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Is Health Care Infected by Baumol's Cost Disease? Test of a New Model

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Is Health Care Infected by Baumol's Cost Disease? Test of a New Model

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Abstract: Rising health care costs are a policy concern across the OECD and relatively little consensus exists concerning their causes. One explanation that has received revived attention is Baumol's Cost Disease (BCD). However, developing a theoretically-appropriate test of BCD has been a challenge. In this paper, we construct a two-sector model firmly based on Baumol's axioms. We then theoretically derive two propositions that can be tested using observable variables. In particular, we predict that: 1) the relative price index of the health care sector, and 2) the share of total labor employed in the health care sector should both be positively related to economy-wide productivity. Using annual data from 27 OECD countries over the years 1995-2013 and from 14 U.S. industry groups over the years 1947-2015, we show that empirical evidence for the existence of BCD in health care is sensitive to model specification and disappears once we address spurious correlation due to contemporaneous trending and other econometric issues.

Keywords: Baumol's Cost Disease, health care industry, panel data

JEL Classifications: I11, J30, E24

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I. INTRODUCTION

It is well known that health care spending has been on the rise across developed countries. When expressed as a share of national output, health expenditures in the OECD have more than doubled over recent decades. In 1960, the OECD average of GDP spent on health care was 3.83%. By 2010, it had climbed to 9.13%, a 138% increase. While this upward trend was suspended during the global financial crisis of 2007/2008, health care spending has once again started to rise, especially in Europe (OECD, 2015). This trend has generated academic and policy interest in a better understanding of its driving forces.

On the demand side, a common finding in the literature is that rising incomes are a major determinant of health expenditures (Gerdtham & Jönsson, 2000; Murthy & Okunade, 2009; Prieto & Lago-Peñas, 2012). However, empirical studies grapple with issues of appropriate specification and estimation procedures (Costa-Font et al., 2011) and there is still no consensus – even qualitatively – about the income elasticity of health care demand. Concurrently, the supply side of the industry has become a focus of policy debate across OECD countries (Baltagi & Moscone, 2010; Baltagi et al., 2012; Hartwig, 2008b). In an attempt to look beyond income as a determinant of rising health care spending, there has been a revival of interest in Baumol's Cost Disease (Baltagi et al., 2012; Baumol, 1967, 1993; Nordhaus 2008; Hartwig, 2008b, 2010, 2011a, 2011b; Nixon & Ulmann, 2006; Martins & De la Maisonneuve, 2006).

A key challenge in investigating Baumol's Cost Disease (BCD) is the development of a theoretically-appropriate empirical test. In this study, we build a new theoretical model based strictly on Baumol's axioms and derive two propositions that can be tested using observable variables. In particular, we predict that: 1) the share of total labor employed in the health care sector and 2) the ratio of prices in the health and non-health sectors should both be positively related to economy-wide productivity. Using annual data from 27 OECD countries over the years 1995-2013 and from 14 U.S. industry groups over the years 1947-2015, we find that evidence for the existence of BCD in the health care industry is sensitive to model specification and disappears when more robust specifications and procedures are used to address spurious correlation from contemporaneous trending in the variables and other econometric issues.

The remainder of this paper is organized as follows: Section II introduces the original theoretical pillars of BCD and provides a review of previous empirical studies on BCD in the health sector. Section III presents our theoretical model rooted in Baumol's axioms. Section IV discusses the data we use for our empirical analysis, and introduces some of the econometric issues that we address in our subsequent estimation. The empirical results are presented in Section V. Section VI summarizes our main findings and discusses their policy implications.

II. Baumol's Cost Disease and the Health Sector

II.A Overview

Concerns about rising health expenditures have generated a number of empirical studies aiming to identify its main drivers (for an extensive list of studies see Costa-Font et al., 2011; Gerdtham & Jönsson, 2000). However, much of this empirical work lacks strong theoretical foundations. According to Gerdtham & Jönsson (2000), the field of health economics lacks a sound macroeconomic theory to provide an explanation for the rising cost of health care.

A theory that has received revived interest in this context is the "Cost Disease," [1] first discussed in Baumol and Bowen (1965) for the performing arts industry and later applied to health care in Baumol (1993). Baumol and Bowen's (1965) fundamental insight is demonstrated in a two-sector model in which one sector, by virtue of its production technology, enjoys regular productivity increases; while the other sector, by nature of its production technology, does not. Baumol (1993) modeled health care as a non-progressive, labor-intensive

[1] The focus of the "Cost Disease" is the price component of expenditures (P*Q). Cost and expenditures are used interchangeably as synonyms in this analysis.

sector whose demand continually increases, without corresponding increases in output per man-hour. Because of sluggish productivity growth and little substitutability of capital for labor in the health sector, real costs inexorably climb over time.

II.B Baumol's Cost Disease: Characteristics and Propositions

Baumol's (1967) model is based on the following five fundamental premises: First, economic activities can be grouped into technologically progressive and non-progressive sectors (henceforth, *PS* and *NPS* respectively) in terms of their productivity growth rates. Second, the only input is labor. Third, equilibrium in the labor market causes nominal wages in the two sectors to be the same and grow at the same rate. Fourth, labor is mobile between the two sectors. Finally, nominal wages rise with productivity growth in the progressive sector.

On the basis of the above premises, Baumol (1967) derives two theoretical propositions: (i) "the cost per unit of output of the *NPS* will rise without limit over time, while the unit cost of the *PS* will remain constant" (p. 418) and (ii) the labor share of the *NPS* will increase over time. In the limit, all labor in the economy will be employed in the *NPS*. Thus, BCD implies that the health care sector will consume an increasing share of the economy's resources and thus GDP. Further, it suggests that the increases in costs over time are unavoidable because they are driven by productivity increases outside the health sector (Baumol, 1967, 1993; Hartwig, 2008b; Towse, 1997). These are concerning propositions because they imply that health care will be more and more expensive despite of (or, indeed, because of!) a lack of improvement in health care services.

II.C Tests of Baumol's Cost Disease for the Health Sector: Empirical Review

While the different presentations of BCD (e.g., Baumol 1967, 1993) provide a theoretical framework for understanding the increasing size of the health care industry, the model is not formulated in terms of testable hypotheses. Therefore, previous studies attempting to revive and empirically test BCD (e.g., Nordhaus 2008, Bates & Santerre 2013, Hartwig 2008a, 2008b, 2010, 2011a, 2011b) employ a range of different empirical methods.

Baumol (1993) descriptively analyses the trend of productivity and total spending in the goods and services sectors in the U.S. He concludes that, consistent with BCD, prices of services will continue to rise inevitably due to rising costs and declining labor productivity in the sector. Nixon & Ulmann (2006) expand on this work by studying health expenditures and health outcomes for 15 European Union countries from 1980 to 1995.

The first attempt to empirically test BCD using an estimable model is made by Martins & De la Maisonneuve (2006). They incorporate BCD into a health expenditure forecasting model by regressing the growth of long-term health expenditures on the growth of labor costs (and other variables including income and demographics) across 30 OECD countries. This method has become known as the "labor cost" or "wage growth" approach. The authors report evidence of upward shifts in per capita long-term health expenditures due to a "cost-disease" effect.

Later, Hartwig (2008b) introduced a "wage-productivity growth gap" approach – using the difference between economy-wide wage and productivity growth rates to capture BCD in health spending. In the spirit of Baumol's framework, if wage increases in the *PS* reflect productivity increases but wage increases in the *NPS* are only driven by equalization of wages across sectors (due to a mobile, competitive labor market), then wages in the overall economy will grow faster than overall labor productivity. Hartwig (2008b) finds supporting evidence for BCD in a panel of 19 OECD countries. A similar method is adopted by Colombier (2012) and Bates & Santerre (2013) for 20 OECD countries and 50 U.S. states, respectively.

Hartwig (2008a) relies on an "output-expenditure growth nexus" approach and finds that increases in health care spending reduce subsequent output growth. This is consistent with BCD because increases in health expenditures mean that resources have shifted to a sector with low productivity growth and, as a consequence, subsequent periods should experience reduced output growth.

