980s), that of oil demand shocks actually increases (break in the late 1990s) while that of global demand shocks shows a mixed behavior: it initially decreases (break in the mid 1980s) but then reverts to a high level (break in the mid 2000s). Moreover, over time the volatility of the GDP, conditional to the three oil price shocks, shows a very different behavior: it increases for oil demand shocks, is almost stable for oil supply shocks and heavily falls for global demand shocks. This result reinforces the results in Kilian (2009) as it suggests that the reduced overall impact of oil price shocks on the volatility of the US economy ultimately depends on the specific composition of oil shocks. In this respect, the historical decomposition analysis consistently shows that oil supply shocks are the least important driver of the price of oil all over the period, oil demand shocks were the dominant driver in the early 1980s, while global demand shocks appear to have been dominant in the late 1980s and the 1990s.

Second, at both the aggregate and the sectoral level we find that the change in the volatility of the economic activity due to a shift in any oil shock volatility tends to be contrasted by a contemporaneous modification of the underlying transmission mechanism of the shock to the economy. In the services sector the two factors tend to cancel out, while in the goods sector one of the two factors is always prevailing, though which one depends on the specific oil shock considered. Accordingly, we observe far smaller changes in the output growth volatility of the services sector than in that of the goods sector.

Third, we find that oil demand shocks and global demand shocks tend to produce a larger impact on the economic activity of the goods sector than on that of the services sector. This result, joint with the evidence that the output growth volatility of the services sector, conditional to any oil price shocks, is far lower than that of the goods sector, shows that the services sector is far less sensitive to oil price shocks than the goods sector.

Fourth, the data consistently reports that the implicit contribution of the services sector to the conditional volatility of the GDP increases over time, independently of the kind of oil shock considered. As the services sector is less volatile than the goods sector, we interpret it as an evidence that in the last decades a composition effect was at work in moderating the volatility of the US economy with respect to oil price shocks.

The paper is structured as follows. Section 2 presents stylized facts. Section 3 identify and analyze the oil price shocks. Section 4 presents the main methodology. Section 5 presents the results. Section 6 concludes.

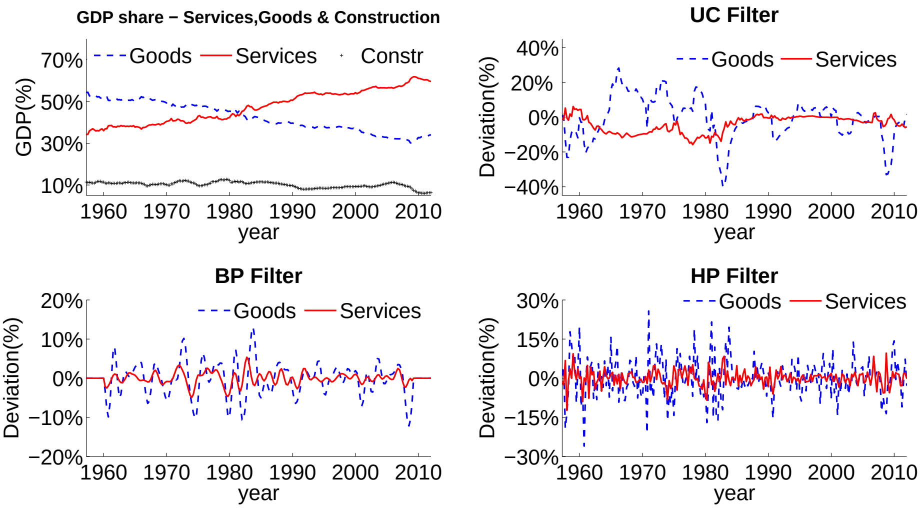
2 Stylized facts and preliminary analysis

In this section we present stylized facts on the different economic behavior held by the services and the goods sector that justify our focus on a GDP composition effect as (part of the) explanation for the great moderation. To construct real aggregate measures of the output at the sectoral level we use quarterly data over the period 1957Q1:2012Q1 (BEA, table 1.5.5, GDP at current level, expanded detail. CPI, all Items City Average IFS). In particular we consider private GDP only and divide it into three sectors: the goods sector, the services sector and the construction sector.[2] The top right panel in figure 1 shows the change in the composition of the US GDP over the period 1957Q1-2012Q1. It is evident the smooth and steady increase in the share of GDP represented by the services sector at the expense of that of the goods sector. The GDP share of the construction sector, instead, appears to be fairly stable around the 10% over all the sample period, but for a decline in the last years, a clear effect of the recent subprime crisis. As the dynamic of the composition of the GDP is entirely captured by the goods and the services sector, we next verify whether the two sectors feature different business cycle properties. To this purpose, we adopt different trend-cycle decomposition techniques to prove that the results are robust to the choice of the filtering methodology. More specifically, we apply to the output growth of the services sector ($Y_{S,t}$) and the goods sector ($Y_{G,t}$) the Hodrick-Prescott filter (HP), the Band Pass filter (BP) and the trend-cycle decomposition with a mixed Gaussian model (PW) by Perron and Wada (2009). The first two filters are hybrid decomposition methods widely used in macroeconomics (i.e. see Canova 2007, chapter 3). The last method, instead, works a statistical trend-cycle decomposition through an unobserved component model that captures potential structural changes in the trend at unknown date.[3] Cyclical fluctuations from the two sectors obtained through the PW filter (top right panel), BP filter (bottom left panel) and HP filter (bottom right panel) are presented in figure 1. Clearly, the services sector always tends

[2] Private GDP is obtained by taken out from the GDP the entry Government consumption expenditures and gross investment. The goods sector is constructed as follows: Personal consumption expenditure on Goods+ Gross fixed domestic investment-residential fixed investment-fixed investment in structures+Net exports of goods. The services sector is constructed as follows: Personal consumption expenditure on services+Net exports of services. The construction sector is obtained as sum of two entries: residential fixed investment + fixed investment in structures.

[3] Perron and Wada (2009) show that when in the trend of a series a structural break is present but not taken into account, different filtering methodologies might deliver very different results.

Figure 1



The HP filter is computed for $\lambda = 1600$. The BP filter captures cycles with periodicity between 6 and 32 quarters. The parameter values used for the PW unobserved component trend-cycle decomposition are those maximizing the likelihood function. The search was performed through the MATLAB function fminunc and repeated 100 times for each variable.

to be far less volatile than the goods sector. As a further evidence, for each trend-cycle decomposition technique we apply to the cyclical components of the two sectors two two-sample non-parametric tests: the Ansari-Bradley test and the Kolmogorov-Smirnov test. Both tests strongly reject the null hypothesis of the equality of the variance of the cyclical component across sectors.

To search for shifts in the unconditional variances of $Y_{S,t}$ and $Y_{G,t}$ we apply the multiple structural break test developed by Bai and Perron to he model suggested by Sensier and Van Dijk 2004 and McConnel and Perez-Quiroz(2000) that we adapt to a multi-period setting:

$$\sqrt{(\pi/2)}\,|Y_{i,t}-\mu_i| = \sigma_{i,t} + u_{i,t},\; t = 1,...,T_1, i = \{S,G\},$$
$$...$$
$$\sqrt{(\pi/2)}\,|Y_{i,t}-\mu_i| = \sigma_{i,t} + u_{i,t},\; t = T_{M+1},...,T, i = \{S,G\},$$

where μ_i is the sample average of $Y_{i,t}$ over the entire sample period and $i = \{S,G\}$ is an index that identifies the specific sector (either Services or Goods). $\sqrt{(\pi/2)}\,|Y_{i,t}-\mu_i|$ is an unbiased estimator of the standard deviation of $Y_{i,t}$ if it follows a normal distribution.

