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Bachelor thesis

2020 **Matyáš Juřena**

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The Effect of Covid-19 on Economic Growth: Cross-Country Determinants

Bachelor thesis

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Abstract

Not only does the COVID-19 pandemic threaten the health of millions of people worldwide, it has also thrown the global economy into a recession. Moreover, differences in the expected decline of countries' economic output exist. Thus, the objective of this thesis is to identify the cross-country determinants of the economic downturn caused by the pandemic. An extensive dataset of 34 explanatory variables describing the characteristics of 145 countries is analyzed. To address the inherent model uncertainty present in the cross-country analysis of such magnitude, we apply the econometric method of Bayesian Model Averaging (BMA). Consequently, we have identified the best regression model, which includes five explanatory variables with reasonable interpretations. To our knowledge, this thesis is the first work studying the cross-country differences in the output decline caused by the coronavirus pandemic. However, a more detailed analysis of the effects of policy measures on the duration of a recession and the speed and size of the expected future recovery is suggested, once data is available.

Keywords

COVID-19, coronavirus, Bayesian Model Averaging

Abstrakt

Pandemie COVID-19 neohrožuje jen životy miliónů lidí na celém světě, ale zároveň i zapříčinila globální recesi. Kromě toho existují rozdíly v očekávaném poklesu hospodářské produkce zemí. Cílem této bakalářské práce je identifikovat determinanty ekonomického útlumu způsobeného pandemií napříč zeměmi. Analyzuje se rozsáhlý soubor 34 proměnných popisujících charakteristiky 145 zemí. Pro řešení inherentní nejistoty modelu přítomné v analýze takové velikosti používáme ekonometrickou metodu Bayesovského modelu průměrování. Následně jsme identifikovali nejlepší regresní model, který zahrnuje pět proměnných s rozumnými interpretacemi. Pokud je nám známo, je tato práce první prací, která studuje rozdíly mezi jednotlivými zeměmi v poklesu produkce způsobené koronavirovou pandemií. Jakmile však budou k dispozici data, navrhuje se podrobnější analýza účinků politických opatření na dobu trvání recese a rychlost a velikost očekávaného budoucího ekonomického oživení.

Klíčová slova

COVID-19, koronavirus, Bayesovské modelové průměrování

Declaration of Authorship

I hereby proclaim that I wrote my bachelor thesis on my own under the leadership of my supervisor and that the references include all resources and literature I have used.

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Prague, May 7, 2020

Signature

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Bachelor's Thesis Proposal

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Proposed Topic:

The Effect of Covid-19 on Economic Growth: Cross-Country Determinants

Preliminary scope of work:

Research question and motivation

The main question of my thesis is: How does the COVID-19 Pandemic affect economic growth around the globe?

The long period of economic growth since the 2008 subprime mortgage crises was put to an end by a swift economic drop – the fastest ever on record. This specific topic is important because the global slow down caused by the spread of the COVID–19 will likely have far-reaching implications for economies and individuals around the globe for years to come.

Contribution

Since the COVID-19 Pandemic is an event without precedents, there is almost no literature covering the topic. Thus, my bachelor thesis can serve as a foundation for further empirical studies of the phenomenon.

Methodology

The IMF's *World Economic Outlook forecast* datasets of projections are going to be used. The work will make use of cross-country regressions to explain the factors (intensity of relations with China, levels of measures taken etc.) driving growth forecast revisions after the eruption of the pandemic.

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    c. Topics for further research

List of academic literature:

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1 Introduction

The current coronavirus pandemic is unprecedented. Due to the globalized world we live in nowadays, the virus has spread abruptly between countries, regions, and even continents. It is arguable that the lock-down policies implemented around the globe – including closures of international borders and country-wide quarantines – has put the human population into a sudden halt never experienced before.

On 31st December 2019, 27 cases of pneumonia of unknown causes were identified in Wuhan City, Hubei province in China. Eight days later, he causative agent was identified by the Chinese Centre for Disease Control and Prevention and it was given the name Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2). The World Health Organization later named the disease caused by the coronavirus COVID-19 (Sohrabi et al., 2020).