Nordhaus (2008) presents a comprehensive analysis of what he calls "Baumol's diseases" using U.S. industry-level data from 1948-2001. Specifically, he regresses industry-level variables such as price, nominal output, real output, wages, employment, and profits on industry-level productivity (expressing everything in logs). In this reduced-form approach, the spirit of BCD is immediately apparent as industry-level trends are driven by exogenous technological change. Consistent with BCD, Nordhaus finds that sectors that are relatively technologically stagnant experience rising relative prices and falling relative real outputs and employment. Hartwig (2010, 2011a) replicates Nordhaus (2008) using Swiss and EU data, respectively.

Recall that Baumol's framework implies that the relative price of services like health care will rise over time with productivity increases in other sectors. Hartwig (2011b) uses this proposition to motivate his study but then focuses on the *consequences*, rather than the *determinants*, of relative price changes. In particular, he uses a "relative medical price" method and finds that the relative price of health care (used as an exogenous regressor) is a significant positive determinant of health care expenditures in the OECD. This is consistent with BCD being responsible for the observed rapid health expenditure growth.

It is important to note, however, that while each of the above studies links its empirical specification to the spirit of the BCD framework, in no case we are aware of is the empirical specification based on a formal theoretical model derived strictly from the full set of Baumol's axioms. For example, the "wage-productivity growth gap" approach introduced by Hartwig (2008b) focuses on economy-wide wage growth, productivity growth, and employment growth as exogenous explanatory variables, sometimes combined into a single "Baumol variable". This set up does not directly relate labor migration into the health sector as a response to productivity (and hence wage) increases. Yet, labor migration into health care is one of the key predictions of Baumol's framework.

Similarly, the "relative medical price" approach in Hartwig (2011b) uses changes in productivity and the relative price of health care as independent explanatory variables – again ignoring how Baumol's BCD hypothesis identifies the relative price of health care as being endogenous to productivity. Nordhaus (2008) and Hartwig (2010, 2011a) do not suffer from these endogeneity problems but their empirical analysis is again based on the spirit of BCD rather than being firmly grounded in Baumol's original work. For example, Nordhaus (2008) writes: "We […] investigate six diseases that *might* be associated with Baumol's analyses." (p.9, emphasis added). The current study is the first to our knowledge to closely follow Baumol's (1967) entire framework in order to develop a directly-testable model.

III. A Theoretical Model for Testing Baumol's Cost Disease

Like Baumol (1967), we start with a two-sector economy consisting of (i) a constant/stagnant productivity sector (representing the health care industry), and (ii) a technically progressive sector. For the purposes of our analysis, the two sectors are respectively referred to as the health (H) and non-health (NH) sectors. Also like Baumol, we assume that the only input into production is labor. The production functions for the two sectors are then given by:

$$Y_H = L_H \tag{1}$$

$$Y_{NH} = \phi\, L_{NH} \tag{2}$$

where ϕ is labor productivity in the non-health sector, L_H and L_{NH} are the quantities of labor employed in the health and non-health sectors, and Y_H and Y_{NH} are the associated real outputs. We can think of ϕ as representing relative labor productivities in the NH and H sectors, with $\phi > 1$ indicating greater productivity in the NH sector.

A key assumption in Baumol (1967, page 419) is that output in both sectors is a constant share of total output in the economy, *Y*. Define *k* as the share of total economy output accounted for by the non-health sector:

$$Y_{NH} = kY \tag{3}$$

Demand equal to supply in the *NH* sector implies that:

$$kY = \phi L_{NH} \quad , \tag{4}$$

so that the quantity of labor employed in the *NH* sector is given by

$$L_{NH} = \left(\frac{k}{\phi}\right) Y \tag{5}$$

Total labor supply is given by *L*, so that

$$L_H + L_{NH} = L \ . \tag{6}$$

It follows that

$$L_{NH} = \left(\frac{k}{\phi}\right)\left(\phi L_{NH} + L_H\right) \tag{7}$$

Equations (6) and (7) constitute two equations in two unknowns, L_H and L_{NH}, as functions of ϕ, *k*, and *L;* allowing us to solve for L_H and L_{NH}:

$$L_{NH} = \left[\frac{k}{(1-k)\phi}\right] L_H , \tag{8}$$

$$L_H = \left[\frac{(1-k)\phi}{((1-k)\phi + k)}\right] L . \tag{9}$$

The labor shares of the two sectors are given by

$$\frac{L_H}{L} = \left[\frac{(1-k)\phi}{((1-k)\phi + k)}\right] \tag{10}$$

and

$$\frac{L_{NH}}{L} = \left[\frac{k}{((1-k)\phi + k)} \right]. \tag{11}$$

Equation (10) implies that the health sector share of the labor force is positively related to productivity in the *NH* sector (ϕ) and the health sector share of national output $(1-k)$. Further,

$$\frac{\partial \left(L_H / L \right)}{\partial \phi} = \left(\frac{L_{NH}}{L} \right) \cdot \frac{(1-k)}{[(1-k)\phi + k]} > 0, \tag{12}$$

with the inequality coming from the fact that both terms on the right hand side are greater than zero.

Let w_{NH} and P_{NH} be the market wage and price level in the *NH* sector. The marginal product of labor in the *NH* sector (MPL_{NH}) is simply ϕ. If we assume that workers are paid their marginal product in the non-health sector, then:

$$MPL_{NH} = \left(\frac{w_{NH}}{P_{NH}} \right) = \phi, \tag{13}$$

so that

$$w_{NH} = \phi \cdot P_{NH} \quad . \tag{14}$$

Equilibrium in the labor market requires workers in the *H* sector to be paid the same,

$$w_H = \phi \cdot P_{NH}. \tag{15}$$

Given the constant returns-to-scale production in the *NH* sector, profits in this sector are given by

$$\pi_{NH} = P_{NH} Y_{NH} - w_{NH} L_{NH} = P_{NH} kY - \phi P_{NH} \left(\frac{k}{\phi} \right) Y = 0 \tag{16}$$

Profits in the *H* sector are given by

$$\pi_H = P_H Y_H - w_H L_H = P_H L_H - w_H L_H = (P_H - w_H) L_H \tag{17}$$

If we impose the condition that competitive equilibrium in the health sector drives profits to zero, then it follows that $P_H = w_H$, so that

$$P_H = \phi \cdot P_{NH} \tag{18}$$

In terms of relative prices, (18) can be expressed as a function of productivity in the *NH* sector:

$$\frac{P_H}{P_{NH}} = \phi \tag{19}$$

and it is obvious that

$$\frac{\partial (P_H / P_{NH})}{\partial \phi} > 0 \tag{20}$$

The preceding analysis has given us two key implications of BCD:

(i) $\dfrac{\partial (L_H / L)}{\partial \phi} > 0$

(ii) $\dfrac{\partial (P_H / P_{NH})}{\partial \phi} > 0$.

The economic intuition underlying these results is as follows: Productivity increases in the non-health sector cause fewer workers to be needed in this sector. As a result, workers are released to the heath sector and the health sector share of the labor force increases. At the same time, higher productivity in the non-health sector raises wages there. Equilibrium in the labor market causes these wage increases to spill over to the health sector. The resulting higher costs of production in the health sector drive up prices, so that the ratio of prices in the health and non-health sectors also rises.

If the parameter ϕ, which measures productivity in the *NH* sector, were observable, then the inequalities above would provide testable hypotheses of BCD, as both (L_H / L), the share of labor employed in the health sector, and (P_H / P_{NH}), the relative price indices of output in the health and non-health sectors, are not difficult to obtain. However, ϕ is frequently unobserved, or non-comparable, especially when working with cross-country data. Therefore, we reformulate the two consequences of the BCD model in terms of economy-wide productivity, *PROD*, which is observable.