Results from the test are reported in table 1. Structural breaks in the unconditional variance are detected for both $Y_{S,t}$ (1984Q2 and 2005Q2) and $Y_{G,t}$ (1983Q1).[4] The evidence of a fall in the variance of the services sector in the middle 1980s contrasts with McConnel and Perez-Quiroz (2000) who had found a break in the late 60s. To control for differences in the results due to different time samples, we repeat the test over the larger period 1957Q2-2011Q4. The test confirms the presence of a break in the middle 1980s (1983Q3). This result then casts further doubts on the early dismissal of the hypothesis that the growing importance of the services sector might play a role in explaining the great moderation. As to the the goods sector, in line with the literature, we find that the variance of $Y_{G,t}$ fell in the middle 1980s. Moreover, we also find a second break which points to a resurgence in the volatility in the second half of the 2000s, a result in accordance with the occurrence of the subprime crisis.[5]

3 Identification and analysis of oil price shocks

3.1 Econometric Model

We follow Kilian (2009) and decompose oil price shocks into three orthogonal structural shocks: oil supply shocks, global demand shocks and oil-market specific demand shocks.[6] To this purpose we estimate the following SVAR model:

$$A_0 X_t = \alpha_0 + A_1(L) X_{t-1} + e_t. \tag{1}$$

X_t is the vector of endogenous variables including the growth rate of the world oil production, the index of global real economic activity and the log of the real price of oil. The recursive structure of A_0 allows for the identification of the three structural shocks $\hat{e}_{j,t}, j = 1, 2, 3$.

Data are monthly and cover the period 1974:1-2009:06. Oil production is given by the global crude oil production (million barrels per day, source IEA).

[4] Table 1 reports the results of the test when the sample period is restricted to 1974Q1-2011Q4 to match the sample period for which oil price shock data are available. Results do not change when the entire sample period 1957Q1-2011Q4 is considered.

[5] We also search for the stability of the coefficients of AR(1) models of $\Delta log Y_t^S$ and $\Delta log Y_t^G$ but the tests reports no evidence of structural breaks. Only for low values of the trimming the sequential procedure reports a break in the parameter of the services sectors toward the end of the sample (2006:Q3). The break disappear for larger values of the trimming like 0.15. However, for any value of the trimming parameter the sup and supF(l+1,l) report no evidence.

[6] Kilian (2009) interprets oil demand shocks as oil-market specific shocks that determine unpredictable changes in the precautionary demand for oil.

Table 1. Multiple break test of the unconditional variance - output growth at the sectoral level (1974Q1-2011Q4)

Tests[1]				**Number of breaks selected**		
VDMAX/UDMAX	supF(2|1)	supF(3|2)	supF(4|3)	Sequential	LWZ	BIC
13.79***	5.13	7.98	0	1*	0	2

Estimates		
$\hat{\sigma}_1$	T_1	$\hat{\sigma}_2$
4.5544	1983Q1	2.509
(0.65454)	$1978Q4 - 1994Q2$	(0.2553)

(a) Services Sector

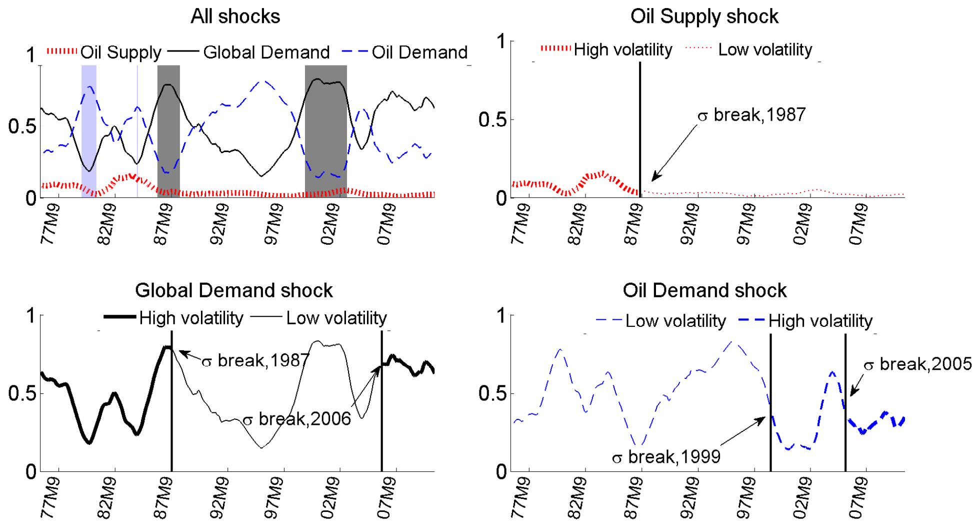
Tests[1]				**Number of breaks selected**		
VDMAX/UDMAX	supF(2|1)	supF(3|2)	supF(4|3)	Sequential	LWZ	BIC
13.0145***	17.71***	2.3065	0.159	0	0	2

Estimates				
$\hat{\sigma}_1$	T_1	$\hat{\sigma}_2$	T_2	$\hat{\sigma}_3$
11.7352	1984Q2	5.831	2005Q2	13.092
(1.3212)	1982Q1-1990Q2	(0.6318)	2000Q1-2007Q2	(2.2061)

(b) Goods Sector

Note: Reported standard errors and confidence intervals are computed allowing for heterogeneity and serial correlation in the disturbances. The covariance matrix is constructed following Andrews (1991) and Andrews and Monahan (1992). Below the estimate of the parameter is reported the standard error; the datebreak estimate reports below the 95% confidence interval. A * indicates significance at the 90%, ** at the 95% and *** at the 99%.
1 The H0 for the VDMAX/UDMAX test is no breaks against the alternative of at least one break. The H0 for the supF(l+1|l) test is l breaks against the alternative of l+1 breaks.

Figure 2. Historical decomposition



The global demand for industrial commodities is given by the global real economic activity index developed by Kilian (2009).[7] The price of oil is given by the US crude oil imported acquisition cost by refiners (dollars per barrel, source IEA). The price index is the CPI all items (index, base year 2005, source IFS).

