Impacts of oil price shocks on the United States economy: A meta-analysis of the oil price elasticity of GDP for net oil-importing economies

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Highlights

- Economic impacts of oil markets shocks are of significant interest to policy makers
- Literature estimates of the oil price elasticity of GDP span a wide range
- Meta-regression analysis is used to control for sources of variation in GDP elasticity estimates
- Meta-regression results are used to simulate the oil price elasticity of GDP for the United States
- Estimated US GDP elasticity is negative, but smaller in magnitude than estimated about a decade ago

Abstract

Policy makers are interested in estimates of the potential economic impacts of oil price shocks, particularly during periods of rapid and large increases that accompany severe supply shocks. Literature estimates of the economic impacts of oil price shocks, summarized by the oil price elasticity of GDP, span a very wide range due to both fundamental economic and methodological factors. This paper presents a quantitative meta-analysis of the oil price elasticity of GDP for net oil importing countries, with a focus on the United States (US). The full range of estimates of the oil price elasticity of GDP for the US in the data is -0.124 to +0.017, accounting for different methodologies, data and other factors. We employ a meta-regression model that controls for key determinant factors to estimate the mean and variance of the GDP elasticity across studies. We use a robust estimation technique to deal with heterogeneity of the data and well-known econometric issues that confront meta-analysis. The resulting regression model is used to simulate the oil price elasticity of GDP for the US, with a mean of -0.020 and 68% confidence interval of -0.035 to -0.006, four quarters after a shock.

Keywords: oil price shocks; GDP elasticity; heterogeneity; meta-analysis; partial-robust-M-regression

1. Introduction

The United States (US) has made considerable progress in reducing oil consumption over the last decade, with even more reductions in oil imports due to the recent boom in domestic production. US petroleum consumption declined by nearly 11 percent from 2005 to 2012, and was 5 percent lower than the 2005 level in 2016 (EIA, 2017). Imports of crude oil and petroleum products were below 2005 levels by 23 percent in 2012 and by 26 percent in 2016. Still, oil remains a large component of energy use in the US, accounting for 37 percent of primary energy consumption and 92 percent of all transportation fuels in 2016 (EIA, 2017a). The oil market remains vulnerable to market shocks arising from a range of causes: geopolitical events, direct attacks on oil supply infrastructure, rapid changes in global economic activity, extra-market actions by oil producers, oil production and transportation accidents, and natural events, such as hurricanes. Understanding the impacts of oil market shocks on the economy has been a focus of policy attention since the turbulent oil market events of the 1970s. Policy makers are interested in estimates of potential damages to the economy, particularly during periods of rapid and large increases in oil prices that accompany severe supply shocks. Such estimates are needed to quantify the economic costs of oil price shocks, and to evaluate the potential benefits of alternative policy responses.

Research on the macroeconomic effects of oil market fluctuations is extensive (Barsky and Kilian, 2004; Blanchard and Gali, 2010; Blanchard and Riggi, 2013; Brown and Yucel, 2002; Hamilton, 2009; Hamilton, 2005; Hamilton, 1983; Huntington, 2005; Jiménez-Rodríguez and Sánchez, 2005; Jones et al., 2004; Kilian, 2014; Kilian, 2008). This literature has generally shown that significant increases in oil prices exert negative economic impacts in net oil importing economies, but there are many remaining issues. In particular, asymmetry in the economic impacts of increases and decreases in oil prices, differences in the impacts of demand and supply driven shocks, and changes in the sensitivity of the economy to oil market shocks over time have produced vigorous discussions in the oil-economy literature (Bernanke et al., 1997; Blanchard and Gali, 2010; Brown and Yucel, 2002; Hamilton, 2009; Hamilton and Herrera, 2004; Hamilton, 1996; Hooker, 1996; Huntington, 2005; Jones et al., 2004; Kilian and Vigfusson, 2014; Kilian and Lewis, 2011; Kilian, 2009; Kilian, 2008a; Nordhaus, 2007). The economic impacts of oil market shocks are usually summarized using the elasticity of gross domestic product (GDP), or other measures of economic output, with respect to the oil price (interchangeably referred to as the "GDP elasticity" in this paper). However, estimates of the oil price elasticity of GDP in the oil-economy literature span a wide range. For example, Huntington's (2005) review suggests that the mean US GDP elasticity is "~-5%" to "~0%", depending on conditions surrounding the shock. Estimates of the mean US GDP elasticity from recent studies (Cashin et al., 2013; Cologni and Manera, 2008; Peersman and Robays, 2009) tend to fall in the middle of this range.

The wide range of estimates for the oil price elasticity of GDP in the literature can be attributed to a multitude of factors, both fundamental and methodological. Fundamental factors include differences in the underlying drivers of oil price changes (supply or demand, natural or geopolitical, etc.), the characteristics of oil price shocks (size, duration, speed, etc.), and changes in the structure and management of the economy since the turbulent oil market of the 1970s. Other fundamental factors include the oil intensity of GDP, condition of the economy (i.e. the business cycle phase) and net position of the economy in oil and other commodity trade at the time of a shock, as well as policy options and responses. Therefore, whether estimates of the economic impacts of oil price shocks in a given study are accurate representations of actual impacts or not depends on how well shocks and mechanisms through which the impacts are transmitted are reflected. There has been a continuous effort to improve methods for identifying oil price shocks and quantifying the economic impacts since the 1970s. The ecosystem of models for estimating the oil price elasticity of GDP includes single-equation econometric, multi-equation econometric (typically vector autoregression-type, VAR-type), large macroeconometric (MACRO), dynamic stochastic general equilibrium (DSGE) and computable general equilibrium (CGE) models. Although these approaches have increased our understanding of the oil-economy relationship tremendously, they also represent an important source of variation in estimates of the GDP elasticity. Thus, estimates of the oil price elasticity of GDP in the oil-economy literature depend almost equally on the empirical data and the methodological choices made in the course of the analysis. Given this, policy-related analysis of the impact of oil prices on the economy would need to be aware of the influence of these fundamental and methodological factors, and account for the resulting uncertainties. This suggests that reliance on a single study, or on simple averages and ranges from a few studies, to choose values of the GDP elasticity for policy analysis may be inadequate because these approaches would not account for the multiple, systematic sources of variation in the literature. In this paper, we seek to identify and account for the sensitivity of GDP elasticity estimates to some of the relevant sources of variation to gain insights from multiple studies, while excluding uncertainties that are due to artifacts of the individual studies.

The current paper employs a meta-analysis approach to summarize available estimates of the GDP elasticity from the recent oil-economy literature. This approach enables a systematic evaluation of the mean and sensitivity of the oil price elasticity of GDP to key driving factors. Specifically, within the limits of the data that can be distilled from the literature, we evaluate the role of the following factors in estimates of the oil price elasticity of GDP for net oil-importing economies, with a focus on the US: (i) Modeling/specification approaches; (ii) Period of data coverage; (iii) Size and duration of the oil price shock; (iv) Oil and other characteristics of the economy; (v) Drivers (demand or supply driven) of the oil price shock. We focus on estimates for the US but use a meta-regression approach that includes some recent non-US studies to better understand the influence of these factors. Although there are several qualitative reviews, this paper presents, to our knowledge, the first meta-analysis of the oil price elasticity of GDP and its determinants. This contrasts with other economic parameters, such as price or income-elasticity of demand for fuel or other goods, which are commonly the subject of meta-analysis (Brons et al., 2008; Gallet and Doucouliagos, 2014; Havranek and Kokes, 2015; Labandeira et al., 2017;

Sornpaisarn et al., 2013; Stern, 2012). The rest of the paper is arranged as follows. Section 2 presents the meta-analysis methodology used for the analysis. Section 3 discusses the meta-analysis results, highlighting a potential application for policy analysis. The paper ends with conclusions.

2. Meta-analysis approach and data

Meta-analysis is a systematic and quantitative approach for synthesizing multiple studies to estimate the combined mean and variance of a parameter of interest (Rosenthal and DiMatteo, 2001). Meta-analysis can be performed using fixed effects, random effects or multivariate meta-regression models. The fixed and random effects models produce weighted means and associated variances using weights that are based on sample sizes or standard errors of the estimates (Borenstein et al., 2007; Stanley and Doucouliagos, 2015). In addition to estimating combined mean and variance, multivariate meta-regression analysis (MRA) is a well-established approach that uses determinant variables to explore sources of heterogeneity across studies, and is the most common form of meta-analysis in the economic literature (Labandeira et al., 2017; Stern, 2012; Stanley 2001; Stanley and Jarrell 1989; Thompson and Higgins, 2002; Van Bergeijk and Lazzaroni, 2015; Van Houwelingen et al., 2002). Given the potential for a high degree of heterogeneity in our data, the meta-regression approach is employed in this paper to estimate the mean and variance of the oil price elasticity of GDP for the US, and to evaluate the role of several key factors.

2.1. Data and sources

The analysis in this paper is restricted to net oil-importing economies[2] and focuses on newer studies, with the initial screening considering those published since the year 2000. To establish the dataset, a search of the literature was performed within the energy economics literature using databases such as ScienceDirect, Scopus, EBSCo, Google Scholar and the general web, with the latter search helping to identify unpublished but potentially significant studies. The literature search produced about 150 papers on topics related to the oil-economy relationship. After initial screening, 19 studies were identified that contain quantitative and accessible estimates of the economic impacts of oil price shocks. One of the final studies was published in 2005 and all others were published since 2008. The author and publication date for these studies are shown in Table 1 and the literature selection criteria are discussed below. Table 1 also includes information on sources, model types, and count of mean estimates of GDP elasticity in our data set. Appendix A contains a list of the 19 papers, as well as the full list of papers initially screened.

Table 1. Information on studies included in the meta-analysis and count of mean estimates

Paper	Source	Model Type[3]	Coun
Hamilton (2005)	New Palgrave Dictionary of Economics	SEEC	36
Cologni and Manera (2008)	Energy Economics Journal	VAR-type	132
Kilian (2008)	Journal of European Economics	SEEC	12
Zhang (2008)	Energy Economics Journal	SEEC	4
Peersman and Van Robays	Economic Policy Journal	VAR-type	120
Kumar (2009)	Economics Bulletin	VAR-type	5
Lutz and Meyer. (2009)	Energy Policy Journal	MACRO	6
Baumeister, et. al. (2010)	Federal Reserve Bank of Australia	VAR-type	96

[2] Oil exporting economies are excluded due to the widely different role of oil in the social and economic structure of most of these economies relative to oil importing economies. Given this, analyses of the economic impacts of oil price shocks and its driving factors tend to focus on net oil importing economies. Oil-economy analyses for oil exporting countries focus on issues such as revenue management, "dutch disease", exchange rate responses, etc.

[3] Model types: SEEC = Single equation econometric Models; VAR-type = Vector auto-regression-type Models; MACRO = Estimated or Calibrated Macro-econometric Models; DSGE = Dynamic Stochastic Computable General Equilibrium Models; CGE = Static or Dynamic Computable General Equilibrium Models;

Korhonen and Ledyaeva	Energy Economics Journal	VAR-type	220
Álvarez, et. al (2010)	Economic Modeling Journal	MACRO/DSGE	43
Strauch et al. (2010)	European Central Bank Paper	MACRO	48
Du et al. (2010)[4]	Energy Policy Journal	VAR-type	9
Gómez-Loscos et. al.(2011)	Energy Economics Journal	VAR-type	5
Levent and Acar (2011)	Energy Policy	CGE	30
Sánchez (2011)	International Economic Policy Journal	DSGE/VAR-type	41
Lutz et al (2012)	Energy Policy Journal	MACRO	14
Cantore et. al. (2012)	Overseas Development Institute	CGE	14
Cashin et. al (2014)	Energy Economics Journal	VAR-type	88
Kilian and Vigfusson	Journal of Money, Credit, and Banking	VAR-type	72

The criteria for choosing the studies included in this meta-analysis are:

1. **Studies focusing on oil importing economies**: The ultimate objective of this paper is to evaluate the mean oil price elasticity of the GDP for the US. As a result, the studies selected for inclusion focus on net oil-importing economies which are most relevant to the US economy. This restriction also excludes the complicated oil-economy relationship in oil exporting economies for which oil tends to account for a significant portion of economic growth or foreign exchange earnings. We incorporate information for many oil-importing economies to exploit variations among regions and their responses to oil price shocks when estimating parameters of the meta-regression models. In addition, an important aspect of this paper is to explore the potential roles of oil market and economic conditions, and we consider whether this can be done using cross-sectional variation among regions.
2. **Studies published since 2000**: This paper focuses on recent estimates to capture more of the history of the oil market and changes in analytical methods for estimating the oil price elasticity of GDP. The initial screening considered studies published in 2000 or later, and the final dataset is based on studies since 2005 (all but one since 2008). Most of these studies still include data back to the 1970s, whereas

[4] This study was dropped from the final dataset for the meta-analysis due to potential omitted variables, which was recognized and extensively discussed by the authors, but unaccounted for in their model.

earlier studies cannot reflect recent data that may be relevant to current policy needs. Although not meta-analytical studies, there are existing reviews and summaries of the impacts of oil price shocks on the macro-economy for the pre-2000 period (Brown and Yucel, 2002; Huntington, 2005; Jones et al., 2004).

