DEAKIN UNIVERSITY AUSTRALIA

Faculty of Business and Law

Department of Economics

ECONOMICS SERIES

SWP 2015/11

The impact of healthcare spending on health outcomes: A meta-regression analysis

Updated May 2016

Craig A. Gallet and Chris Doucouliagos

The impact of healthcare spending on health outcomes:
A meta-regression analysis

By

Craig A. Gallet[a]
California State University at Sacramento
Sacramento, CA USA

and

Hristos Doucouliagos[b]
Deakin University
Victoria, Australia

[a] Gallet (corresponding author): Professor of Economics, Department of Economics, California State University, Sacramento, 6000 J Street, Sacramento, CA 95833, USA. Email: cgallet@csus.edu. Phone: 916-278-6099. Fax: 916-278-5768

[b] Doucouliagos: Professor of Economics, Department of Economics, Deakin University, 221 Burwood Highway, Burwood, 3125, Victoria, Australia. Email: douc@deakin.edu.au. Phone: 61-3-9244-6531.

ABSTRACT

Numerous studies report estimates of the elasticity of health outcomes (most often measured by a mortality rate or life expectancy) with respect to healthcare spending, which we examine using meta-regression analysis (MRA). Correcting for a number of issues, including publication selection bias, healthcare spending is found to have the greatest impact on the mortality rate compared to life expectancy. Indeed, conditional on several features of the literature, the spending elasticity for mortality is in the neighborhood of -0.13, whereas it is roughly equal to +0.04 for life expectancy. MRA results reveal that the spending elasticity for the mortality rate is particularly sensitive to data aggregation, the specification of the health production function, and the nature of healthcare spending. The spending elasticity for life expectancy is most sensitive to the age at which life expectancy is measured and the decision to control for the endogeneity of spending in the health production function.

1. Introduction

Increases in healthcare spending have garnered much attention among academics, policymakers, and the public at large. Across OECD countries, for example, healthcare spending is currently averaging nearly 10% of GDP, and at over 17% in the United States is quite disconcerting to many (OECD, 2015). At the same time, there have been noticeable advances in health outcomes. For instance, the average infant mortality rate among OECD countries has fallen more than 80 percent since 1970, while average life expectancy has increased roughly 15 percent over the same period (OECD, 2015).

In light of these observations, it is not surprising that studies have examined the link between healthcare spending and health outcomes. Typically utilizing a production function approach, whereby healthcare spending is an input into the production of health, these studies regress health outcomes (most commonly a mortality rate or life expectancy) on healthcare spending and other determinants. Such studies report multiple estimates of the elasticity of health outcome with respect to healthcare spending (defined as the ratio of the percentage change in health outcome to the percentage change in healthcare spending), which we label as the "spending elasticity". Most spending elasticities fall within the inelastic range, but there is significant variation in elasticities. For instance, regarding mortality, some studies (e.g., Hitiris and Posnett, 1992; Thornton, 2002) report spending elasticities in the neighborhood of zero, implying that spending has little influence on mortality, whilst other studies (e.g., Crémieux et al., 1999; Martin et al., 2012) report spending elasticities significantly greater than zero in absolute value. Furthermore, studies have examined whether or not the influence of healthcare spending is tied to the nature of spending, be it on pharmaceuticals or non-pharmaceuticals (e.g., Crémieux et al., 2005; Guindon and Contoyannis, 2012), or on the part of the public or the private sector (e.g., Gupta et al., 2003; Asiskovitch, 2010).

Since the efficacy of healthcare policy is often tied to the relationship between healthcare spending and health outcomes, it is important to understand why spending elasticities differ in the literature. Accordingly, in this new quantitative review of this literature, we do this by conducting a meta-regression analysis (MRA). Focusing on studies which utilize a mortality rate or life expectancy as health outcomes, this involves separately regressing estimates of the spending elasticity for each health outcome on variables controlling for study attributes. However, since publication selection bias has been detected in a number of topics in health economics (e.g., see Costa-Font et al., 2011; Doucouliagos et al., 2012), our MRA addresses this issue as well.

Briefly, MRA results reveal strong publication selection bias for the mortality rate literature, but not for the life expectancy literature. Also, these two spending elasticities respond differently to features of the literature. For instance, amongst other factors, the spending elasticity for the mortality rate is most sensitive to data aggregation, the specification of the health production function, and the nature of healthcare spending; while the spending elasticity for life expectancy is most sensitive to the age at which life expectancy is measured and whether or not endogeneity of healthcare spending is addressed. Finally, the spending elasticity for the mortality rate is much larger in absolute value compared to its life expectancy counterpart, indicating that healthcare spending has the greatest impact on the mortality rate.

In the remaining sections, the literature on the spending elasticity is summarized, followed by a discussion of the meta-data, MRA model, and estimation results. The paper concludes with summary comments.

2. Summary of literature

There is a great deal of literature on the relationship between healthcare spending and health outcomes. Although a few studies assess this relationship by focusing on narrowly-defined health indicators, such as smoking prevalence and sexually transmitted disease (e.g., Chesson et al., 2005; Taurus et al., 2005), the number of spending elasticities reported in these studies is very small. Following MAER-net guidelines (Stanley et al., 2013), which require that an MRA examine a comparable effect size (in our case, the spending elasticity) within a literature, since the bulk of the literature on healthcare spending and health outcomes uses either a mortality rate (i.e., number of deaths relative to a population) or life expectancy (i.e., average years expected to live) as indicators of health outcomes, we focus on these two health outcomes in this MRA.

Regarding mortality and life expectancy, there is substantial variation in how each is measured in the literature. For instance, the vast majority of studies of the impact of healthcare spending on mortality focus on either the infant mortality rate (i.e., mortality rate for children under the age of 1) or the under-5 mortality rate (i.e., mortality rate for children under the age of 5), whilst a few studies (e.g., Hitiris and Posnett, 1992; Thornton, 2011) examine the mortality rate of the entire population. Amongst OECD countries, the large 80 percent decrease in the average infant mortality rate since 1970, compared to the modest 15 percent increase in life expectancy, is consistent with studies that have found the spending elasticity (in absolute value) is larger for infant mortality than for life expectancy (e.g., see Crémieux et al., 1999; Nixon and Ulmann, 2006). Such results are consistent with there being (i) substantial returns to spending among the very young and (ii) biological constraints on human longevity (see Manton et al., 1991).

Concerning life expectancy, studies either measure it from birth, or from an older age (such as age 60 or 80). Some studies (e.g., Comanor et al., 2006; Asiskovitch, 2010) find life expectancy at an older age is more responsive to healthcare spending, which could be tied to medical advances in the treatment of diseases most often afflicting older individuals (e,g., heart disease and cancer).