The COVID-19 outbreak has been declared a global pandemic by the World Health Organization on March 11th. The number of confirmed COVID-19 cases outside of China has increased 13-fold in the two weeks prior to the notice, amounting to more than 118,000 cases and 4,291 deaths in 114 countries as of the date of the announcement (Sohrabi et al., 2020; WHO, 2020, March 11). At the time of this writing (May 3rd, 2020), the total number of confirmed COVID-19 cases has reached 3,481,349 - an increase of more than 2 million cases in the past month. More than a million of COVID-19 patients have already recovered from the disease. Out of the remaining 2,162,097 active cases, some 50 thousand patients worldwide are in a serious or critical state. The total death toll of the disease is 244,663.

Not only does the pandemic pose a significant threat to the population of the world, but also to its economic outputs. The global stock exchanges' prices plummeted at breakneck speed in March, with the S&P 500 stock market index falling 30% from its record high in just 22 days – the fastest drop of such magnitude in recorded history. The International Monetary Fund's (IMF) has estimated the global output to decline by 3% in 2020. However, differences in the expected decline of countries' economic growth exist.

Thus, the main objective of this thesis is to estimate the variables impacting the early effects of the COVID-19 pandemic on the economic growth based on collected cross-country evidence. The body of economic research on this topic is very thin, if not nonexistent. Thus, this work hopes to become one of the first building blocks in the future research of the current issue.

This bachelor thesis is organized as follows: the definition of a pandemic, the occurrences of pandemics in human history, and their impacts on the economy are introduced in Section 2. Section 3 provides a description of the supply and demand shocks currently present and the consequential economic stimulus policies implemented, alongside with a general characterization of the contemporary global coronavirus pandemic. The extensive dataset of 35 explanatory variables is commented on in Section 4. Section 5 describes the methodology used for the Bayesian model averaging method. The results of our econometric analysis are discussed in Section 6 and the final Section 7 concludes the findings of this thesis.

2 Pandemics

This chapter provides a definition of pandemics, an introduction into the history of past pandemics, and a description of the connectedness of pandemics and economics.

2.1 What is a pandemic?

A disease outbreak is called an epidemic when the disease spreads quickly and it affects many individuals at the same time i.e., there is a sudden increase in the number of cases of the disease. An epidemic might turn into a pandemic when it spreads over a large area. To be more precise, the most internationally accepted definition of the term pandemic is: "an epidemic occurring worldwide, or over a very wide area, crossing international boundaries and usually affecting a large number of people" (Last, 2001). The definition as such is quite broad. To be more concrete, most pandemics generally share the following key characteristics:

- *Wide geographic range.* Epidemic diseases are referred to as pandemic whenever they spread in large geographic areas. WHO declares a disease to be pandemic once it expands in at least two WHO regions[1].
- *Disease transmission.* Pandemics imply unanticipated spread in between geographical spaces. A disease can be transmitted directly (person to person) or indirectly (person to vector to person) (Morens et al., 2009). Furthermore, out-of-season spread distinguishes influenza (flu) pandemics from periodically repetitive disease outbreaks, such as the common flu, which are commonly not regarded as epidemics.
- *Novelty.* Usually, only new diseases or different mutations of previously known diseases are described by the term pandemic (Qiu et al., 2017).
- *Severity.* Only severe or fatal diseases are considered pandemics, where the specific fatality ratio is used to estimate severity (Donaldson et al., 2009).
- *Explosiveness and high attack rate.* Diseases are usually not classified as pandemics if they have low rates of transmission. The West Nile virus, for instance, was not classified as a pandemic because its transmission was slow, even though it spread to the Middle East, Russia, and the Western Hemisphere. (Qiu et al., 2017).
- *Minimal immunity of population.* Low population immunity is characteristic of pandemics, allowing the disease to spread more easily (Fangriya, 2015).
- *Contagiousness and infectiousness.* Non-infectious diseases that are wide-spread and have a rising global incidence, such as obesity, are most

[1] WHO member states are grouped into a total of six regions: the African Region, the Eastern Mediterranean Region, the European Region, The South-East Asia Region, the Western Pacific Region, and the Region of the Americas (WHO, 2010).

often not regarded as pandemics because they are not transmissible (Qui et al., 2017).

