Effects of Health and Economic Crisis on Healthcare Spending in the United States

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Abstract:

This study aims to identify significant factors associated with US healthcare spending. Using data from the OECD, BLS, and CDC, the analysis incorporates factors previously analyzed in the literature, such as income and life expectancy, while also examining the importance of nation-wide health crises in the form of the HIV/AIDS and opioid epidemics. Spending measures for the US healthcare market at both an aggregate and segmented level were regressed on variables such as income, unemployment, life expectancies, alcohol consumption, and the crude death rates per one hundred thousand people for health crises. These regressions, which also controlled for non-stationarity in the data, show no significant effects of health crises on healthcare spending, nor the price of healthcare over time across any segments, although health crisis data was somewhat unreliable. Important factors from the literature also appear to have little effect on such measures, although public spending appears most sensitive to control variables, while income and unemployment remain significant factors of healthcare spending and price. Specifically, unemployment – used as a proxy for economic crises – appears to positively impact healthcare spending in all segments and prices in the US. Elasticity of total healthcare spending relative to income appears to be below unity indicating total healthcare as a necessity good in the US, which is consistent with much of the recent literature. Elasticities for specific segments differ, though, finding private health spending by organizations to be a luxury and health spending by individuals to be a necessity. Further study with higher periodicity and more reliable health crisis data would be beneficial to better understand the effects of health and economic crises on total healthcare spending and its segments in the US.

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1 Introduction

The United States has by far the highest level of aggregate healthcare spending as a percent of GDP among members of the Organization for Economic Co-operation and Development (OECD). The share of healthcare spending in GDP grew from approximately 6.2% in 1970 to approximately 17% in 2019 (OECD 2020). For US policymakers, it is important to understand what factors cause such a large level and growth in spending. This study aims to find evidence for new drivers – specifically health and economic crises – of total healthcare spending in the US, controlling for other factors previously found in the literature. This study is organized as follows: literature review, methodology, results, and conclusions.

1.1 Review of the Literature

The large literature on drivers of healthcare spending both within and across countries has not yet reached a consensus on relative contributions of different factors, as studies often document conflicting results. Many studies focus specifically on why there is an *increase* in healthcare spending (both nominally and in real terms), not solely on the level of healthcare spending itself. Many such studies attribute the rise in healthcare spending to increasing service prices of healthcare, often due to technological innovations and doctors using more expensive treatments (Deileman, et al. 2017). Along with this technological trend are many other unobservable trends, such as culture and societal taste regarding healthcare (Tajudeen, Tajudeen and Dauda 2018).

Actual factors of healthcare spending that also tend to contribute to the increase in healthcare spending are health status indicators. Such indicators include population aging (Deileman, et al. 2017) as well as the proportion of the elderly in the overall population of study (Thorton and Rice 2008). Healthcare service factors such as number of the physicians, hospitals, and overall availability of healthcare services have also been attributed to the increase in healthcare spending (Thorton and Beilfuss 2016). Conversely, it was found that healthcare spending decreased while medical consultations and pharmaceutical spending increased in the United Kingdom (UK) in the wake of the Great Recession (Portela and Thomas 2013).

There is also literature describing the effects of healthcare spending itself on the overall health of the populations of study. Such studies focus on specific measures of health status as they relate to the cyclicality of healthcare spending. One such study finds that, in the US, informal healthcare (family members taking care of their elderly family) is countercyclical to GDP while elderly death rates and formal care (nursing homes) are procyclical (Mommaerts and Truskinovsky 2020). In this study, Mommaerts and Truskinovsky (2020) imply that during economic booms more people send their elderly family members to nursing homes and in those periods elderly death rates are higher while in recessions there are fewer nursing home residents and fewer elderly deaths – which would indicate the need for further study of the effectiveness of nursing homes. Similar findings, although not contained only to elderly death rates, were that nations with more procyclical healthcare spending tended to have higher aggregate death rates and lower overall life expectancies (Liang and Tussing 2019).

The literature remains conflicted about key factors and their effects, but where almost all articles on this topic agree is that there is no consensus regarding healthcare models. A major review of the literature stated that the results of all 20 papers reviewed were so contradictory that a general model for healthcare spending could not be specified (Martin and Gonzalez 2011). A similar finding from Martin and Gonzalez (2011) was how contradictory the literature was when discussing the elasticity of healthcare spending relative to income.

Most articles cited in this study find healthcare spending elasticity to be below unity, indicating healthcare as a necessity good in their respective populations of study. Such studies include those by Moscone and Tosetti (2010), Freeman (2003), Di-Matteo and Di-Matteo (1998), and Baltagi and Moscone (2010). Although there appears to be a consensus in the literature cited for this study, Khan and Husnain both cite an elasticity below unity and state that "To assess whether HCE [health care expenditure] is a luxury or necessity good, empirical results shown in the literature vary and are often conflicting." (Khan and Husnain 2019, 214) Understanding the elasticity of healthcare spending has been of increasing importance in the literature, though, due to the rise in healthcare spending globally as well as the multitude of literature citing increasing spending on personal health as a share of personal income in many developed nations (Hall and Jones 2007).

Few literary sources seem to approach the reasons behind such differing literature regarding both factors of healthcare spending as well as elasticity measures. At least for elasticity, Di-Matteo (2003) argued that elasticity measures could depend greatly on the level of income in each population analyzed. Specifically, it is noted that at higher levels of income healthcare elasticity may appear to act more as a necessity good, while at lower levels of income healthcare may act more as a luxury good (Di-Matteo 2003). These findings are especially true in more developed nations as most of the literature cited in this study focused on members of the OECD.

Just as varying in the literature as factors of healthcare spending and its elasticity are the methods used for finding such factors and elasticities. As described by Di-Matteo and Cantarero-Prieto:

> "Studies have used international, national and regional level data to examine the determinants of health expenditures with simple bivariate cross-sectional techniques, multivariate regression, pooled time series regressions, error-correction approaches as well as non-parametric techniques." (Di-Matteo and Cantarero-Prieto 2018, 13)

Other methodologies included structural time series models to account for unobservable factors of healthcare spending (Tajudeen, Tajudeen and Dauda 2018), mean group, and common correlated effects mean group analyses (Khan and Husnain 2019) to specifically evaluate healthcare elasticity across multiple nations. The most common method found while reviewing the literature for this study was multiple linear regression (MLR) modeling using ordinary least squares (OLS) estimation of parameters after taking the natural logarithm transforms of both independent and dependent variables to obtain elasticity measures. There does exist literature which takes this method a step further by introducing two-stage and three-stage OLS estimations as well (Thorton and Rice 2008).