3.2 Historical decomposition and structural break tests

We compute the contribution of each oil price shocks to changes in the price of oil through an historical decomposition analysis. A 24 month-window symmetric moving average of the historical decomposition is reported in the top left panel of figure 2. The contributions of global demand shocks and oil-demand shocks both outweigh that of oil supply shocks, especially in the second half of the period. In the panel, blue-light shaded areas highlight periods in which oil demand shocks have been dominant, while dark-grey shaded areas point out to periods in which global demand shocks have been dominant.[8]

To take into account the possibility that the size of oil price shocks may vary over time (good luck hypothesis) we search for breaks in their unconditional

[7] available at http://www-personal.umich.edu/~lkilian

[8] To determine whether one shock dominates the others in a given moment we consider for each shock the interval comprised between its contribution to changes in the price of oil in that moment ± one-standard deviation. A shock dominates the others in a given moment if its interval lies above and does not overlap with those of the other shocks.

volatility via the multiple break test by Bai and Perron (Table 2). Oil supply shocks, the least important shock in driving oil price changes, indeed behaves according to the good luck hypothesis as its volatility dwindle after a break in 1987 (figure 2, top right panel). The volatility of global demand shocks, instead, falls after a break in 1987 but then reverts to a high level after a second break in the mid 2000s (figure 2, bottom left panel). Opposite to the good luck hypothesis is the behavior of oil demand shocks, whose volatility is low in the first part of the sample, picks up after a break in 1999 and then further increases after a second break in 2006 (figure 2, bottom right panel). If we consider both the relative importance of each oil price shocks in driving the price of oil and the changes in their volatility over time, we find a mixed evidence in favor of the hypothesis that it is a dwarfing in the volatility of oil price to explain the reduced impact of oil price shocks on the US economy in recent times.

The results from the structural break test allow us, for each shock, to split the data into subperiods in which the shock is homoscedastic. This eases the task to single out changes in the transmission mechanism of the shocks. For oil supply shocks we define two subperiods. The first subperiod is defined over the period 1976Q1:1992Q1, and captures high-volatility oil supply shocks, while the second one is defined over the period 1992Q2:2011Q4 and captures low-volatility oil supply shocks. Similarly, we define three subperiods for global demand shocks. The first subperiod is then defined over the period 1976Q1:1993Q4, and captures high-volatility global demand shocks, the second one is defined over the period 1994Q1:2006Q4 and captures low-volatility global demand shocks, while the third subperiod is defined over 2007Q1:2011Q4, and captures high-volatility global demand shocks. Finally, the structural break test reports two breaks in the volatility of oil demand shocks, the first in the middle 1990s and the second in the mid 2000s. As data would be insufficient to allow for estimation in the third subperiod, we consider two subsamples only by merging the last two subperiods into one as in both the volatility of oil demand shocks is far higher than in the first subperiod. Thus, the first subperiod is defined over the period 1976Q1:1995Q4, and captures low-volatility oil demand shocks, while the second one is defined over the period 1996Q1:2011Q4 and captures high-volatility oil demand shocks. For any shock the specific breakdate between subperiods always lies within the 95% confidence interval determined by the Bai-Perron test and allows for the the subperiods to be nearly evenly divided.

Table 2. Multiple break test of the unconditional variance - oil price shocks (1975M1-2011M12)

Tests[1]				**Number of breaks selected**		
VDMAX/UDMAX	supF(2|1)	supF(3|2)	supF(4|3)	Sequential	LWZ	BIC
30.773***	5.228	6.14	8.05	1***	1	1

Estimates		
$\hat{\sigma}_1$	T_1	$\hat{\sigma}_2$
1.2689	1987M7	0.5786
(0.1206)	1987M2-1992M2	(0.0349)

(a) Oil Supply Shocks

Tests[1]				**Number of breaks selected**		
VDMAX/UDMAX	supF(2|1)	supF(3|2)	supF(4|3)	Sequential	LWZ	BIC
16.75***	2.567	1.6	0	2*	0	2

Estimates				
$\hat{\sigma}_1$	T_1	$\hat{\sigma}_2$	T_2	$\hat{\sigma}_3$
1.2689	1987M10	0.7051	2006M5	1.3341
(0.1206)	1984M1-1993M10	(0.0413)	2001M4 - 2007M1	(0.1737)

(b) Global Demand Shock

Tests[1]				**Number of breaks selected**		
VDMAX/UDMAX	supF(2|1)	supF(3|2)	supF(4|3)	Sequential	LWZ	BIC
80.709***	11.769*	4.16	5.63	2**	1	1

Estimates				
$\hat{\sigma}_1$	T_1	$\hat{\sigma}_2$	T_2	$\hat{\sigma}_3$
0.5531	1999M2	0.868	2004M9	1.7743
(0.038)	1994M10-2003M2	(0.083)	2003M2 - 2005M3	(0.123)

(c) Oil demand shock

Note: Reported standard errors and confidence intervals are computed allowing for heterogeneity and serial correlation in the disturbances. The covariance matrix is constructed following Andrews (1991) and Andrews and Monahan (1992). Below the estimate of the parameter is reported the standard error; the datebreak estimate reports below the 95% confidence interval. A * indicates significance at the 90%, ** at the 95% and *** at the 99%.

1 The H0 for the VDMAX/UDMAX test is no breaks against the alternative of at least one break. The H0 for the supF(l+1|l) test is l breaks against the alternative of l+1 breaks.

4 Econometric analysis of the impact of oil price shocks

In this section we show that the transmission mechanism of each oil price shock differs across sectors and, within a same sector, across subperiods. Second, for each shock we analyze whether the change across periods in the conditional GDP volatility can be explained by either the modification of the transmission mechanism of the shock and/or the shift in the volatility of the shock. We find that these two factors alone are not sufficient and argue that a plausible complementary candidate to fill the gap is the growing weight of the services sector in the composition of the GDP.

4.1 Data

We adjust the real aggregate measures of the sectoral and aggregate output that we used in section 2 in two dimensions. First, we narrow the sample to the period 1976Q1:2011Q4 to match it with that of oil price shocks. Second, we take out from the GDP and the output of the good sector the contributions of "Motor vehicle net of government spending in the sector" (source BEA, table 7.2.5B) and "Gasoline and other energy goods" (source BEA, table 1.5.5). These adjustments are required to avoid the suspicion that differences in the impact of oil price shocks across sectors be driven by these two subsectors because of a direct or indirect oil price shock propagation mechanism.[9]

4.2 Econometric Model

We follow Kilian (2009) and estimate the model:

$$Y_{k,t} = \hat{e}_{i,t} A_{i,k}(L) + \nu_t, \tag{2}$$

where $Y_{k,t}$ is the series of output growth of variable $k = \{GDP, S, G\}$, where S stands for the services sector and G stands for the goods sector; $\hat{e}_{i,t}$ is the regressor matrix containing L lags of the (estimated) oil price shock specified by the index $i = \{OS, GD, OD\}$, where OS stands for oil supply shocks, GD stands for global demand shocks and OD stands for oil demand shocks. The vector

[9] Several authors consider shifts in the car expenditure pattern as core to the functioning of the demand channel of transmission of oil price shocks. See Bresnahan and Ramey (1993) and, more recently, Kilian (2008).

of estimated parameters $\hat{A}_{i,k}(L)$ is interpreted in terms of impulse response coefficients and capture the transmission mechanism of the oil price shock $\hat{e}_i$ to the variable Y_k. Confidence intervals are obtained by applying a block-bootstrap (four blocks) to take into account heteroscedasticity and serial correlations of the errors. We control for oil-saving technological change that might lower the economic impact of oil price shocks by scaling the series of the oil structural shocks for their economic importance (Nordhaus 2008).[10] [11]

4.3 Counterfactual analysis

To disentangle the contribution to the change across subperiods in the conditional volatility of a variable due to changes in the transmission mechanism $\left(\hat{A}_{i,k}(L)\right)$ from that due to changes in the size of underlying oil price shock $(\hat{e}_i)$ we perform a simple counterfactual analysis.