2.2 Pandemics in history

Little information regarding epidemics exists prior to 1500. The oldest found record is that of Thucydides, who described the spread of a very violent disease in the Greek city of Athens (430 BC) (Hays, 2006). Later, reports of similar diseases appeared all over Europe: 664 A.D in England; 1173-1174 in England, France and Italy; 1357 in Florence, Italy; 1414 in France; and 1427 in France and England. However, these reports contained little or no information regarding the number of infected individuals and the number of deaths (Creighton 1894). Widespread epidemics occurred in Europe in 1510, 1557, and 1580. The 1580 epidemic is also the first well-described pandemic in human history and we know that it spread from Asia to Africa, Europe and it was eventually even observed in the Americas (Will et al., 2002). More influenza epidemics occurred in Europe in the 17th and 18th centuries, some of which became pandemics. The most severe of them occurred in 1781-1782 and it affected both North and South America as well as most of Europe (Crosby, 1993). Three influenza pandemics occurred in the 19th century. The very severe 'Russian flu' pandemic of 1889-1890, which also happens to be the first influenza for which detailed records were registered, originated in Russia and spread to Europe, North America, South America, and Asia. It is estimated that approximately 40% of the world's population was infected and approximately 1 million people died of the disease (Crosby, 1993; Enserink, 2006).

In the 20th century, there were three influenza pandemics: the 1918-1919 'Spanish Flu', also known as the Great Influenza Pandemic, the 'Asian Flu' in 1957-1958 and the 'Hong Kong Flu' in 1968-1969 (WHO, 2011). The 'Spanish Flu' is the most devastating pandemic recorded to date with estimates of lethality at 3.5% and the upper boundary of the total number of deaths amounting up to 100 million (Frost et al. 1930; Niall et al. 2002).

Its global spread has been significantly eased by the high fluctuation of army bodies during and after World War 1, especially throughout Europe and the USA. Additionally, some historians believe that the pandemic likely caused WW1 to end prematurely. In terms of its economic consequences, the 'Spanish flu' pandemic might have caused the largest negative macroeconomic shock for the world outside of World War I, World War II, and the Great Depression of the early 1930s (Crosby 1976; Patterson 1986).

It might be worth pointing out that all the pandemics of the 20th century are most likely to have emerged from China, if we allow ourselves to include Hong Kong to be a geographical part of China for the sake of this simplified statement.

In the 21st century, there were at least 6 large virus outbreaks - hantavirus pulmonary syndrome, severe acute respiratory syndrome, H5N1 influenza, H1N1 influenza, Middle East respiratory syndrome, and Ebola virus disease epidemic (Gostin et al., 2016). The first influenza pandemic of the 21st century was the H1N1 influenza 2009 virus (A/2009/H1N1), which has caused over 18,000 deaths worldwide (Rewar et al., 2015).

2.3 Pandemics and economics

The overall economic costs can be divided into three categories: direct costs, indirect costs, and long term burden.

The direct costs include the extra spending on hospitals, staff, and medication required to deal with a disease outbreak. These costs can understandably be quite significant. For instance, the Ebola outbreak in 2015 cost USD 6 billion in direct costs (medication, staff, hospitals, etc.) in Sierra Leone alone (Gostin Friedman, 2015). The estimates by the Global Health Risk Framework for the Future (GHRF) Commission state that infectious disease outbreaks cost the world approximately USD 60 billion in direct costs annually on average (Maurice, 2016).

The lost earnings of those who die during a disease outbreak are one of the main long term burdens. For instance, Prager et al (2016) have calculated that 80% of the economic losses in the case of a pandemic in the USA would be linked to the sum of expected future lifetime earnings of those who would die.

Indirect costs are not insignificant neither, as they consist of all the elements leading to a GDP decline. Take the SARS 2003 epidemic as an example - it is estimated to have caused an annual GDP decrease of 1% in China and 0.5% in South Korea in 2003 (MacKellar, 2007). The income losses linked to the SARS outbreak in East and Southeast Asia were estimated to range between USD 12.3 - 28.4 billion (Fan, 2003). Outside of lower production and consumption losses, past pandemics have at times also affected the social order in some of the affected countries. For instance, the Ebola pandemic of 2015 has shaken political stability in West Africa, disrupted public services such as education, and transport and also reduced the quality of life of families and whole communities, which were often forced to be isolated (Nabarro & Wannous, 2016).

3 The coronavirus pandemic

The causative agent of the COVID-19 disease, the coronavirus SARS-CoV-2, is introduced at the beginning of this section. Then, the most important developments of the 2020 coronavirus pandemic are summarized in an overview. Next, the supply and demand shocks affecting the world economies are described. The last part of this chapter comments on the 'anti-coronavirus' monetary and fiscal policies that are being implemented by policymakers around the world.