Although many findings in the literature appeared robust each study had its own set of limitations; of those limitations there were a few common trends. A succinct description of such limitations was pointed out by Khan and Husnain:

> "…, many of the previous studies have not considered the presence of cross-section dependence, stationarity of variables, and unobservable heterogeneity issues with regard to HCE [health care expenditure] and income relationship." (Khan and Husnain 2019, 213)

The chief issue of cross-section dependence in many studies was often the use of GDP as an independent variable or as the proxy for income. There is evidence of Granger causality between GDP and aggregate healthcare spending in many members of the OECD, who tended to be the nations of interest in many of these studies. In a study of OECD members, it was shown that GDP Granger caused healthcare spending in eight nations, healthcare spending was shown to Granger cause GDP in another eight nations, and in two nations healthcare spending and GDP were found to Granger cause each other (Devlin and Hansen 2001). The implication of that study is that GDP is not econometrically exogenous to aggregate healthcare spending across many nations (Devlin and Hansen 2001), implying that using GDP in any form for a regression of healthcare spending would create a significant model misspecification and not provide a viable measure for elasticity nor evidence of income as a possible factor of healthcare spending.

As for issues of non-stationarity, Di-Matteo and Cantarero-Prieto in their recent study of healthcare spending in Canada and Spain argue that non-stationarity may not be a true issue when examining aggregate healthcare spending (Di-Matteo and Cantarero-Prieto 2018). That being said, Di-Matteo and Cantarero-Prieto still did control for non-stationarity in their analysis, while many other studies did not.

A separate issue was the focus on *aggregate* healthcare spending itself. Many studies focused exclusively on total healthcare spending or on government healthcare spending, not accounting for likely differences in spending habits of private individuals when compared to their governments (Yu, et al. 2013). As a result, there is little to no literature regarding out-of-pocket or private healthcare spending.

Similarly, there exists a significant emphasis was on healthcare *spending*, when many such studies take an economic approach to healthcare spending but fail to examine supply and/or demand of healthcare at any level of aggregation. Because of the economic assumptions of most literature, each study assumes healthcare spending will be the equilibrium of healthcare supply and demand, yet do not attempt examining either. Understanding factors for each part of the product of supply and demand may lead to more insightful information for policymakers.

1.2 Motivation

This study aims to add to the literature by documenting how health and economic crises affect the level of healthcare spending in the US. In doing so, this study addresses many shortfalls of the literature by accounting for non-stationary data, examining multiple segments of the US healthcare market, using household disposable income to measure healthcare spending elasticities instead of GDP, and by addressing possible questions of supply and demand of healthcare. There have been similar studies examining the importance of disease prevalence on healthcare spending in the US which attributed much of the increase in spending to the rise of obesity in the US population (Thorpe 2006), although more recent studies with a similar methodology have found disease prevalence to be insignificant as a factor of healthcare spending in the US (Deileman, et al. 2017). There have also been studies which examine health outcomes as related to economic crises (Granados and Rodriguez 2015); (Faramarzi, et al. 2019), but such studies focus on population health as the dependent – not spending – and consider European and Mediterranean populations - not the US population.

1.3 Hypotheses

The following hypotheses were tested in this study:

(1) Economic crises create negative demand shocks in the US healthcare market.
   - H^1_0: Economic crises have negative coefficients in regressions.
   - H^1_1: Economic crises have coefficients that are positive or insignificantly different from zero.

(2) Health crises create positive demand shocks in the US healthcare market.
   - H^2_0: Health crises have positive coefficients in regressions.
   - H^2_1: Health crises have coefficients that are negative or insignificantly different from zero.

2 Methods

2.1 Data

Data for this study were drawn from three main sources: The Center for Disease Control and Prevention (CDC), the Bureau of Labor Statistics (BLS), and the OECD. All data collected were annual observations of each variable in the time period 1970 – 2013.

The main dependent variable was annual aggregate healthcare spending, as reported by the OECD. I considered the total healthcare spending per capita (abbreviated to *TOT*), and its three components: annual out-of-pocket spending per capita (*OOPEXP*), annual spending by private entities such as insurance and non-profit organizations per capita (denoted *VOLUNTARY*), and annual government spending per capita (denoted *COMPULSORY*). It is important to note the latter three components comprise *TOT*, namely *TOT = OOPEXP + VOLUNTARY + COMPULSORY*. (OECD 2020)

All of these components were analyzed as there has been little study for any segmentation of healthcare. All articles cited either studied total aggregate spending or only government spending, with little differentiation from other literature (Yu, et al. 2013), implying that other segments of healthcare, such as *OOPEXP* and *VOLUNTARY*, may react differently to drivers of healthcare spending previously found in the literature.

Changes in aggregate spending can reflect price or quantity changes and indeed much of the literature studying healthcare spending growth in the US emphasizes price inflation for healthcare services. The OECD does not provide a price index associated with the total healthcare expenditure variables used. Instead, I use data from the BLS on the Consumer Price Index for urban medical care (*CPI*) in the US (U.S. Bureau of Labor Statistics 2021). This *CPI* measure was used as a separate dependent variable to analyze the effects of the healthcare regressions on prices of aggregate healthcare.

The final dependent variable is a quantity measure for total healthcare spending per capita, *TOT_q*, as calculated by dividing the spending per capita, reported by the OECD, by *CPI*, reported by the BLS. Similar to the medical care *CPI* this measure is only proportional to the actual level of healthcare quantity per capita consumed annually in the US (U.S. Bureau of Labor Statistics 2020). Because this metric was created by dividing the spending from one data source by the price from another data source it likely contains significant measurement error. Therefore, the *Results* de-emphasize this variable, but include it for completeness (discussed more in *Results* and *Limitations*).

The key independent variables are the economic and health crises. I use the unemployment rate as a proxy for economic crises, which is consistent with existing literature (Faramarzi, et al. 2019); (Portela and Thomas 2013). Specifically, I use the annual unemployment rate (abbreviated to *unemp*) in the US reported by the OECD (OECD 2020).

The proxies for heath crises I used were the crude death rates of national epidemics. I focus on two major epidemics in recent US history: The Human Immunodeficiency Virus that causes the Acquired Immunodeficiency Syndrome (HIV/AIDS) epidemic and the opioid epidemic. As described by the CDC, an epidemic occurs when an illness's infection and death rates rise above their expected rates, respectively (Centers for Disease Control and Prevention 2021), leaving a relatively open description of such crises. Both the HIV/AIDS and opioid epidemics do have large literature bases supporting them as health crises in the US (National Institutes of Health National Institute on Drug Abuse 2021); (Scandlyn 2000), though, which led them to be used as the proxies for health crises in this study. I use data from the CDC on crude death rates, or average number of deaths per 100,000 US residents, for each epidemic, respectively. The crude death rates were acquired from the compressed mortality files on CDC's WONDER database (Centers for Disease Control and Prevention, National Center for Health Statistics n.d.); (Centers for Disease Control and Prevention, National Center for Health Statistics n.d.) and a National Institutes of Health (NIH) article describing and providing data on the opioid epidemic (National Institutes of Health National Institute on Drug Abuse 2021).