Define economy-wide productivity as

$$PROD \equiv \frac{Y}{L} \tag{21}$$

Note that economy-wide productivity is a weighted average of productivity in the *NH* and *H* sectors,

$$PROD = \frac{Y}{L} = \phi\left(\frac{L_{NH}}{L}\right) + \left(\frac{L_H}{L}\right); \tag{22}$$

and that both $\left(\frac{L_{NH}}{L}\right)$ and $\left(\frac{L_H}{L}\right)$ are functions of ϕ (cf. Equations 10 and 11). Thus,

$PROD = f(\phi)$ and

$$\phi = f^{-1}(PROD). \tag{23}$$

We will demonstrate that

(i) $\frac{\partial(L_H/L)}{\partial PROD} = \frac{\partial(L_H/L)}{\partial\phi} \cdot \frac{\partial\phi}{\partial PROD} > 0$, and

(ii) $\frac{\partial(P_H/P_{NH})}{\partial PROD} = \frac{\partial(P_H/P_{NH})}{\partial\phi} \cdot \frac{\partial\phi}{\partial PROD} > 0$.

To prove the above, it is sufficient to show that $\frac{\partial\phi}{\partial PROD} > 0$.

$$PROD = \phi\left(\frac{L_{NH}}{L}\right) + \left(\frac{L_H}{L}\right) = \phi - (\phi - 1)\frac{L_H}{L} \tag{24}$$

$$\frac{\partial PROD}{\partial\phi} = 1 - \left(\frac{L_H}{L}\right) - (\phi - 1) \cdot \frac{\partial\left(L_H/L\right)}{\partial\phi} \tag{25}$$

It is straightforward to show that

$$\frac{\partial PROD}{\partial\phi} = \left(\frac{L_{NH}}{L}\right) \cdot \left\{\frac{1}{[(1-k)\phi + k]}\right\} \tag{26}$$

so that $\frac{\partial PROD}{\partial\phi} > 0$ and thus $\frac{\partial\phi}{\partial PROD} > 0$.

The above analysis provides two implications of BCD that are testable using readily available data:

(i) $$\frac{\partial(L_H/L)}{\partial PROD} > 0 \tag{27.a}$$

(ii) $$\frac{\partial(P_H/P_{NH})}{\partial PROD} > 0 \tag{27.b}$$

Expressions (27.a) and (27.b) state that (i) the share of labor employed in the health sector (L_H/L) and (ii) the price index of goods produced in the health sector relative to the price index of goods produces in the non-health sector (P_H/P_{NH}) should both be increasing functions of economy-wide productivity.

The above model incorporates all the five properties that characterize Baumol's (1967) cost disease framework and generates hypotheses that are testable with observable data. Further, the hypotheses given by expressions (27.a) and (27.b) are sufficiently specific – and not obviously consistent with alternative theories – that they are strong candidates for testing whether BCD can explain rising health care costs across countries.

IV. Methods

Identification of the BCD effect relies on concurrent, within-country movement in (i) the health sector share of the labor force, (L_H/L); (ii) prices in the health and non-health sectors, (P_H/P_{NH}); and (iii) productivity. Our analysis is careful to control for variation in other variables that may move contemporaneously with productivity. We include a wide range of health and demographic variables that could also affect costs in the health care sector, including the age and gender composition of the population, life expectancy, infant mortality, and tobacco and alcohol consumption. GDP growth may have its own effect on the economy's price and input allocations, and is positively associated with productivity. Therefore, we also include it to avoid omitted variable bias.

IV.A Sample, Data Description and Sources

Variables required for this study include the health price index, overall consumer price index, GDP in current prices, total number of hours worked, health sector employment, and total labor force. Importantly, our non-health price index is generated from the overall consumer price index and the health price index. Using a precise measure of non-health prices is an improvement over previous studies which rely on the GDP deflator instead (e.g., Hartwig 2008a, 2008b, 2011b). Productivity is measured as the ratio of GDP to the number of hours worked.

We were unable to obtain a comprehensive and consistent data set with health care prices for all OECD countries. Fortunately, the EUROSTAT 2014 Online Database contains data for many OECD countries. All other variables in our country-level analysis were sourced from OECD Health Statistics, 2014. Our final sample covers the years 1995 to 2013 and includes data for 27 out of 34 OECD countries: Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom, and U.S. As described in more detail in section V.C, we also test BCD using an alternative dataset: U.S. industry-level data for 14 broad industries (including health care) for the years 1947 to 2015.

FIGURES 1 through 3 plot the three variables that are the focus of our OECD analysis. FIGURE 1 shows a time series of the share of total employment in the health sector (*LHL*) for selected countries. There is wide variation in the series across countries, with values ranging from 2.1% (Turkey) to 20.1% (Norway). For most, but not all countries, this share has been increasing over time.

FIGURE 2 shows the ratio of prices in the health and non-health sectors (*PHPNH*) for selected countries. Here again, there is wide variation across countries. There is also wide variation within countries. For example, in Hungary, *PHPNH* first rises over time, then falls. In the United Kingdom, the price ratio is relatively flat. The behaviors of the series over time are quite idiosyncratic.

Lastly, FIGURE 3 plots productivity (*PROD*) for a selected sample of countries. While there is wide variation across countries in the levels, there is much greater uniformity in the trending behavior of the respective series over time: productivity has been on the rise with a brief exception during the global financial crisis.

The three time series alert us to the need to include country fixed effects to address factors that influence differences in the levels of the respective dependent variables. We also need to address trending behavior carefully. Alternative methods will be employed to control for spurious correlation due to coincident trending.

TABLE 1 reports descriptive statistics for our sample. The demographic and health variables display much variation across countries. Share of the population with age greater than 64 ranges from 5.4% (Turkey) to 21.1% (Germany). The minimum life expectancy at birth in our sample is 67.9 (Estonia), and the maximum is 83.2 (Spain), with a mean of 78.5. Infant mortality ranges from 0.9 per 1,000 live births (Iceland), to 40.9 (Turkey). There are also wide differences in lifestyle behaviors that can impact health outcomes. Minimum tobacco consumption is 557 grams per person (Finland), with a maximum value of 3,741 grams per person (Greece). Alcohol consumption ranges from 1.2 liters per person (Turkey), to a maximum of 15.1 liters per person (France).

IV.B Estimation Methods

We begin by using standard panel data estimators for estimating the theoretical predictions of Equations (27.a) and (27.b). In particular, we use Pooled Ordinary Least Square (POLS), Two-Way Fixed Effects (2WFE), and Fixed Effects (FE) with country-specific linear time trends. In subsequent analysis, we address a set of estimation issues using recent “mean group” estimators. These estimators include the Pesaran and Smith’s (1995) Mean Group (MG) estimator; Pesaran’s (2006) Common Correlated Effects Mean Group (CCEMG) estimator; and the Augmented Mean Group (AMG) estimator of Eberhardt and Teal (2010).

V. Results and Discussion

V.A Baseline Estimates

Our baseline estimates of the effect of productivity on the labor share of the health sector are reported in TABLE 2. Three specifications are presented for each of three estimation procedures: POLS, 2WFE, and FE with country-specific time trends. The first specification includes the productivity variable plus a variety of demographic control variables. The second specification adds lifestyle variables for tobacco and alcohol consumption. Finally, the third specification adds a variable for economic growth.

The bottom of TABLE 2 reports a series of diagnostic tests and measures. We test the specifications estimated by (i) 2WFE and (ii) FE with country-specific time trends for significance of the respective country and time variables (“Country and time effects”). Another measure to evaluate the respective country and time effects is the Bayesian Information Criterion (BIC). The BIC allows one to compare specifications across regressions, with lower values indicating “better” specifications according to this diagnostic. For example, the regression results in Columns (1) and (4) have identical specifications except that Column (4) includes fixed effects for country and year. The BIC value in Column (1) is 214.4, compared to a value of -808.4 in Column (4). This indicates that country and year fixed effects add valuable explanatory power to the specification. We also include the results of the Ramsey Regression Equation Specification Error Test (RESET). The RESET regresses the dependent variable on non-linear combinations of its predicted values. It then performs an *F*-test of joint significance of the predicted value terms. Failure to reject is consistent with the equation being correctly specified. Rejection of the joint hypothesis is an indication of misspecification.

We note that the specifications reported in TABLE 2 use the logged value of *LHL* for the dependent variable, along with logged values for life expectancy, infant mortality, and alcohol and tobacco consumption. While we obtained identical qualitative results for specifications where the variables were not logged, the model specification (RESET) results were somewhat improved when the variables were logged.[2]

Our initial analysis is supportive of the BCD hypothesis. The POLS and 2WFE results all find a positive relationship between productivity (*PROD*) and the labor share of the health sector. The coefficient on the productivity variable is generally highly significant, with *p*-values less than 0.01 in all but one of the regressions. While these results provide evidence in favor of the BCD hypothesis, further analysis is not supportive.