3.1 SARS-CoV-2

Coronaviruses form a large family of viruses, which can potentially cause illness in animals or humans. In humans, numerous known coronaviruses cause respiratory infections ranging from the common cold to more serious diseases such as Middle East Respiratory Syndrome or Severe Acute Respiratory Syndrome. Severe acute respiratory syndrome coronavirus 2, SARS-

CoV-2 in short, is the most recently discovered coronavirus, which causes the coronavirus disease 2019 (COVID-19). The symptoms of COVID-19 are usually dry cough, fever, and tiredness. Some individuals may also have aches, pains, sore throat, and diarrhea. The symptoms commonly start to show around five or six days after exposure but they can take up to 14 days to appear. Moreover, a significant portion of infected individuals are asymptomatic, i.e. they do not show any symptoms of the disease, which causes the virus to spread more rapidly due to the lack of precautionary measures taken by such individuals. Most infected people have only very mild symptoms and approximately 80% of those infected recovers from the disease without the need for hospital treatment. The remaining 20% of patients become seriously ill and develop breathing difficulties. (Microbiology, 2020; WHO, 2020b) The disease's fatality rate[2] ranges from 2.3% in China up to 7.2% in Italy. The large difference in fatality rates in different countries might be partially justified by population demographics since the virus seems to be fatal predominantly in patients aged 65 and above (Onder et al., 2020). Currently, a medical cure for COVID-19 does not exist.

3.1.1 Health recommendations

The virus spreads predominantly from person to person through tiny droplets that are transmitted when a COVID-19-positive individual speaks, coughs, or sneezes. The aforementioned droplets are quite heavy and, thus, are pulled towards the ground by gravity and do not travel very far. That is why social-distancing recommendations, such as staying at least two meters away from others, are being enforced around the world. These droplets do also lend on objects and surfaces, such as tables or handrails. People can get infected by touching such surfaces and then touching their eyes, mouth, or nose and that is the reason for the global recommendations on regular hand-washing. Yet another recommendation is self-isolation - those who have symptoms of the disease or are known to have been in contact with an infected person are recommended to stay at home and not go to work,

[2] The proportion of deaths compared to the total number of infected people (Harrington, 2020).

school, or public places (WHO, 2020b).

3.2 Spread of the pandemic

The virus originated in Mainland China and it has exponentially spread through Eastern Asia to the Middle East, Europe, the Americas, Australia, and Africa. The United States of America have registered the largest total number of cases in the world with the state of New York being hit the worst. As of May 3rd, there were 3,481,349 confirmed COVID-19 cases, 244,663 COVID-19-related deaths and 1,137,349 patients have recovered from the disease.

The following paragraphs provide a brief overview of facts and figures connected to the brisk advance of the virus throughout the world.

December & January On December 31st, 2019 Chinese Health officials informed the WHO about patients with an unknown type of pneumonia. Most of the patients were reported to have been to the Huanan Seafood Wholesale Market, which was closed by authorities the next day. On January 7, Chinese authorities identified a new type of coronavirus, nCoV, and on January 11th the first nCov-related death was recorded. Wuhan, the capital city of Hubei province in China with over 11 million inhabitants, was put under a complete lockdown on January 23rd. A week later WHO declared a global public-health emergency (Secon et al., 2020).

February The Philippines recorded the first COVID death outside of China on February 2nd. On February 9th the death toll of 811 in China has already surpassed that of the 2002-2003 SARS epidemic. WHO named the newly discovered disease COVID-19 on February 11th. Outbreaks in Italy and Iran, the first major epicenters of the pandemic outside of China, began in short succession on February 19th and 21st, respectively (Secon et al., 2020).

March Confirmed cases began to spike in Spain in early March and Italy, the worst-hit country outside of China at the time, imposed a nationwide lockdown on March 8th. WHO declared the outbreak a pandemic three days later on March 11th - surprisingly late[3]. US President Trump banned travel from 26 European countries on the same date. On March 19th China reported no new *locally spread* infections for the first time since the pandemic outbreak. Numerous other countries globally have adopted quarantine and lockdown measures throughout the month of March and as of March 31st, more than one third of the global population was under some form of lockdown (Secon et al., 2020).