3. **Studies with accessible quantitative information on macroeconomic impacts and study characteristics**: In order to specify a meta-regression model, studies must present information necessary to estimate the oil price elasticity of GDP from its findings, along with data on study characteristics and other factors. The impacts of oil price shocks on the economy are commonly presented in the form of impulse response functions (IRF), which provide the time pattern of the impacts following a single shock. While the graphical, instead of tabular, presentation of these IRFs in most studies make it difficult to extract the necessary information, we employed recent software capabilities to extract data from plots of impulse response functions in an accurate manner.

More than 2000 point estimates of the macroeconomic impacts of oil price shocks were extracted from the studies. About half of these are mean estimates, and the other half are high/low bounds where available. Most of the estimates are changes in the gross domestic product (GDP), but a few are changes in industrial output or value-added. For the meta-analysis, these gross impacts are standardized to elasticities using the size of the initial price shock. The vast majority of estimates are based on quarterly data, but a few of studies are based on annual data. Annualized estimates were further standardized to a common quarterly frequency by division with 4. In addition to the GDP elasticity data, study characteristics were extracted from the literature and other sources in the following categories:

1. **Modeling approaches**: Methodology (model specification and estimation approach) is often found to be influential in MRA, but an attempt to exhaustively account for the dimensions of various approaches to modeling the economic impacts of oil price shocks is unlikely to be successful in an

MRA. Yet, much can be learned by identifying the broad classes of methods or models employed in the literature as a proxy for the composite structure and implementation of these approaches.

2. **Drivers of oil price shocks**: Despite the many options for identifying shocks in the oil-economy literature, there are remaining methodological and interpretational difficulties (Baumeister and Hamilton, 2015). We capture this aspect of the oil-economy literature by identifying whether a given study claims to identify supply- or demand-driven shocks or incorporates supply or demand variables in its model. In addition, information on whether a study's estimates are based on analysis with linear or non-linear transformation of the oil price is collected to account for the potential influence of these specifications in the estimates. Non-linear oil price transformations include separate positive or negative oil price changes, and the net oil price index (Hamilton, 2003; Lee et. al., 1995; Mork, 1989), but not the logarithm of oil price.
3. **Other oil price shock characteristics**: The size and duration of shocks may be important factors in evaluating estimates of the oil price elasticity of the GDP, given potential non-linearity of the time profile of economic impacts following a shock. Although both temporary and permanent shocks may have long-lasting effects, the time profile of their economic impacts would be expected to differ and not be proportional to one another. However, we found that while shocks do vary in size, most of the available analyses can be described as reporting results for one time, permanent shocks, within the context of each modeling framework.
4. **Period spanned by the data**: Contributions by different types of shocks to changes in the oil price vary in magnitude and sign over time. It is not possible to explicitly model changes in economic structure and condition in the meta-analysis, since each data point is derived from parameters that were estimated from many years of economic data. However, to the extent that different shocks and economic conditions dominate over different segments of the period spanned by the data in a study, the latter may provide a way to reflect the impacts of these factors in an aggregated manner.

5. **Regional economic and energy characteristics**: To evaluate the potential role of aggregate economic conditions and energy characteristics in the sensitivity of a region to oil price shocks we extract data from the EIA (2015) international energy database for countries included in the dataset of GDP elasticity estimates. Again, because each MRA data point embodies many years of economic data, we rely on summary observations for the energy-economic characteristics.
6. **Other study characteristics**: Publication date and data frequency are often used in meta-analysis to capture the influence of changes in the available data and methods on study parameter estimates. These attributes play a negligible role in the current paper given its focus on studies since 2000 and the finding that most of the available estimates are based on quarterly data.

2.2. Summary of the data

Table 2 summarizes the distribution of mean oil price elasticities of GDP that were extracted from the literature by region, and partitioned into short-run (SR), medium-run (MR) and long-run (LR) based on elapsed time since the start of the shock.[5] Out of a total of about 1000 point estimates of the mean GDP elasticity, nearly one-third of the estimates are for the US and about six-tenths for European economies. The remaining estimates are for Japan, China, Australia and two African sub-regions. Table 2 contains two averages for Europe: one for the Euro Area as a single unit and the other for an average of individual European countries. Germany and United Kingdom are kept separate in Table 2 due to differences in their economic characteristics and estimated impacts of oil price shocks in the literature. The overall range of these data across regions, modeling approaches, and SR to LR is wide at -0.17 to 0.09, but only a few estimates are in the upper portion of this range. Given this, the overall mean estimate for the SR, MR and LR are -0.017, -0.023 and -0.008, respectively. Corresponding values for the US are -0.019, -0.036 and -0.025. Most of the regional estimates are between -0.05 and 0.05. As would be expected, the regional LR

[5] We define SR = less than or equal to 4 quarters; MR = between 5 to 12 quarters; and LR = greater than 12 quarters.

estimates are narrower in range than their SR and MR counterparts. Figure 1 shows the time profile of regional average elasticities following the start of the shock, and reflects the high level of variation in the data across regions and quarters after the shock. The small value of the average LR estimates in Table 2 is also seen in the near zero value of the estimate for "All Regions" in Figure 1 after twelve quarters. Most studies present results for only a few time periods after the shock, so there are comparatively few LR (>12 quarters) estimates. Given that the economic impact of an oil price shock depends on a multitude of factors that differ across regions and studies, Figure 1 finds that there is no fixed pattern to the time profile of the oil price elasticity of the GDP across regions. However, the patterns of average estimates for the US and Europe, which represent about nine-tenths of the data, are similar to the overall average, particularly over the first eight quarters. Below, we provide a visual exploration of potential sources of variation in the oil price elasticity data, as a background for the MRA in this paper.

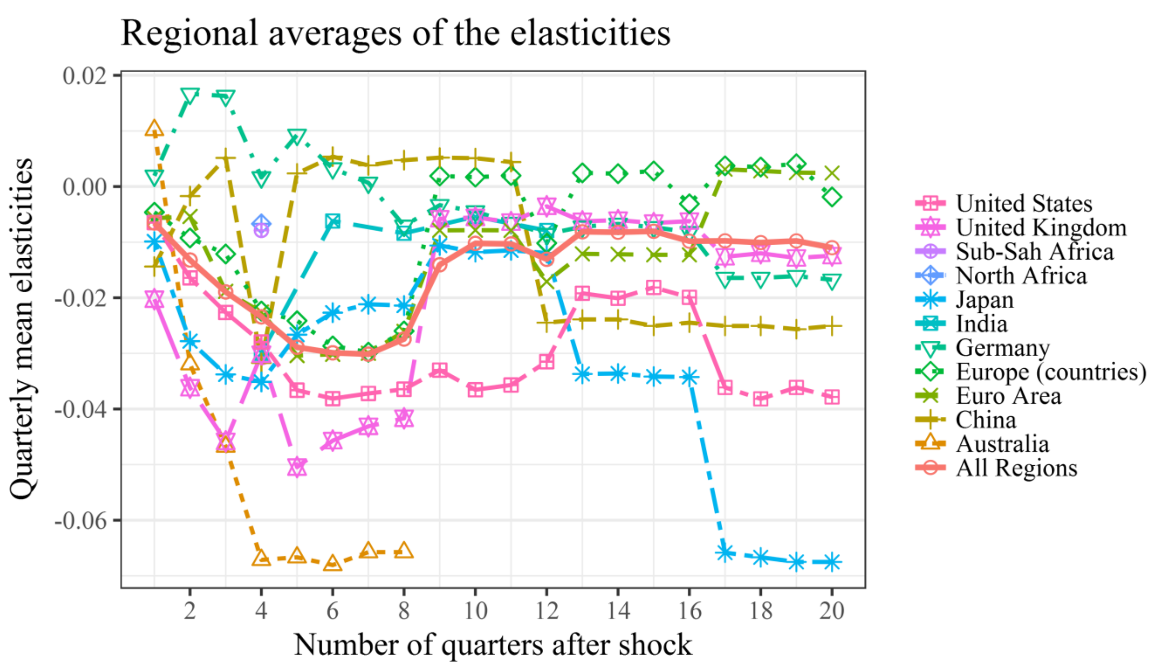

Figure 1. Regional and overall quarterly mean oil price elasticities of the GDP

Table 2. Summary of the data: estimates of mean oil price elasticity of the GDP from the literature

Regions	Length after Shock[6]	Number of Observations	Mean	Median	Minimum	Maximum
United States	SR	83	-0.019	-0.008	-0.124	0.016
	MR	114	-0.036	-0.032	-0.132	0.017
	LR	12	-0.025	-0.036	-0.040	0.000
Australia	SR	8	-0.034	-0.020	-0.119	0.022
	MR	8	-0.067	-0.067	-0.131	0.000
Euro Area	SR	40	-0.014	-0.010	-0.155	0.014
	MR	62	-0.022	-0.013	-0.162	0.005
	LR	16	-0.008	-0.005	-0.028	0.003
Europe (countries)	SR	111	-0.014	-0.005	-0.156	0.022
	MR	164	-0.019	-0.013	-0.137	0.054
	LR	91	0.001	0.002	-0.041	0.090
United Kingdom[7]	SR	23	-0.031	-0.014	-0.166	0.004
	MR	28	-0.028	-0.008	-0.174	0.002
	LR	12	-0.008	-0.012	-0.013	0.000
Germany	SR	20	0.006	0.004	-0.016	0.030
	MR	26	-0.003	-0.001	-0.037	0.024
	LR	13	-0.009	-0.014	-0.017	0.010
North Africa	SR	2	-0.007	-0.007	-0.011	-0.003
Sub-Saharan Africa	SR	12	-0.008	-0.006	-0.030	0.000
Japan	SR	35	-0.028	-0.003	-0.154	0.024
	MR	42	-0.018	-0.001	-0.078	0.021
	LR	12	-0.045	-0.067	-0.068	-0.001
China	SR	15	-0.015	0.009	-0.096	0.024
	MR	22	0.003	0.015	-0.030	0.024
	LR	8	-0.025	-0.025	-0.026	-0.024
India	SR	3	-0.030	-0.035	-0.046	-0.009
	MR	4	-0.007	-0.007	-0.008	-0.005
All Regions	SR	352	-0.017	-0.006	-0.166	0.030
	MR	470	-0.023	-0.011	-0.174	0.054
	LR	164	-0.008	-0.003	-0.068	0.090

[6] Length after shock: SR = less than or equal to 4 quarters; MR = between 4 and 12 quarters; LR = greater than 12 quarters;

[7] United Kingdom is included in the analysis because it moved between net petroleum exports and imports over time. North Africa includes only two countries, Morocco and Tunisia. The former is a net petroleum importing country, and the latter has moved between small net petroleum imports and exports over time. Sub-Saharan Africa consists of a "Rest of Africa" region and individual countries mostly in East Africa that are net petroleum importers - some of these countries have recently discovered oil and gas resources.