There are other notable features of the literature. First, while many studies focus on the relationship between healthcare spending and health outcomes among OECD countries (e.g., Hitiris and Posnett, 1992; Crémieux et al., 1999), increasingly other studies direct attention towards non-OECD countries (e.g., Gupta et al., 2003; McGuire, 2005). If there are diminishing returns to healthcare spending, such that healthcare spending has its largest impact on health outcomes among less developed countries (which spend less on healthcare), then this could lead to differences in the spending elasticity between OECD and non-OECD countries, *ceteris paribus*.

Second, as mentioned previously, there are differences in how spending is measured, be it on pharmaceuticals or non-pharmaceuticals, and whether it is on behalf of the public or private sector. For instance, Crémieux et al. (2005) and Liu et al. (2008) find pharmaceutical spending has a larger impact on health outcomes than non-pharmaceutical spending. Yet Guindon and Contoyannis (2012) fail to find evidence of this. Furthermore, some comparisons of public and private healthcare spending find public spending has a greater impact on health outcomes than private spending (e.g., Gupta et al., 2003; Lichtenberg, 2004), whilst others fail to find sizable differences in public and private spending elasticities (e.g., Leigh and Jencks, 2007; Caliskan, 2009).

Third, several studies explore gender differences in the relationship between healthcare spending and health outcomes, with some providing evidence that spending has a greater influence on female health (e.g., Ivaschenko, 2005), others finding the opposite holds (e.g., Crémieux *et al.*, 1999), and still others finding no significant difference across genders (e.g., Nixon and Ulmann, 2006).

Fourth, studies differ in data characteristics and specification of the production function. For example, most studies estimate health production functions using panel data at the national level. Yet some studies rely on data at the sub-national level, such as at the state or province levels (e.g., Crémieux et al., 1999; Martin et al., 2008). Also, studies differ in the inclusion of other variables (e.g., income) in the health production function.

Lastly, it is possible that healthcare spending is influenced by health outcomes. Such reverse causation could bias the spending elasticity when using ordinary least squares (*OLS*), and so a number of studies have used instrumental variables (*IV*) procedures to correct for endogeneity concerns (e.g., Gupta et al., 2002; Bokhari et al., 2007; Martin et al., 2008).

3. Meta-data issues

Our MRA model seeks to uncover attributes of the literature which influence the reported spending elasticity for mortality and life expectancy. Before presenting the model, we discuss a number of issues concerning the meta-data.

3.1. Studies included in meta-data

Following recommended guidelines for conducting a meta-analysis (see Liberati et al., 2009; Stanley et al., 2013), to identify studies to include in the analysis, we performed multiple

English language searches (over the 2014-15 period) on EconLit, Google Scholar, and Social Science Research Network (using combinations of the following keywords: "healthcare spending", "healthcare expenditure", "pharmaceutical spending", "pharmaceutical expenditure", "health outcomes", "health status", "life expectancy", "mortality", and "health production function") for papers published (or completed, in the case of working papers) in 2015 or prior years. While these electronic searches identified the bulk of studies, we also perused literature reviews (e.g., Nolte and McKee, 2004; Nixon and Ulmann, 2006), in addition to the reference sections of all studies identified, to find a few more studies. As we discuss below, in order to address publication selection bias, not only do included studies need to report spending elasticities, but they must also report associated standard errors or provide information allowing us to calculate standard errors. This led to the inclusion of 65 studies in the meta-data. Table 1 provides a listing of these studies, as well as a few of their attributes.

Perusing Table 1, it is interesting to note that many studies which strictly examine life expectancy report a lower mean (absolute) spending elasticity compared to studies which strictly examine mortality. Again, with the bulk of mortality studies addressing infant or under-5 mortality, this suggests the health returns to spending are higher among children, *ceteris paribus*. Furthermore, although not consistently observed across all the studies listed in Table 1, several studies of non-OECD countries (e.g., Gupta et al., 2002; Akinkugbe and Mohanoe, 2009) report larger mean (absolute) spending elasticities compared to studies of OECD countries (e.g., Hitiris and Posnett, 1992, Shaw et al., 2005). This is consistent with there being diminishing returns to healthcare spending, i.e., the health returns to spending are higher (lower) in less (more) developed countries. At this point, however, since we are not controlling for the influence of multiple factors on spending elasticities, we caution inferring too much from the absolute means reported in Table 1.

3.2. Outliers

The 65 studies provide 888 comparable estimates of the spending elasticity for mortality or life expectancy. However, before commencing with the MRA, it is important to explore the existence of outliers. In our experience, outliers typically result from reporting and/or coding errors. Since erroneous observations can distort MRA, it is important to remove them from the meta-data. To identify outliers, we estimated the following *FAT-PET* (*i.e.*, funnel-asymmetry test and precision-effect test, see Stanley and Doucouliagos, 2012) meta-regression:

$$E_{ij} = \beta_0 + \beta_1 SE_{ij} + u_{ij}, \tag{1}$$

where E_{ij} is the i^{th} estimate of the spending elasticity reported in the j^{th} study, SE_{ij} is its corresponding standard error, and u_{ij} is an error term. Equation (1) was estimated separately for the spending elasticity associated with mortality (48 studies with 631 elasticities) and life expectancy (28 studies with 257 elasticities). After estimating (1), we identified as outliers observations with a meta-regression standardized residual greater than 3.5, which corresponded to two mortality rate observations and one life expectancy observation. These three observations were removed from the MRA, which not only reduced the number of elasticities in the final meta-data set for the mortality rate (life expectancy) to 629 (256), but due to the elimination of Hall et al. (2012) also reduced the number of studies to 64 in the meta-data set.

3.3. Publication selection bias

Publication selection bias occurs if reported spending elasticities are not representative of all elasticities generated by researchers. For example, some researchers may have a preference to report a certain finding, such as healthcare spending decreasing (increasing) mortality (life expectancy), or spending elasticity estimates significantly different from zero. This not only has adverse effects on statistical inference, but as Stanley (2008) and Stanley and Doucouliagos (2012) find, often exaggerates the reported average elasticity.

If the literature is free of publication selection bias, then it should have a distribution of reported elasticities that is approximately symmetric around the underlying population elasticity (Stanley and Doucouliagos, 2012). Funnel plots offer a way of detecting this by illustrating the reported elasticity estimates against their associated precision (measured as the inverse of their standard errors). Selection bias will distort the funnel. For example, a preferential reporting of negative spending elasticities (in the case of the mortality rate) or positive spending elasticities (in the case of life expectancy) will be revealed as asymmetry (e.g., a long tail) in the distribution.