April As of the beginning of April, 74% of European countries have imposed a national lockdown. The global count of COVID-19 infections surpassed 1 million on April 2nd. On April 7th, the British prime minister Boris Johnson was moved into intensive care ten days after publicly announcing his positive COVID-19 test. On April 10th the virus' global death toll surpassed 100,000. At this point, more than 22 million Americans have filed for unemployment since mid-March. Only thirteen days after reaching 1 million, the number of confirmed COVID-19 cases globally surpassed 2 million on April 15th. It has been declared that the economy has declined by 3.8% in the eurozone- the worst performance since records began in 1995 - and by 3.5% in the EU in the first quarter of 2020 (Al-Ubaydli, 2020; Eurostat, 2020; Taylor, 2020; Secon et al., 2020).

3.3 Economic impacts

Major car manufacturers completely suspended their production in numerous countries. Border closures, national quarantines, social distancing, and other measures made operations of services drastically harder, if not impossible, with transportation, entertainment, retail, and tourism sectors being hit the worst. Most professional sports leagues were suspended until further notice and the Tokyo Olympic Games were postponed until 2021 for the

[3] WHO's inapt response to the outbreak has later led to severe criticism of the organization and even calls for the resignation of Tedros Adhanom Ghebreyesus, WHO Director General (Yip, 2020). Moreover, Donald Trump has cut the US funding towards the organization on April 14th (Smith, 2020).

first time in their history. The number of job losses in the United States has reached an unprecedented high.

The world's economy is more digitized and complex than ever before. Nonetheless, most economic activities require the proximity of individuals, which is in direct contradiction with the advised health recommendations. Even though the economic impacts are a secondary issue from the pandemic point of view, the economic consequences of the sudden global halt are substantial. According to the International Monetary Fund's (IMF) projections, the 2020 global growth is estimated at -3 percent - a decrease of over 6 percentage points relative to the projections made in October 2019 – an outcome considerably worse than during the 2009 global financial crisis. The decline is expected to be -6.1% in the group of *advanced economies*, including the United States of America (-5.9%), Japan (-5.2%), the United Kingdom (-6.5%), Germany (-7.0%), France (-7.2%), Italy (-9.1%), and Spain (-8.0%). In comparison, the *emerging and developing economies* are projected to contract by -1.0% in 2020. The only sub-category with a projected positive growth rate is *Emerging Asia*[4] with an expected 1.0% growth in 2020 (IMF, 2020b).

The following paragraphs provide an overview of how the global shocks in supply and demand are affecting the world's economy and what policy measures are being implemented to overcome these shocks.

3.3.1 Supply shocks

The role and importance of China on the global trade have grown significantly in the past decades - the country has developed into a primary producer of high-value products and components, a large customer of global commodities and industrial products, and an attractive consumer marketplace. Specifically, Wuhan - the city where the pandemic started - plays an important part in many global supply chains. Its major industries include pharmaceuticals, bio-engineering, opto-electronic technology and modern

[4]According to IMF's categorization, Emerging Asia consists of the following countries: China, India, Indonesia, Malaysia, the Philippines, Thailand, and Vietnam (IMF, 2019)

manufacturing, such as automotive or steel and iron manufacturing. More than 200 of the Fortune Global 500 firms are present directly in Wuhan. Further, Wuhan and the Hubei province lockdown have severely affected the logistics within China. In response to the pandemic, the local authorities have prolonged Chinese New Year's holidays and even after the end of the national holidays, only about 70% of factories have reopened and at sub-optimal capacities (Deloitte, 2020).

Since we live in a substantially globalized world, a supply shock in one nation translates into a supply shock in other nations. Accordingly, the decline of Chinese production is associated with a major contraction of international trade flows. Chinese exports decreased by 17% over January and February, whilst the country's imports decreased by 4 percent in comparison to the same period of the previous year. Such a sharp drop is unprecedented, even if compared to the impacts of the 2002-2003 SARS outbreak or the 2008-2009 global financial crisis. These facts have severe implications for producers and consumers around the globe. For instance, 10% of all imported inputs into the German manufacturing sector originate in China, particularly in the electronics, computing, and textile manufacturing sectors. Further decrease of international trade is caused by (i) similar declines in production in the large number of COVID-19-affected countries worldwide, (ii) the inefficiencies in the complicated logistics of the international trade. The customs procedures, for example, have reportedly become rather cumbersome. Moreover, some countries have imposed large restrictions on trade with certain regions. The combined magnitude of these effects is staggering: the World Trade Organization's worst-case scenario for the year 2020 predicts a decrease of -31.9% in world merchandise trade due to the COVID-19 pandemic (Al-Ubaydli, 2020; Seric et al., 2020; WTO, 2020).