2.3. Sources of variations in the oil price elasticity of GDP data

2.3.1. Standard error of study estimates

Conventional meta-analysis studies depend on availability of comparable estimates of parameters of interest from different studies, and corresponding estimates of standard errors. Although the GDP elasticity provides a common measure of the economic impacts of oil price shocks across the oil-economy literature, these estimates are in most cases complex functions of model coefficients. Thus, standard errors are either not available or difficult to evaluate. Studies based on single equation econometric (SEEC) models provide the most direct estimates of the GDP elasticity, but even in these cases the resulting elasticities depend on the dynamics of model variables, leading to a non-linear time profile of impacts. In conventional meta-analysis, short- and long-run estimates are usually analyzed separately to address the issue of dynamics. Such an approach is inadequate in the current paper primarily because the incremental economic impacts of an oil price shock over the medium term are at least as important as the short- and long-run impacts. Since the impacts of an oil price shock represent the outcome of an economy-wide adjustment process following an oil market shock, these involve a wide range of economic processes and policies that could vary significantly over the short- to long-term.

In the case of VAR-type studies, point-estimates of confidence bounds are generally considered inadequate for measuring the precision of the time-linked profile of net economic impacts. Instead, many studies present only the mean profile of impacts while others use bootstrapping or other simulation methods to simultaneously evaluate confidence bounds over the period following a shock. In addition, standard errors for macro-econometric and equilibrium models are generally not evaluated. Missing measures of precision is a common issue in the meta-analysis literature. A systematic review by Wiebe et al. (2006) identified nearly 30 different methods for calculating missing standard deviation values for a meta-analysis, noting that there is no standard method. One potential method is to replace the missing standard errors with the mean of available standard errors, adjusted for differences in sample sizes. This assumes that standard errors are similar across studies and differ only in the sample sizes. We evaluate what we refer to as pseudo-standard errors in this paper using the following approach. Approximate standard errors are calculated for studies that present confidence intervals (upper and lower bounds at some confidence level) for the economic impacts[8]. For studies without upper and lower confidence bounds, pseudo-standard errors are calculated by multiplying the mean GDP elasticity estimates by the sample size weighted-average of t-statistics implied by the other studies. Sample sizes are the number of quarters of data associated with the estimates. The approach used to calculate missing standard errors in this paper is equivalent to the coefficient of variation method highlighted in Wiebe et al. (2006), which in our case assumes that mean to standard error ratios are similar across studies. This is a more appropriate assumption for the data in this paper, since the precision of a GDP elasticity estimate depends on many other factors beyond the sample size.

Figure 2 is a funnel plot of the pseudo-standard errors (reversed y-axis), with the mean GDP elasticity estimates on the x-axis. The second row of charts in Figure 2 restricts the y-axis to pseudo-standard errors less than or equal to 0.1 for additional clarity. Funnel plots are so-called because statistical theory implies that the dispersion of effect estimates would be negatively correlated with the precision of the estimates (Iwasaki and Tokunaga, 2014). Asymmetry of the funnel plot is usually used in the meta-analysis literature to visually identify publication bias. Figure 2 shows that the funnel plot is asymmetric, with the dashed vertical line indicating the unweighted mean GDP elasticity of about -0.018. The plot is more symmetric when the data is restricted to the -0.05 to +0.05 interval, but the unweighted mean is now only -0.008. The chart also shows that estimates with assigned pseudo-standard errors cover almost the same range as those calculated from upper/lower CI bounds. The assigned standard errors are of course

[8] These standard errors are calculated as (Upper Bound – Lower Bound)/(2xCritical t-value). The critical t-value is either 1.46 for 68% CI bounds or 1.96 for 95% CI bounds.

perfectly correlated with the mean values since they are based on a single *t*-value estimate. Asymmetry of the funnel plot is not a definitive proof of publication bias, and is strictly applicable only to a fixed effect model which assumes that estimates come from a single underlying population (Terrin et al., 2003). When the fixed effects model is not applicable to the data, asymmetry of the funnel plot could indicate other sources of heterogeneity (Sterne et al., 2011; Sutton and Higgins, 2008), such as differences across countries, methodologies and time profiles of impacts in the data for this paper. In any case, the pseudo-standard errors in Figure 2 are unlikely to be adequate replacements for the actual, unknown, standard errors of the GDP elasticity estimates, and thus suspect as the basis for measuring the precision of estimates across studies. Still, we evaluate their utility for isolating heterogeneity in the meta-regressions, but expect determinant (explanatory) variables to play a central role in explaining variations in GDP elasticity estimates from the literature.

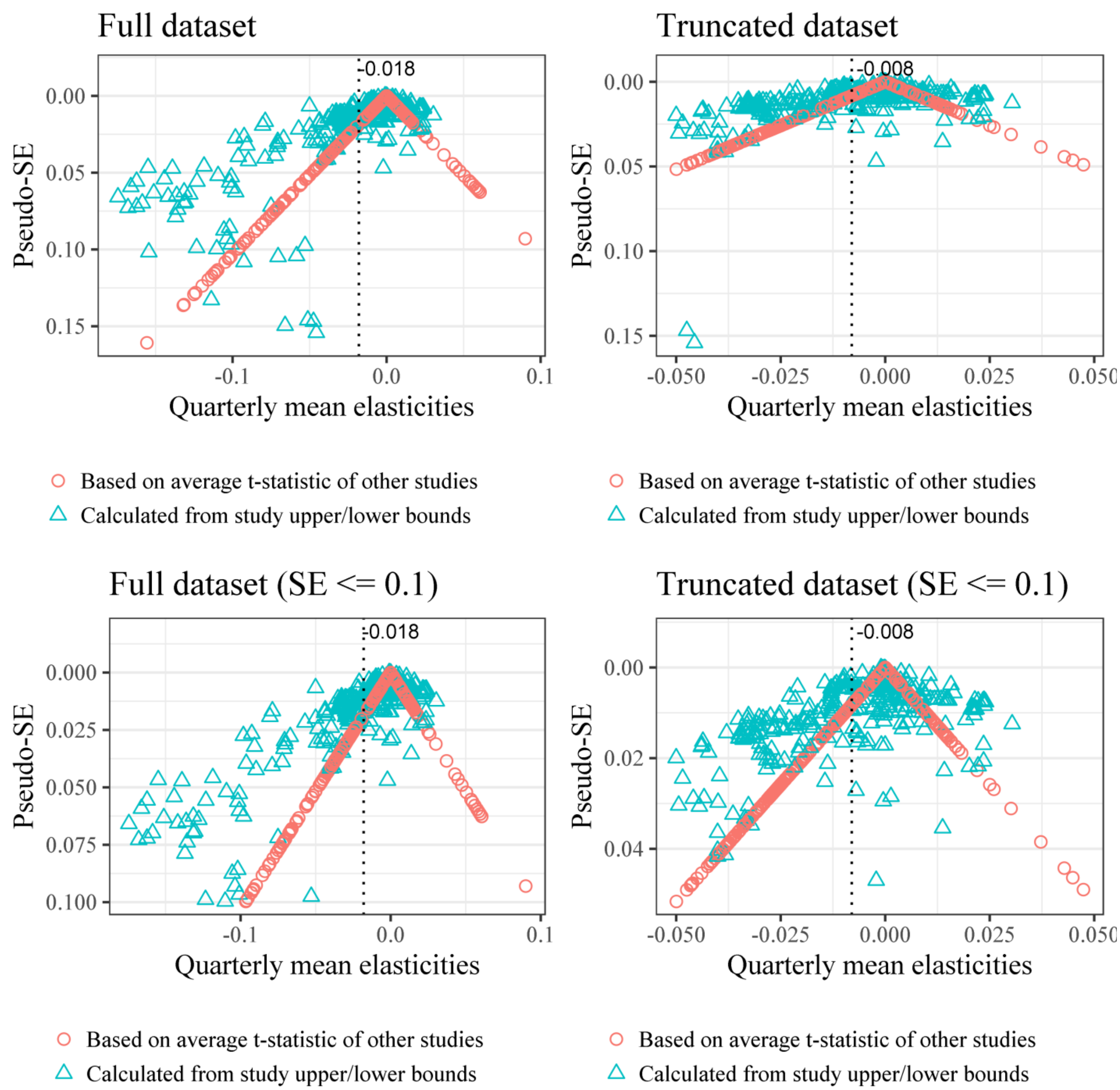

Figure 2. Funnel plots of pseudo-standard errors approximated from study data

2.3.2. Study and regional characteristics

Figure 3 shows averages of GDP elasticities over categories of potential determinant variables (years spanned by the data; model class; price variable type; supply variables or shocks; demand variables or shocks) to provide a background for the potential roles of these variables in the MRA. Table B.1 of

Appendix B shows counts of data points for each of these variables by group. In all cases, category averages in Figure 3 are plotted over time, measured as number-of-quarters since the shock. Since the long-run is not well-represented in the data as highlighted above, the discussion here focuses on the first ten quarters following a shock. Note that these averages are not definitive on the influence of each variable, since GDP elasticities are determined by many factors that could be correlated. Years covered by the data have been categorized into start-year and end-year intervals of 1949-1980, 1981-1990, 1991-2000 and 2001-2016. Most of the elasticities in the chart for start-year categories are negative. Also, the chart suggests that the farther back in time the start-year, the larger the average magnitude of elasticities, except for the last category, which although being the most recent has the largest magnitude of elasticities. In particular, the profile for 2001-2016 averages suggests that it is dominated by results from computable general equilibrium models since studies using this approach are based almost exclusively on annual, rather than quarterly, data. The end-year chart is just as interesting because in this dataset GDP elasticity estimates are present for only two of the four end-year categories (1981-1990 and 2001-2016). This makes sense given the degree of freedom requirements of econometric studies, which constitute about 75% of the data. Estimates for the 1981-1990 end-year category are generally larger (-0.12 to -0.03) than for the 2001-2016 category (-0.025 to -0.0001). Overall, these averages appear to match findings that the vulnerability of advanced economies to oil price shocks has declined over time (Blanchard and Gali, 2010), and suggest that years spanned by the data could be an important determinant in the MRA. Note also that the start and end-year variables are strictly applicable to only econometrically estimated models. Accordingly, these variables are both set to the single most recent year of the data used for non-econometric models.

Average GDP elasticities over model class categories suggest that estimates for VAR-type and DSGE models are close for the first four quarters, but the former are more negative than the latter over the following four quarters. Averages for macro-econometric models are between those for VAR-type and

DSGE models, and SEEC models have the largest magnitude, negative-valued, averages. The pattern for CGE models generally matches estimates for the 2001-2016 category in the start-year chart, as discussed above. The price variable chart implies that there is little difference between averages from studies that use linear versus non-linear price specifications up to the eighth quarter, but estimates for the non-linear price variable are more negative after the eighth quarter than for the linear price variable. Again, note that CGE and MACRO models are generally based on linear price variables, whereas the other model classes could be specified using linear or non-linear price variables.

The inclusion of explicit variables to distinguish among supply and demand shocks seems to be important. The supply shock/variable chart suggests that average GDP elasticities are larger in magnitude (and more negative) up to eight quarters after the shock when a supply shock or variable is included than when not, with minimum values of about -0.05 versus -0.02. The opposite result is observed in the chart for demand shock or variable, except for the fourth quarter average. Although these variables are not precisely defined, these supply and demand shock or variable averages match the overall understanding in the literature that supply shocks have more negative economic impacts than demand shocks.