Figures 1 and 2 are funnel plots of the spending elasticity for the mortality rate and life expectancy, respectively. They indicate that the majority of the spending elasticity estimates are negative (positive) for the mortality rate (life expectancy). It also appears that the distribution of the estimates is asymmetric, most noticeably for the mortality rate. This suggests it is important to control for any preferential reporting bias when estimating meta-regressions.

As further evidence, we formally assessed the presence of publication selection bias using the *FAT-PET* test. Stanley (2008) shows that testing the significance of the coefficient of *SE* in Equation (1) offers a test for the presence of publication selection bias. While we suppress the estimation results of Equation (1) to conserve space (results available upon request), results indicate the presence of publication selection bias, most noticeably with the mortality rate elasticity. Accordingly, our MRA controls for the possibility of publication selection bias.

3.4. Statistical power

According to McCloskey and Ziliak (1996), researchers tend to focus on statistical significance (Type I errors) and often ignore statistical power (Type II errors). This omission can be serious, as low statistical power means a low probability of rejecting a false null hypothesis. However, low power can also lead to falsely accepting the null as researchers mine the data to establish statistically significance.

Ioannidis et al. (2016) highlight the importance of exploring statistical power by showing how meta-analysis can be used to calculate statistical power in a literature. They point out that using a conventional 5% level of statistical significance and an 80% level of power, an econometric estimate will have adequate power when its standard error is smaller than the absolute value of the underlying effect divided by 2.8. We use this relationship to assess whether or not the literature in our meta-data has adequate power. As recommended by Ioannidis et al. (2016), we use a simple (fixed-effect) weighted average of all reported healthcare spending elasticities to estimate the meta-average elasticity. Statistical power is then assessed by comparing the standard error of each estimate to the absolute value of the estimated meta-average elasticity divided by 2.8. An estimate is deemed to be adequately powered if the reported standard error of the estimated elasticity is less than this threshold.

Utilizing this procedure, 59% of the reported spending elasticity estimates have adequate power. To put this in context, Ioannides et al. (2016) find that half of the 159 economics research areas they surveyed have nearly 90% of their results under-powered. Hence, the literature on the relationship between healthcare spending and health outcomes is better than average in terms of statistical power.

4. MRA model

Our MRA seeks to explain variation in reported spending elasticities. This is important, since as highlighted in Section 2, studies estimate the spending elasticity utilizing different types of data and specifications of the health production function. To control for the influences of these choices on spending elasticities, we take the meta-data set containing all 885 observations and split it into two, one corresponding to spending elasticities for the mortality rate (629 observations) and the other corresponding to spending elasticities for life expectancy (256 observations). We then estimate different versions of the following meta-regression for each health outcome:

$$E_{ij} = \beta_0 + \beta_1 SE_{ij} + \mathbf{x}'_{ij}\boldsymbol{\gamma} + u_{ij}, \tag{2}$$

where $\mathbf{x}$ is a vector of moderator (typically dummy) variables and $\boldsymbol{\gamma}$ is a vector of coefficients. This is an extension of Equation (1), wherein data were collected from the 64 studies on several moderator variables to account for commonly adopted features of the literature.

Specifically, in light of Section 2, several variables are included in $\mathbf{x}$. First, when estimating Equation (2) with mortality rate meta-data, we differentiate between the mortality of children (i.e., the infant and under-5 mortality rates) from the mortality of the general population by including the dummy *Child* (equals 1 if the spending elasticity pertains to the infant or under-5 mortality rate, 0 not). When estimating Equation (2) with life expectancy meta-data, we control for age by including the dummy *Older*, which equals 1 if life expectancy is measured at an older age (i.e., age 40, 60, 80, etc.) and 0 if it is measured at birth. For both mortality and life expectancy, we also include the variable *Female* (equals 1 if the spending elasticity is specific to female health outcomes, 0 not) to control for gender.

Second, to control for the nature of healthcare spending, we include the dummies *OECD* (equals 1 if healthcare spending strictly pertains to OECD countries, 0 not), *Pharm* (equals 1 if healthcare spending strictly pertains to pharmaceuticals, 0 not), and *Public* (equals 1 if healthcare spending strictly pertains to the public sector, 0 not). In addition, since studies differ in how healthcare spending is measured, such as in per capita terms or as a share of overall income or spending, we include the dummy *Share* (equals 1 if healthcare spending is measured as a share of income or spending, 0 not).

Third, several moderator variables control for data, specification, and estimation choices. In particular, coupled with the majority of spending elasticities being estimated with panel data aggregated to the national level, most studies include per capita income as a determinant of health, with some studies also introducing dynamics into the health production function by including lagged spending and/or lagged health outcomes. The inclusion of lagged spending, as opposed to contemporaneous spending, is an alternative way of addressing potential bias resulting from the contemporaneous endogeneity of healthcare spending. To account for these choices, we include the dummies *Panel* (equals 1 if panel data used, 0 not), *Sub-national* (equals 1 if sub-national data used, 0 not), *Income* (equals 1 if per capita income included in the production function, 0 not), *Lag spending* (equals 1 if lagged healthcare spending included in the production function, 0 not), and *Lag outcome* (equals 1 if lagged mortality (life expectancy) included in the mortality (life expectancy) production function, 0 not). Furthermore, in addition *Working paper* (equals 1 if study is a working paper, 0 if study is published), we also include in **x** the average year (denoted *Average year*) of the data used in each primary study (measured as the deviation from the mean year of 1992). This allows us to explore time variation in spending elasticities. Finally, some studies address endogeneity of healthcare spending in the production function by using instrumental variables, and so we include the variable *Endogeneity* (equals 1 if an instrumental variables procedure is used, 0 not). Table 2 provides summary statistics of the meta-data.

5. Estimation procedures and results

5.1. Estimation procedures

Results from the estimation of Equation (2) for the mortality rate and life expectancy are provided in Tables 3 and 4, respectively. Initially, a general model is estimated with all moderator variables and all comparable observations included (Column (1)). Rather than use *OLS*, which assigns equal weight to all elasticity estimates and thereby generates biased estimates (see Stanley and Doucouliagos, 2015), this model is estimated using unrestricted fixed-effects weighted least squares (*FE-WLS*), which weights each estimate by its inverse variance (i.e., $1/SE_{ij}^2$). Hedges and Olkin (1985) show that inverse variance provides 'optimal weights'.