Another important part of the economic impacts of a pandemic is its burden on the supply of labor. Firstly, those infected with the disease are not able to work for a substantial amount of time. Further, prophylactic absenteeism — i.e. when healthy workers pull themselves out of their workplaces with the intent of not contracting the disease — significantly reinforces the issue. Moreover, many workers are enforced to stay at home with their children due to school closures. As of the beginning of April, 188 countries have imposed country-wide school closures, which represents approximately 1.6 billion students (that is, 91% of all learners) being out of school (Al-Ubaydli, 2020). For instance, a survey of Chinese citizens conducted by Zhang et al. (2020) in late February discovered that 25% of the labor force stopped working, 38% worked from home, and 27% continued working at an office.

3.3.2 Demand shocks

Baldwin Weder di Mauro (2020) mention two aspects of demand shocks worth distinguishing: practical and psychological. The practical aspects are quite straightforward - consumers are likely to seek to reduce their risk of contracting the disease and decrease the demand for products and service which might involve close contact with others. As for the psychological demand shock, some of us might still remember the last time the globalized world has experienced it — during the 2008-2009 global financial crisis. The uncertainty about future economic developments led to both firms and individuals adopting the 'wait-and-see' strategy — they tended to postpone investments and purchases. This behavior transformed the financial shock into a global demand shock. Arguably, the uncertainty of the current situation might be of an even higher magnitude. Moreover, Baldwin Weder di Mauro (2020) suggest that the psychological aspect of the current demand shocks might be unintentionally synchronized throughout the world by the international media and personal communication channels. Such a synchronization could, in turn, undermine the demand side of the global economy even further.

The largest negative demand shocks are already being experienced by various industries, such as the hospitality industry, the entertainment industry, and the travel industry. The decrease in demand further spills over to all other upstream and downstream sectors. For instance, a decrease in the aviation industry translated into lower demand for jet fuel, which is one of the reasons for the drastic fall of oil prices. To continue with the example, the aviation industry is expected to incur US$ 61 billion worth of losses due to the coronavirus-related demand decline, and an estimated 25 million civil aviation jobs are endangered (Al-Ubaydli, 2020). The demand shocks that are currently being experienced in the aforementioned industries were roughly predicted by the US Congressional Budget Office (2006), which estimated that in case of a severe pandemic, the three worst-hit industries would be Arts and recreation, Accommodation/food services, and Transportation and warehousing (including air, rail, and transit).

3.4 Policy measures

Governments around the globe implement policy measures to limit the health and economic impacts of the COVID-19 pandemic. These measures are primarily concerned with containment of the spread of the virus and they include restrictions on social gatherings, social-distancing measures, school closures, local and nation-wide lockdowns, and border closures, amongst others. The biggest issue in connection to the pandemic is the extreme pressure it imposes on the national healthcare systems and the above-mentioned containment policies aid in slowing the spread of the virus and, hence, help hospitals and other medical facilities grapple with the burden.

It is clear to see that the implemented containment measures have significantly impacted the daily lives of people around the world and, in turn, the economy as a whole. A large number of businesses have become unable to operate either due to governmental restrictions or due to the infection itself. Thus, governments around the world are trying to 'freeze' the economy so it could recover faster after the pandemic is over. Specific sectors of the economy are expected to experience an especially acute fallout shock. Thus, targeted fiscal, monetary, and financial market measures will need to be implemented by the policymakers in order to help the most affected businesses and households (IMF, 2020b).

3.4.1 Monetary measures

There are two primary objectives of monetary policies related to the coronavirus pandemic. Firstly, it is the prevention of a liquidity crisis. Policymakers are trying to enhance the supply of credit required by businesses because otherwise the businesses, whose revenues have decreased sharply, might be forced to default on their financial obligations, which would, in turn, create severe problems along the commercial chain. The second objective is traditionally Keynesian — the stimulation of the economy by encouraging all the economic agents to keep spending on investments and consumption (Al-Ubaydli, 2020).