Both of these epidemics have a year they started (1979 for HIV/AIDS and 1999 for the opioid epidemic by the CDC data). Prior to these start years, each epidemic was either rarely measured or simply did not exist in the US, respectively, indicating that there could not have been a measured crude death rate as there was nothing to measure. As a result, each epidemic was assumed to have crude death rates with values of zero prior to the years they started.

The data for HIV/AIDS contained noted measurement error, creating years with unreliable estimates for the crude death rate. These years included 1979-1986 and also happened to be the early years of the HIV/AIDS epidemic. To remedy this data issue a secondary binary variable was created called *reliable*, which was 1 in years with reliable data and 0 in years with unreliable data. Namely, in years 1979 – 1986 *reliable* = 0, and in all other years *reliable* = 1. To account for this unreliable data further an interaction term between the *reliable* variable and the HIV/AIDS crude death rate, namely the product of these two variables, was used in the regressions. The addition of the *reliable* binary variable and interaction term between *reliable* and the HIV/AIDS crude death rate allowed the analysis to not lose excessive degrees of freedom on an already limited sample while still maintaining data that was as accurate as possible and accounted for inaccuracies.

Abbreviated names for the health crisis variables are *aids_crude* for the HIV/AIDS crude death rate, *aids_rel_inter* for the interaction term between the HIV/AIDS crude death rate and the *reliable* binary variable, and *opioid_crude* for the opioid crude death rate. The *reliable* binary variable is not considered a health crisis itself nor have an abbreviated name in the regressions.

Other data from the OECD included all control variables that are not health crises in the US. Such control variables were found by examining the work of Thorton and Beilfuss (2016), then using variables found to be statistically significant in their model that were also available from the OECD and spanned the period of analysis. Such factors included average household disposable income (abbreviated to *income*), average alcohol consumption per person 15+ years old (abbreviated to *alc*), the proportion of elderly population to working age population (abbreviated to *elderly*), life expectancy at birth (abbreviated to *life_exp*), and life expectancy at

65 (abbreviated to *life_exp65*). Life expectancy at 65 was not a measure in the Thorton and Beilfuss (2016) study, but other studies citing population aging as an important factor of healthcare spending, as well as Thorton and Beilfuss finding life expectancy in general to be significant, prompted the use of a metric for population health as well as the elderly population living longer, hence the use of the life expectancy at 65 years old. (OECD 2020)

Extended descriptions for data from the CDC, BLS, and OECD may be found in Appendices A, B, and C, respectively.

2.2 Regression Methodology

The methodology for this paper is very similar to those of other papers, specifically Thorton and Beilfuss (2016), as the basic methodology is a multiple linear regression model estimated using OLS with robust standard errors (“HC1” estimated robust standard errors) on data transformed by taking the natural logarithm of both the left and right-hand sides. This study differs from Thorton and Beilfuss, though, by implementing first differencing, a linear time trend, and a constant in the regression.

First differencing is used to account for major non-stationarity in the data, after taking the natural logarithm to be in line with other literature. By first differencing the natural logarithm the regression coefficients both control for most non-stationarity as well as offer direct estimates for elasticities of healthcare spending in relation to each exogenous variable.

The linear time trend is used to account for any non-stationarity still present as well as unobservable factors that may cause a trend in the data, such as societal preferences (Tajudeen, Tajudeen and Dauda 2018) and technological advancement’s effects on healthcare (Deileman, et al. 2017). The constant is used to ensure all estimates are unbiased as well as stay consistent with standard economic literature.

There were two model specifications for this study: the baseline model (BM) and the crisis model (CM). The BM is a direct comparison of this study’s data with findings from the literature and is closest in specification to Thorton and Beilfuss (2016). The CM is where the effects of health crises are found and use a similar specification to the BM so that its coefficients may be compared with the BM, and hence be compared with the literature in a more direct way. Equations (1) and (2) describe the BM and CM specifications, respectively.

$$\Delta ln(y_t) = \alpha + \delta_e \Delta ln(unemp) + \vec{\beta}\Delta ln(\vec{X}) + \gamma t + \varepsilon_t \tag{1}$$

$$\Delta ln(y_t) = \alpha + \delta_e \Delta ln(unemp) + \vec{\beta}\Delta ln(\vec{X}) + \gamma t + \varphi reliable + \vec{\delta}_h \Delta ln\left(\overrightarrow{health - crises}\right) + \varepsilon_t \tag{2}$$

In the BM specification, the dependent variables – y_t – were *TOT*, *TOT_q*, and the medical care *CPI* as described in *Data*. In the CM specification, the dependent variables were *TOT, TOT_q, CPI*, *OOPEXP*, *VOLUNTARY*, and *COMPULSORY*. α describes the constant, *t* indicates the linear time trend with its coefficient γ, and ε_t describes the error term in each period. The *X* vector indicates all control variables coming from the OECD (*income, alc, elderly*, *life_exp,* *life_exp65*), while *unemp* is described separately since it is a variable of interest used to proxy economic crises (even though it also comes from the OECD). The *health-crises* vector indicates all the health crisis data from the CDC (*opioid_crude, aids_crude, aids_rel_inter*). δ_e describes the coefficient on economic crises and δ_h describes the coefficients on health crises. As described in *Data, reliable* is separate from the health crises, hence it is specified outside of the *health-crisis* vector with its own coefficient, φ.

In terms of the hypotheses, H^1_0 tests $\delta_e < 0$ and H^2_0 tests for all $\delta_h > 0$.

2.3 Software

Software for data cleaning and model estimation was Python 3.8.3 run in Jupyter Notebooks with packages numpy, pandas, statsmodels, and stargazer. The Microsoft Suite was used in formatting tables and the write-up of the study.

All code and data for this study can be found in a GitHub repository linked in Appendix D. The repository, data, and code are made available for the purpose of replication, although may also be used to test the data with separate methods and hypotheses.

3 Results

3.1 Data Summary

Table 1 describes summary statistics for each continuous variable used in the BM and CM regressions, as described in *Methods*. It is important to note is that *opioid_crude* and *aids_crude* have a lower number of observations than other variables in the data because of their start-years. The number of observations for each only reflects the number of years in which there existed measurements for those health crises. Also, the interaction term between the HIV/AIDS crude death rate and the *reliable* variable (*aids_rel_inter*) are not listed here as *reliable* is a binary variable and all variation in the interaction term *aids_rel_inter*, comes from the *aids_crude* variable, whose distribution is already described in Table 1.