Next, we explore robustness of the meta-regressions in several ways. First, if health care spending is endogenous to health outcomes, then *OLS* estimates will be biased. While the inclusion of *Endogeneity* in Equation (2) controls for the response of the spending elasticity to endogeneity correction in the health production function, to see if the MRA results are also sensitive to such bias, we estimate the general model with a subset of observations, i.e., those for which spending elasticities strictly pertain to models corrected for spending endogeneity. Since the sample size is substantially reduced, note that a few moderator variables are dropped from the MRA due to their lack of variation. Further, note that we do not find a significant difference in standard errors from *OLS* estimates compared to their *IV* counterparts; and so, with respect to the estimation of Equation (2), pooling data from *OLS* and *IV*-based studies, and weighing these estimates by their inverse variance, does not give greater weight to potentially-biased *OLS* estimates.

Second, Column (3) explores the robustness of the general model by re-estimating the Column (1) specification using only estimates with adequate statistical power (defined using a conventional standard of 80%). This new estimator, known as *WAAP* (for Weighted Average of the Adequately Powered), is proposed by Ioannidis et al. (2016). An advantage of this estimator is that by discarding estimates that lack statistical power, *WAAP* reduces publication selection bias when it is correlated with the lack of statistical power.

Third, in Column (4) we report the general model results using random effects weights (estimated with restricted maximum likelihood, *REML*), which includes the inverse variance in the weights (but now constructed as $1/(SE_{ij}^2 + \tau^2)$, where τ^2 is an estimate of the excess between-study heterogeneity). While using random effects is popular, Stanley and Doucouliagos (2015, 2016) show that unrestricted *FE-WLS* is superior in the presence of publication selection bias (also see Henmi and Copas, 2010; Stanley and Doucouliagos, 2012). Even in the absence of selection bias, unrestricted *FE-WLS* performs as well as random effects (Stanley and Doucouliagos, 2015; Stanley and Doucouliagos, 2016) and hence is our preferred method for statistical inference.

Fourth, many authors employ a model reduction strategy for MRA (Stanley and Doucouliagos, 2012). Accordingly, we remove from the general model in Column (1) all variables that are not individually statistically significant at least at the 0.30 level of statistical significance (*F*-test for redundant variables is 0.94 with *p*-value of 0.49 for mortality and 0.73

with p-value of 0.65 for life expectancy). These results, labeled the specific model, are provided in Column (5).

A few other methods were considered to explore the robustness of the meta-regressions. In particular, (i) similar to Gallet and Doucouliagos (2014) we applied the wild bootstrap method of Cameron et al. (2008) to correct standard errors for data dependence, (ii) we replaced the inverse variance weights with sample size, (iii) we estimated a multilevel (or hierarchical linear) model, and (iv) we considered whether institution and regional differences play a role in shaping the size of the spending elasticity by matching data on country-level democracy, economic freedom, per capita income, as well as various region dummy variables. However, since the results of these alternative methods (which are available upon request) did not appreciably change the results reported below, we chose to leave them out of Tables 3 and 4.

5.2. Mortality rate results

Table 3 presents results for the mortality rate. Rather than address each of the meta-regressions individually, we instead focus on the commonalities across Columns (1) through (5). Perusing Table 3, regarding those coefficients most often statistically significant, several results emerge. First, since the coefficient of *SE* is significant in all meta-regressions, this indicates the presence of publication selection bias with respect to the mortality literature. Furthermore, its coefficient being negative and exceeding 1 in absolute value indicates that publication bias is substantial and favors healthcare spending reducing mortality (see Doucouliagos and Stanley, 2013).

Second, the coefficient of *Sub-national* is positive and significant in most models, indicating healthcare spending at the sub-national level has smaller mortality effects, *ceteris* *paribus*. Interestingly, Costa-Font et al. (2011) find the influence of income on healthcare spending is lower at the sub-national level as well, which they argue is indicative of aggregation bias.

Third, controlling for other variables that could affect mortality (i.e., income and to a lesser extent lagged health outcome (mortality)), as well as lagging healthcare spending, also affects the spending elasticity. For instance, omitting income from the health production function increases the absolute value of the spending elasticity, which in light of the strong correlation between income and healthcare spending (see Costa-Font et al., 2011), suggests not including income in the production of mortality contributes to omitted variable bias, leading to an overstatement of the effect of healthcare spending on mortality. Furthermore, as mentioned earlier, including lagged spending in the health production function is an alternative way of addressing the endogeneity of contemporaneous healthcare spending. Accordingly, although *IV* estimation of the health production function does not significantly affect the spending elasticity (i.e., the coefficient of *Endogeneity* is insignificant), endogeneity correction via the inclusion of lagged spending does affect the spending elasticity.

Fourth, for three of the five columns in Table 3, the spending elasticity is significantly higher (in absolute value) when spending is specific to the public sector, thus indicating that the nature of healthcare spending matters somewhat. Given their lack of significance, however, other variables (i.e., *Child*, *Female*, *Share*, *Panel*, *Working paper*, *Average Year*, *OECD,* and *Pharm*) appear to have little influence on the spending elasticity.

Lastly, for illustrative purposes, we can use the MRA coefficients to derive predictions of the spending elasticity. In particular, while the constant is an estimate of the spending elasticity when all moderator variables are set to zero (labeled the baseline elasticity), which ranges between -0.14 and -0.04 across the five columns of Table 3, we can consider deviations from this baseline by allowing combinations of moderator variables not set to zero. As an example, using the results from Column (5), in light of their significance if we set *Public*, *Income*, and *Lag spending* equal to 1, this generates a predicted elasticity for public spending (conditional on including income and lagged spending in the health production function) equal to -0.11 (95% confidence interval of -0.16 to -0.07). This not only falls in the inelastic range, but it is also in the range of values reported in the literature (see Table 1). Similar values of this elasticity (labeled *Predicted E* at the bottom of Table 3) are found across the five columns of results. With each lying well within the inelastic range, this indicates the influence of healthcare spending on mortality is quite modest.

5.3. Life expectancy results

Table 4 reports the results for life expectancy. The coefficient of *SE* is statistically insignificant in all five meta-regressions, which indicates that this branch of the literature is free of publication selection bias.

Regarding the coefficients that are statistically significant, evidence does suggest that healthcare spending has a greater impact on life expectancy when measured from an older age. Yet the difference in the magnitude of the spending elasticity between age groups is small. For instance, based on the specific model of Column (5), the spending elasticity merely increases from 0.013 at the baseline (which, amongst other factors, corresponds to life expectancy at birth) to 0.02 when life expectancy is at an older age, *ceteris paribus*. Also, unlike the mortality rate, for life expectancy there is a tendency to report larger spending elasticities (i) when they are reported in working papers and (ii) when endogeneity of healthcare spending is addressed using an *IV* method. Finding that endogeneity-correction using *IV* procedures influences the spending elasticity suggests that future studies be aware of this when estimating life expectancy production functions.