First of the commonly adopted policies is the lowering of interest rates to almost zero, an effort to encourage borrowing and spending. For example, the US Federal Reserve has reduced interest rates by 0.50% from 1.75% to 1.25% at the beginning of March 2020, followed by another reduction to 0.25% two weeks later (Al-Ubaydli, 2020). Asset-purchase programs through which central banks acquire commercial banks' assets at a premium in order to provide them with liquidity have also been invoked by numerous central banks (Goldman, 2020).

Although monetary policies' execution is far easier than that of fiscal policies, their importance is secondary in comparison to fiscal policies in terms of supporting the economy during the current pandemic (Al-Ubaydli, 2020). Guerrieri et al. (2020) argue that the monetary policies' ineffectiveness during a pandemic can be caused by the Keynesian multiplier being smaller than usual due to the government's ability to increase spending only in some sectors of the economy.

3.4.2 Fiscal measures

Similarly, also fiscal policies implemented by governments support several main objectives: providing businesses and households with a cushion against the impacts of coronavirus slowdown; preserving economic relationships for the post-pandemic era, especially by curtailing firm closures; and incentivizing compliance with protective measures (such as social distancing) amongst individuals. Tax, social security, mortgage, rental payments, and other fees have been waived in almost every affected country and the effectiveness of such measures will likely impact the speed of future economic recovery (Al-Ubaydli, 2020; IMF, 2020b).

The sheer amount and variety of fiscal policies are significant and almost impossible to categorize appropriately. To demonstrate their scale and magnitude, the example of selected measures put into action in the United States follows:

- Paycheck Protection Program and Health Care Enhancement, which includes (i) forgivable small business loans and guarantees to prevent small businesses from dismissing workers; (ii) small business grants; (iii) US$75 billion for hospitals; and (iv) US$25 billion for expansion of virus testing operations (IMF, 2020a).

- An estimated US$2.3 trillion (approximately 11% of the country's GDP!!) is allocated to the Coronavirus Aid, Relief and Economy Security (CARES) Act, which includes (i) one-time tax deductions to individuals, (ii) unemployment benefits expansion; (iii) US$24 billion to establish a food safety net for the most vulnerable; (iv) loans, guarantees and Federal Reserve 13(3) Emergency Lending program to prevent corporate bankruptcy; (v) transfers to state and local governments; and (vi) US$49.9 billion for international assistance (IMF, 2020a).

- Coronavirus Preparedness and Response Supplemental Appropriations Act and Families First Coronavirus Response Act, which together provide around 1% of US GDP for (i) the development of vaccines, therapeutics, and diagnostics; virus testing; support for the Centers for Disease Control and Prevention responses. (ii) 2 weeks of paid sick leave; 2/3 pay emergency leave for those infected by the virus; food assistance. (iii) 60-day suspension of obligations to federal student loans (IMF, 2020a).

The effectiveness of fiscal policies will play a major role in stabilizing economies. Bayer et al. (2020) have estimated that the *CARES act* could stabilize the output and consumption in the US by up to 50% under the assumption that the money transfers would be paid directly to the unemployed/quarantined households.

4 Data Description

This chapter provides an overview of the different categories and the sources of data used for the subsequent econometric analysis. A complete list of included explanatory variables is shown in the Appendix.