For each oil price shock $(\hat{e}_i)$ and each variable (Y_k) we first compute the fitted value in each of the two subsamples, that is $\hat{Y}^I_{k,t} = \hat{e}^I_{i,t}\hat{A_{i,k}}^I(L)$ for the first subperiod and $\hat{Y}^{II}_{k,t} = \hat{e}^{II}_{i,t}\hat{A_{i,k}}^{II}(L)$ for the second subperiod. We can then obtain for each subperiod a measure of the overall volatility of $\hat{Y}_{k,t}$ conditional to the shock $\hat{e}_i\left(\sigma^2_{\hat{Y}^I_k}\left|\hat{e}^I_i\right., \sigma^2_{\hat{Y}^{II}_k}\left|\hat{e}^{II}_i\right.\right)$. By construction, these conditional volatilities solely depend on the variance of the underlying shock $(\hat{e}_i)$ and the transmission mechanism $\left(\hat{A_{i,k}}(L)\right)$ in that subperiod. Thus, the change in the conditional volatility of $Y_{k,t}$ across subperiods $\left(\sigma^2_{\hat{Y}^I_k}\left|\hat{e}^I_i\right. - \sigma^2_{\hat{Y}^{II}_k}\left|\hat{e}^{II}_i\right.\right)$ captures both the variation in the transmission mechanism and the shift in the shock volatility.[12] We then perform a counterfactual analysis to single out the specific contribution of changes in the transmission mechanism. To this purpose, for any subperiod we compute the fitted values for $Y_k\left|\hat{e}_i\right.$ that would result if

[10]The economic importance of an oil shock at a given period t is computed as the ratio between the current value of oil consumption over nominal GDP (Nordhaus 2008). The current value of oil consumption is computed by multiplying the US petroleum consumption (million of barrels, source IEA) by the nominal price of oil.

[11]Results are not qualitatively different when the estimation is performed without controlling for the oil intensity. We interpret this result as a further evidence that oil price shocks mainly produce effects through demand channels rather than by increasing the marginal cost of production (supply channel).

[12]

If, for example, we observe $\sigma^2_{\hat{Y}^I_k}\left|\hat{e}^I_i\right. > \sigma^2_{\hat{Y}^{II}_k}\left|\hat{e}^{II}_i\right.$, we can only conclude that changes in both the transmission mechanism $\left(\hat{A}_{i,k}\right)$ and the volatility of $\hat{e}_i$ led to a decrease in the overall conditional volatility of $\hat{Y}_{k,t}$ to shock $\hat{e}_i$.

the shocks were those observed in that subperiod but the transmission mechanism were the one observed in the other subperiod. More specifically, we compute $\hat{Y}_{k,t}^{I,CA} = e_{i,t}^{I}\hat{A_{i,k}}^{II}(L)$, the expected value of Y_k in the first subperiod given the shocks observed in that subperiod $\left(e_{i,t}^{I}\right)$ but with the transmission mechanism estimated in the second subperiod $\hat{A_{i,k}}^{II}(L)$. Similarly we compute $\hat{Y}_{k,t}^{II,CA} = e_{i,t}^{II}\hat{A_{i,k}}^{I}(L)$. We can then obtain the conditional counterfactual variances $\left(\sigma^2_{CA,\hat{Y}_k^I}\left|\hat{e}_i^I\right., \sigma^2_{CA,\hat{Y}_k^{II}}\left|\hat{e}_i^{II}\right.\right)$. The difference between $\sigma^2_{\hat{Y}_k^I}\left|\hat{e}_i^I\right.$ and $\sigma^2_{CA,\hat{Y}_k^I}\left|\hat{e}_i^I\right.$ (or between $\sigma^2_{\hat{Y}_k^I}\left|\hat{e}_i^I\right.$ and$\sigma^2_{CA,\hat{Y}_k^{II}}\left|\hat{e}_i^{II}\right.$) can be ascribed to changes in the transmission mechanism only as the subperiods are specifically chosen so that within it the shock is homoscedastic.

4.4 Measuring the composition effect

Our setup permits us to construct a simple measure to assess whether the change in the composition of the GDP plays any role in affecting the conditional variance of the output growth of the GDP with respect to an oil price shock $\left(\sigma^2_{GDP}\left|\hat{e}_i\right.\right)$. Indeed, by construction we have that $GDP_t = Services_t + Goods_t$. It follows that $Y_{GDP,t} = \alpha_{S,t}Y_{S,t} + (1-\alpha_{S,t})\,Y_{G,t}$, where $\alpha_{S,t}$ is the GDP share of the services sector at time t. If we set $\alpha_{S,t} = \alpha_S^I$ for $t = 1,..,T_1$, we can interpret it as the average share of GDP represented by the services sector in the first subperiod. It is then easy to see that:

$$Var\left(Y_{GDP}^j\left|\hat{e}_i\right.\right) = \sigma^2_{GDP^j}\left|\hat{e}_i^j\right. = \left(\alpha_{i,S}^j\right)^2\sigma^2_{S^j}\left|\hat{e}_i^j\right. + \left(1-\alpha_{i,S}^j\right)^2\sigma^2_{G^j}\left|\hat{e}_i^j\right. + 2\alpha_{i,S}^j\left(1-\alpha_{i,S}^j\right)\sigma_{SG^j}\left|\hat{e}_i^j\right.,$$

where the index $j = \{I, II\}$ specifies the subperiod and the oil price shock is specified by the index $i = \{OS, GD, OD\}$. As for each $\hat{e}_i$ and each subperiod we can compute the values for $\sigma^2_{GDP}\left|\hat{e}_i\right.$, $\sigma^2_S\left|\hat{e}_i\right.$, $\sigma^2_G\left|\hat{e}_i\right.$ and $\sigma_{SG}\left|\hat{e}_i\right.$, we can also compute the implicit value of $\alpha_{i,S}$ in that subperiod. An increase in $\alpha_{i,S}$ across subperiods is then interpreted as a larger weight of the services sector in the determination of the overall conditional volatility of the Y_{GDP} with respect to shock $\hat{e}_i$.

By performing such analysis for any oil price shock and subperiod, at the sectoral and the aggregate level, we can draw conclusions on the roles played by the good luck hypothesis, the good policy hypothesis and the composition effect hypothesis in the change across subperiods of $\sigma^2_{GDP}\left|\hat{e}_i\right.$.

5 Results

5.1 Oil price shocks - full sample analysis

To evaluate whether oil price shocks transmit differently across sectors we estimate model (2) over the entire sample for $Y_{k,t}$, $k = \{S, G\}$, and for each of the three oil price shocks. On the basis of the impulse response and cumulative impulse response functions we then observe that the impact of oil demand shocks on the output growth of the goods sectors ($Y_{G,t}$) (Figure 3a and 3b, top right panel) is larger than that on the output growth of the services sector ($Y_{S,t}$) (Figure 3a and 3b, top left panel) and is statistically significant for several horizons. For the other two shocks the evidence is mixed. On one side, the impulse responses to oil supply shocks and global demand shocks are not statistically significant at any horizon for both sectors (Figure 3a, middle and bottom panels). On the other side, the size of the impact on the $Y_{G,t}$ appears far larger.