Table 1: Summary statistics for all continuous variables used in BM and CM regressions.

Variables	N	Mean	St. Dev.	Min	Max
TOT	44	3471.47	2604.71	326.96	8610.60
OOPEXP	44	543.10	288.96	121.69	1034.40
COMPULSORY	44	1576.30	1262.72	121.62	4210.81
VOLUNTARY	44	1895.17	1345.60	205.34	4399.79
CPI	44	193.40	121.52	33.96	425.13
unemp	44	6.41	1.52	3.99	9.71
income	44	21479.02	12404.46	4105.50	43949.71
alc	44	9.15	0.76	8.10	10.40
elderly	44	12.01	1.01	9.81	14.12
life_exp	44	75.43	2.19	70.90	78.80
life_exp65	44	17.13	1.17	15.05	19.20
opioid_crude	15	5.47	1.60	2.90	7.90
aids_crude	35	8.00	4.91	0.00	16.19

3.2 Total Spending and Prices of Healthcare

Table 2 describes the regression results for both the BM and CM specifications on total healthcare spending (*TOT*) as well as the medical care *CPI*. Between both model specifications (BM specification in 1 and 2, CM specification for 3 and 4) we see exceedingly similar results in both statistically significant coefficients as well as direction and magnitude of such coefficients.

Table 2: OLS regressions results with HC1 estimated robust standard errors (in parentheses) of BM (models 1, 2) and CM (models 3, 4) specifications for *TOT* and *CPI* as dependent variables.

Dependent (Model #)	Δln(TOT) (1)	Δln(CPI) (2)	Δln(TOT) (3)	Δln(CPI) (4)
const	0.05^{*}	0.03	0.05^{*}	0.04^{*}
	(0.02)	(0.02)	(0.02)	(0.02)
Δln(unemp)	0.05^{**}	0.06^{***}	0.05^{*}	0.06^{***}
	(0.02)	(0.02)	(0.02)	(0.02)
Δln(income)	0.81^{***}	0.53^{**}	0.79^{***}	0.49^{**}
	(0.18)	(0.19)	(0.19)	(0.17)
Δln(alc)	-0.28^{*}	-0.37^{*}	-0.29	-0.32
	(0.13)	(0.15)	(0.15)	(0.16)
Δln(elderly)	0.11	0.42^{**}	0.13	0.26
	(0.24)	(0.15)	(0.30)	(0.20)
Δln(life_exp)	-0.38	0.15	0.12	1.11
	(2.10)	(1.84)	(2.19)	(2.07)
Δln(life_exp65)	0.20	0.10	0.22	0.02
	(0.61)	(0.52)	(0.69)	(0.57)
t	-0.001^{*}	0.00	-0.001^{*}	0.00
	0.00	(0.00)	0.00	(0.00)
reliable			-0.01	-0.02^{*}
			(0.01)	(0.01)
Δln(opioid_crude)			0.01	-0.01
			(0.01)	(0.01)
Δln(aids_crude)			0.00	0.00
			(0.00)	(0.00)
Δln(aids_rel_inter)			0.00	0.02
			(0.01)	(0.01)
Observations	43	43	43	43
R^2	0.84	0.68	0.85	0.75
Adjusted R^2	0.81	0.62	0.80	0.66
Residual Std. Error	0.015 (df=35)	0.016 (df=35)	0.015 (df=31)	0.015 (df=31)
F Statistic	31.97^{***} (df=7; 35)	26.66^{***} (df=7; 35)	26.01^{***} (df=11; 31)	36.70^{***} (df=11; 31)

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

When comparing the BM specification for total healthcare spending to the literature, specifically Thorton and Beilfuss (2016), *income* appears to be significant in both with *unemp* statistically significant in this study but not in Thorton's and Beilfuss's model. *unemp* may be more significant in this study because Thorton and Beilfuss included a binary variable for the year 2009 (indicating the Great Recession) while also controlling for unemployment, leading to a possible misspecification of the BM and CM as this study included the year 2009 but not a binary variable to control for it.

Model 1 agrees with most of the recent literature by estimating an elasticity between 0 and 1 for *income*, indicating that total healthcare spending appears to be a necessity good in the US. Alcohol consumption is also found to be significant in both studies, although the signs are opposite between Thorton and Beilfuss and this study. The last variable included in both studies was elderly population which was found statistically significant in Thorton and Beilfuss (2016) but not in this study, at least in the BM. Finally, the linear time trend is statistically significant for this study, which is similar to findings from Deileman, et al. (2017) and Tanjudeen, Tanjudeen, and Duada (2018), although in this study the time trend is found to be negative, which contradicts such literature that argues for an increasing trend in healthcare spending.

The BM specification for *CPI* (model 2) is very similar to the BM specification for *TOT* and as such shows that healthcare prices – in the form of the *CPI* – tend to increase with *income* and *unemp* while decreasing with alcohol consumption levels (*alc*). Unlike the *TOT* model, *CPI* is positively affected by the proportion of elderly population to working age individuals (*elderly*) while being unaffected by the time trend.

Results from the CM specification (models 3 and 4) are almost identical to the BM specifications for *TOT* and *CPI*, respectively. *income* and *unemp* are still very statistically significant, with the *income* coefficient on *TOT* showing that total healthcare spending has an elasticity between 0 and 1 indicating it as a necessity good in the US. Similarly, the CM specification shows that healthcare spending and prices both increase with *income* and *unemp*. The major differences are that control variables other than *income* and *unemp* are insignificant with the CM specification.

Health crises, namely *opioid_crude*, *aids_crude*, and *aids_rel_inter*, appear entirely insignificant in models 3 and 4, indicating that health crises appear to have no statistically significant effects on healthcare spending or prices. The *reliable* dummy variable cannot be interpreted as a health crisis, so although it is significant in the CM specification for *CPI* it does not necessarily indicate an effect of health crises on healthcare prices.

These results appear to disagree with both null hypotheses. H^1_0 assumes that economic crises, in the form of the unemployment rate, would have negative effects on total healthcare spending and aggregate prices – both were shown to be positive in the BM model that compares such variables to the literature as well as with the CM specification which also controls for health crises. H^2_0 assumed that health crises would have positive effects on healthcare spending and prices but coefficients for all health crises variables were statistically insignificantly different from zero, indicating that they in fact have no effect on *TOT* or *CPI* with these data and model specifications. In fact, at least for the *TOT* models, including health crises lowered the adjusted R-squared of the model indicating an overspecification penalty as the health crises variables appear to be extraneous. Therefore, there appears to be sufficient evidence to reject both H^1_0 and H^2_0, indicating that the alternatives are preferred.