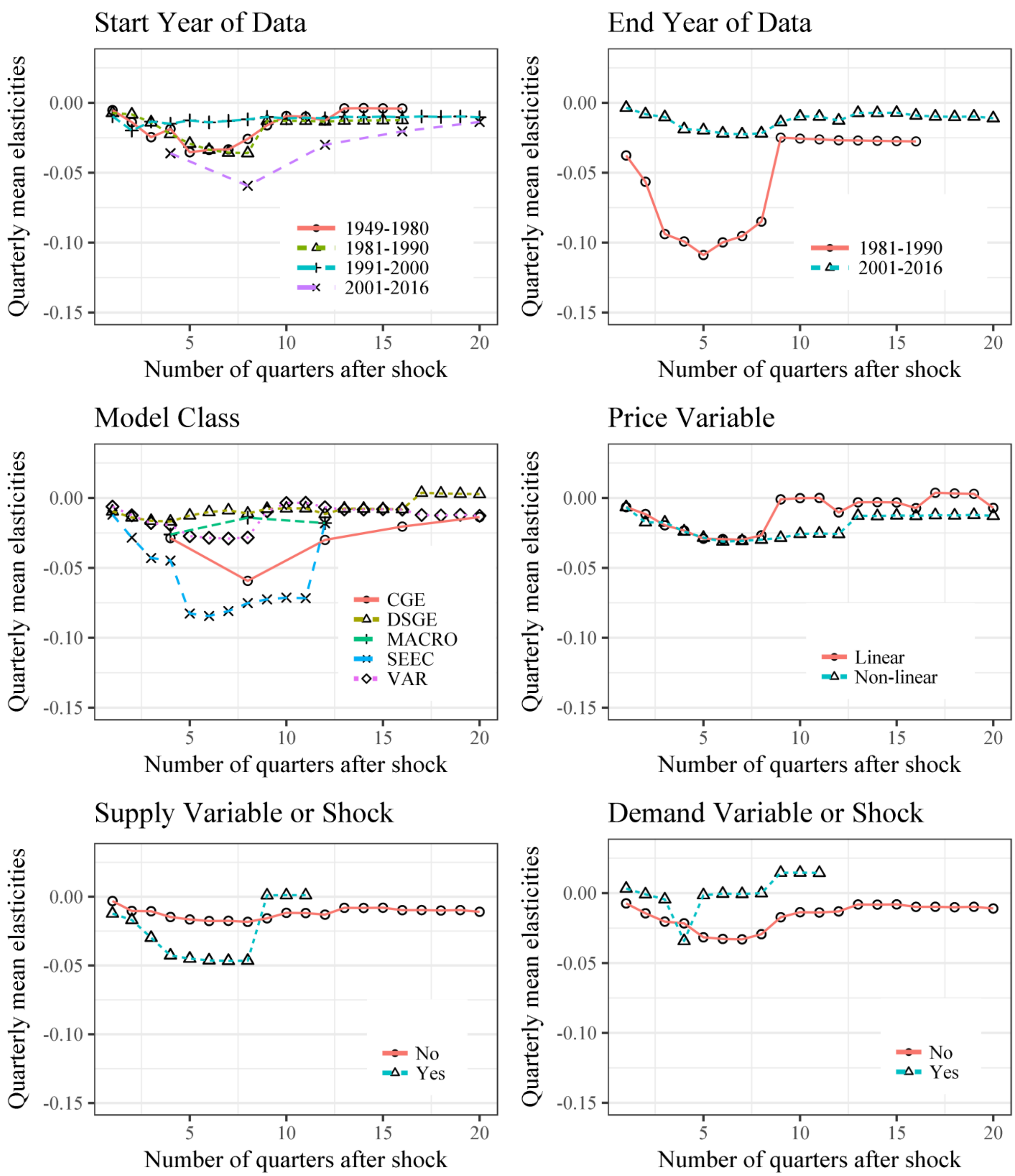

Figure 3. Quarterly mean oil price elasticities of the GDP by variable categories

Figure 4 shows the 1995 and 2005 data for real GDP, energy consumption, petroleum consumption and net petroleum import for most of the regions to supplement data from the individual studies. Values for the Euro Area are the combined values for its component countries. The data show that the largest absolute changes in total energy consumption between 1995 and 2005 occurred in China, US, Euro Area and India, with smaller changes in other countries. China's energy consumption and real GDP nearly doubled, but the economy expanded at a faster rate than energy consumption in both the US and Euro Area. Changes in regional petroleum consumption are slightly more or less proportional to the changes in energy consumption. Although changes in net imports of petroleum over this period are similar to those for petroleum consumption, there are notable differences. Net imports of petroleum by the US grew at about twice the rate of increase in petroleum consumption, China's net petroleum imports nearly quintupled, and the United Kingdom moved from a net exporter towards becoming a net importer of petroleum between 1995 and 2005.

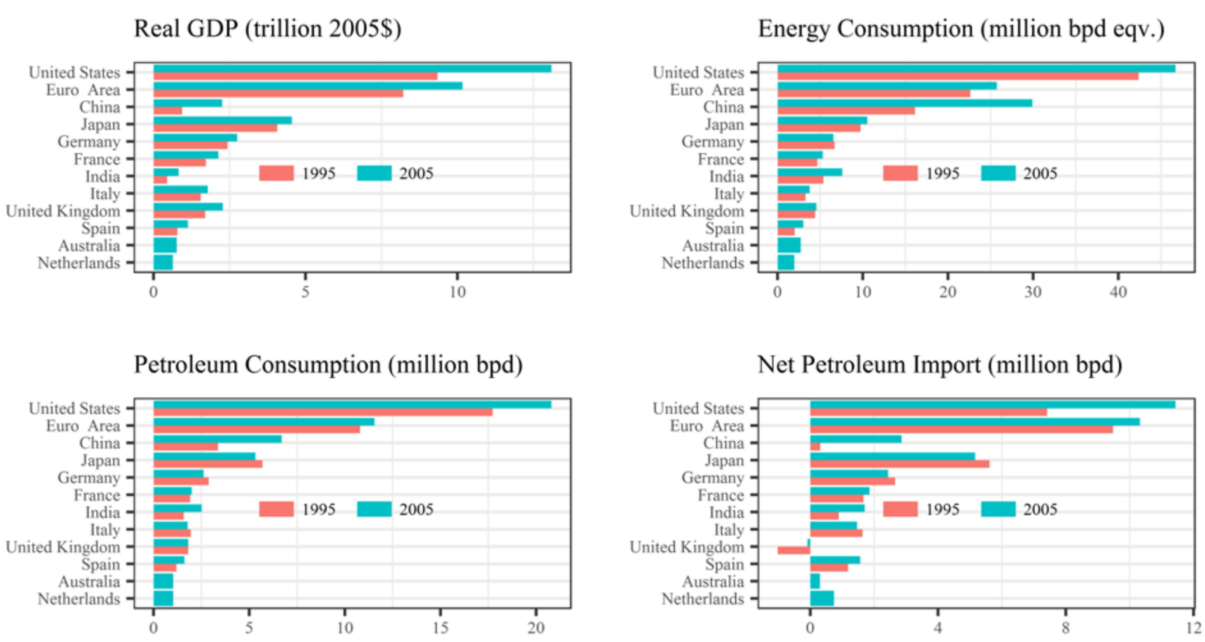

Figure 4. Historical GDP and energy variables by region (1995 and 2005)

3. Meta-regression analysis

In this section, the data presented above are used to perform an initial meta-analysis and a full MRA. First, keeping in mind that the pseudo-standard errors are non-conventional, we estimate an initial set of models often used in the meta-analysis literature to test for evidence of publication bias and presence of a true mean effect. Second, we estimate a full meta-regression model that accounts for the role of different factors in variations of the GDP elasticity in the literature. In addition to publication bias, meta-analysis studies are confronted by a number of common econometric issues. In our case the following issues deserve attention: heterogeneity due to differences in study characteristics, potential over-representation and correlation of multiple estimates from the same study or studies sharing common factors (e.g. country studied), multicollinearity among the determinant variables, heteroscedasticity of residuals, and potential serial correlation induced by the time-linked profile of the economic impacts following a shock. Below, in sections 3.1 and 3.2, we present the meta-regression specifications estimated in this paper, highlighting how the above econometric issues are addressed. We then, in sections 3.3 and 3.4, discuss estimation results for the initial meta-analysis and full MRA.

3.1. Meta-regression specifications

Let e_i (i=1…n) represent point estimates of mean GDP elasticities extracted from the literature, β_0 the true value of GDP elasticity and u_i a zero-mean, normally distributed error term. The basic meta-regression model can be written as in equation (1):

$$e_i = \beta_0 + u_i \ and \ u_i \sim N\left(0, \sigma_i^2\right) \ or \ e_i \sim N\left(\beta_0, \sigma_i^2\right) \tag{1}$$

An ordinary least squares (OLS) estimate of equation (1) gives β_0 as the unweighted mean of vector *e*. Weighted regressions of equation (1) lead to three types of estimators common in the meta-analysis literature: fixed effects (FE), random effects (RE), and unrestricted weighted least squares (WLS). All three weighted estimators of equation (1) correspond to estimating equation (2) using different variance parameters, v_i^2 to calculate weights ($1/v_i$):

$$e_i \sim N(\beta_0, v_i^2) \tag{2}$$

The variance, v_i^2, for the RE estimator is equal to $(\sigma_i^2 + \tau^2)$, with τ^2 being the between-study or heterogeneity variance. Both the FE and WLS estimators assume that the between-study variance, τ^2, is zero, so that the variance, v_i^2, can be specified as $\varphi\sigma_i^2$, where φ is a constant of proportionality (see Stanley and Doucouliagos, 2015) and with φ taking a fixed value of 1 for the FE estimator but unrestricted for the WLS estimator.

A test for potential publication bias, known as the funnel asymmetry test (FAT), is performed through a least square regression of equation (3), but is usually estimated using WLS with weights given by $1/SE_i$ to reduce possible heteroscedasticity of the residuals (Galindo et al., 2015; Havranek et al., 2012), where SE_i are the standard errors of the study effect estimates. Significance of the β_1 coefficient is taken as an indicator of publication bias, but given the heterogeneity of our data as discussed previously, and the use of pseudo-standard errors in place of the actual, unknown, standard errors in this paper, it is better interpreted as an overall measure of heterogeneity.

$$e_i = \beta_0 + \beta_1 SE_i + u_i \tag{3}$$

Equation (4) is a modified form of the FAT equation (3), and is known as the Precision Effect Estimator with Standard Error (PEESE) or the Heckman meta-regression. Equation (4) assumes that the relationship between standard errors and publication bias is quadratic (Galindo, et al., 2015; Havranek et al., 2012; Stanley and Doucouliagos, 2007), with VR_i being the reported variance of the estimates or SE_i^2.

$$e_i = \beta_0 + \beta_1 VR_i + u_i \tag{4}$$

Equation (5) extends equation (4) to the Heckman's mixed-effects (ME) meta-regression model which includes a fixed component (represented by β_0) as well as additive random error terms analogous to the RE model, including within study, u_i, and between-study, $r_{i,j}$, components (Havranek et al., 2012).

$$e_{i,j} = \beta_0 + \beta_1 VR_{i,j} + u_i + r_{i,j} \tag{5}$$

Although equation (5) attempts to account for both heterogeneity and heteroscedasticity in the data it does not explicitly capture the systematic relationship between GDP elasticities and the potential determinants highlighted above. For this purpose, we evaluate meta-regression models incorporating determinant variables in equations (6a) and (6b):

$$e_i = \beta_0 + \sum_k \alpha_k X_{i,k} + \varepsilon_i \tag{6a}$$

$$e_i = \beta_0 + \beta_1 VR_i + \sum_k \alpha_k X_{i,k} + \varepsilon_i \tag{6b}$$

Equation (6a) assumes that heterogeneity in the study data can be explained by the determinants, $X_{i,k}$ (k=1…m) that influence variations in GDP elasticities with α_k coefficients, and ε_i is the residual term.

Equation (6b) includes the variance of estimates as a further explanatory variable to account for remaining heterogeneity or publication bias, following Havranek et al. (2012).

3.2. Variables in the full meta-regression

The determinant variables in equations (6a) and (6b) are based on the study characteristics and economic/energy variables illustrated in Figures 3 and 4, as well as other variables that were extracted from the literature for each study. These variables are codified in the MRA as follows:

1) Size of the oil price shock (rate of price increase) is aimed at evaluating the potential for non-linear economic impacts of oil price shocks with size.
2) A linear trend term (number of quarters since the start of shock) to capture the time-linked profile of the economic effects of a shock.
3) The "normalized average quarterly elasticity" is a cross-sectional correlation term, calculated by normalizing the quarterly overall average GDP elasticity ("All Regions" in Figure 1) by its maximum absolute value. This term is designed to correct for cross-sectional correlation among the GDP elasticities, particularly given the extraction of multiple estimates from the same study and other common factors among the estimates. The term is patterned after the common correlated-effects (CCE) estimator of Pesaran (2006; 2003) used to correct for cross-sectional dependence in panel data. In addition, by reflecting the average time profile of elasticities in the data, this term complements the linear trend term (2) to account for potential correlations of the economic impacts over the time sequence following a shock.
4) The real GDP per capita ($thousands) for 2005 is included to capture the role of an economy's size in its sensitivity to oil price shocks.[9]

[9] A single year was chosen for the measure of energy-economy variables because of the cross-sectional nature of the meta-analysis data. Although 1995 is the approximate midpoint of the periods covered by

5) The ratio of petroleum consumption to energy use (both in million bbl/d) for 2005 is included as a measure of the importance of petroleum in regional energy use. It is measured as a share of total energy consumption to normalize the effect of petroleum consumption across countries.
6) The ratio of net petroleum imports to energy use (both in million bbl/d) for 2005 is included as a measure of a region's dependence on petroleum imports, and as a ratio of a region's energy use for comparability with (5).
7) Dummy variables are used to capture other aspects of the data that cannot be explicitly or consistently measured across studies:
    a. Eight epoch dummy variables are used to represent different periods of the global energy market and economy, taking a value of 1 for each 5-year interval between 1970 and 2015 that is partly or fully covered by the study data.[10] These dummy variables are not mutually exclusive. Thus, an estimate of the GDP elasticity based on data spanning the entire 1970-2015 period would have a value of 1 for all eight dummy variables.
    b. Five dummy variables are used to categorize the model classes used in each study as macro-econometric (MACRO), vector auto-regression (VAR-type), dynamic stochastic general equilibrium (DSGE), computable general equilibrium (CGE) models and single-equation econometric (SEEC).
    c. Regional dummies are included to represent features of regional economies not captured by the other factors, and include dummy variables for the United States, Australia, Europe (countries), Euro Area, North Africa, Sub-Saharan Africa, Japan, China and India. Within Europe, separate

most of the studies, we use 2005 because the data is more complete as shown in Figure 4 and the patterns across countries are similar for 1995 and 2005.