The result that global demand shocks are not statistically significant is not surprising. Indeed, a boom in the global demand has a positive direct impact on the economic activity in any sector that might counteract the contemporaneous negative effect of the induced increase in the price of oil.

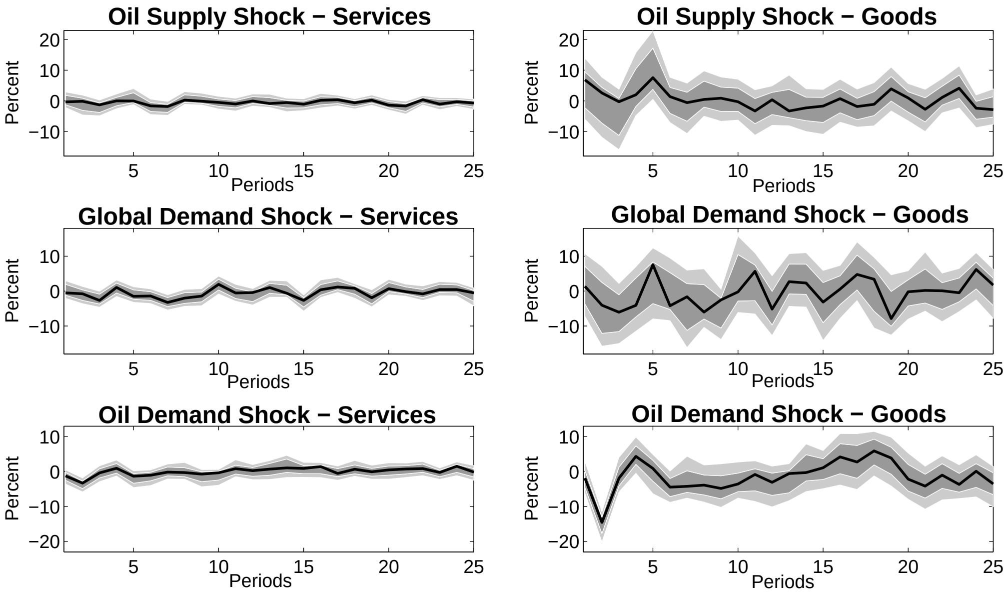
5.2 Oil supply shocks

We estimate model (2) with $Y_{k,t}$, $k = \{GDP, S, G\}$, and $\hat{e}_{i,t} = \hat{e}_{OS,t}$ over the two subperiods. The first subperiod is defined over the period 1976Q1:1992Q1 and captures high-volatility oil supply shocks, while the second subperiod is defined over the period 1992Q2:2011Q4 and captures low-volatility oil supply shocks. Figure 4 reports the impulse response to a unitary size structural shock to the oil supply of the output growth rate of the services sector (top panels), the GDP (middle panels) and the goods sector (bottom panels).

The left panels report the response in the first subperiod, right panels report the response in the second subperiod. From the figure it clearly emerges that the transmission mechanism of oil price shocks strengthened in the second subperiod for any variable. The counterfactual analysis confirms it (table 3a): for example, if the transmission mechanism in the second subperiod had been the one operative in the first subperiod, the conditional standard deviation of the GDP $\left(\sigma_{CA,\hat{Y}_k^{II}} \left| \hat{e}_{OS}^{II} = 0.91\right.\right)$ would have been far smaller than that observed

Figure 3 - Oil price shocks, full sample

(a) Impulse response



(b) Cumulative impulse response

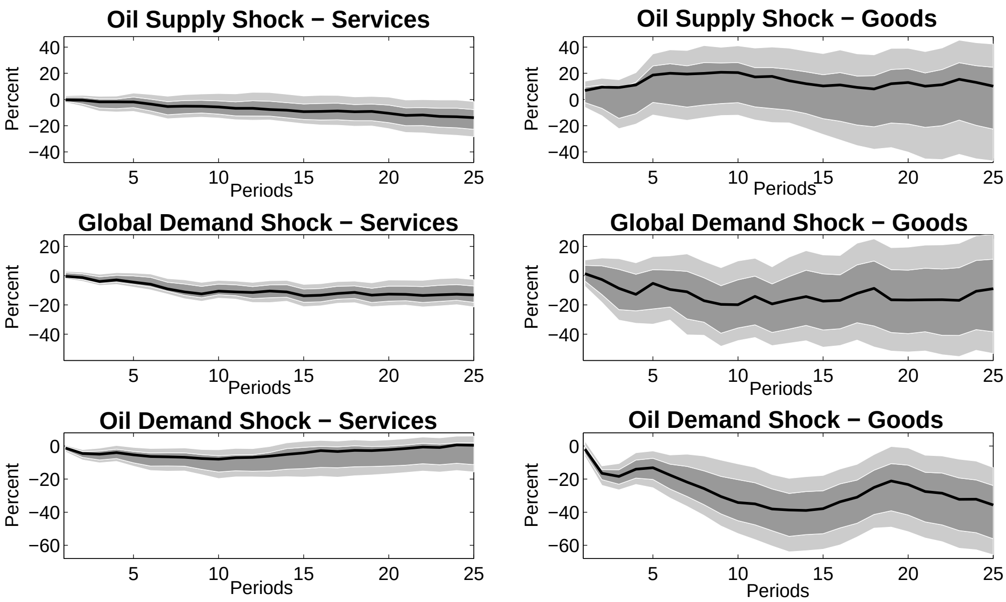


Table 3. Conditional variances and counterfactual analysis

(a) Oil Supply Shock

	Period I	Period II		
	High Variance (1976Q1:1992Q1)	Low Variance (1992Q2:2011Q4)	Counterfactual Analysis	ΔTransmission Mechanism
	$\sigma_{\hat{Y}_k^I} \mid \hat{e}_{OS}^I$	$\sigma_{\hat{Y}_k^{II}} \mid \hat{e}_{OS}^{II}$	$\sigma_{CA,\hat{Y}_k^{II}} \mid \hat{e}_{OS}^{II}$	$\hat{A}_{OS,k}^I(L) \rightarrow \hat{A}_{OS,k}^{II}(L)$
Services	2,17	2,13	0,71	Amplify
GDP	3,36	3,51	0,92	Amplify
Goods	6,78	8,03	1,88	Amplify
$\alpha_{OS,S}$	58%	72%		