3.3 Total Quantity of Healthcare

Table 3 displays the regression results for the BM and CM specifications of *TOT_q*, the total healthcare quantity measure in the US, as regressed on variables from both specifications.

Table 3: OLS regressions results with HC1 estimated robust standard errors (in parentheses) of BM (model 5) and CM (model 6) specifications for *TOT_q* as the dependent variable.

Dependent (Model #)	Δln(TOT_q) (5)	Δln(TOT_q) (6)
const	0.01	0.01
	(0.03)	(0.03)
Δln(unemp)	-0.01	-0.01
	(0.02)	(0.02)
Δln(income)	0.28	0.30
	(0.21)	(0.24)
Δln(alc)	0.09	0.02
	(0.14)	(0.17)
Δln(elderly)	-0.31	-0.12
	(0.23)	(0.27)
Δln(life_exp)	-0.52	-0.99
	(2.23)	(2.04)
Δln(life_exp65)	0.10	0.20
	(0.65)	(0.59)
t	0.00	0.00
	(0.00)	(0.00)
reliable		0.01
		(0.01)
Δln(opioid_crude)		0.02
		(0.01)
Δln(aids_crude)		0.00
		(0.00)
Δln(aids_rel_inter)		-0.01
		(0.01)
Observations	43	43
R^2	0.41	0.49
Adjusted R^2	0.30	0.30
Residual Std. Error	0.016 (df=35)	0.016 (df=31)
F Statistic	4.31^{**} (df=7; 35)	2.62^{*} (df=11; 31)

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

For both specifications (models 5 and 6, respectively) there are no statistically significant coefficients for any independent variable. The first impression from this finding is that there are no significant effects from any of the variables in the regression, including economic or health crises (with the unemployment rate and epidemic crude death rates as proxies, respectively).

This interpretation is nuanced, though, as *TOT_q* was calculated by dividing the spending measure, *TOT*, by the price measure, *CPI*, even though these data came from separate datasets. Although both are measured in the same location, time frame, and aggregation level, they may not match up perfectly as there are likely nuances to *TOT* not captured in the measurement of *CPI*, and vice versa. As a result, there likely exists measurement error in *TOT_q*, which may indicate it is not an accurate proportional measure of total healthcare quantity in the US, let alone an exact measure.

Therefore, the interpretations from these models may indicate that there are no effects of health and economic crises on total healthcare quantities in the US for the time period 1970 – 2013, but because of the possibility for measurement error, another study with accurate quantity measurements would be necessary to safely conclude these findings are accurate. As such, no matter the findings from these models, they have no bearings on the rejection of both null hypotheses as discussed previously for models 1 – 4 in Table 2.

3.4 Segmented Healthcare Spending

Unlike previous literature, this study contains a segmented analysis of the US healthcare market when examining possible factors of healthcare spending. Table 4 displays results from the CM specification of aggregate healthcare spending for out-of-pocket (*OOPEXP*) consumers, private insurance plus non-profit organizations (*VOLUNTARY*), and public sector or government (*COMPULSORY*) spending.

Table 4: OLS regression results of the segmented analysis using CM specification on *OOPEXP*, *VOLUNTARY*, and *COMPULSORY* (models 7, 8, 9, respectively) with HC1 estimated robust standard errors (in parentheses).

Dependent (Model #)	Δln(OOPEXP) (7)	Δln(VOLUNTARY) (8)	Δln(COMPULSORY) (10)
const	0.03	0.01	0.10^{***}
	(0.04)	(0.04)	(0.02)
Δln(unemp)	-0.02	0.02	0.08^{***}
	(0.03)	(0.03)	(0.02)
Δln(income)	0.76^{*}	1.10^{***}	0.38
	(0.36)	(0.31)	(0.22)
Δln(alc)	-0.09	-0.50	0.01
	(0.25)	(0.26)	(0.15)
Δln(elderly)	0.02	0.14	0.11
	(0.42)	(0.36)	(0.36)
Δln(life_exp)	3.26	4.06	-5.10^{*}
	(3.06)	(3.02)	(2.09)
Δln(life_exp65)	-0.51	-0.93	1.75^{**}
	(1.00)	(1.02)	(0.61)
t	0.00	0.00	-0.002^{***}
	(0.00)	(0.00)	0.00
reliable	-0.03^{***}	-0.01	0.00
	(0.01)	(0.01)	(0.01)
Δln(opioid_crude)	0.03	0.03	-0.02
	(0.02)	(0.02)	(0.01)
Δln(aids_crude)	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)
Δln(aids_rel_inter)	-0.01	0.00	0.01
	(0.01)	(0.01)	(0.01)
Observations	43	43	43
R^2	0.66	0.76	0.85
Adjusted R^2	0.54	0.67	0.79
Residual Std. Error	0.023 (df=31)	0.021 (df=31)	0.016 (df=31)
F Statistic	11.92^{***} (df=11; 31)	17.44^{***} (df=11; 31)	18.68^{***} (df=11; 31)

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Similar to *TOT*, there appears to be no significant effects from health crises on any of the US healthcare market segments. This provides further evidence that health crises truly have no effect on healthcare spending in the US as they appear to have no effect on the medical care *CPI* or any segment of the US healthcare market (models 3, 4, 7, 8, 9, respectively).

Economic crises, as proxied with unemployment, appear to significantly effect *COMPULSORY* healthcare spending only, with a positive coefficient indicating that as an economic crisis occurs the US government starts spending more on healthcare. This finding, along with the positive coefficient on *unemp* for *TOT* (Table 2, model 3), implies that healthcare spending in the US is in fact countercyclical, specifically from government healthcare spending. This may be beneficial to the average US citizen as less cyclical healthcare spending had been correlated with lower death rates (Liang and Tussing 2019), implying that the US government may in fact be helping to lower the average US death rate with countercyclical healthcare spending behavior.