Concerning the remaining variables, compared to the mortality rate meta-regressions, significance is sparser in the life expectancy meta-regressions. For instance, while the coefficients of *OECD*, *Lag spending*, and *Average year* are significant in the specific model, they are not significant across most versions of the general model. Furthermore, several variables (i.e., *Share*, *Panel*, *Sub-national*, and *Income*) are not only insignificant across all general models, but they are dropped from the specific model as well. Accordingly, unlike mortality, the omission of income from the health production function for life expectancy appears to not influence the spending elasticity.

Similar to mortality, we can use the results from Table 4 to construct predicted spending elasticities for life expectancy. As an example, given their significance, if we deviate from the baseline by setting *Older*, *Lag spending*, and *Endogeneity* equal to 1, then based on the results in Column (5) this generates a predicted elasticity equal to 0.03, with a 95% confidence interval of 0.01 to 0.05. Denoted *Predicted E* at the bottom of Table 4, this elasticity is similar across the five columns of results. These elasticities being much smaller in comparison to their mortality rate counterparts indicate that healthcare spending has a smaller influence on life expectancy compared to mortality.

6. Concluding comments

There are several useful results associated with our quantitative review of this literature. First, although publication selection bias is an important issue with the literature on healthcare spending and mortality, it is relatively unimportant for studies of healthcare spending and life expectancy.

Second, spending elasticities for the mortality rate are higher (in absolute value) compared to life expectancy. This suggests healthcare spending is more readily manifest in mortality data than in life expectancy data. Indeed, based on our predicted elasticities, it appears that public healthcare spending has roughly three-times greater influence on mortality than on life expectancy. Even so, since the spending elasticities are small, there are limits to how much health outcomes improve in response to changes in healthcare spending. For instance, healthcare spending (as a percent of GDP) has nearly doubled among OECD countries since 1970 (OECD, 2015). However, deviating from the baseline by setting *OECD* equal to 1 in each of the specific models, we predict mortality (life expectancy) would fall (rise) by only 8% (0.40%) in response to this doubling of spending, *ceteris paribus*. Given infant mortality (life expectancy) among OECD countries fell (rose) by 80% (15%) during this period (OECD, 2015), our prediction is far off. Hence, this suggests other factors (e.g., income, demographics, and lifestyle choices) likely play a collectively more important role in improving health.

Third, given the evidence that the type of healthcare spending matters (e.g., public versus private spending) to mortality, whereas other evidence suggests life expectancy at birth responds differently to healthcare spending than life expectancy at an older age, policymakers should be aware of this when allocating healthcare spending.

Lastly, our results highlight how specification and estimation choices influence spending elasticities. For example, from Column (5) of Table 3, the inclusion of income in the health production function causes the spending elasticity for mortality to decrease in absolute value by roughly 0.07 from its baseline; whereas including lag spending in the mortality production function, while important as a means of addressing dynamics and causality issues, has a nearly opposite influence on the spending elasticity. Furthermore, from Column (5) of Table 4, controlling for endogeneity of healthcare spending in the life expectancy production function nearly triples the magnitude of the spending elasticity from its baseline. Such sensitivities suggest that greater effort be given in the literature to reporting spending elasticities across a variety of specification and estimation choices.

References

Akinkugbe, O., Mohanoe, M., 2009. Public health expenditure as a determinant of health status in Lesotho. Social Work in Public Health 24 (1 – 2), 131-147.

Asiskovitch, S., 2010. Gender and health outcomes: the impact of healthcare systems and their financing on life expectancies of women and men. Social Science & Medicine. 70 (6), 886-895.

Bokhari, F.A., Gai, Y., Gottret, P., 2007. Government health expenditures and health outcomes. Health Economics. 16 (3), 257-273.

Caliskan, Z., 2009. The relationship between pharmaceutical expenditure and life expectancy: evidence from 21 OECD countries. Applied Economics Letters. 16 (16), 1651-1655.

Cameron, A.C., Gelbach, J.B., Miller, D.L., 2008. Bootstrap-based improvements for inference with clustered errors. Review of Economics and Statistics. 90 (3), 414-427.

Chesson, H.W., Harrison, P., Scotton, C.R., Varghese, B., 2005. Does funding for HIV and sexually transmitted disease prevention matter? Evaluation Review. 29 (1), 3-23.

Comanor, W.S., Frech III, H.E., Miller Jr., R.D., 2006. Is the United States an outlier in health care and health outcomes? A preliminary analysis. International Journal of Health Care Finance and Economics. 6 (1), 3-23.

Costa-Font, J., Gemmill, M., Rubert, G., 2011. Biases in the healthcare luxury good hypothesis?: A meta-regression analysis. Journal of the Royal Statistical Society: Series A (Statistics in Society). 174 (1), 95-107.

Crémieux, P.Y., Ouellette, P., Pilon, C., 1999. Health care spending as determinants of health outcomes. Health Economics. 8 (7), 627-639.

Crémieux, P.Y., Meilleur, M.C., Ouellette, P., Petit, P., Zelder, M., Potvin, K., 2005. Public and private pharmaceutical spending as determinants of health outcomes in Canada. Health Economics. 14 (2), 107-116.

Doucouliagos, C. (H.), Stanley, T.D., Giles, M., 2012. Are estimates of the value of a statistical life exaggerated? Journal of Health Economics. 31 (1), 197-206.

Doucouliagos, C. (H.), Stanley, T.D., 2013. Theory competition and selectivity: are all economic facts greatly exaggerated? Journal of Economic Surveys. 27 (2), 316-39.

Gallet, C.A., Doucouliagos, H., 2014. The income elasticity of air travel: A meta-analysis. Annals of Tourism Research. 49, 141-155.

Guindon, G., Contoyannis, P., 2012. A second look at pharmaceutical spending as determinants of health outcomes in Canada. Health Economics. 21 (12), 1477-1495.

Gupta, S., Verhoeven, M., Tiongson, E.R., 2002. The effectiveness of government spending on education and health care in developing and transition economies. European Journal of Political Economy. 18 (4), 717-737.

Gupta, S., Verhoeven, M., Tiongson, E.R., 2003. Public spending on health care and the poor. Health Economics. 12 (8), 685-696.

Hall, S.G., Swamy, P.A.V.B., Tavlas, G.S., 2012. Generalized cointegration: a new concept with an application to health expenditure and health outcomes. Empirical Economics. 42 (2), 603-618.

Hedges, L.V., Olkin, I., 1985. Statistical Methods for Meta-Analysis. Academic Press: Orlando.

Henmi, M., Copas, J.B., 2010. Confidence intervals for random effects meta-analysis and robustness to publication bias. Statistics in Medicine. 29 (29), 2969–83.