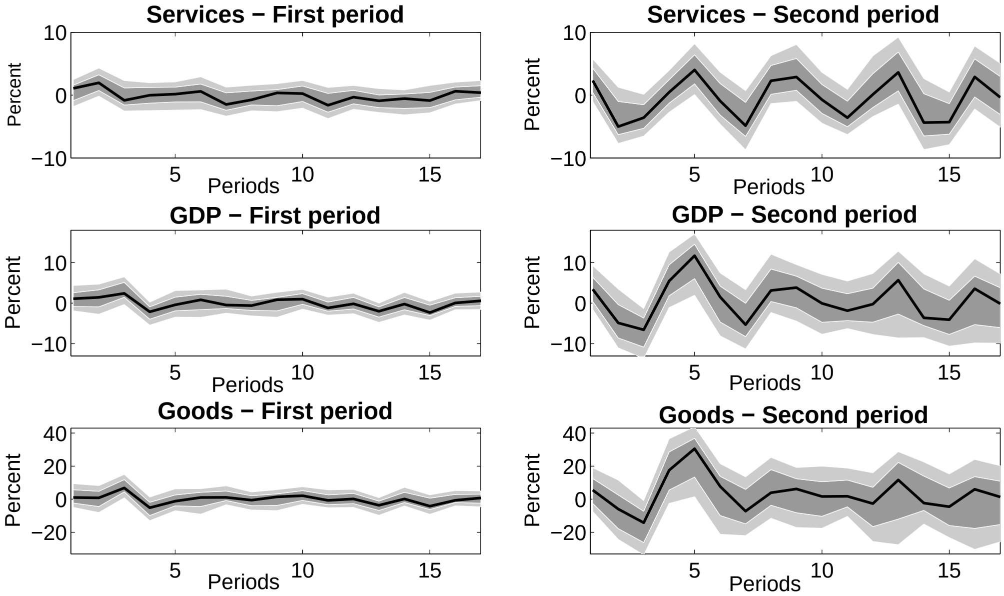
(b) Global Demand Shock

	Period I	Period II		
	High Variance (1976Q1:1991Q2)	Low Variance (1993Q3:2006Q4)	Counterfactual Analysis	ΔTransmission Mechanism
	$\sigma_{\hat{Y}_k^I} \mid \hat{e}_{GD}^I$	$\sigma_{\hat{Y}_k^{II}} \mid \hat{e}_{GD}^{II}$	$\sigma_{CA,\hat{Y}_k^{II}} \mid \hat{e}_{GD}^{II}$	$\hat{A}_{GD,k}^I(L) \rightarrow \hat{A}_{GD,k}^{II}(L)$
Services	2,72	1,44	1,39	Amplify
GDP	4,18	2,79	1,95	Amplify
Goods	7,97	6,76	4,30	Amplify
$\alpha_{GD,S}$	58%	69%		

(c) Oil Demand Shock

	Period I	Period II		
	Low Variance (1976Q1:1995Q4)	High Variance (1996Q1:2011Q4)	Counterfactual Analysis	ΔTransmission Mechanism
	$\sigma_{\hat{Y}_k^I} \mid \hat{e}_{OD}^I$	$\sigma_{\hat{Y}_k^{II}} \mid \hat{e}_{OD}^{II}$	$\sigma_{CA,\hat{Y}_k^{II}} \mid \hat{e}_{OD}^{II}$	$\hat{A}_{OD,k}^I(L) \rightarrow \hat{A}_{OD,k}^{II}(L)$
Services	2,39	2,32	5,90	Weaken
GDP	3,43	4,43	8,69	Weaken
Goods	6,64	10,80	15,39	Weaken
$\alpha_{OD,S}$	58%	72%		

Figure 4. Impulse Response - Oil supply shocks



$\left(\sigma_{\hat{Y}_k^{II}} \left| \hat{e}_{OS}^{II} = 3.51 \right.\right)$. Similar results hold for the goods and the services sectors.

The results on the amplification of the transmission mechanism of oil supply shocks are in accordance to Baumeister and Peersman (2008) who find that in recent times the US oil demand has become more inelastic than in the 1970s. Accordingly, the impact of a oil supply shock of any given size would increase more the price of oil now than in the past.

Table 3a also shows that the joint effect of both a lower variance of oil supply shock and a stronger transmission mechanism led to a decrease in the overall conditional volatility of the output growth of the GDP $\left(\sigma_{Y_{GDP}^{II}} \left| \hat{e}_{OS}^{II} < \sigma_{Y_{GDP}^{I}} \right| \hat{e}_{OS}^{I}\right)$, left almost unaffected that of the services sector $\left(\sigma_{Y_S^{II}} \left| \hat{e}_{OS}^{II} \approxeq \sigma_{Y_S^{I}} \right| \hat{e}_{OS}^{I}\right)$, but increased that of the goods sector $\left(\sigma_{Y_G^{II}} \left| \hat{e}_{OS}^{II} > \sigma_{Y_G^{I}} \right| \hat{e}_{OS}^{I}\right)$. Thus, while for the conditional variance of the services sector the lower size of the supply shocks (good luck hypothesis) is almost exactly counterbalanced by the amplification of the transmission mechanism (good policy hypothesis), the latter prevails in the case of the goods sector. The fact that the conditional variance of the GDP decreases across subperiods is no surprise when we take into account that across subperiods the contribution of the services sector ($\alpha_{OS,S}$) has strongly increased from 58% to 72%. Such a result is a first evidence that, at least for oil supply shocks, the advent of the era of services plays a role in lowering the GDP volatility.

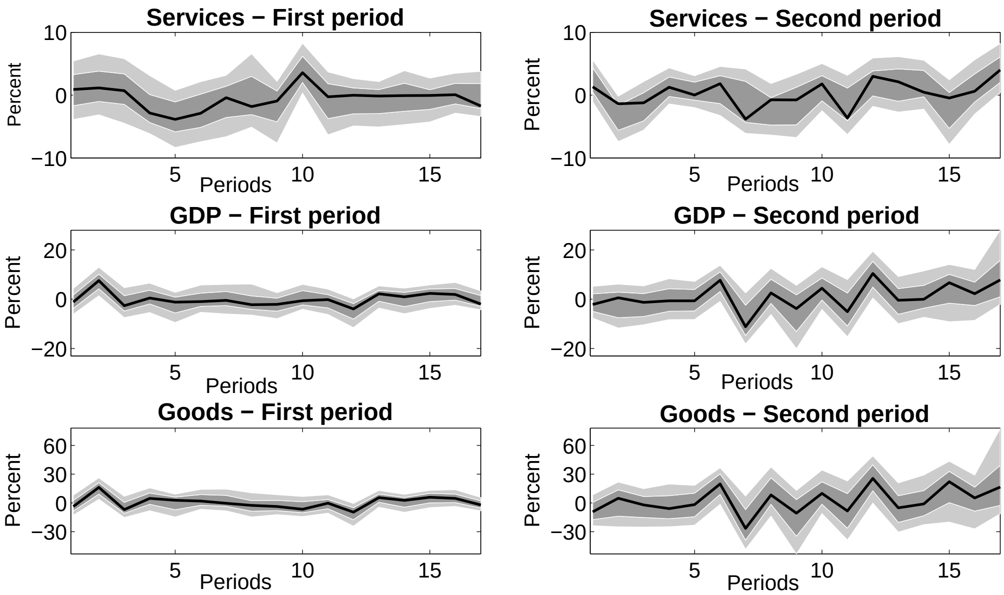
5.3 Global demand shocks

The structural break test reports that the volatility of global demand shocks shrank in the mid 1980s and then picked up again in the mid 2000s. As data are insufficient to allow for estimation in the third subperiod, we estimate model (2) for $Y_{k,t}$, $k = \{GDP, S, G\}$, and $\hat{e}_{i,t} = \hat{e}_{GD,t}$ over the first two subperiods. The first subperiod is defined over the period 1976Q1:1993Q4, and captures high-volatility global demand shocks, while the second one is defined over the period 1994Q1:2006Q4 and captures low-volatility global demand shocks. Figure 5 reports the impulse responses to a unitary size structural shock to the global demand activity index of the output growth of the services sector (top panels), the GDP (middle panels) and the goods sector (bottom panels). Left panels report the response in the first subperiod, right panels report the response in the second subperiod. From the figure it emerges that in the second subperiod the transmission mechanism of global demand shocks appears to amplify their impact on Y_{GDP} and tY_G.