OOPEXP and *COMPULSORY* experience elasticities indicating healthcare in those segments as necessity goods (although the coefficient for *COMPULSORY* was statistically insignificant). *VOLUNTARY*, on the other hand, experiences an elasticity greater than 1, indicating *VOLUNTARY* healthcare spending as a luxury good. *OOPEXP* is out-of-pocket spending by individual US healthcare consumers while *VOLUNTARY* is healthcare spending by private organizations (whether they are large corporations, insurance companies, or non-profits), with these differences likely indicating very different levels of income in either segment as *OOPEXP* will behave similarly to the income of an average individual in the US while the income of a corporation or organization (as captured in *VOLUNTARY*) will be at a significantly higher level since it acts similarly to the income of an entire organization. This appears to be a similar finding to the literature stating that healthcare spending elasticities relative to income are dependent on the level of income (Di-Matteo 2003), although in reverse. The findings of Di-Matteo (2003) describe healthcare as a luxury good at lower levels of income and as a necessity good at higher levels of income; the opposite appears to be true based on the coefficients for *income* in models 7 and 8, respectively. Finding a study that replicates either results from this study or those from Di-Matteo (2003) are necessary for understanding the disagreement between such elasticities of healthcare segments in the US.

COMPULSORY appears to be the only of these three segments that is affected by any of the exogenous variables other than *income* and *unemp*. Coefficients on *life_exp*, *life_exp65*, and the time trend are all statistically significant. *life_exp* may indicate that as the population health rises life expectancy at birth increases causing individuals to require less healthcare resources in the current periods and therefore the US government does not need to spend as much on their health. Conversely, as life expectancy at 65 increases it would appear that the US government bears much of the burden on providing healthcare spending to the elderly population in the US to preserve elderly health status in the current period, therefore increasing *COMPULSORY* in the present. These findings may suggest that better population health has a long-term lagged increase on public healthcare spending in the US.

Finally, the time trend is negatively statistically significant for *COMPULSORY*, which may indicate that as time passes the government prefers to spend less on healthcare. Considering the constant is also statistically significant and positive it may just be that the government prefers to increase its healthcare spending at a decreasing rate over time (as all data are first differenced). This may suggest a preference captured by the time trend, similarly described by Tanjudeen, Tanjudeen, and Duada (2018).

3.5 Limitations

This study faced multiple limitations, among which were issues of non-stationarity, periodicity, irregularities in health crisis data, and interpretations of results when combining separate datasets.

Non-stationarity, although addressed with transforming the data using the natural logarithm and then first differencing, likely did not account for all non-stationarity. This is evident as some of the regression equations contained either a statistically significant constant, linear time trend, or both. Similarly, many of the variables trended together, likely creating some issues of multicollinearity (although not explicitly tested for). These issues combined likely accounted for the large R-squared values found in the regressions, even though so few coefficients were statistically significant.

The periodicity of the data, namely all data being annual and already heavily aggregated, meant any short-term variations in the data would not be captured by the models of this study. Specifically, if there was a short-term effect of any of the independent variables (possibly from omitted variable bias) that caused a significant change in healthcare spending lasting less than a year this study would not capture such variations. This lack of granularity may imply that some of the results and interpretations are sub-optimal, but, considering how similar this methodology was to the literature, that may not be the case. It is still the case that this study and much of the literature would not be able to account for many short-term effects.

As described in *Methods*, there were many assumptions when using health crisis data in this study. Those included the *reliable* dummy variable's creation as well as assuming the crude death rate of the epidemics used were zero in years prior to their "start date." Due to a lack of literature revolving this topic (lending to the novelty of this study) this methodology appeared to be the most econometrically sound given the data used. Further study on such variables with differing data and methodologies would help to confirm or deny such a claim.

Lastly, the quantity measure, *TOT_q*, likely contains heavy measurement error and therefore may be meaningless. It may have been wiser to conduct a similar approach to finding a quantity measure as in other literature, such as pharmaceutical spending, the number of medical consultations (Portela and Thomas 2013), or the number of doctors (Thorton and Beilfuss 2016), but those are not perfect measures for healthcare quantity either. The method used in this study, namely dividing the spending measures from OECD data with the medical care CPI measures from the BLS, may have been the optimal approach for regressing aggregated healthcare quantity consumed, but further research to find if there truly is significant measurement error, or to recreate this study with other data and methodologies, are necessary to agree or disagree with the findings of this study.

4 Conclusions

The main result of this study was to reject both null hypotheses presented. Regression results showed no significant effects of health crises on any aggregation of US healthcare spending, while economic crises appear to have a positive (not negative, as hypothesized) effect on healthcare prices, total healthcare spending, and government health spending in the US. These results indicate that there appears to be no demand effect from health crises while there is likely a demand increase in healthcare during economic crises felt mostly by the US government.

When comparing this study with the literature it would appear that it agrees that unemployment and income are major factors of US aggregate healthcare spending. Similarly, the regression results indicate that price and spending increase together, with many of the factors that affect spending also affecting price in the same direction, possibly indicating price as the main driver of the US healthcare spending increases in recent decades, similar to the findings of Deileman, et al. (2017).

Conversely, this study disagrees that other factors found in the literature are significant. Some such factors do appear to be significant in certain segments of the US healthcare market, specifically government healthcare spending. Considering the focus on either total or government healthcare spending in the literature it may be the case that "factors of healthcare spending" in the literature only affect total and government spending specifically because they were the only segments actively studied – lending to their significance on total and government healthcare spending in this study. Other segments may have entirely different factors – leading to the lack of significance for such factors on other segments and a need for further study of each segment.

Elasticity of healthcare relative to income in the US is a more complicated subject. The main regressions agree with some of the most recent literature that the US experiences healthcare spending as a necessity good, but the segmented analysis shows that finding is only on average and not across all segments in the US healthcare market, individually. Government spending (although its income coefficient was statistically insignificant) and out-of-pocket expenditures experienced healthcare as a necessity good, but private spending from organizations were shown to be a luxury good. This finding agrees with Di-Matteo (2003) that the level of income is likely a factor of the elasticity of healthcare relative to income – although this study finds the opposite of Di-Matteo as higher income segments were shown to experience healthcare as a luxury and lower income segments were shown to experience healthcare as a necessity in this study.

The limitations of this study indicate the need for further research with segmented price, quantity, and spending measures for healthcare at a higher periodicity (monthly or quarterly data instead of annual) and with more accurate measures for health crises. Specifically for health crises, including both death rate measures, and disease prevalence measures may provide more insight into the effects of health crises on the US healthcare system. Such research would be able to replicate and possibly agree with the findings of this study and/or other literature.

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6.1 Appendix A

Crude death rate data for the HIV/AIDS epidemic were recorded from the CDC Wonder *Compressed Mortality* files (1979 – 1998 and 1999 – 2015). The definition of "crude death rate" as described in the study was found in the documentation page for the *Compressed Mortality* files. The "crude death rate" is described as the total number of deaths attributed to a cause of death in a given year divided by the total population of the US in that year and then multiplied by 100,000. In essence, it is the average number of deaths for a specific cause of death aggregated out to an average population of 100,000 US residents. (Centers for Disease Control and Prevention, National Center for Health Statistics n.d.) (Centers for Disease Control and Prevention, National Center for Health Statistics n.d.)