[10] Actually, the first of these categories includes all data periods between 1949 and 1975, but there are only a couple of studies that use data before 1970. We evaluated different options for representing period spanned by the data in the MRA, including a dummy variable for each year or mid-year of the data relative to a given year (e.g. 2000) as a continuous variable. The final specification was chosen to minimize multi-collinearity in the regression data matrix, while providing a close representation to including each year in the data.

dummy variables are included for the United Kingdom and Germany based on initial screening of the data.

d. One linear/non-linear price dummy variable takes a value of 1 when an estimate is based on a linear price variable and 0 when an asymmetric price variable, such as NOPI (Hamilton, 2003), is used.

e. Two dummy variables are used to indicate the supply and demand drivers underlying a GDP elasticity estimate. One dummy variable takes a value of 1 when a supply shock or variable is associated with the estimate and 0 otherwise. The other dummy variable takes a value of 1 when a demand shock or variable is associated with the estimate and 0 otherwise.

The baseline for the full regression model in this paper is represented by the following dummy variables, which are dropped during the estimation: 1) US regional dummy; 2) single equation econometric (SEEC) model dummy; 3) 1981 to 1985 data period dummy. In addition, we center the following continuous variables to give the intercept term a more meaningful interpretation: 1) size of shock is centered at +5%; 2) linear trend term is centered at 1, representing the first quarter after shock; 3) real GDP ($2005) is centered at $40,000; 4) petroleum-energy use ratio is centered at 0.4; 5) net petroleum import-energy use ratio is centered at 0.2. The last three variables are centered to values close to those for the US to match the baseline US regional dummy variable. Thus, the intercept can be interpreted as an estimate of the GDP elasticity for the United States given these variable values, with the "normalized average quarterly elasticity" term set to zero.

3.3. Initial meta-analysis results

Table 3 presents results of the initial meta-analysis, based on pseudo-standard errors for the GDP elasticities. We found that restricting the data to cases with pseudo-standard errors calculated from study upper/lower bounds did not change the estimates in Table 3 significantly. Each of the coefficient estimates in Table 3 is accompanied by its usual standard error, as well as study cluster-robust standard errors. Cluster-robust standard errors adjust for potential correlations among estimates belonging to each cluster group as shown in Table 3. The “Uncorrected for publication bias” estimates are estimates of the mean GDP elasticity (β_0) from equation (1), which are all negative and significant at the 1% level. The OLS estimate, which is the unweighted mean of the GDP elasticity data, is about -0.019, whereas the other estimates are 1 to 2 orders smaller in magnitude. Estimates for the WLS and FE models are identical at -0.0003, and -0.0016 for the RE model. The FAT/PET estimates of GDP elasticity (β_0) and publication bias (β_1) coefficients are significant and nearly identical across all four estimators. However, the FAT/PET estimates of the GDP elasticity are positive, contradicting the “Uncorrected for publication bias” results and the expectation for net petroleum importing economies. The Precision Effect Estimator with Standard Error (PEESE), which assumes a quadratic relationship between publication bias and the standard error, restores the negative estimate for β_0, but the weighted estimates are significant only when based on non-clustered standard errors. Coefficient estimates for the three weighted PEESE estimators are identical at -0.0012, whereas the OLS estimate is -0.0094. Estimates for the ME estimator with two-level (study/country) and three-level (study/country/number of quarters after shock) are essentially the same as for the PEESE-RE estimator.

Overall, Table 3 indicates that the data used in this paper do contain non-zero GDP elasticities, which on average are negative. The positive and low magnitude of the FAT/PET estimate of the GDP elasticity is in line with Monte Carlo evidence that its estimates have a downward bias (Galindo et al., 2015). The PEESE estimator produces negative estimates of the GDP elasticity along with significant estimates of the β_1 coefficient, implying a crucial role for publication bias or heterogeneity in the data. In addition, the nearly identical PEESE and ME estimates imply that heterogeneity in the GDP elasticities data is not simply the result of clustering or correlations among the estimates. A comparison of the OLS versus weighted (WOLS, FE and RE/ME) estimates implies that weights based on the pseudo-standard errors cause most of the variation in the GDP elasticities to be attributed almost entirely to publication bias or heterogeneity, instead of just differences in sampling information across studies. Given that these pseudo-standard errors are approximations of the unknown standard errors, the resulting weighted regressions may not be appropriate. Assuming instead that the OLS version of the PEESE estimator is unbiased, White's consistent estimator can be used, in place of the weighted regressions, to correct for heteroscedasticity in the residuals. This implies that both coefficients in the PEESE-OLS estimator remain significant at the 1% level. Still, the estimated mean GDP elasticity of -0.0094 is an average over all systematic sources of variations in the economic impacts of oil price shocks, which may not be applicable to a given country or region, such as the US. We turn to a full meta-regression model in the next section to provide a basis for estimating country- or region-specific GDP elasticities from the literature[11].

Table 3. Initial meta-analysis results[12]

Type of Estimate	Variable	OLS	WLS	FE	RE/ME
(a) Uncorrected for publication bias					
	Constant	-0.0186	-0.0003	-0.0003	-0.0016
		(0.0011)***	(0.0001)***	(0)***	(0.0003)***
		(0.0062)***	(0.0006)	(0.0001)***	(0.0015)
(b) Funnel Asymmetry & Precision Effect Tests (FAT/PET)					
	Constant (β_0)	0.0032	0.002	0.002	0.002
		(0.001)***	(0.0003)***	(0.0002)***	(0.0002)***
		(0.0027)	(0.0008)**	(0.0008)**	(0.0008)**
	Standard error (β_1)	-0.9998	-0.9428	-0.9428	-0.9428
		(0.0282)***	(0.034)***	(0.0591)***	(0.0592)***
		(0.0771)***	(0.1579)***	(0.1687)***	(0.1687)***
(c) Precision Effect Estimator with Standard Error (PEESE)					

[11] Efforts to estimate this model for the US alone lead to estimates of the mean GDP elasticity that are about twice the upper end of the mean estimates in Table 2, emphasizing the importance of explanatory variables. We also find that it becomes necessary to drop most of the potential variables discussed above from a US only MRA due to severe multi-collinearity issues. Thus, the rest of this paper focuses on the MRA using data for multiple countries.

[12] [1]Note: OLS (WLS) is Ordinary (Weighted) Least Squares and FE (RE) is Fixed (Random) Effect estimators. The values in parentheses are the standard errors (first is the ordinary standard error; second is the cluster-robust standard error). The asterisks ***, ** and * imply rejection of the null hypothesis at the 1%, 5% and 10% significance level, respectively.

Constant (β_0)	-0.0094 (0.0009)*** (0.0048)**	-0.0012 (0.0003)*** (0.0011)	-0.0012 (0.0001)*** (0.0011)	-0.0012 (0.0002)*** (0.0011)
Variance (β_1)	-7.764 (0.2916)*** (0.9138)***	-10.9521 (0.4961)*** (0.8841)***	-10.9521 (1.048)*** (0.8864)***	-10.9521 (1.0481)*** (0.8864)***
(d) Multi-level Mixed Effect (ME) – clustered by study & country				
Constant (β_0)	-	-	-	-0.0012 (0.0018) (0.0011)
Variance (β_1)	-	-	-	-10.9521 (1.1255)*** (0.8864)***
(e) Multi-level Mixed Effect (ME) – clustered by study, country & number quarters after shock				
Constant (β_0)	-	-	-	-0.0012 (0.0022) (0.0011)
Variance (β_1)	-	-	-	-10.9521 (1.1436)*** (0.8864)***

3.4. Full meta-regression results

3.4.1. OLS diagnostics and the final regression model

Table 4 presents a number of diagnostics for the OLS estimation of equations (6a) and (6b). The top panel of Table 4 shows the global linear model validation tests of Pena and Slate (2012), and suggests that the models violate OLS assumptions. In particular, skewness and kurtosis tests imply violation of the normal error distribution assumption, and the link test suggests that the model may not be linear. The heteroscedasticity test implies that the null hypothesis of homoscedastic errors cannot be rejected, but the Breusch-Pagan test rejects the null hypothesis of homoscedasticity for both equations, implying a need to address this issue in the final model. Figure 5 provides a visual confirmation of these tests. Panel (a) shows that the residual vs. fitted chart for the OLS estimate of equation (6a) is nearly linear, whereas the OLS estimate of equation (6b) displays a high degree of non-linearity. Given that the only difference between the two estimates is the VR_i term, Figure 5 suggests that this term is best excluded from the linear meta-regression model in this paper. The residuals are almost evenly distributed around the lines in panel (a), which matches the result of the validation test in Table 4 that heteroscedasticity is not a major issue in these regressions. However, Panel (b) of Figure 5 shows Q-Q plots that indicate the residuals are not approximately normally distributed on both two ends of the distribution. Panel (c) shows charts of Cook's distance versus leverage. Cook's distance is a measure of the influence of each observation in the regression, and leverage is a measure of outliers in the data matrix. These charts suggest that only a few observations have Cook's distance or leverage larger than the majority of the data in the OLS regressions, most noticeable for equation (6b) with the VR_i term.

The bottom portion of Table 4 shows variance inflation (VIF) factors used to evaluate multi-collinearity in the data matrix. Multi-collinearity in the data matrix leads to unstable and inflated estimates of model coefficients. VIF is based on the extent to which each variable can be predicted by the others, with a value of 1 indicating no multi-collinearity. Rules of thumb are used to evaluate the seriousness of multi-collinearity, including: 1) 2-4 indicate little concern; 2) 4-10 indicate a need for further investigation; 3) greater than 10 indicate severe multi-collinearity (see O'brien, 2007 for a discussion of factors that influence the interpretation of the VIF). Table 4 shows that most of the variables in equations (6a) and (6b) have VIF values greater than 4. The regional, model and years of data dummy variables are particularly affected, with VIF values of more than 10 in most cases. Among the continuous variables, only the energy and economic variables have VIF values greater than 3. The presence of many dummy variables in a regression tends to lead to multicollinearity because random linear combinations of these 1 or 0 variables can become highly correlated with each other or with the intercept term. Given the importance of the dummy variables to the analysis in this paper, we explicitly address multi-collinearity in the final regression model.