Hitiris, T., Posnett, J., 1992. The determinants and effects of health expenditure in developed countries. Journal of Health Economics. 11 (2), 173-181.

Ioannidis, J., Stanley, T.D., Doucouliagos, C. (H.), 2016. The power of bias in economics research. The Economic Journal, forthcoming.

Ivaschenko, O., 2005. The patterns and determinants of longevity in Russia's regions: evidence from panel data. Journal of Comparative Economics. 33 (4), 788-813.

Leigh, A., Jencks, C., 2007. Inequality and mortality: long-run evidence from a panel of countries. Journal of Health Economics. 26 (1), 1-24.

Liberati, A., Altman, D.G., Tetzlaff, J., Mulrow, C., Gotzsche, P.C., Ioannidis, J.P.A., Clarke, M., Devereaux, P.J., Kleijnen, J., Moher, D., 2009. The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate healthcare interventions: explanation and elaboration. Annals of Internal Medicine. 151(4), 65-94.

Lichtenberg, F.R., 2004. Sources of US longevity increase, 1960–2001. Quarterly Review of Economics and Finance. 44 (3), 369-389.

Liu, L., Cline, R.R., Schondelmeyer, S.W., Schommer, J.C., 2008. Pharmaceutical expenditures as a correlate of population health in industrialized nations. Annals of Pharmacotherapy. 42 (3), 368-374.

Manton, K.G., Stallard, E., Tolley, H.D., Carnes, B.A., Cassel, C., 1991. Limits to human life expectancy: evidence, prospects, and implications. Population and Development Review. 17 (4), 603-637.

Martin, S., Rice, N., Smith, P.C., 2008. Does health care spending improve health outcomes? Evidence from English programme budgeting data. Journal of Health Economics. 27 (4), 826-842.

Martin, S., Rice, N., Smith, P.C., 2012. Comparing costs and outcomes across programmes of health care. Health Economics. 21 (3), 316-337.

McCloskey, D., Ziliak, S.T., 1996. The standard error of regressions. Journal of Economic Literature. 34 (1), 97-114.

McGuire, J.W., 2005. Basic health care provision and under-5 mortality: a cross-national study of developing countries. World Development. 34 (3), 405-425.

Nixon, J., Ulmann, P., 2006. The relationship between health care expenditure and health outcomes. European Journal of Health Economics. 7 (1), 7-18.

Nolte, E., McKee, M., 2004. Does Health Care Save lives? The Nuffield Trust: London.

Organization for Economic Cooperation and Development (OECD), 2015. OECD Health Statistics, 2015.

Shaw, J.W., Horrace, W.C., Vogel, R.J., 2005. The determinants of life expectancy: an analysis of the OECD health data. Southern Economic Journal 71 (4), 768-783.

Stanley, T.D., 2008. Meta-regression methods for detecting and estimating empirical effect in the presence of publication selection. Oxford Bulletin of Economics and Statistics. 70 (1), 103-27.

Stanley, T.D., Doucouliagos, H., 2012. Meta-Regression Analysis in Economics and Business. Routledge: Oxford.

Stanley, T.D., Doucouliagos, H., 2015. Neither fixed nor random: weighted least squares meta-analysis. Statistics in Medicine. 34 (13), 2116-2127.

Stanley, T.D., Doucouliagos, H., 2016. Neither fixed nor random: weighted least squares meta-regression analysis. Research Synthesis Methods, forthcoming.

Stanley, T.D., Doucouliagos, H., Giles, M., Heckemeyer, J.H., Johnston, R.J., Laroche, P., Nelson, J.P., Paldam, M., Poot, J., Pugh, G., Rosenberger, R.S., Rost, K., 2013. Meta-analysis of economics research reporting guidelines. Journal of Economic Surveys. 27 (2), 390-394.

Taurus, J.A., Chaloupka, F.J., Farrelly, M.C., Giovino, G.A., Wakefield, M., Johnston, L.D., O'Malley, P.M., Kloska, D.D., Pechacek, T.F., 2005. State tobacco control spending and youth smoking. American Journal of Public Health. 95 (2), 338-344.

Thornton, J.A., 2002. Estimating a health production function for the US: some new evidence. Applied Economics. 34 (1), 59-62.

Thornton, J.A., 2011. Does more medical care improve population health? New evidence for an old controversy. Applied Economics. 43 (24), 3325-3336.

Table 1
Studies included in MRA.

Study (Year Published)	Health Outcome	Level of Development	Mean (absolute) Spending Elasticity
Akinkugbe and Mohanoe (2009)	LE, M	Non-OECD	0.30
Akkoyunlu et al. (2010)	LE	OECD	0.01
Amaghionyeodiwe (2009)	M	Non-OECD	0.20
Anand and Ravallion (1993)	LE, M	Non-OECD	0.27
Anyanwu and Erhijakpor (2009)	M	Non-OECD	0.25
Asiskovitch (2010)	LE	OECD	0.07
Auster et al. (1969)	M	OECD	0.08
Baldacci et al. (2003)	M	Non-OECD	0.15
Baltagi et al. (2012)	LE	OECD	0.09
Barlow and Vissandjée (1999)	LE	Mix	0.01
Bayati et al. (2013)	LE	Non-OECD	0.01
Berger and Messer (2002)	M	OECD	0.10
Bhargava and Yu (1997)	M	Non-OECD	0.05
Bokhari et al. (2007)	M	Mix	0.33
Caliskan (2009)	LE	OECD	0.02
Carrin and Politi (1996)	LE, M	Non-OECD	0.07
Çevik and Taşar (2013)	M	Mix	0.24
Comanor et al. (2006)	LE	OECD	0.14
Conley and Springer (2001)	M	OECD	0.24
Crémieux et al. (1999)	LE, M	OECD	0.26
Crémieux et al. (2005)	LE, M	OECD	0.09
Elola et al. (1995)	M	OECD	0.31
Farag (2009)	M	Non-OECD	0.13
Farag et al. (2013)	M	Non-OECD	0.23
Fayissa and Gutema (2005)	LE	Non-OECD	0.10
Fayissa and Traian (2013)	M	Non-OECD	0.06
Filmer et al. (1997)	M	Non-OECD	0.14
Filmer and Pritchett (1999)	M	Non-OECD	0.11
Frech and Miller (2004)	LE	OECD	0.03
Gani (2009)	M	Non-OECD	0.20
Gebregziabher and Niño-Zarazúa (2014)	M	Non-OECD	0.11
Grekou and Perez (2014)	M	Non-OECD	0.05
Guindon and Contoyannis (2012)	LE, M	OECD	0.10
Gupta et al. (2002)	M	Non-OECD	0.30
Gupta et al. (2003)	M	Non-OECD	0.21
Hadley (1982)	M	OECD	0.17
Halicioglu (2011)	LE	OECD	0.16
Hall et al. (2012)	LE	OECD	0.29

Table 1
Continued.