When the specification includes country-specific time trends, the positive coefficients on the productivity variable decrease in size and become insignificant (cf. Columns 7-9). Recall that the rationale for including country-specific time trends was to control for coincident trending in the productivity and labor share variables. This rationale finds multiple supports. The FE and country-specific time trends are jointly significant well below the 1% significance level. Further, the BIC values indicate substantial improvement over the corresponding POLS and 2WFE specifications. For example, Column (7) has a BIC value of -947.2 compared to -808.4 in Column (4), indicating that country fixed effects with country-specific time trends provide a better fit than country and year fixed effects, even after penalizing for the inclusion of additional variables. And finally, the RESET fails to reject the null hypothesis of no misspecification in two of the three models including country-specific time trends (cf. Columns 7 and 9). In contrast, the hypothesis of no misspecification is rejected in every one of the POLS and 2WFE models (cf. Columns 1 through 6).

[2] The data and programs used to generate the tables and figures in this study are available from the authors upon request.

Our findings are robust to the inclusion of the lifestyle (tobacco and alcohol consumption) and economic growth variables. While these variables sometimes attain statistical significance on their own, they have little effect on the main variable of interest in our preferred specifications. Columns (7) through (9) all report negative and insignificant productivity coefficients. As a result, we conclude that the evidence does not support the prediction of Equation (27.a) in our preferred specifications.

TABLE 3 reports the results of estimating the relationship between productivity and the ratio of prices in the health and non-health sectors (*PHPNH*).[3] According to Equation (27.b), the BCD hypothesis predicts a positive relationship between these variables. The results in the table are very similar to those from TABLE 2. As before, the POLS and 2WFE estimates provide support for the BCD hypothesis. And also as in the previous case, this support disappears when we include country-specific time trends.

The coefficient on the productivity variable turns from positive and generally significant in Columns (1) through (6), to negative and statistically insignificant in Columns (7) through (9). Post-estimation diagnostics again provide support for the latter specifications. As was the case in TABLE 2, the results are little changed by the inclusion of the lifestyle and economic growth variables. We thus conclude that there is no evidence to support the BCD hypothesis when we test the prediction of Equation (27.b).

V.B Panel Time-Series Estimation

A number of empirical issues could potentially alter the preceding results. Our data are likely to be characterized by serial correlation because both the labor share and price ratio series are expected to be persistent over time. To check for serial correlation, we use a test for panel data developed by Wooldridge (2002) and discussed in Drukker (2003). Cross-sectional

[3] Unlike the specifications in TABLE 2, none of the variables in TABLE 3 are logged. This time the RESET results preferred the unlogged versions of the respective variables. However, the conclusions regarding the significance of the productivity variables were qualitatively identical when the specifications included the logged form of these variables.

dependence is also likely to be a problem because factors driving these variables in one country are likely to be present in other countries. To investigate cross-sectional dependence, we use a test developed by Pesaran (2004). It has the advantage of being applicable to unbalanced data such as ours. Serial correlation and cross-sectional dependence cause inefficient estimates and biased standard errors (Chudik & Pesaran, 2013; Reed & Ye, 2011; Sarafidis & Wansbeek, 2012; Sarafidis et al., 2009). Endogeneity constitutes another issue that could arise if there were factors that were common to both economy-wide productivity and the respective dependent variables, such as technology shocks in the health sector. And finally, nonstationarity may be an issue. In addition to generating spurious correlations, nonstationarity may overwhelm structural relationships, making them difficult to observe in the data.

In order to address the econometric issues identified above, we re-estimate the relationship between productivity and the two dependent variables using a variety of panel time series estimators including: PCSE, MG, CCEMG and AMG. "PCSE" stands for the Panel-Corrected Standard Error procedure of Beck and Katz (1995). PCSE is a quasi-FGLS procedure that performs a Prais-Winsten transformation on the variables to address serial correlation, and then parametrically adjusts the standard errors for cross-sectional correlation. The next three estimators – MG, CCEMG and AMG – are designed, to varying degrees, to address heterogeneous slope coefficients, cross-sectional dependence, nonstationarity, and endogeneity.

The framework for the MG, CCEMG, and AMG estimators is as follows: Let y_{it} be the value of the dependent variable (*LHL*, *PHPNH*) for country *i* in year *t*. Let $\boldsymbol{x}_{it}$ be a vector or explanatory variables corresponding to this observation, including the productivity variable, *PROD*. The relationship between y_{it} and $\boldsymbol{x}_{it}$ is given by:

$$y_{it} = \boldsymbol{\beta}_i' \boldsymbol{x}_{it} + u_{it} \tag{28}$$

where u_{it} is the composite error term and countries are allowed to respond differently to changes in $\boldsymbol{x}_{it}$. The error term u_{it} has three components: a country-specific fixed effect (α_i), a set of unobservable factors that are common across countries at a point in time and that may be nonstationary ($\boldsymbol{f}_t$), and an i.i.d error term (ε_{it}),

$$u_{it} = \alpha_i + \boldsymbol{\gamma}_i' \boldsymbol{f}_t + \varepsilon_{it}. \qquad (29)$$

In the context of our analysis, the factors can be thought of as common technology shocks to the health sector or as unobservable risk factors associated with the health sector[4]. Equation (29) assumes country-specific factor loadings ($\boldsymbol{\gamma}_i'$), which allows countries to respond differently to these common shocks. One consequence of the specification in Equation (29) is that it incorporates cross-sectional dependence across countries.

The individual explanatory variables, $x_{k,it}$, are also assumed to have three components,

$$x_{k,it} = \pi_{ki} + \boldsymbol{\delta}_{ki}' \boldsymbol{g}_{kt} + \sum_{j=1}^{J} \rho_{jki} f_{jki} + \upsilon_{kit} \ . \qquad (30)$$

where π_{ki} is a country fixed effect, υ_{kit} is an i.i.d. error term, and $\boldsymbol{\delta}_{ki}' \boldsymbol{g}_{kt} + \sum_{j=1}^{J} \rho_{jki} f_{jki}$ is a set of factors which may be nonstationary, each of which has country-specific factor loadings ($\boldsymbol{\delta}_{ki}'$, ρ_{jki}) and J of which are common to the error term. When $J > 0$, endogeneity is present.

The MG, CCEMG, and AMG estimators are designed for moderate-*T*, moderate-*N* panel data, such as our OECD dataset. All three procedures estimate country-specific regressions and have the option of including country-specific time trends. Coefficients are averaged across the country-specific regressions to get estimates of mean effects. The MG estimator differs from the CCEMG and AMG estimators in that it assumes there is no cross-sectional dependence and that the factor loadings are all zero, or that their effect can be captured by a linear time trend. The CCEMG and AMG estimators differ in how they control for unobserved factors.

[4] Baltagi & Moscone (2010) adopt a similar multi-factor error structure to analyze the heterogeneous relationship between health and income in OECD countries.

The top part of TABLE 4 reports the results of testing Models (7) – (9) in TABLES 2 and 3 for serial correlation and cross-sectional dependence. As expected, all the specifications show strong evidence of serial correlation, with *p*-values well below 0.01. While not reported, when the models estimate a common AR(1) parameter, the associated values range from 0.4 to 0.5. Unfortunately, it is not possible to test for cross-sectional dependence in every specification. While Pesaran's test allows for unbalanced data, it does require that there be sufficient time series overlap in the data series. For the specifications that include more explanatory variables, and hence fewer observations, this is a problem. Nevertheless, the evidence from Model (7) in both the *LHL* and *PHPNH* equations strongly indicates that the data are characterized by cross-sectional dependence. As a result of these tests, we turn to estimation procedures that are designed to address problems of serial and/or cross-sectional dependence.