Based on the diagnostics discussed above, the full model results presented in this paper are for equation (6a). In addition, based on the findings of Stanley and Doucouliagos (2015) and the results in Table 3 we estimate equation (6a) with the WLS estimator using $1/SE_i$ as weights. Since all the estimators discussed so far are not robust to the presence of multi-collinearity as illustrated by the VIF values in Table 4, we employ the partial robust M-regression (PRM) estimator to address this important issue. The PRM estimator combines the advantages of partial least squares (PLS) with the robustness of M-regressions. M-regressions are weighted OLS estimators, where the weights are computed iteratively during the estimation process. The PRM weights are computed to correct for both outliers and leverage in the data (Serneels et al., 2005). PLS addresses multi-collinearity by performing least squares regressions with orthogonal components of the data matrix from which coefficients of the original variables are then recovered (Mevik and Wehrens, 2007). Since the PRM is a weighted regression, it is similar to WLS and helps to address heteroscedasticity in the residuals. In addition, Hedges et al (2010) found that correlations among study estimates can be adequately addressed with a robust variance estimation framework, suggesting that the PRM estimator may also account for remaining correlations among estimates of the GDP elasticity from the literature. The third and fourth columns of Figure 5 are diagnostic charts for the PRM estimator for equation (6a) and (6b), respectively. Panel (a) shows that the PRM estimates of equation (6a) and 6(b) have a similar pattern of residuals as the OLS estimate for equation (6a), but are more non-linear on the negative end of the fitted values. Panel (b) shows that the distribution of residuals from the PRM estimator for equation (6a) is closer to the theoretical normal distribution than the OLS residuals, whereas those for the PRM estimator of equation (6b) depart significantly from the normal distribution.

Table 4. Diagnostic tests for OLS estimates of the full meta-regression model

	OLS (Eq. 6a)	OLS (Eq. 6b)
Overall model tests (p-values)		
Global	0.00	0.00
Skewness	0.00	0.00
Kurtosis	0.00	0.00
Link Function	0.00	0.00
Heteroscedasticity	0.29	0.00
Variance inflation factor (VIF) for evaluating multi-collinearity		
Size of shock (as rate price change; centered at 0.05)	2.66	2.66
Number of quarters after shock (centered at 1)	1.38	1.39
Normalized average quarterly elasticity	1.20	1.25
2005 Real GDP per capita (thousand $2005; centered at $40K)	16.43	16.47
2005 Petroleum-energy use ratio (centered at 0.4)	5.35	5.36
2005 Net petroleum import-energy use ratio (centered at 0.2)	45.98	46.07
Region dummy ((baseline: United States)		
Australia	1.44	1.46
Euro Area	7.19	7.23
Europe (countries)	12.31	12.38
United Kingdom	7.04	7.04
Germany	4.80	4.83
Sub-Saharan Africa	6.90	6.90
Japan	7.18	7.19
China	5.86	5.86
India	2.25	2.26
Model class dummy (baseline: Single equation econometric)		
Computable general equilibrium	29.52	29.74
Dynamic stochastic general equilibrium	18.18	18.30
Macro-econometric	19.73	19.79
VAR-type	29.64	29.64
Price type dummy: (Linear=1)	5.74	6.27
Oil supply shock/variable dummy: (Yes=1)	13.00	13.73
Oil demand shock/variable dummy: (Yes=1)	6.14	6.37
Years covered by data dummy (baseline: 1981-1985)		
2011-2015	14.40	14.46
2006-2010	19.37	19.60
2001-2005	15.20	15.33
1996-2000	21.94	21.95
1991-1995	84.70	84.71
1986-1990	62.69	62.71
1976-1980	6.27	6.40
1970-1975	10.20	10.43
Variance	NA	1.71

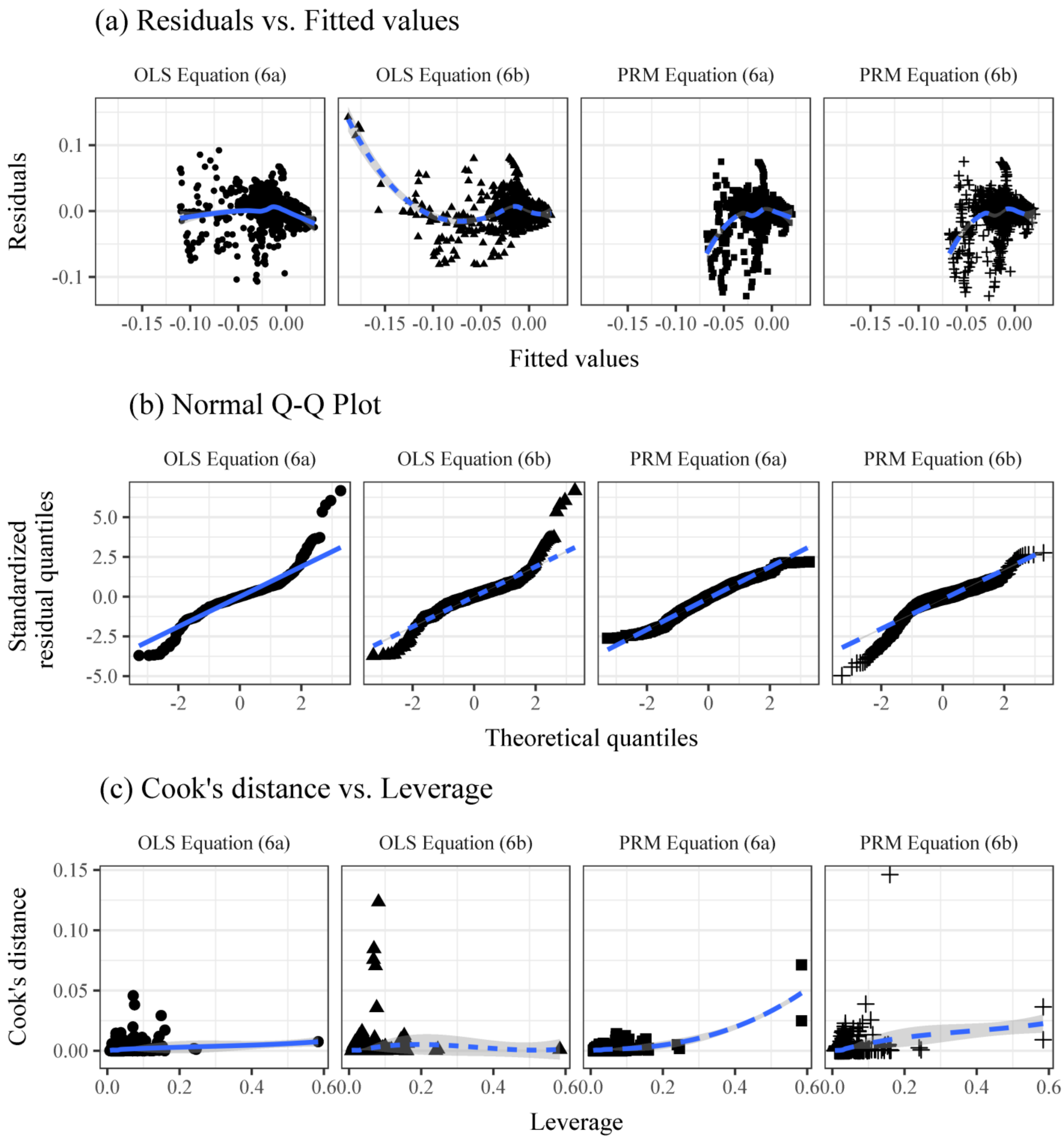

Figure 5. Diagnostic plots for OLS and PRM estimates of the full meta-regression model

3.4.2. Discussion of final coefficient estimates

The OLS, WLS, and PRM estimation results for the full meta-regression in equation (6a) are presented in Table 5. The corresponding full results for equation (6b) are shown in Table B.2 of Appendix B, and show that PRM estimates of the coefficients are nearly identical for equations (6a) and (6b). In addition, the publication bias term in the PRM estimator of equation (6b) is insignificant. Standard errors of the coefficient estimates in Table 5 are based on a heteroscedasticity-robust covariance matrix. Compared to the WLS and PRM estimates, the OLS estimates in Table 5 show the inflation effect of multi-collinearity on the coefficients estimates. The magnitude of many of the OLS coefficients, particularly dummies for model class and years covered by data, are significantly larger than those of the WLS and PRM, with PRM coefficient estimates having the smallest magnitudes overall. The majority of the PRM coefficients also have signs that are consistent with both the OLS and WLS estimates. Although the coefficient estimates have nearly identical signs, the number of significant values for the WLS is smaller than for the OLS, whereas the PRM estimator produces more significant estimates than the OLS. This suggests that the PRM estimator, by addressing multiple econometric issues common in MRA, is better able to clarify the individual roles of the determinant variables than the OLS and WLS estimators. Table 6 shows results of F-tests comparing the full model with models excluding each group of variables. Significance of the F-test indicates that a given group of variables contributes significantly to the model. Table 6 implies that all variable groups contribute significantly to the model, except for number of quarters after the shock under the PRM estimator, and size of shock and energy-economy variables under the OLS and WLS estimators. Based on these findings the following discussion focuses on the PRM coefficients for equation (6a) in Table 5 as the final model in this paper.

The PRM intercept estimate is -0.053, and can be interpreted as the GDP elasticity corresponding to the Baseline of the regression equation. Recall that the Baseline for equation (6a) corresponds to the following variable values: 1) US regional dummy; 2) single equation econometric (SEEC) model dummy;

3) 1981 to 1985 data period dummy; 4) size of shock at +5%; 5) linear trend term at 1, representing the first quarter after shock; 6) real GDP is centered at $40,000; 7) petroleum-energy use ratio at 0.4; 8) net petroleum import-energy use ratio at 0.2. Although these are based on values close to those for the US, the Baseline represents only one of many potential economic conditions. For example, depending on its purpose, it may be more representative, as we do in the example simulation below, to calculate elasticities averaged over all model types, rather than a specific model.

The positive coefficient estimate for "size of shock" in Table 5 implies that the GDP elasticity is less negative for larger oil price shocks, by about 0.007 for a 100% increase in the size of the shock. Thus, the magnitude of the total economic impact of larger oil price shocks would increase at a decreasing rate if the GDP elasticity implied by all other coefficients is negative, but would increase at an increasing rate otherwise. The coefficient estimates on the linear trend term (number of quarters after shock) and "normalized average quarterly elasticity" terms are -0.0006 and 0.0045, respectively. Since the first term increases over time and the second decreases over time[13] the signs of these coefficients imply that the GDP elasticity becomes more negative with the number of quarters following a shock. However, the linear trend coefficient has a very small magnitude, and the value of the "normalized average quarterly elasticity" term eventually plateaus since it changes little after the first 10 quarters.

Coefficient estimates on the energy-economy variables are all small and negative, but significant only for real GDP per capita. The coefficient on real GDP per capita is -0.0003, that for petroleum-energy use ratio is -0.0025, and that for net petroleum import-energy use ratio is -0.0007. Given the centering of these variables, the coefficients reflect the marginal effect of changes in their values, but total effects must be computed net of the centering values. Thus, the petroleum-energy use ratio which is centered at 0.4

[13] Recall that being the normalized form of the overall regional average of the GDP elasticities in Figure 1 the vector of "normalized average quarterly elasticity" values are fixed.

implies that a complete dependence on petroleum leads to slightly more negative GDP elasticities by about -0.0015, not -0.0025. The incremental impact of complete dependence on petroleum imports for energy use on the GDP elasticity is about -0.0006, since it is centered at 0.2. Although these results match expectations for net oil importing economies and the wealth transfer effects of petroleum import dependence, statistical insignificance and small economic impact of the energy-related coefficient estimates mean that the results are not definitive due to a number of reasons. One, the meta-analysis data is inherently cross-sectional in nature, necessitating our use of data for a single, "representative" year for these variables, whereas the variables evolve over time. Second, it is most likely that the effects of these less well-defined variables are captured in other variables, particularly the regional and years of data dummy variables with which regional energy and economic features are likely to be correlated. Once these more composite effects are accounted for it would not be a surprise that the energy-economic variables are insignificant as in Table 5. This conclusion is supported by the VIF values for petroleum-related variables in Table 4, and differences between their PRM and OLS (or WLS) estimates in Table 5.

Regional dummy variables reflect potential features of individual regions affecting estimates of GDP elasticities in the data, which are not captured by other variables in Table 5, relative to the baseline US region. The coefficient estimate for the Australia dummy is about 0.0057, implying that the GDP elasticity for Australia is slightly less negative relative to the US baseline region, all else equal. Estimates for most of the other regions, except China and India, are positive with the largest estimate of about 0.019 for Germany, 0.015 for Europe (countries), and 0.013 for United Kingdom. The coefficient estimate on the regional dummy variable is -0.0087 for China and -0.0006 for India. All regional dummy coefficients, except those for Euro Area, Sub-Saharan Africa and India are significant. These estimates indicate that, all else equal, other regions in the analysis, except China and India, are less sensitive to an oil price shock than the US. Recall that a reason for separating Germany from other European economies in defining the regional dummy variables is because a number of studies have found positive or negative but small economic impacts of positive oil price shocks on the German economy (Cashin et al., 2012; Peersman and Robay, 2009). Also, the United Kingdom has transitioned between net petroleum imports and exports over time.