International Classification of Disease (ICD) codes used to define deaths for HIV/AIDS in the 1979 – 1998 *Compressed Mortality* file were: ICD-9 042 – 044, and 708.9. (Centers for Disease Control and Prevention, National Center for Health Statistics n.d.)

ICD codes used to define deaths for HIV/AIDS in the 1999 – 2015 *Compressed Mortality* file were: ICD-10 B20-24, I88.0, I88.1, I88.8, I88.9, J84.0, J84.1, J84.8, J48.9, L04.0 – L04.3, L04.8, L04.9, 098.7, R59.1, R62.8, R64, and R75. (Centers for Disease Control and Prevention, National Center for Health Statistics n.d.)

Opioid overdose crude death rates and descriptions were found in an article written by the CDC. ICD codes used to define deaths for opioid overdoses were: ICD-10 T40.0 – T40.4, T40.6. (National Institutes of Health National Institute on Drug Abuse 2021)

All medical data from the sources listed here are deidentified and available to the general public.

6.2 Appendix B

Medical care CPI is described by the BLS as:

> "The medical care index is one of eight major groups in the Consumer Price Index (CPI) and is divided into two main components: medical care services and medical care commodities, each containing several item categories. Medical care services, the larger component in terms of weight in the CPI, is organized into three categories: professional services, hospital and related services, and health insurance. Medical care commodities, the other major component, includes medicinal drugs and medical equipment and supplies." (U.S. Bureau of Labor Statistics 2020)

This measure for the medical care CPI was found on the Federal Reserve of St. Louis (FRED) website (U.S. Bureau of Labor Statistics 2021).

6.3 Appendix C

The following table provides a full description of all variables used in this study from the OECD databases.

Measure	Description
Alcohol Consumption	“Alcohol consumption is defined as annual sales of pure alcohol in litres per person aged 15 years and older. Alcohol use is associated with numerous harmful health and social consequences, including an increased risk of a range of cancers, stroke and liver cirrhosis. Alcohol also contributes to death and disability through accidents and injuries, assault, violence, homicide and suicide. This indicator is measured in litres per capita (people aged 15 years and older).” (OECD 2020)
Elderly Population	“The elderly population is defined as people aged 65 and over. The share of the dependent population is calculated as total elderly and youth population expressed as a ratio of the total population. The elderly dependency rate is defined as the ratio between the elderly population and the working age (15-64 years) population. The comparability of elderly population data is affected by differences, both within and across countries, in how regions and the geography of rural and urban communities, are defined. Elderly people tend to be concentrated in few areas within each country, which means that a small number of regions will have to face a number of specific social and economic challenges due to population ageing. These demographic trends have a number of implications for government and private spending on pensions, health care, and education and, more generally, for economic growth and welfare. This indicator is measured as a percentage of population.” (OECD 2020)
Health Spending	“Health spending measures the final consumption of health care goods and services (i.e. current health expenditure) including personal health care (curative care, rehabilitative care, long-term care, ancillary services and medical goods) and collective services (prevention and public health services as well as health administration), but excluding spending on investments. Health care is financed through a mix of financing arrangements including government spending and compulsory health insurance (“Government/compulsory”) as well as voluntary health insurance and private funds such as households’ out-of-pocket payments, NGOs and private corporations (“Voluntary”). This indicator is presented as a total and by type of financing (“Government/compulsory”, “Voluntary”, “Out-of-pocket”) and is measured as a share of GDP, as a share of total health spending and in USD per capita (using economy-wide PPPs).” (OECD 2020)
Household Disposable Income	“Disposable income is closest to the concept of income as generally understood in economics. Household disposable income measures the income of households (wages and salaries, self-employed income, income from unincorporated enterprises, social benefits, etc.), after taking into account net interest and dividends received and the payment of taxes and

	social contributions. Net signifies that depreciation costs have been subtracted from the income presented. "Real” means that the indicator has been adjusted to remove the effects of price changes. Household gross adjusted disposable income is the income adjusted for transfers in kind received by households, such health or education provided for free or at reduced prices by government and NPISHs. This indicator is presented both in terms of annual growth rates (for real net disposable income) and in terms of USD per capita at current prices and PPPs (gross adjusted disposable income). All OECD countries compile their data according to the 2008 System of National Accounts (SNA 2008).” (OECD 2020)
Life Expectancy at 65	“Life expectancy at age 65 years old is the average number of years that a person at that age can be expected to live, assuming that age-specific mortality levels remain constant. However, the actual age-specific death rate of any particular birth cohort cannot be known in advance. If rates are falling, as has been the case over the past decades in OECD countries, actual life spans will be higher than life expectancy calculated using current death rates. The methodology used to calculate life expectancy can vary slightly between countries. This can change a country’s estimates by a fraction of a year. This indicator is presented by gender and is measured in years.” (OECD 2020)
Life Expectancy at Birth	“Life expectancy at birth is defined as how long, on average, a newborn can expect to live, if current death rates do not change. However, the actual age-specific death rate of any particular birth cohort cannot be known in advance. If rates are falling, actual life spans will be higher than life expectancy calculated using current death rates. Life expectancy at birth is one of the most frequently used health status indicators. Gains in life expectancy at birth can be attributed to a number of factors, including rising living standards, improved lifestyle and better education, as well as greater access to quality health services. This indicator is presented as a total and per gender and is measured in years.” (OECD 2020)
Unemployment	“The unemployed are people of working age who are without work, are available for work, and have taken specific steps to find work. The uniform application of this definition results in estimates of unemployment rates that are more internationally comparable than estimates based on national definitions of unemployment. This indicator is measured in numbers of unemployed people as a percentage of the labour force and it is seasonally adjusted. The labour force is defined as the total number of unemployed people plus those in employment. Data are based on labour force surveys (LFS). For European Union countries where monthly LFS information is not available, the monthly unemployed figures are estimated by Eurostat.” (OECD 2020)

6.4 Appendix D

Full datasets and regression/code files may be found on the following GitHub repository for evaluation and replication purposes.

https://github.com/leeorei/health-economic-crises-healthcare-Intrator

7 Works Cited

Baltagi, Badi H., and Francesco Moscone. 2010. "Health care expenditure and income in the OECD reconsidered: Evidence from panel data." *Economic Modelling* 27: 804-811.

Centers for Disease Control and Prevention. 2021. *Epidemic Disease Occurrence.* May 18. Accessed March 24, 2021. https://www.cdc.gov/csels/dsepd/ss1978/lesson1/section11.html.