The last four rows of TABLE 4 report the productivity coefficients resulting from estimating Models (7) to (9) using these alternative estimation procedures. In the interest of brevity, we only report the productivity coefficient estimates and associated *z*-statistics. The alternative estimation procedures produce a wide range of estimates for the productivity coefficient. Nevertheless, while some of the estimated coefficients are positive, all are insignificant, with none coming close to even a 10 percent level of significance. Thus, after controlling for an assortment of econometric issues, we reach the same conclusion that we obtained in TABLES 2 and 3. We conclude that there is little evidence to support the BCD hypotheses that productivity is related to either the share of labor in the health sector, or the ratio of prices in the health and non-health sectors.

V.C A Further Test

One concern with our OECD analysis is that the time period may be too short to measure long-run relationships. To address this concern, we expand our analysis and test the two BCD hypotheses using U.S. Bureau of Economic Analysis (BEA) data on 14 broad industry groups, including health care, over a 69-year time period from 1947 to 2015. In addition to the extended time period, the BEA data have the advantages of including both industry-level employment and prices. Nordhaus (2008) used this dataset in his test of the BCD hypothesis (see discussion above).

To accommodate our test for more than two sectors, we transform the previous analysis into a two-stage analysis. In the first stage, we estimate a panel of industry-specific equations

(i) $\left(\frac{L_i}{L}\right)_t = \alpha_{i0} + \alpha_{i1} PROD_t + \alpha_{i2} t + \varepsilon_{Lt},$ and (31.a)

(ii) $\left(\frac{P_i}{P}\right)_t = \beta_{i0} + \beta_{i1} PROD_t + \beta_{i2} t + \varepsilon_{Pt},$ (31.b)

$i = 1, 2, \ldots, 14$, $t = 1947, 1948, \ldots, 2015$; where $PROD_t$ is defined as in (27.a) and (27.b), and $\left(\frac{L_i}{L}\right)_t$ and $\left(\frac{P_i}{P}\right)_t$ are the ratio of industry i's employment (L_i) and price level (P_i) to the economy's total employment (L) and overal price level (P), respectively.

In the second stage, we take the estimated productivity coefficients from the first stage regressions and regress them on a measure of industry-level "progressivity:"

(i) $\hat{\alpha}_i = \gamma_0 + \gamma_1 \overline{PROD}_i + \nu_{Lt},$ and (32.a)

(ii) $\hat{\beta}_i = \delta_0 + \delta_1 \overline{PROD}_i + \nu_{Pt},$ (32.b)

$i = 1, 2, \ldots, 14$; where $\hat{\alpha}_i$ and $\hat{\beta}_i$ are the estimated productivity coefficients from Equations (31.a) and (31.b), and $\overline{PROD}_i$ is average productivity growth in industry *i* over the sample period. The multi-sector BCD predictions corresponding to Equations (27.a) and (27.b) are thus:

(i) (cf. Equation 32.a): $\gamma_1 < 0,$ and (33.a)

(ii) (cf. Equation 32.b): $\delta_1 < 0.$ (33.b)

The inequality in (33.a) follows directly from the two-sector model of Equation (27.a). According to (27.a), $\frac{\partial(L_H/L)}{\partial PROD} > 0$ and $\frac{\partial(L_{NH}/L)}{\partial PROD} < 0$. In the context of Equation (31.a), that implies that $\alpha_{H1} > \alpha_{NH1}$, while $\overline{PROD}_H < \overline{PROD}_{NH}$. Thus, a two-sector regression of the health and non-health sectors where the estimated α_{i1}'s are regressed on their productivities, $\overline{PROD}_i$'s, should produce a negative coefficient on the productivity variable if the BCD hypothesis is correct. The extension to more than two sectors/industries is straightforward.

The relationship between the inequality in (33.b) and (27.b) is a little less direct. The Appendix demonstrates that $\frac{\partial(P_H/P_{NH})}{\partial PROD} > 0$ can be rewritten as $\frac{\partial(P_H/P)}{\partial PROD} > 0$, where P is the economy-wide price level. That being established, the inequality in Equation (33.b) follows analogously to that in (33.a).

As noted above, a number of econometric issues need to be addressed in the first stage panel estimation: slope heterogeneity (including industry-specific time trends), serial correlation, cross-sectional dependence, and possible nonstationarity. Accordingly, we employ the AMG estimator to obtain industry-specific productivity coefficients.[5] The second stage cross-sectional analysis uses OLS with heteroskedasticity-robust standard errors to account for the fact that the dependent variable consists of estimated coefficients with different standard errors.

TABLE 5 presents the results of our two-stage analysis. The key results are reported in the bottom panel. If the BCD hypothesis were correct, we would expect the reported productivity coefficients to be negative in the two regressions (Equations 32.a and 32.b).

[5] We could not implement the CCEMG estimator for the BEA, industry-level dataset. The CCEMG procedure requires the use of cross-sectional averages of the dependent and independent variables to account for unobserved common factors. Unlike in our OECD analysis where economy-wide productivity differs across countries, Equations (31.a) and (31.b) use the same national productivity series across industries. Implementing CCEMG with this kind of set-up creates perfect multicollinearity between the independent variable and its cross-sectional average.

Instead, one is negative, one is positive, and both are statistically insignificant. The corresponding *p*-values are 0.53 and 0.91.

While some industries accord with expectations in the industry-level estimates from the first-stage analysis – for example, health care experiences a rising share of employment and increasing relative prices when economy-wide productivity increases (cf. Panel A of TABLE 5) – overall, the relationships do not differ significantly between slow-growing (non-progressive) and fast-growing (progressive) industries. This corroborates our cross-country, OECD analysis above.

VI. Conclusion

This study makes a number of contributions to the literature on BCD. We develop a theoretical model of BCD that provides an explicit link between the theory underlying BCD and estimated models. We propose two new tests that capture the main characteristics of the BCD framework. Using a wide variety of model specifications and panel data estimators, we then implement these tests on a sample of 27 OECD countries over the period 1995-2013, as well as a sample of 14 U.S. industry groups over the years 1947-2015. A feature of this analysis is that it utilizes a precise measure of the non-health price index, as opposed to the GDP deflator employed in other studies.

Our two key tests consist of estimating the relationship between country productivity and (i) the share of the economy's labor force employed in the health sector, and (ii) the ratio of prices in the health and non-health sectors. We show that BCD implies positive correlations for both sets of relationships. We find no evidence to support the BCD using our preferred specification and estimation procedures.

It may be that the failure of the BCD model can be attributed to technology improvements and the resulting substitutability of capital for labor inputs. Recent innovations, such as computer-assisted surgery, are likely to lead to further departures from the original

BCD framework. As a result, it may no longer be appropriate to think of the health sector as technologically "nonprogressive" – if it ever was. In any case, the findings of this study indicate that health care does not seem to be "trapped" in a dismal world of stagnant productivity and inexorably rising costs.

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FIGURE 1
Time Series of the Share of Labor in the Health Sector (*LHL*)
for Selected OECD Countries