Study (Year Published)	Health Outcome	Level of Development	Mean (absolute) Spending Elasticity
Hitiris and Posnett (1992)	M	OECD	0.07
Husain (2002)	LE	Non-OECD	0.04
Issa and Ouattara (2012)	M	Mix	0.15
Ivaschenko (2005)	LE	Non-OECD	0.07
Jiménez-Rubio (2011a)	M	OECD	0.26
Jiménez-Rubio (2011b)	M	OECD	0.23
Joumard et al. (2008)	LE, M	OECD	0.24
Kabir (2008)	LE	Non-OECD	0.03
Kaushal et al. (2013)	M	Non-OECD	0.09
Leigh and Jencks (2007)	M	OECD	0.05
Leu (1986)	M	OECD	0.08
Lichtenberg (2004)	LE	OECD	0.01
Liu et al. (2008)	LE	OECD	0.03
Martin et al. (2008)	M	OECD	0.57
Martin et al. (2012)	M	OECD	1.38
McGuire (2005)	M	Non-OECD	0.05
Miller and Frech (2000)	LE, M	OECD	0.05
Nixon and Ulmann (2006)	LE, M	OECD	0.18
Or (2001)	LE, M	OECD	0.24
Rad et al. (2013)	M	Non-OECD	0.02
Rajkumar and Swaroop (2008)	M	Mix	0.18
Santerre et al. (1991)	M	OECD	0.21
Shaw et al. (2005)	LE	OECD	0.04
Siddiqui and Mahmood (1994)	LE, M	Mix	0.02
Thornton (2002)	M	OECD	0.07
Thornton (2011)	M	OECD	0.21
Thornton and Rice (2008)	M	OECD	0.15

Notes: LE = Life expectancy, M = Mortality rate, OECD = Spending elasticity estimated with data predominantly from OECD countries, Non-OECD = Spending elasticity estimated with data predominantly from non-OECD countries, Mix = Spending elasticity estimated with data from a similar share of OECD and non-OECD countries. Since healthcare spending is expected to improve health outcomes, the typical spending elasticity associated with the mortality rate (life expectancy) is negative (positive). Accordingly, the absolute value of the mean spending elasticity for each study is reported in the last column to facilitate comparisons across studies. To conserve space, only those studies cited in the body of the paper are included in the reference section. A reference list containing all 65 studies is available upon request.

Table 2
Descriptive statistics.

	Mortality Rate		Life Expectancy	
Variable	Mean	Standard Deviation	Mean	Standard Deviation
Spending elasticity	-0.194	0.215	0.027	0.073
SE	0.102	0.085	0.030	0.103
Child	0.903	0.296	--	--
Older	--	--	0.630	0.484
Female	0.103	0.305	0.331	0.471
OECD	0.377	0.489	0.844	0.363
Pharm	0.099	0.298	0.377	0.486
Public	0.652	0.477	0.256	0.438
Share	0.375	0.485	0.160	0.367
Panel	0.576	0.495	0.755	0.431
Sub-national	0.272	0.445	0.397	0.490
Income	0.909	0.287	0.817	0.387
Lag spending	0.040	0.196	0.191	0.394
Lag outcome	0.103	0.305	0.082	0.274
Working paper	0.137	0.344	0.089	0.286
Average year	0.643	10.339	-0.235	4.594
Endogeneity	0.404	0.491	0.047	0.211

Table 3
Estimation results for mortality rate.

Variable	General model (1)	General model, endogeneity (2)	General model, adequate power (3)	General model, random effects (4)	Specific model (5)
Constant	-0.089**	-0.114	-0.042	-0.139***	-0.072**
	(2.64)	(0.97)	(1.45)	(2.81)	(2.66)
SE	-1.876***	-1.864***	-2.883***	-1.214***	-1.948***
	(6.24)	(4.85)	(7.36)	(4.48)	(8.22)
Child	0.004	-	0.003	-0.004	-
	(0.18)		(0.14)	(0.12)	
Female	-0.005	0.008	-0.001	-0.008	-
	(0.57)	(0.30)	(0.21)	(0.48)	
OECD	-0.018	-0.013	-0.020	-0.040*	-0.008
	(1.35)	(0.36)	(1.40)	(1.72)	(0.89)
Pharm	0.028	0.003	0.022	0.090**	0.029
	(1.13)	(0.09)	(0.96)	(2.19)	(1.35)
Public	-0.025	-0.045**	-0.016	-0.044***	-0.031**
	(1.64)	(2.06)	(0.81)	(2.77)	(2.14)
Share	0.016	0.009	0.014	0.044**	-
	(0.66)	(0.51)	(0.62)	(2.08)	
Panel	0.014	0.040	0.002	0.015	-
	(0.67)	(0.77)	(0.10)	(0.69)	
Sub-national	0.074***	0.026	0.070***	0.067***	0.065***
	(4.42)	(0.36)	(3.93)	(2.72)	(4.50)
Income	0.062***	0.100	0.050**	0.070**	0.067***
	(2.89)	(1.15)	(2.25)	(2.13)	(3.10)
Lag spending	-0.079***	-0.100***	-0.081***	-0.031	-0.079***
	(5.72)	(5.39)	(6.19)	(1.28)	(6.11)
Lag outcome	0.020*	-0.001	0.012	0.030*	0.026*
	(1.89)	(0.02)	(1.42)	(1.93)	(1.69)
Working paper	-0.011	-0.009	-0.026	0.0230	-
	(0.61)	(0.36)	(1.41)	(0.97)	
Average year	-0.001	-0.002	-0.001	-0.003**	-
	(0.91)	(0.82)	(0.63)	(2.36)	
Endogeneity	-0.007	-	0.004	-0.017	-
	(0.59)		(0.53)	(0.96)	
n (k)	629 (47)	279 (20)	284 (34)	629 (47)	629 (47)
Adjusted R^2	0.40	0.65	0.33	0.69	0.39
Predicted E	-0.13	-0.16	-0.09	-0.15	-0.11
(95% CI)	(-0.20 to -0.06)	(-0.29 to -0.02)	(-0.16 to -0.01)	(-0.25 to -0.04)	(-0.16 to -0.07)

Notes: The dependent variable is the spending elasticity. All columns report unrestricted weighted least squares, using inverse variance weights. Columns (1), (2), (3), and (5) use fixed effects weights, while Column (4) uses random effects weights. Column (1) reports results of the general model using all observations. Column (2) uses only estimates that accommodate endogeneity in the health production function. Column (3) reports the *WAAP* estimator results. Column (5) is the specific model. n (k) denotes number of observations (studies). Figures in parentheses are absolute *t*-statistics using standard errors adjusted for clustering of observations within studies. *Predicted E* is the predicted spending elasticity for public spending, conditional on income and lagged spending being included in the health production function.
*** p<0.01; ** p<0.05; * p<0.10.