Model class dummy variables reflect differences in the methodology and structure of different studies. Coefficient estimates for the MACRO and CGE dummies are both negative, about -0.011 and -0.004, respectively, relative to a value of zero for the SEEC model class. The other model class coefficients are positive with values of 0.017 for the DSGE and 0.007 for VAR-type models. Thus, the latter two models produce more positive GDP elasticities than the SEEC model class, all else equal. However, these coefficients must be interpreted in incremental terms, and relative to the underlying data. As explained above, the data in this paper are dominated by estimates from VAR-type models, and some of the variables in the model, such as years covered by the data and price type dummies, are not informative for all model classes.

The coefficient estimate for the price type dummy variable is positive with a value of about 0.008, implying that a study using a linear price variable is likely to estimate a less negative GDP elasticity than one using a non-linear price variable. The non-linear price variable is typified in the oil-economy literature by the NOPI measure of Hamilton (2003), which captures only increases in the oil price that are above a certain threshold. Thus, a positive estimate for the linear price variable matches the use of non-linear price variables to isolate supply shocks in the literature, and the visual implications of the corresponding chart in Figure 3. Coefficient estimates for the supply shock or variable and demand shock or variable dummies are both negative, but the magnitude for the former is about twice that for the latter. A negative estimate matches the supply shock or variable chart in Figure 3, but not the demand shock or variable chart. For the latter, Figure 3 suggests that a demand shock could be associated with negative, zero or positive GDP elasticities on average relative to a case with no demand shock or variable. Instead, the results in Table 5 imply that the marginal or incremental effect of a demand-driven price shock, just as for a supply shock, is negative relative to a no demand shock case. This incremental effect makes sense since the marginal economic impact of a demand-driven price increase in a net oil importing economy may be negative after controlling for the original driver of the demand shock, such as economic growth. Table 5 implies that the magnitude of the incremental economic impact of a demand-driven price shock is about half that of a supply shock.

Coefficient estimates for the data period or "epoch" dummy variables capture changes in the economic impacts of an oil price shock over time as determined by changes in the structure of the economy, as well as market conditions or even policy responses. As noted above, these epoch dummies are composite indicators that may also capture the impacts of changes in the types of oil price shocks (length, severity, and cause, such as supply or demand-based) over time. For a given study, the corresponding dummy variables in Table 5 take a value of 1 for each period that is included in the data (partially or completely), with coefficients that are relative to a value of zero for the period from 1981-1985. The sum of coefficients on the epoch dummy variables (i.e. the net effect of including all data-periods in a study) is 0.042 and differences among the coefficients generally match expectations. Recall that these dummy variables are not mutually exclusive, but can be described as chains that differ across estimates in length, as well as location of the start and end years of the data. In particular, the coefficient on the dummy variable for 1970-1975 has the second largest magnitude and is negative at about -0.016. All the remaining coefficients, except for 1991-1995, are positive with the largest being for 2011-2015 at 0.020. These patterns match the well-known narrative in the oil-economy literature that oil prices during the 1970s were driven largely by exogenous supply shocks that tend to have larger negative impacts on the economy. Most of the oil price increases since 1991, particularly during the 2000 to 2007 period, are thought to be driven by demand shocks, with simultaneous increases in oil prices and economic growth. In addition, changes in the structure and management of the economy, oil market structure, and policy responses, among others have made the economy less vulnerable to oil price shocks than in the 1970s (Blanchard and Gali, 2010).

Table 5. Meta-regression results for the three estimation methods[14],[15]

Variables	OLS (Eq. 6a)	WLS (Eq. 6a)	PRM (Eq. 6a)
Constant	-0.0038	0.0072	-0.0531**
	(0.0160)	(0.0083)	(0.0030)
Size of shock	0.0052	-0.0004	0.0071**
(as rate of price change; centered at 0.05)	(0.0039)	(0.0016)	(0.0007)
Number of quarters after shock	-0.0005**	-0.0002**	-0.0006**
(centered at 1)	(0.0002)	(0.0001)	(0.0000)
Normalized average quarterly elasticity	0.0212**	0.0063**	0.0045**
	(0.0032)	(0.0017)	(0.0006)
2005 Real GDP per capita	-0.0002	0.0000	-0.0003**
(thousand $2005; centered at $40K)	(0.0002)	(0.0001)	(0.0000)
2005 Petroleum-energy use ratio	-0.0227	0.0135	-0.0025
(centered at 0.4)	(0.0359)	(0.0167)	(0.0084)
2005 Net petroleum import-energy use ratio	-0.0025	-0.0201	-0.0007
(centered at 0.2)	(0.0297)	(0.0175)	(0.0083)
Region dummy (baseline: United States)			
Australia	0.0181*	0.0060	0.0057**
	(0.0097)	(0.0065)	(0.0017)
Euro Area	0.0047	0.0025	0.0008
	(0.0061)	(0.0032)	(0.0014)
Europe (countries)	0.0190**	0.0087**	0.0148**
	(0.0054)	(0.0032)	(0.0013)
United Kingdom	0.0066	-0.0027	0.0130**
	(0.0068)	(0.0040)	(0.0019)
Germany	0.0214**	0.0102**	0.0194**
	(0.0071)	(0.0043)	(0.0017)
Sub-Saharan Africa	-0.0010	0.0048	0.0024
	(0.0134)	(0.0174)	(0.0070)

[14] Baseline (United States; economic impacts estimated from a single equation econometric model (SEEC), data covering 1981 to 1985, size of shock at +5%, first quarter after shock, real GDP ($2005) at $40,000, petroleum-energy use ratio at 0.4 and net petroleum import-energy use ratio at 0.2; OLS (WLS) is Ordinary (Weighted) Least Squares; PRM is Partial Robust M-Regression (Serneels et al., 2005)
[15] Standard errors are in parentheses are based on a heteroscedasticity robust covariance matrix. * and ** indicate significance at the 10% and 5% levels, respectively.

Variables	OLS (Eq. 6a)	WLS (Eq. 6a)	PRM (Eq. 6a)
Japan	0.0005	0.0080**	0.0088**
	(0.0068)	(0.0040)	(0.0017)
China	-0.0071	0.0082*	-0.0087**
	(0.0112)	(0.0045)	(0.0018)
India	0.0182	0.0165	-0.0006
	(0.0121)	(0.0119)	(0.0024)
Model class dummy (baseline: Single equation econometric)			
Computable general equilibrium	-0.0775**	-0.0379*	-0.0044
	(0.0250)	(0.0219)	(0.0075)
Dynamic stochastic general equilibrium	-0.0327**	-0.0265**	0.0166**
	(0.0133)	(0.0075)	(0.0026)
Macro-econometric	-0.0296**	-0.0179	-0.0110**
	(0.0116)	(0.0140)	(0.0025)
VAR-type	0.0011	-0.0077	0.0072**
	(0.0080)	(0.0113)	(0.0018)
Price type dummy: (Linear=1)	0.0258**	0.0035	0.0080**
	(0.0048)	(0.0025)	(0.0009)
Supply shock/variable dummy: (Yes=1)	-0.0619**	-0.0345**	-0.0151**
	(0.0083)	(0.0117)	(0.0014)
Demand shock/variable dummy: (Yes=1)	-0.0504**	-0.0248**	-0.0082**
	(0.0085)	(0.0119)	(0.0015)
Years covered by data dummy (baseline: 1981-1985)			
2011-2015	0.0615**	0.0333**	0.0202**
	(0.0084)	(0.0134)	(0.0015)
2006-2010	0.0159**	0.0046	0.0082**
	(0.0045)	(0.0029)	(0.0008)
2001-2005	-0.0028	0.0058	0.0051
	(0.0195)	(0.0224)	(0.0066)
1996-2000	-0.0013	0.0104	0.0126*
	(0.0218)	(0.0184)	(0.0069)
1991-1995	-0.0230**	-0.0232	-0.0004
	(0.0099)	(0.0169)	(0.0021)
1986-1990	0.0303**	0.0203	0.0022*
	(0.0073)	(0.0130)	(0.0013)
1976-1980	-0.0240**	-0.0149	0.0105**
	(0.0083)	(0.0137)	(0.0014)
1970-1975	-0.0221**	-0.0172	-0.0161**
	(0.0068)	(0.0108)	(0.0014)
Sample size	959	959	959

Variables	OLS (Eq. 6a)	WLS (Eq. 6a)	PRM (Eq. 6a)
Adjusted R^2	0.51	0.23	0.26
Standard error of regression	0.025	0.030	0.028

Table 6. Partial F-tests for coefficient groups in the full meta-regression model

	OLS (Eq. 6a)	WLS (Eq. 6a)	PRM (Eq. 6a)
F(Size of shock)	1.75	-0.45	34.43*
F(Number of quarters after shock)	5.7*	4.08*	-74.11
F(Normalized average quarterly elasticity)	44.82*	28.23*	11.55*
F(Energy-economy variables)	1.44	0.37	9.76*
F(Region dummy)	8.14*	2.92*	7.2*
F(Model class dummy)	12*	9.05*	10.44*
F(Price type dummy)	37.84*	11.23*	10.46*
F(Supply or demand shock/variable dummy)	45.6*	54.4*	32.18*
F(Years covered by data dummy)	54.6*	51.34*	41.02*

*Means significance at the 10% level or below

3.4.3. Example simulation to estimate US oil price elasticity of GDP

The estimated coefficients in Table 5 provide a basis for calculating the oil price elasticity of US GDP for policy analysis, using values of the different variables within a range not far outside those of the estimation data. We provide an example of how the meta-regression results can be used for this purpose by performing Monte Carlo simulations with 250,000 replications. To focus on the US, all other regional dummy variables are set to zero since the US regional dummy variable is the baseline. All data period dummy variables are set to 1 to represent estimates based on data over the period from 1970-2015. For model agnosticism, the model class dummies are randomized using the uniform distribution (that is, the alternative values are equally-weighted). The following additional variables are also randomized using the uniform distribution: 1) Shock sizes from +1% to +100% at 10% intervals; 2) Number of quarters after the shock between 1 and 12; 3) Price variable dummy set to 1 or 0; 4) Supply shock or variable dummy set to 1 or 0; 5) Demand shock or variable dummy set to 1 or 0. Values of the “normalized average quarterly elasticity" variable are determined from the vector of values used in the estimation, extracted based on the number of quarters after the shock. The real GDP per capita was set to $44,500, and petroleum-energy use ratio and net petroleum import-energy use ratio were set to 0.51 and 0.15 respectively, which are the approximate 2014 values for the US. Values for all centered variables were adjusted for the centering value. Model parameters are also randomized using the multivariate normal distribution based on the heteroscedasticity-consistent covariance matrix of the coefficients.

Simulated estimates for the US are summarized in Figure 6, showing the mean, one- and two-standard deviation confidence intervals (i.e. 68% CI and 95% CI) up to 12 quarters following a shock. The mean US estimate is negative over the entire period with the magnitude increasing from about 0.015 to 0.024 over the 12 quarters. The 68% CI over the 12 quarters is -0.038 to -0.001, and the 95% CI is -0.051 to +0.012.