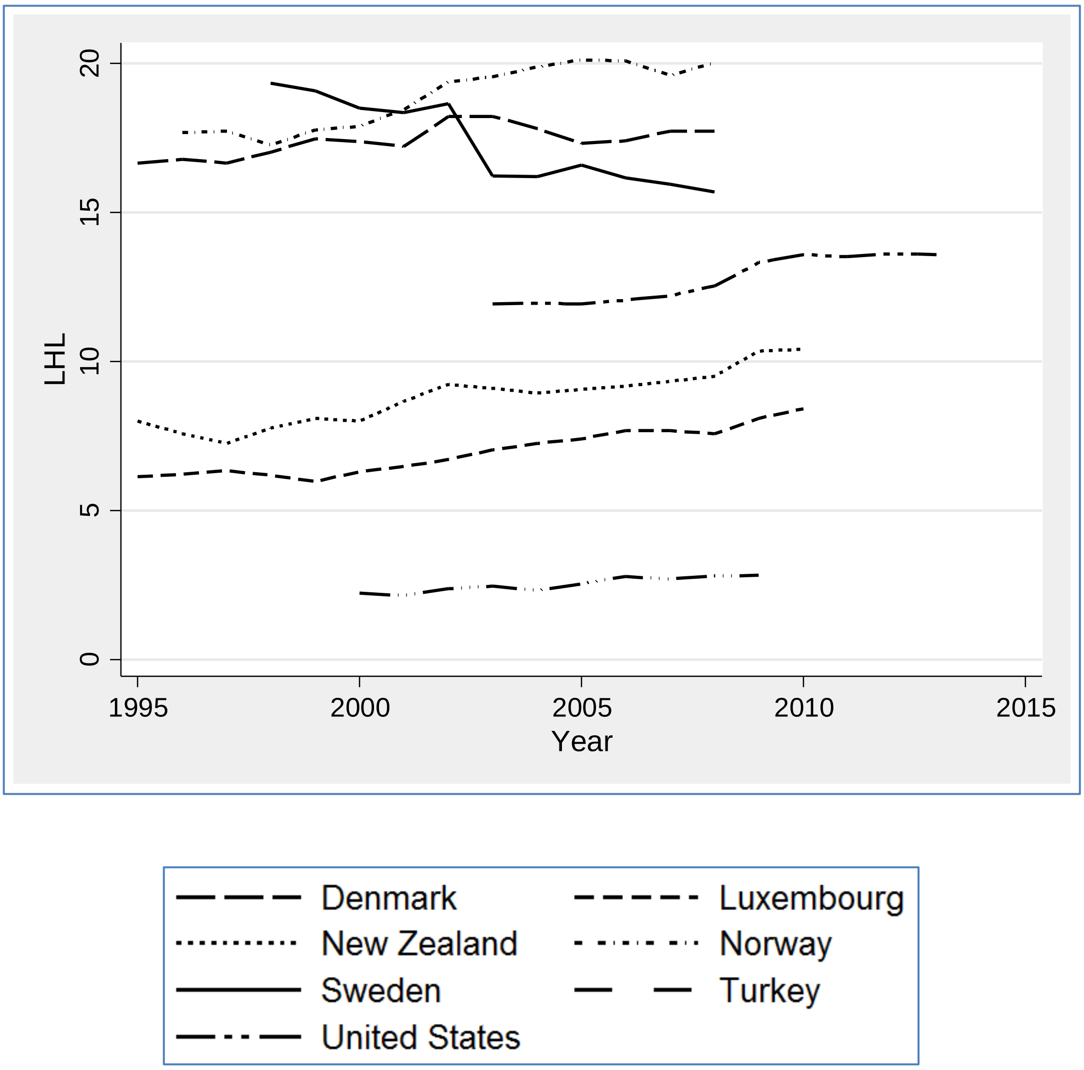

FIGURE 2
Time Series of the Ratio of Prices in the Health and Non-Health Sectors (*PHPNH*) for Selected OECD Countries