Table 4
Estimation results for life expectancy.

Variable	General model (1)	General model, endogeneity (2)	General model, adequate power (3)	General model, random effects (4)	Specific model (5)
Constant	0.004	-0.015	0.002	0.003	0.013***
	(0.21)	(0.72)	(0.10)	(0.09)	(8.08)
SE	1.222	0.540	1.387	0.268	1.051
	(1.08)	(1.05)	(1.04)	(0.69)	(1.32)
Older	0.012**	0.014	0.011*	0.040*	0.007*
	(2.15)	(1.64)	(1.89)	(1.94)	(1.87)
Female	-0.000	-0.018**	-0.000	0.012	-
	(0.06)	(2.38)	(0.01)	(0.95)	
OECD	-0.012	0.014	-0.012	0.041	-0.009**
	(1.24)	(0.79)	(1.24)	(1.44)	(2.24)
Pharm	0.010	0.020**	0.011	-0.003	-
	(0.71)	(2.35)	(0.73)	(0.23)	
Public	-0.007*	-0.001	-0.007*	0.003	-0.004
	(1.95)	(0.10)	(1.90)	(0.22)	(0.84)
Share	0.023	-	0.023	0.013	-
	(0.91)		(0.90)	(0.34)	
Panel	0.001	0.005	0.003	-0.031	-
	(0.12)	(0.93)	(0.21)	(1.62)	
Sub-national	-0.004	-	-0.004	-0.017	-
	(0.98)		(1.02)	(1.30)	
Income	-0.000	-0.003	-0.001	-0.024	-
	(0.04)	(0.69)	(0.03)	(1.44)	
Lag spending	-0.025	-0.013	-0.025	-0.025**	-0.012***
	(1.62)	(0.84)	(1.62)	(2.24)	(2.73)
Lag outcome	0.011	0.023***	0.013	0.028	-
	(0.77)	(3.43)	(0.81)	(0.91)	
Working paper	0.028**	-	0.026*	0.035**	0.022**
	(2.34)		(1.96)	(2.23)	(2.10)
Average year	-0.003	0.001*(1.74)	-0.003	0.001	-0.002***
	(1.53)	-	(1.51)	(0.30)	(9.48)
Endogeneity	0.045*		0.044*	0.065*	0.022***
	(1.80)		(1.79)	(1.65)	(3.83)
n (k)	256 (27)	41 (9)	246 (26)	256 (27)	256 (27)
Adjusted R^2	0.13	0.38	0.13	0.20	0.13
Predicted E	0.04	0.01	0.03	0.08	0.03
(95% CI)	(0 to 0.08)	(-0.03 to 0.05)	(-0.01 to 0.08)	(0.01 to 0.15)	(0.01 to 0.05)

Notes: The dependent variable is the spending elasticity. All columns report unrestricted weighted least squares, using inverse variance weights. Columns (1), (2), (3), and (5) use fixed effects weights, while Column (4) uses random effects weights. Column (1) reports results of the general model using all observations. Column (2) uses only estimates that accommodate endogeneity in the health production function. Column (3) reports the *WAAP* estimator results. Column (5) is the specific model. n (k) denotes number of observations (studies). Figures in parentheses are absolute *t*-statistics using standard errors adjusted for clustering of observations within studies. *Predicted E* is the predicted spending elasticity for life expectancy at an older age, conditional on endogeneity correction and lag spending being included in the health production function.
*** p<0.01; ** p<0.05; * p<0.10.

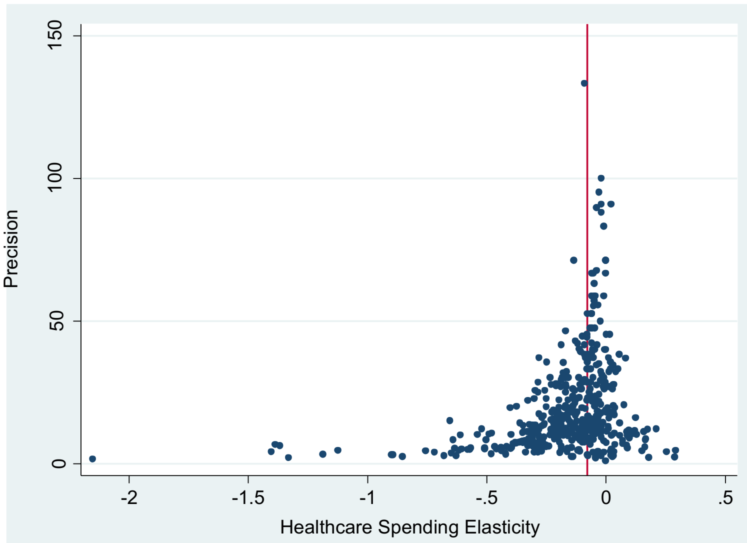

Figure 1. Healthcare spending elasticity, mortality rate (n = 629)

Note: The vertical line denotes the weighted average elasticity, -0.079.

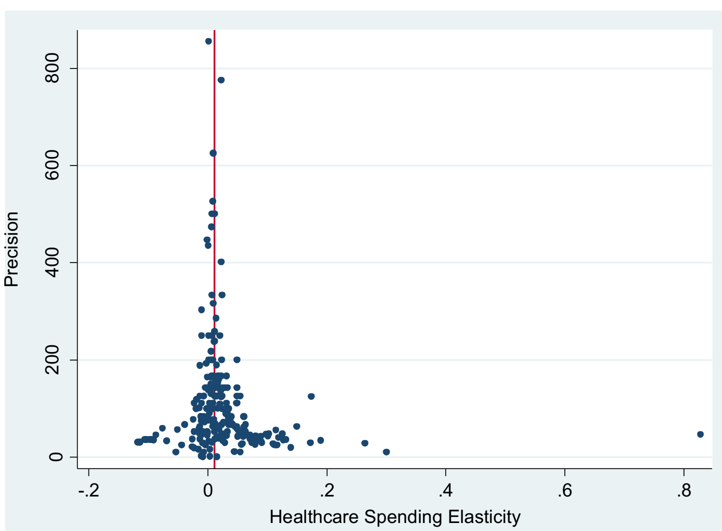

Figure 2. Healthcare spending elasticity, life expectancy (n = 256)

Note: The vertical line denotes the weighted average elasticity, 0.011.