Centers for Disease Control and Prevention, National Center for Health Statistics. n.d. *Compressed Mortality File 1979-1998.* Comp. Series 20, No. 2A, 2000 and CMF 1989-1998, Series 20, No. 2E, 2003 Compressed Mortality File CMF 1968-1988. Accessed March 31, 2021. http://wonder.cdc.gov/cmf-icd9.html.

Centers for Disease Control and Prevention, National Center for Health Statistics. n.d. *Compressed Mortality File 1999-2015 Archive on CDC WONDER Online Database.* Comp. CMF 1999-2015 Series 20 No. 2U. Accessed March 31, 2021. http://wonder.cdc.gov/cmf-icd10-archive2015.html.

Deileman, Joseph L., Ellen Squires, Anthony L. Bui, Madeline Campbell, Abigail Chapin, Hannah Hamavid, Cody Horst, et al. 2017. "Factors Associated With Increases in US Health Care Spending, 1996-2013." *JAMA 318(17)* 1668-1678.

Devlin, Nancy, and Paul Hansen. 2001. "Health care spending and economic output: Granger causality." *Applied Economics Letters* 8: 561-564. doi:10.1080/13504850010017357.

Di-Matteo, Livio. 2003. "The income elasticity of health care spending. A comparison of parametric and non-parametric approaches." *European Journal of Health Economics* 4 (1): 20-29.

Di-Matteo, Livio, and David Cantarero-Prieto. 2018. *The Determinants of Public Health Expenditures: Comparing Canada and Spain.* Munich: Munich Personal RePEc Archive (MPRA), July 13. Paper.

Di-Matteo, Livio, and Rosanna Di-Matteo. 1998. "Evidence on the determinants of Canadian provincial government health expenditures: 1965-1991." *Journal of Health Economics* 17 (2): 211-228.

Faramarzi, Ahmad, Javad Javan-Noughabi, Ahmad Sadeghi, and Aziz Rezapour. 2019. "Impact of the economic crisis on healthcare resources: A panel data analysis in Eastern Mediterranean countries during 2005 to 2013." *Clinical Epidemiology and Global Health 7(1)* 98-101.

Freeman, Donald G. 2003. "Is health care a necessity or a luxury? Pooled estimates of income elasticity from US state-level data." *Applied Economics* 35 (5): 495-502.

Granados, Jose A. Tapia, and Javier M. Rodriguez. 2015. "Health, economic crisis, and austerity: A comparison of Greece, Finland, and Iceland." *Health Policy 119* 941-953.

Hall, Robert E., and Charles I. Jones. 2007. "The value of life and the rise of health spending." *Quarterly Journal of Economics* 122: 39-72.

Khan, Muhammad Arshad, and Muhammad Iftikhar Ul Husnain. 2019. "Is health care a luxury or necessity good? Evidence from Asian countries." *International Journal of Health Economics and Management* 19: 213-233. doi:10.1007/s10754-018-9253-0.

Liang, Li-Lin, and A. Dale Tussing. 2019. "The cyclicality of government health expenditure and its effects on population health." *Health Policy 123* 96-103.

Martin, Jose J. Martin, and M. Puerto Lopez del Amo Gonzalez. 2011. "Review of the literature on the determinants of healthcare expenditure." *Applied Economics 43(1)* 19-46.

Mommaerts, Corina, and Yulya Truskinovsky. 2020. "The cyclicality of informal care." *Journal of Health Economics 71* 102306.

Moscone, Francesco, and Elisa Tosetti. 2010. "Health expenditure and income in the United States." *Health Economics* 19 (12): 1385-1403.

National Institutes of Health National Institute on Drug Abuse. 2021. "Overdose Death Rates." *National Institute on Drug Abuse*. January 29. Accessed March 24, 2021. https://www.drugabuse.gov/drug-topics/trends-statistics/overdose-death-rates.

OECD. 2020. *Alcohol Consumption (indicator).* Accessed November 5, 2020. doi:10.1787/e6895909-en.

OECD. 2020. *Elderly Population (indicator).* doi:10.1787/8d805ea1-en (Accessed on 05 November 2020).

OECD. 2020. *Health spending (indicator).* doi:10.1787/8643de7e-en (Accessed on 05 November 2020).

OECD. 2020. *Household disposable income (indicator).* doi:10.1787/dd50eddd-en (Accessed on 05 November 2020).

OECD. 2020. *Life expectancy at 65 (indicator).* doi:10.1787/0e9a3f00-en (Accessed on 10 November 2020).

OECD. 2020. *Life expectancy at birth (indicator).* doi:10.1787/27e0fc9d-en (Accessed on 05 November 2020).

OECD. 2020. *Unemployment rate (indicator).* doi:10.1787/52570002-en (Accessed on 05 November 2020).

Portela, Conceicao, and Steve Thomas. 2013. "Impact of the economic crisis on healthcare resources: An European approach." *International Journal of Healthcare Management 6(2)* 104-113.

Scandlyn, Jean. 2000. "When AIDS became a chronic disease." *The Western Journal of Medicine* 172 (2): 130-133. doi:10.1136/ewjm.172.2.130.

Tajudeen, Olufunmilayo S., Ibrahim A. Tajudeen, and Risikat O. Dauda. 2018. "Quantifying Impacts of Macroeconomic and Non-economic Factors on Public Health Expenditure: A Structural Time Series Model." *African Development Review* 20 (2): 200-218.

Thorpe, Kenneth E. 2006. "Factors accounting for the rise in health-care spending in the United States: The role of rising disease prevalence and treatment intensity." *Public Health* 120 (11): 1002-1007. doi:j.puhe.2006.09.001.

Thorton, James A., and Jennifer L. Rice. 2008. "Determinants of healthcare spending: a state level analysis." *Applied Economics 40(22)* 2873-2889.

Thorton, James A., and Svetlana N. Beilfuss. 2016. "New evidence on factors affecting the level and growth of US health care spending." *Applied Economics Letters 23(1)* 15-18.

U.S. Bureau of Labor Statistics. 2020. *Consumer Price Index - Measuring Price Change in the CPI: Medical Care.* November 25. Accessed March 15, 2021. https://www.bls.gov/cpi/factsheets/medical-care.htm.

U.S. Bureau of Labor Statistics. 2021. *Consumer Price Index for All Urban Consumers: Medical Care in U.S. City Average [CPIMEDSL].* Accessed March 25, 2021. https://fred.stlouisfed.org/series/CPIMEDSL.

Yu, Yihua, Li Zhang, Fanghua Li, and Xinye Zhen. 2013. "Strategic Interaction and the Determinants of Public Health Expenditure in China: A Spatial Panel Perspective." *The Annals of Regional Science* 50 (1): 203-221.