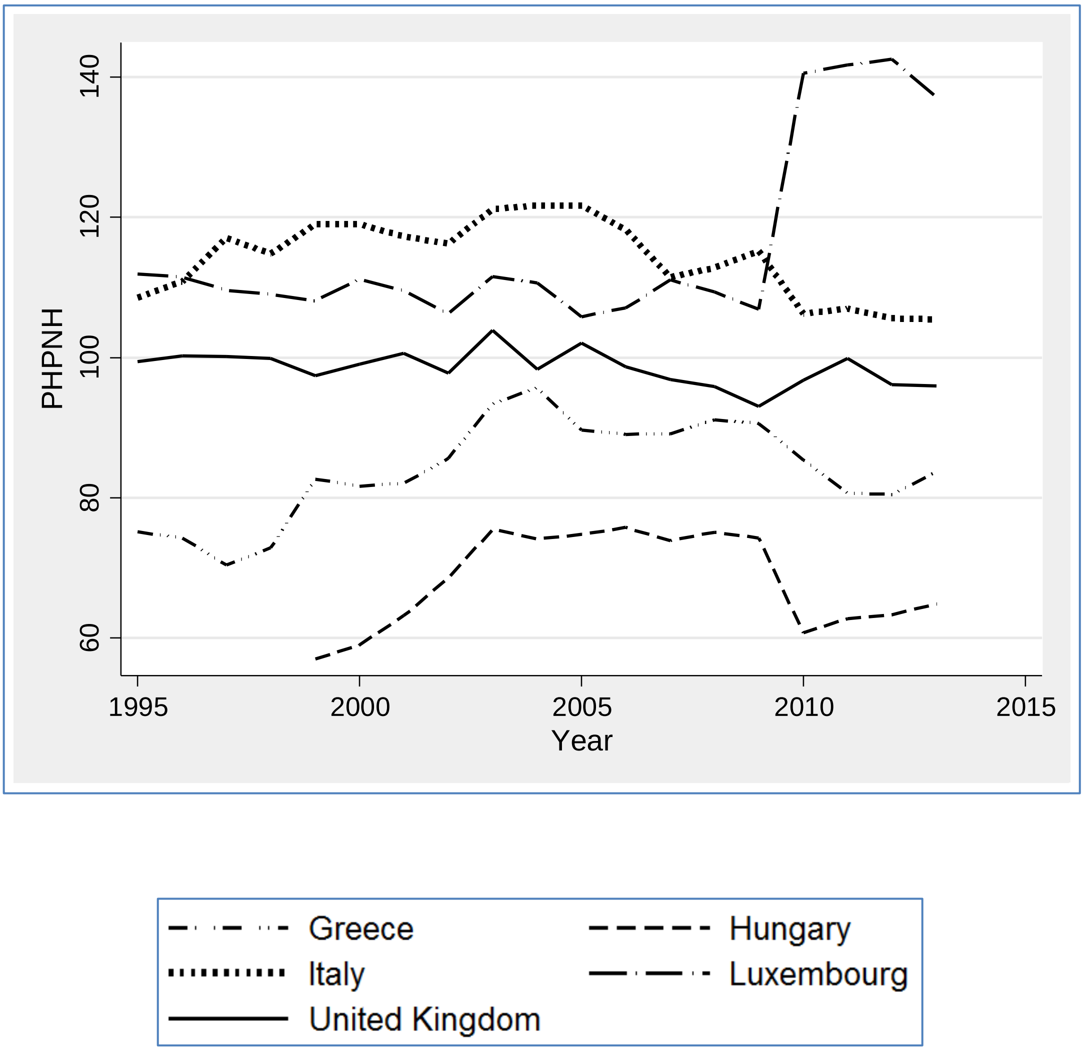

FIGURE 3
Time Series of Productivity (*PROD*) for Selected OECD Countries

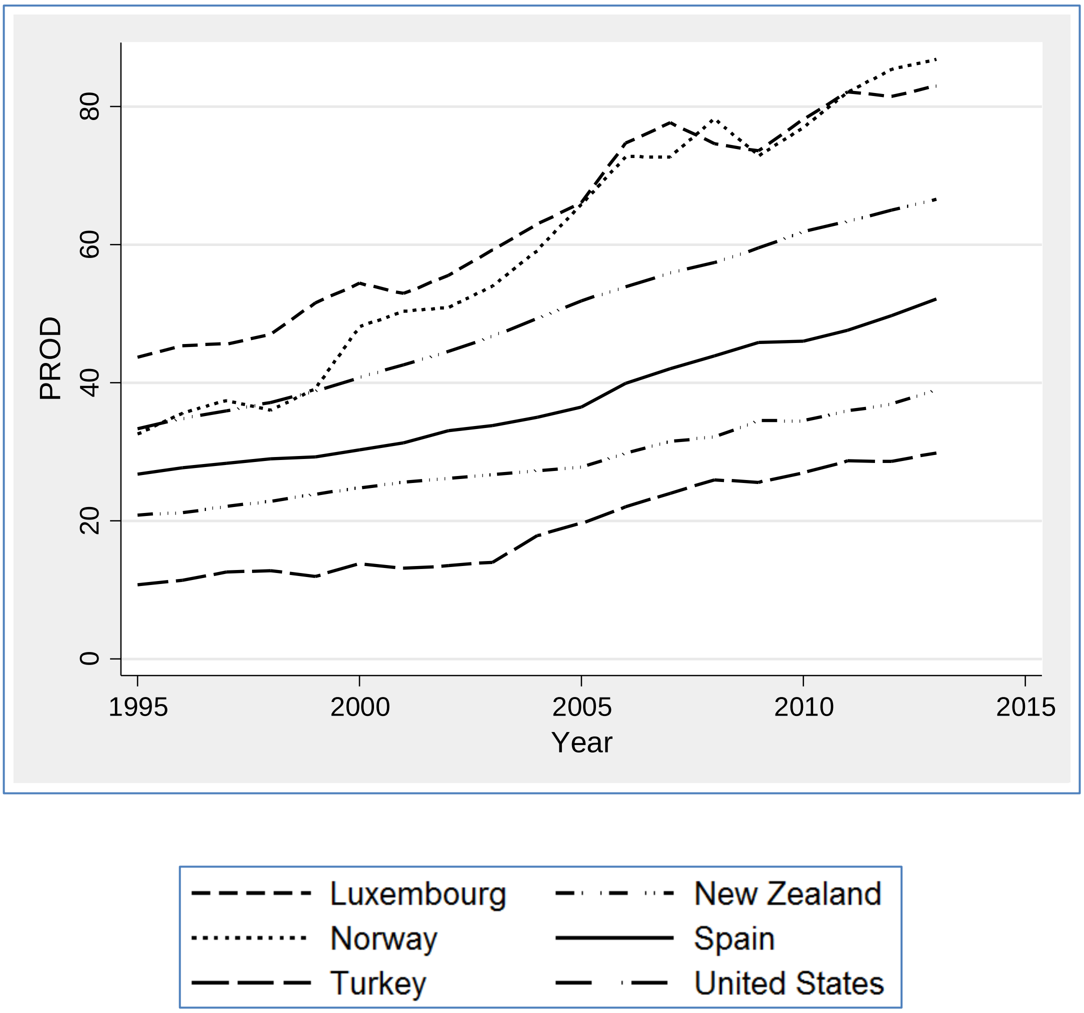

TABLE 1
Descriptive Statistics

Variable	***Obs***	***Mean***	***Std Dev***	***Min***	***Max***
Ratio of prices in the health and non-health sectors (*PHPNH*)	383	99.66	14.15	55.58	142.6
Health sector share of the labor force (*LHL*)	392	9.94	4.09	2.15	20.13
Productivity (*PROD*)	506	38.31	14.30	10.76	86.85
Population < 15 years (% of total)	513	18.0	3.1	12.9	32.1
Population > 64 years (% of total)	513	15.0	2.7	5.4	21.1
Male population (% total)	513	49.0	0.8	46.1	51.1
Life expectancy at birth (in years)	511	78.5	2.8	67.9	83.2
Infant mortality (per 1,000 live births)	507	5.2	4.2	0.9	40.9
Tobacco consumption (grams per capita ≥ 15 years)	328	1758	603	557	3741
Alcohol consumption (liters per capita ≥ 15 years)	491	9.9	2.7	1.2	15.1
GDP growth rate (%)	509	2.4	3.0	-14.7	11.7

NOTE: The sample consists of annual data for years 1995-2013 from 27 OECD countries: Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom, and U.S. *PHPNH* is calculated using the health price index and the overall consumer price index. *LHL* is the fraction of the total labor force employed in the health sector. *PROD* is measured as the ratio of GDP to the number of hours worked.

TABLE 2
Baseline Estimates:
Determinants of Health Sector Share of the Labor Force (*LHL*)

	POLS			*2WFE*			*FE with Country-Specific Time Trends*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PROD	0.5607*** (9.03)	0.6245*** (9.84)	0.6282*** (9.72)	0.0901 (1.32)	0.1993*** (3.37)	0.1991*** (3.34)	-0.0471 (-0.54)	-0.0467 (-0.64)	-0.0794 (-1.09)
Age < 15	0.0990*** (8.63)	0.0714*** (6.07)	0.0711*** (5.94)	0.0155** (2.06)	0.0053 (0.75)	0.0057 (0.80)	0.0147 (1.37)	0.0385*** (4.03)	0.0394*** (4.16)
Age > 64	0.0799*** (5.54)	0.0852*** (6.51)	0.0858*** (6.50)	-0.0048 (-0.69)	0.0047 (0.62)	0.0038 (0.49)	-0.0066 (-0.47)	-0.0046 (-0.36)	-0.0037 (-0.30)
Male	0.0126 (0.33)	0.1158** (2.43)	0.1200** (2.49)	-0.1093*** (-3.53)	-0.0610** (-2.26)	-0.0634** (-2.32)	-0.0780** (-2.19)	-0.0394 (-1.37)	-0.0350 (-1.22)
ln(Life expectancy)	-2.1007** (-2.10)	-5.4472*** (-5.93)	-5.5594*** (-5.96)	3.4223*** (3.47)	5.5085*** (5.20)	5.5502*** (5.21)	-1.2405 (-1.21)	1.0207 (1.03)	0.5893 (0.59)
ln(Infant mortality)	-0.4804*** (-8.42)	-0.5612*** (-9.65)	-0.5614*** (-9.61)	0.0602 (2.20)	0.0133 (0.44)	0.0119 (0.39)	0.0048 (0.18)	-0.0062 (-0.22)	-0.0066 (-0.24)
ln(Tobacco consumption)	----	-0.3050*** (-5.36)	-0.3125*** (-5.43)	----	-0.0857** (-2.45)	-0.0884** (-2.50)	----	-0.1022*** (-2.64)	-0.0960** (-2.47)
ln(Alcohol consumption)	----	0.1699*** (3.43)	0.1704*** (3.38)	----	-0.1911*** (-3.49)	-0.1925*** (-3.47)	----	-0.0536 (-0.93)	-0.0694 (-1.22)
GDP growth rate	----	----	0.0018 (0.30)	----	----	0.0013 (0.75)	----	----	0.0029*** (2.75)
Obs.	384	258	256	384	258	256	384	258	256
N	27	19	19	27	19	19	27	19	19
Adj. R^2	0.534	0.749	0.749	0.981	0.991	0.991	0.988	0.995	0.995
Country and time effects	----	----	----	F=209.21 (p=0.000)	F=180.10 (p=0.000)	F=177.4 (p=0.000)	F=280.11 (p=0.000)	F=2971 (p=0.000)	F=301.89 (p=0.000)
BIC	214.4	8.393	14.54	-808.4	-681.3	-668.3	-947.2	-812.1	-806.0
RESET	12.96 (p=0.000)	20.90 (p=0.000)	21.10 (p=0.000)	F=14.96 (p=0.000)	F=4.98 (p=0.002)	F=5.41 (p=0.001)	F=2.06 (p=0.105)	F=3.51 (p=0.016)	F=1.58 (p=0.196)

NOTE: The dependent variable is ln(*LHL*). "POLS", "2WFE" and "FE with Country-Specific Time Trends" stand for OLS regression without fixed effects, OLS regression with fixed effects for country and year, and OLS regression with fixed effects for country and country-specific linear time trends. Unless otherwise indicated, numbers in parentheses report cluster-robust standard errors, with clustering by country. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 3
Baseline Estimates:
Determinants of Ratio of Prices in the Health and Non-Health Sectors (*PHPNH*)