The counterfactual analysis shows that in the second subperiod the transmission mechanism actually amplified the effect of global demand shocks on any sector (table 3b, $\sigma_{CA,Y_k^{II}} \left| \hat{e}_{GD}^{II} < \sigma_{Y_k^{II}} \right| \hat{e}_{GD}^{II}$ for $k = \{GDP, S, G\}$), though the services sector is barely affected. We also find that the joint effect of a lower variance of global demand shocks and a stronger transmission mechanism led, across subperiods, to a decrease in the overall conditional volatility of all the sectors (table 3b, $\sigma_{Y_k^{II}} \left| \hat{e}_{GD}^{II} < \sigma_{Y_k^{I}} \right| \hat{e}_{GD}^{I}$ for any $k = \{GDP, S, G\}$). Finally, we also observe that the implicit contribution of the services sector to the variance of Y_{GDP} ($\alpha_{GD,S}$), conditional to global demand shock, increases from 58% to 68%.

We then conclude that both the shrinking of global demand shocks and the composition effect concurred in reducing the conditional volatility of the GDP. As global demand shocks dominated in the late 1980s and in the 1990s, we argue that these two factors are also at the root of the reduced impact of oil price shocks observed in the last decades.

Figure 5. Impulse response - Global Demand Shocks



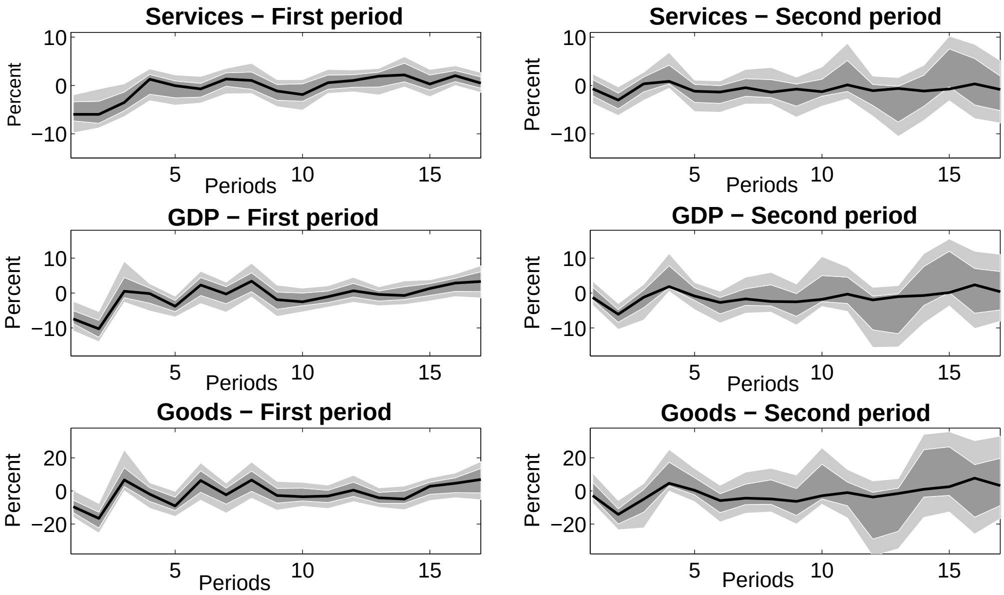
5.4 Oil demand shocks

We estimate model (2) for $Y_{k,t}$, $k = \{GDP, S, G\}$, and $\hat{e}_{i,t} = \hat{e}_{OD,t}$ over two subsamples. The first subperiod is defined over the period 1976Q1:1995Q4, and captures low-volatility oil demand shocks, while the second one is defined over the period 1996Q1:2011Q4 and captures high-volatility oil demand shocks.

Figure 6 reports the impulse response to a unitary size structural shock of the oil demand of the output growth of the services sector (top panels), the GDP (middle panels) and the goods sector (bottom panels). Left panels report the response in the first subperiod, right panels report the response in the second subperiod. From the figure it emerges that in the second subperiod the transmission mechanism seems to weaken the impact of oil demand shocks on Y_{GDP} and Y_S, at least for the initial periods, with Y_G apparently unaffected.

The counterfactual analysis confirms a weakening in the transmission mechanism of oil demand shocks in the second subperiod in any sector (table 3c, $\sigma_{CA,Y_k^{II}} \left| \hat{e}_{OD}^{II} > \sigma_{Y_k^{II}} \right| \hat{e}_{OD}^{II}$ for $k = \{GDP, S, G\}$). It also finds that the joint effect of a higher variance of oil demand shocks with a weaker transmission mechanism led to a moderate increase in the conditional volatility of Y_{GDP} $\left(\sigma_{Y_{GDP}^{II}} \left| \hat{e}_{OD}^{II} > \sigma_{Y_{GDP}^{I}} \right| \hat{e}_{OD}^{I}\right)$, a high increase in that of Y_G $\left(\sigma_{Y_G^{II}} \left| \hat{e}_{OD}^{II} > \sigma_{Y_G^{I}} \right| \hat{e}_{OD}^{I}\right)$,

Figure 6. Impulse response - Oil demand shocks



and left almost unaffected the conditional variance of Y_S $\left(\sigma_{Y_S^{II}} \left| \hat{e}_{OD}^{II} \approxeq \sigma_{Y_S^{I}} \right| \hat{e}_{OD}^{I}\right)$. Interestingly, the observed increase across periods in $\sigma_{Y_{GDP}|\hat{e}_{OD}}$ is in accordance to Balke et al. (2010), who find that in recent times economic efficiency and oil demand both increased.

The increase over time in the volatility of oil demand shocks is strong enough to drive upwards the conditional variances of both Y_{GDP} and Y_G, a result opposite to the one that would be predicted by the good luck hypothesis. In this respect, Kilian's insight that to understand the overall economic impact of oil price shocks we have to consider the composition of the underlying sources help us reconcile this result with the evidence that in recent times the economic impact of oil price shocks weakened. Indeed, the historical decomposition analysis finds that since the late 1980s and at until the 1990s global demand shocks have been predominant.

Finally, we check if the contribution of the service sector ($\alpha_{OD,S}$) to the variance of the GDP, conditional to oil demand shocks, that is implicitly defined in the data has increased across subperiods. We find that $\alpha_{OD,S}$ increases from 58% to 72%, a result identical to the one found for oil supply shocks and almost identical to the one found for global demand shocks. We interpret it as a further evidence in favor of the hypothesis that changes in the GDP composition play a role in affecting the macroeconomic volatility.