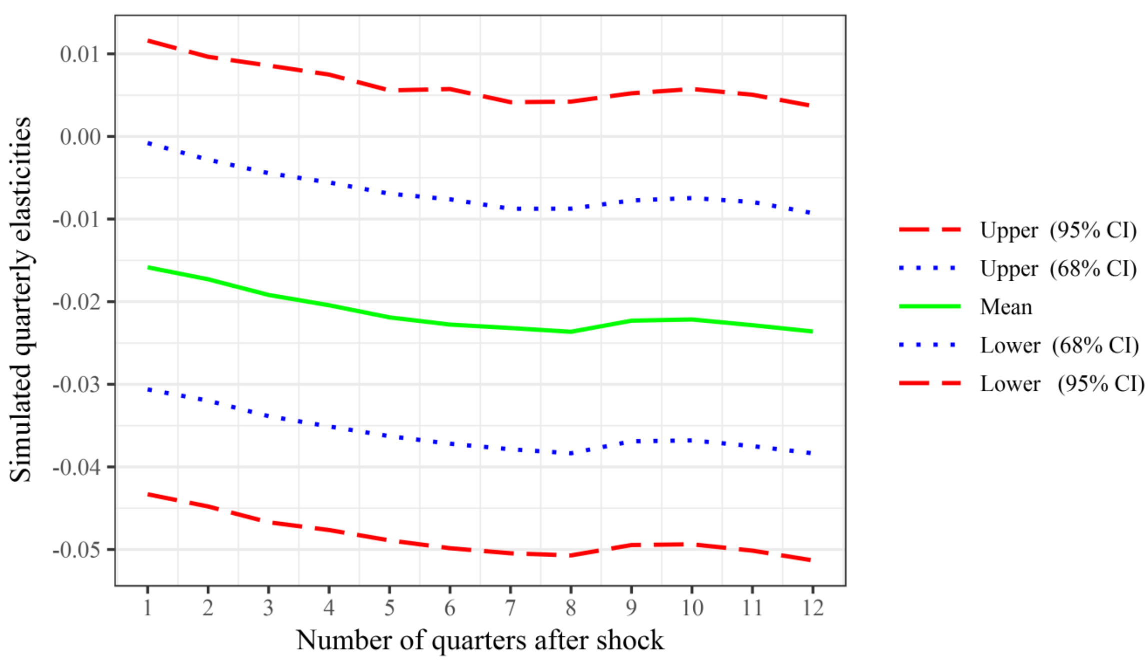

Figure 6. Summary of simulated GDP elasticities for the United States by quarter

4. Conclusions and policy implications

Due to the important role of petroleum in economic activities and its vulnerability to potentially severe shocks, policy makers are keenly interested in understanding the economic impacts of oil price shocks. This paper provides the first, to our knowledge, quantitative meta-analysis of the oil price elasticity of GDP, which is a summary measure of the overall economic impacts of oil price shocks. The GDP elasticity data distilled from the literature are found to vary with multiple fundamental economic and methodological factors, leading to considerable heterogeneity in the data. In addition, standard errors of GDP elasticity estimates are difficult to obtain from the literature in the same form as for conventional meta-analysis because these are complex functions of model parameters and data. We estimate pseudo-standard errors from lower and upper bounds of impulse response functions where available, and imputed standard errors for others. However, we found these to be of little value for our meta-analysis. Thus, our final quantitative model is a meta-regression model that explicitly includes study characteristics and other data to help account for systematic sources of variation in the GDP elasticity estimates. In addition, several econometric issues that are common to meta-analysis studies were addressed with a robust estimator that corrects for multicollinearity, outliers, leverage, and heteroscedasticity in the data.

Overall, we found that the recent empirical literature implies a statistically significant, non-trivial, mean GDP elasticity with respect to oil prices, but with a smaller magnitude than was commonly estimated a decade or more ago. We also found that the range of estimates remains wide; highlighting the important roles played by fundamental and methodological, as well as idiosyncratic, sources of variation in estimates of the GDP impacts of oil price shocks. Coefficient estimates in the final meta-regression model indicate a role for methodology in determining estimation results. Differences in the structure of the economy across regions are shown by differences in the sign and significance of regional variables, with most regions having less negative oil price elasticity of GDP relative to the US baseline region. Furthermore, approaches that seek to identify and distinguish between price shocks originating from supply or demand changes generally lead to more negative elasticity estimates, but with a larger magnitude for the former. Coefficients on dummy variables for period spanned by study data relative to 1981-1985 are all positive, except for 1970-1975 and 1991-1995. The estimate for 1970-1975 is sizable and significant, whereas that for 1991-1995 is small and insignificant. These coefficients support the general notion that the sensitivity of the economy to oil price shocks has declined since the 1970s.

The meta-regression coefficients provide a basis for estimating the oil price elasticity of US GDP for policy analysis in three ways. First, the estimates presented in Figure 6 represent a readily available overall summary of the mean and variation of the oil price elasticity of the GDP for the US based on the data in this paper. The estimated mean US GDP elasticity from the Monte Carlo simulation is about -0.02, four quarters after a shock, which is close to the raw mean from the US data used in this paper as shown in Table 2. Second, when values of the explanatory variables are expected to change significantly the coefficient estimates in Table 5 can be used to recalculate elasticities or generate a distribution of estimates with the type of Monte Carlo simulation used above. The first approach has been used for previous energy-security related analysis within the ORNL BenEStock model (Leiby et. al. 2016). The value adopted for that analysis is about -0.02, which matches the mean estimates in Figure 6. Lastly, coefficients of the meta-regression model could be directly incorporated in a policy model, allowing the GDP elasticity to be updated as the explanatory variables change during the simulations.

Although the results of this paper are in line with expectations and can be viewed with some confidence, three caveats are in order. First, results of a meta-analysis must be interpreted in the context of its non-standard data generating process, particularly given the non-availability of reliable standard errors for the GDP elasticity estimates in the current paper. Second, the oil-price GDP elasticity data for the meta-analysis are derived mostly from time series studies, so each of those studies produce one or more estimates that embody the oil-price GDP relationship across a span of multiple years. Thus, the meta-regression model is essentially cross-sectional in nature. We use the cross-sectional variation in energy-economy variables to seek some insight into the role of these inherently time-bound variables. Coefficients on the energy consumption variables turn out to be small in explaining variations in estimates of the GDP elasticity in the literature. Finally, as with any linear regression model, the range of variable values over which the estimated coefficients are valid is narrower than the full range of those variables. In particular, the meta-regression model presented here explains variations in estimates of mean GDP elasticities extracted from the literature, and thus may not capture the potentially non-linear response of the economy to large changes in the explanatory variables. These cautionary notes are not impediments to the overall findings of this analysis, but remind the reader to interpret the results in the context of a meta-analytical framework. One promising way to improve the analysis in this paper is to work with study authors to obtain reliable estimates of standard errors associated with their estimates. Although this may be impossible for some studies, it would be possible in many cases and could prove informative for the type of meta-regression presented in this paper. Another way to improve the analysis is to expand the literature database with new studies as they become available. These and others are reserved for future efforts.

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Appendix A: List of papers reviewed for the meta-analysis

List of papers included in the meta-analysis

1. Álvarez Luis J., Samuel Hurtado, Isabel Sánchez, Carlos Thomas (2011). The impact of oil price changes on Spanish and euro area consumer price inflation. Economic Modelling 28 : 422–431
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Appendix B: Additional data summary and results tables

Table B.1. Frequencies of variable categories in the data

Years Covered by Data

Start Year	Count	End Year	Count
1949	36	1978	1
1957	4	1985	49
1970	74	1989	3
1971	12	1990	16
1975	5	1993	1
1979	161	2001	1
1980	180	2003	132
1986	169	2004	47
1990	16	2005	36
1994	1	2006	246
1995	220	2007	115
1997	43	2008	168
2001	1	2009	7
2004	30	2010	48
2009	6	2011	88
2012	28	2012	28

Price type

Category	Count
Non-linear	302
Linear	684

Oil supply shock/variable

Category	Count
No	728
Yes	258

Oil demand shock/variable

Category	Count
No	912
Yes	74

Model type

Category	Count
Computable general equilibrium	44
Dynamic stochastic general equilibrium	75
Macro-econometric	71
Single equation econometric	52
VAR-type	744

Table B.2. Meta-regression results for the three estimation methods with a publication bias term[16],[17]

Variables	OLS (Eq. 6b)	WLS (Eq. 6b)	PRM (Eq. 6b)
Constant	-0.0018	0.0077	-0.0531**
	(0.0137)	(0.0080)	(0.0174)
Size of shock	0.0026	-0.0006	0.0071
(as rate of price change; centered at 0.05)	(0.0035)	(0.0013)	(0.0045)
Number of quarters after shock	-0.0003	-0.0002**	-0.0006**
(centered at 1)	(0.0002)	(0.0001)	(0.0002)
Normalized average quarterly elasticity	0.0122**	0.0044**	0.0045
	(0.0029)	(0.0012)	(0.0036)
2005 Real GDP per capita	-0.0001	0.0000	-0.0003
(1000 $2005; centered at $40K)	(0.0001)	(0.0001)	(0.0002)
2005 Petroleum-energy use ratio	-0.0488	0.0043	-0.0025
(centered at 0.4)	(0.0319)	(0.0143)	(0.0404)
2005 Net petroleum import-energy use ratio	0.0192	-0.0114	-0.0007
(centered at 0.2)	(0.0309)	(0.0143)	(0.0393)
Region dummy (baseline: United States)			
Australia	0.0076	0.0044	0.0057
	(0.0068)	(0.0048)	(0.0086)
Euro Area	-0.0021	0.0007	0.0008
	(0.0059)	(0.0025)	(0.0075)
Europe (countries)	0.0127**	0.0064**	0.0148**
	(0.0053)	(0.0023)	(0.0067)
United Kingdom	0.0048	-0.0020	0.0130
	(0.0077)	(0.0035)	(0.0098)
Germany	0.0128*	0.0069**	0.0194**
	(0.0066)	(0.0029)	(0.0084)
Sub-Saharan Africa	-0.0056	0.0035	0.0024
	(0.0186)	(0.0065)	(0.0237)
Japan	0.0037	0.0060**	0.0088
	(0.0067)	(0.0030)	(0.0084)
China	-0.0074	0.0090**	-0.0087
	(0.0082)	(0.0039)	(0.0105)

[16] Baseline (United States; economic impacts estimated from a single equation econometric model (SEEC), data covering 1981 to 1985, size of shock at +5%, first quarter after shock, real GDP ($2005) at $40,000, petroleum-energy use ratio at 0.4 and net petroleum import-energy use ratio at 0.2; OLS (WLS) is Ordinary (Weighted) Least Squares; PRM is Partial Robust M-Regression (Serneels et al., 2005)

[17] Standard errors are in parentheses are based on a heteroscedasticity robust covariance matrix. * and ** indicate significance at the 10% and 5% levels, respectively.

Variables	OLS (Eq. 6b)	WLS (Eq. 6b)	PRM (Eq. 6b)
India	0.0068	0.0106	-0.0006
	(0.0127)	(0.0071)	(0.0161)
Model class dummy (baseline: Single equation econometric)			
Computable general equilibrium	-0.0452*	-0.0258**	-0.0044
	(0.0238)	(0.0118)	(0.0301)
Dynamic stochastic general equilibrium	-0.0177	-0.0174**	0.0166
	(0.0115)	(0.0059)	(0.0146)
Macro-econometric	-0.0188	-0.0125**	-0.0110
	(0.0126)	(0.0062)	(0.0160)
VAR-type	0.0007	-0.0059	0.0072
	(0.0093)	(0.0050)	(0.0118)
Price type dummy: (Linear=1)	0.0079**	-0.0010	0.0080
	(0.0039)	(0.0020)	(0.0049)
Supply shock/variable dummy: (Yes=1)	-0.0398**	-0.0231**	-0.0151**
	(0.0060)	(0.0035)	(0.0077)
Demand shock/variable dummy: (Yes=1)	-0.0296**	-0.0135**	-0.0082
	(0.0068)	(0.0038)	(0.0087)
Years covered by data dummy (baseline: 1981-1985)			
2011-2015	0.0446**	0.0240**	0.0202**
	(0.0072)	(0.0037)	(0.0091)
2006-2010	0.0068*	0.0018	0.0082
	(0.0040)	(0.0019)	(0.0050)
2001-2005	0.0030	0.0078	0.0051
	(0.0188)	(0.0092)	(0.0239)
1996-2000	0.0016	0.0054	0.0126
	(0.0206)	(0.0104)	(0.0261)
1991-1995	-0.0205**	-0.0174**	-0.0004
	(0.0092)	(0.0037)	(0.0116)
1986-1990	0.0216**	0.0126**	0.0022
	(0.0058)	(0.0035)	(0.0074)
1976-1980	-0.0129**	-0.0083**	0.0105
	(0.0064)	(0.0034)	(0.0081)
1970-1975	-0.0139*	-0.0118**	-0.0161
	(0.0080)	(0.0047)	(0.0102)
Publication bias term (variance of estimates)	-5.0274**	-8.5858**	-0.0007
	(0.3167)	(0.4555)	(0.4018)
Sample size	959	959	959
Adjusted R^2	0.62	0.63	0.26
Standard error of regression	0.022	0.025	0.028