	POLS			***2WFE***			***FE with Country-Specific Time Trends***		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PROD	0.3110*** (6.17)	0.1134 (1.28)	0.1455 (1.64)	0.8570*** (6.96)	1.0112*** (6.50)	1.0045*** (6.37)	-0.1587 (-0.81)	-0.2335 (-0.96)	-0.1931 (-0.79)
Age < 15	0.1566 (0.37)	0.0323 (0.05)	0.0434 (0.07)	-3.8538*** (-4.52)	-5.8166*** (-4.37)	-5.7151*** (-4.26)	-3.1860*** (-2.97)	-2.9458 (-1.53)	-2.6804 (-1.39)
Age > 64	-0.4720 (-0.92)	0.1725 (0.25)	0.2915 (0.42)	-2.5627*** (-3.74)	-4.0438*** (-4.18)	-3.9622*** (-4.04)	3.0640*** (3.17)	2.8439* (1.94)	3.0153** (2.05)
Male	0.9809 (0.84)	7.2082*** (3.50)	7.3550*** (3.60)	-13.334*** (-5.00)	-14.271*** (-3.22)	-14.767*** (-3.28)	-4.8124 (-1.52)	-8.8371** (-1.99)	-8.8307** (-1.98)
Life expectancy	2.5511*** (5.83)	1.7411*** (3.05)	1.6824*** (2.96)	4.4834*** (4.41)	-0.5052 (-0.24)	-0.7730 (-0.36)	2.7175** (2.14)	1.7882 (1.06)	1.4402 (0.84)
Infant mortality	0.3431 (1.48)	0.1989 (0.68)	0.2549 (0.88)	1.1137*** (3.82)	0.8503 (2.41)	0.8624** (2.41)	0.0413 (0.07)	-1.7417*** (-2.60)	-1.7196** (-2.58)
Tobacco consumption	----	-0.0057*** (-3.52)	-0.0060*** (-3.75)	----	0.0011 (0.39)	0.0008 (0.26)	----	-0.0021 (-0.71)	-0.0027 (-0.90)
Alcohol consumption	----	0.3770 (0.98)	0.4355 (1.14)	----	-0.7409 (-0.89)	-0.6231 (-0.74)	----	3.1489*** (3.46)	2.9972*** (3.25)
GDP growth rate	----	----	0.5625** (2.04)	----	----	0.0983 (0.35)	----	----	0.1812 (1.25)
Obs.	382	215	213	382	215	213	382	215	213
N	21	14	14	21	14	14	21	14	14
Adj. R^2	0.452	0.426	0.442	0.799	0.796	0.795	0.856	0.879	0.880
Country and time effects	----	----	----	F=18.09 (p=0.000)	F=13.05 (p=0.000)	F=12.32 (p=0.000)	F=26.75 (p=0.000)	F=29.48 (p=0.000)	F=28.42 (p=0.000)
BIC	2904.3	1648.4	1632.5	2705.5	1557.5	1549.5	2592.4	1429.0	1419.6
RESET	F=21.32 (p=0.000)	F=13.04 (p=0.000)	F=10.03 (p=0.000)	F=7.57 (p=0.000)	F=2.01 (p=0.114)	F=2.26 (p=0.084)	F=1.90 (p=0.130)	F=2.53 (p=0.059)	F=1.92 (p=0.128)

NOTE: The dependent variable is *PHPNH*. "POLS", "2WFE" and "FE with Country-Specific Time Trends" stand for OLS regression without fixed effects, OLS regression with fixed effects for country and year, and OLS regression with fixed effects for country and country-specific linear time trends. Unless otherwise indicated, numbers in parentheses report cluster-robust standard errors, with clustering by country. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 4
Additional Tests:
Analysis of Health Sector Share of the Labor Force (*LHL*) and Ratio of Prices in the Health and Non-Health Sectors (*PHPNH*)

	LHL			***PHPNH***		
	Model (7)	***Model (8)***	***Model (9)***	***Model (7)***	***Model (8)***	***Model (9)***
POST-ESTIMATION TESTS FROM TABLE 2 AND 3 REGRESSIONS						
For Serial Correlation	F = 50.492 (p = 0.000)	F = 28.886 (p = 0.000)	F = 26.135 (p = 0.000)	F = 179.535 (p = 0.000)	F = 39.279 (p = 0.000)	F = 41.190 (p = 0.000)
For Cross-sectional Dependence	z =11.447 (p = 0.000)	----	----	z = 3.646 (p = 0.000)	----	----
ESTIMATES OF THE PRODUCTIVITY COEFFICIENT USING ALTERNATIVE ESTIMATION PROCEDURES:						
(1) PCSE	-0.0133 (-0.16)	----	----	-0.0109 (-0.04)	----	----
(2) MG	0.4194 (1.02)	0.0529 (0.30)	0.0433 (0.21)	-0.4608 (-1.05)	0.3823 (0.43)	1.2333 (0.87)
(3) CCEMG	2.2300 (1.08)	-0.3052 (-0.57)	0.9498 (1.30)	-1.2845 (-1.15)	1.6711 (0.38)	-1.7717 (-1.23)
(4) AMG	-0.1185 (-0.47)	-0.0263 (-0.18)	-0.1789 (-0.95)	0.0706 (0.17)	0.7511 (0.98)	1.5263 (1.18)

NOTE: The top part of the table reports results of testing for serial correlation and cross-sectional dependence following estimation of the respective models in TABLES 2 and 3. The specific tests are described in the text. The bottom part of the table reports the results of estimating the models using alternative estimation procedures. "PCSE" stands for Beck and Katz's (1995) Panel-Corrected Standard Error estimation. "MG", "CCEMG", and "AMG" stand for Pesaran and Smith's (1995) Mean Group estimator; Pesaran's (2006) Common Correlated Effects Mean Group estimator; and the Augmented Mean Group estimator of Eberhardt and Teal (2010), respectively. Unless otherwise noted, numbers in parentheses are z-statistics corresponding to coefficient estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 5
Test of the BCD Hypothesis Using U.S. Industry-Level Data

A. FIRST-STAGE RESULTS		
Industry	***Equation (31.a)*** $\hat{\gamma}_1$	***Equation (31.b)*** $\hat{\delta}_1$
Agriculture, forestry, and fishing	-1.0378*** (-8.91)	-26.7086*** (-9.08)
Mining	-1.4248*** (-6.21)	-9.1940** (-2.24)
Construction	0.2497** (2.41)	3.5953*** (6.59)
Manufacturing	0.7104*** (5.65)	-3.3201*** (-2.63)
Transportation	-0.8818*** (-5.18)	4.6949*** (5.40)
Information	-0.2829 (-0.92)	10.3930*** (5.99)
Utilities	0.5941*** (3.33)	2.0602** (2.29)
Wholesale trade	0.3590*** (4.53)	4.9146* (1.67)
Retail trade	0.8227*** (4.94)	-11.4947*** (-16.48)
Finance, insurance, and real estate	0.6874*** (9.75)	4.7357*** (10.46)
Arts	-1.3371*** (-3.68)	5.8685*** (6.86)
Health care	0.7637*** (6.23)	7.4356*** (7.93)
Educational services	-0.1243 (-1.39)	6.5977*** (14.99)
Government	0.2316* (1.92)	0.4220 (1.42)
B. SECOND-STAGE RESULTS		
Variable	***Equation (32.a)*** $\hat{\alpha}_{i1}$	***Equation (32.b)*** $\hat{\beta}_{i1}$
Industry productivity, $\overline{PROD}$	-0.5411 (-0.11)	33.3543 (0.64)

NOTE: First-stage results report the productivity coefficients from estimating Equations (31.a) and (31.b) using the Augmented Mean Group (AMG) panel estimator of Eberhardt and Teal (2010). The dependent variables are industry employment shares and industry price ratios, respectively. The explanatory variables consist of a constant, economy-wide productivity and a time trend, all with industry-specific coefficients. The second-stage results report the results of estimating Equations (32.a) and (32.b) using OLS with heteroskedasticity-robust standard errors. Numbers in parentheses are *z*-statistics corresponding to coefficient estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

APPENDIX

Define P as the economy-wide price index, which is a weighted average of P_H and P_{NH},

$P = (1-k) \cdot P_H + k \cdot P_{NH}$.

It follows that:

$$\frac{P_H}{P} = \frac{P_H}{(1-k)\cdot P_H + k\cdot P_{NH}} = \frac{1}{(1-k)+k\cdot(P_{NH}/P_H)} .$$

and from (19):

$$\frac{P_H}{P} = \frac{1}{(1-k)+k\cdot(1/\phi)} = \frac{\phi}{(1-k)\cdot\phi+k} .$$

$$\frac{\partial(P_H/P)}{\partial PROD} = \frac{\frac{\partial\phi}{\partial PROD}[(1-k)\cdot\phi+k]-\phi[\frac{\partial\phi}{\partial PROD}(1-k)]}{[(1-k)\cdot\phi+k]^2} = \frac{\partial\phi}{\partial PROD} \cdot \left(\frac{k}{[(1-k)\cdot\phi+k]^2}\right)$$

From Equation (26), we know that $\frac{\partial\phi}{\partial PROD} > 0$.

It follows that

$$\frac{\partial(P_H/P)}{\partial PROD} > 0 .$$