6 Conclusions

In the paper we provide evidence that the change in the composition of the US economic structure, characterized by the smooth increase in the GDP share of the services sector at the expense of that of the goods sector, has contributed to moderate the volatility of the US GDP conditional to oil price shocks. Moreover, we cast some doubts on the ability of the good luck hypothesis to explain alone the great moderation by showing that when the volatility of an oil price shock shrinks it is possible that the transmission mechanism of the shock to the economy counteracts such a change by amplifying the impact of the shock. These results then open the way to the possibility of a composition effect as an alternative and complementary explanation of the great moderation. However, as our analysis is limited to the case of the US economy and focuses on oil price shocks only, further empirical investigation is required.

References

[1] Ahmed, S., Levin, A., Wilson, B.A., 2004. Recent U.S. Macroeconomic Stability: Good Policies, Good Practices, or Good Luck?. The Review of Economics and Statistics 86(3), 824-832.

[2] Andrews, D. W. K., Ploberger, W., 1994. Optimal Tests When a Nuisance Parameter Is Present Only under the Alternative. Econometrica 62(6), 1383-1414.

[3] Bai, J., Perron, P., 2003. Computation and Analysis of Multiple Structural Change Models. Journal of Applied Econometrics 18(1), 1-22

[4] Bai, J., Perron, P., 1998. Estimating and Testing Linear Models with Multiple Structural Changes. Econometrica 66, 47-78.

[5] Balke, N. S., Brown, S.P.A.,Yücel, M. K., 2010. Oil price shocks and U.S. economic activity: an international perspective. Working Papers 1003, Federal Reserve Bank of Dallas.

[6] Baxter, M., King, R.C., 1999. Measuring business cycles:approximate band-pass filters for economic time series. Review of Economics and Statistics 81,575-593.

[7] Barsky, R., Killian, L., 2004. Oil and the Macroeconomy since the 1970s. Journal of Economic Perspectives 18(4), 115-134

[8] Baumeister, C., Peersman, G., 2008. Time-Varying Effects of Oil Supply Shocks on the US Economy. Working Papers of Faculty of Economics and Business Administration, Ghent University.

[9] Bernanke, B. S., Gertler, M., Watson, M., 1997. Systematic Monetary Policy and the Effects of Oil Price Shocks. Brookings Papers on Economic Activity, 28(1), 91-157.

[10] Blanchard, O., Simon, J., 2001 .The Long and Large Decline in U.S. Output Volatility. Brookings Papers on Economic Activity, 32(1), 135-174.

[11] Blanchard, O. Galí, J., 2007. The macroeconomic effects of oil shocks: why are the 2000s so different from the 1970s? in: International Dimensions of Monetary Policy, pages 373-421 National Bureau of Economic Research, Inc.

[12] Bohi, D. R., 1991. On the Macroeconomic Effects of Energy Price Shocks. Resources and Energy 13(2), 145-62.

[13] Boivin, J., Giannoni, M., 2006. Has Monetary Policy Become More Effective. Review of Economics and Statistics 88, 445–62

[14] Bresnahan, T., Ramey, V., 1993. Segment Shifts and Capacity Utilization in the U.S. Automobile Industry. American Economic Review Papers and Proceedings 83, 213-218.

[15] Canova, F., 2007. Methods for applied macroeconomic research. Princeton University Press.

[16] Chang-Jin, K., Morley, J., Piger, J., 2008. Bayesian counterfactual analysis of the sources of the great moderation. Journal of Applied Econometrics, 23(2), 173-191.

[17] Ferderer, J. P., 1996. Oil Price Volatility and the Macroeconomy: A Solution to the Asymmetry Puzzle. Journal of Macroeconomics 18, 1-16.

[18] Hamilton, J. D., 1996. This is what happened to the oil price-macroeconomy relationship. Journal of Monetary Economics 38(2), 215-220.

[19] Hamilton, J. D., 2003. What is an oil shock? Journal of Econometrics 113(2), 363-398.

[20] Hamilton, J. D., Herrera, A. M., 2004. Oil Shocks and Aggregate Macroeconomic Behavior: The Role of Monetary Policy: Comment. Journal of Money, Credit and Banking 36(2), 265-86.

[21] Hansen, B., 2001. The new econometrics of structural changes: dating breaks in the US labor productivity. The journal of economic perspective 15(4), 117-128.

[22] Herrera, A. M., Lagalo, L. G., Wada, T., 2011. Oil Price Shocks And Industrial Production: Is The Relationship Linear? Macroeconomic Dynamics, 15(S3), 472-497

[23] Herrera, A., Pesavento, E., 2009. Oil price shocks systematic monetary policy and the "great moderation". Macroeconomic dynamics 13(1), 107-137.

[24] Hodrick, R., Prescott,E., 1997. Postwar US business cycles: an empirical investigation. Journal of Money, Credit and Banking 92, 307-328.

[25] Leduc, S., Sill, K. 2007 .Monetary Policy, Oil Shocks, and TFP: Accounting for the Decline in U.S. Volatility. Review of Economic Dynamics 10(4), 595-614.

[26] Lee, K., Ni, S., Ratti, R.A., 1995. Oil shocks and the macroeconomy: the role of price variability. Energy Journal 16, 39–56.

[27] Justiniano, A., Primiceri, G.E., 2008. The Time-Varying Volatility of Macroeconomic Fluctuations. American Economic Review, 98(3), 604-41.

[28] Kahn, J. A., McConnell, M.M., Perez-Quiros., G. 2002. On the Causes of the Increased Stability of the U.S. Economy. Economic Policy Review, Federal Reserve Bank of New York, 183–202

[29] Kilian, L., 2008. The economic effects of energy price shocks. Journal of Economic Literature 46, 871–909.

[30] Kilian, L., 2009. Not all oil price shocks are alike: disentangling demand and supply shocks in the crude oil market. American Economic Review 99, 1053–69.

[31] Kim, C., Nelson, C., 1999. Has the U.S. Economy Become More Stable? A Bayesian Approach Based on a Markov-Switching Model of the Business Cycle. Review of Economics and Statistics 81, 608-16.

[32] McConnel, M.M., Perez-Quiros, G., 2000. Output fluctuations in the United States: what has changed since the early 1980s? American Economic Review 90(5), 1464-76.

[33] Nakov, A., Pescatori, A., 2010. Oil and the Great Moderation. Economic Journal, 120(543), 131-156.

[34] Nordhaus, W. D., 2008. Who's Afraid of a Big Bad Oil Shock? Brookings Papers on Economic Activity 2, 219-238.

[35] Perron, P., Wada, T., 2009. Let's take a break: Trends and cycles in US real GDP. Journal of Monetary Economics 56, 749-765.

[36] Primiceri, G., 2005. Time varying structural vector autoregressions and monetary policy. Review of Economic Studies, 72(3), 821-852.

[37] Sensier, M., Van Dijk, D., 2004. Testing for volatility changes in US macroeconomic time series. Review of economics and statistics 86(3), 833-839.

[38] Sims, C., Zha, T., 2006. Were There Regime Switches in U.S. Monetary Policy?. American Economic Review 96(1), 54-81.

[39] Stock, J.H., Watson, M.W, 2002. Has the Business Cycle Changed and Why?. NBER Macroeconomic Annuals 17, 159-218.