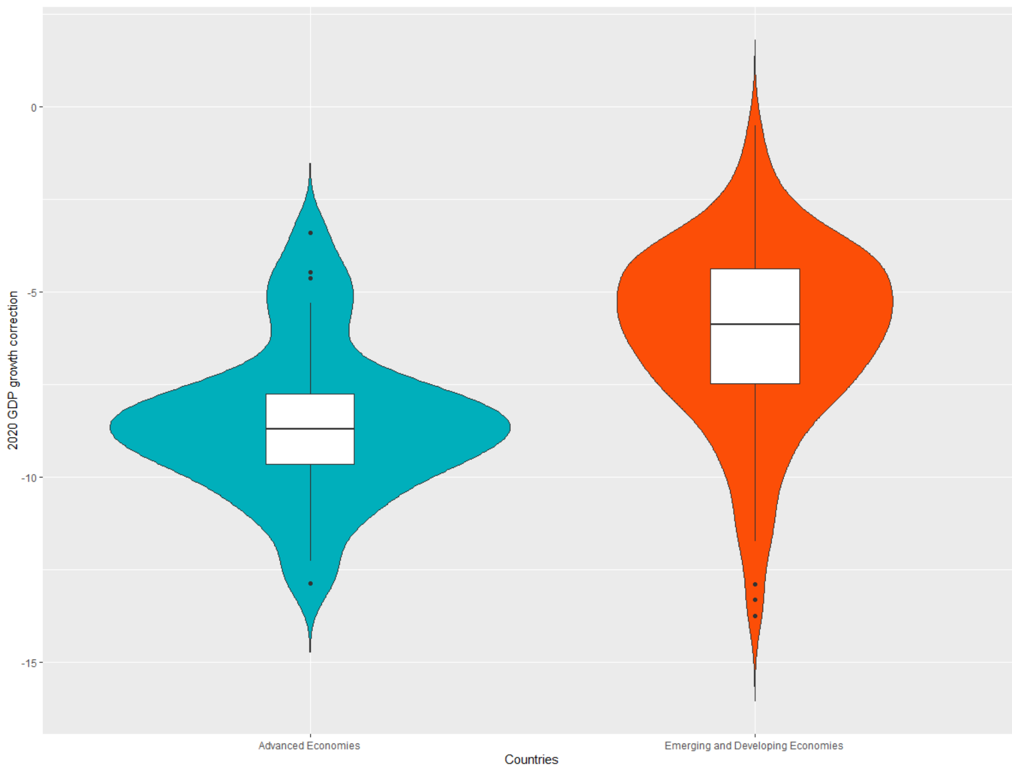
4.1 Growth Revisions

To analyze the expected economic impact of the COVID-19 pandemic, this thesis focuses on the revisions of projected GDP growth in 2020, which are obtained by comparing forecasts before the crisis (October 2019) and after the virus has spread internationally (April 2020). In contrast to comparing the actual growth outcomes, for which data is not available yet, this approach brings about various advantages. Firstly, differences in the cyclical position of countries or other expected adaptations in growth do not affect the projected growth revisions. Further, the revisions take into account the policy responses and their anticipated success (Gelos et al., 2009).

IMF's *World Economic Outlook forecasts* (WEO) dataset is the source of GDP growth projections used in this thesis. The World Economic Outlook is a survey published semiannually in October and April. This survey is accompanied by an exhaustive dataset of characteristics for 194 countries and autonomous regions. Several of these characteristics have been included in our final dataset as explanatory variables (See Appendix A for details).

Figure 1 shows the difference between expected growth revisions for the groups of *Advanced economies* and *Emerging and developing economies*. It can be seen that the growth revisions are, in general, expected to be more negative for the group of advanced economies. There is also a smaller spread of expected results within the advanced economies group, likely due to the countries being more similar in comparison to the group of emerging and developing economies. Nonetheless, it is exactly the (dis)similarities amongst the countries which motivate our econometric analysis, whose objective is to determine the characteristics causing the differences in the projected output growth revisions.

Figure 1: 2020 GDP Growth Revisions



4.2 Explanatory variables

A large number of variables is used to capture various country characteristics. They can be categorized into five broad groups: (i) COVID-19-related, (ii) Financial structure & GDP, (iii) Healthcare system, (iv) Trade, and (v) Governance and Digitization.

COVID-19-related characteristics The first group of variables is concerned with information related to the virus itself. Intuitively, the number of

COVID-19 confirmed cases and the number of COVID-19-related deaths might be indicative of the pandemic's impact on individual countries. The peculiar ways in which the virus spreads and the demographics of the majority of its victims, both of which were mentioned in Chapter 3, are the reasons behind the inclusion of two more variables directly related to COVID-19 - population density and the share of the population aged 65 and above.

Financial structure & GDP Firstly, a subset of variables estimates the financial structure of countries. During a crisis, capital flows usually reverse and currencies depreciate. Such development might transform into financial pressure and a credit collapse, or even into serious national balance sheet difficulties. Presumably, countries with substantial current account deficits, low reserves, and a high level of debt could experience greater output declines within the current global pandemic (Gelos at el., 2009). Additionally, two variables from this category fall into the *GDP* subset: *Services (% of GDP) and Purchasing Power Parity (PPP) per capita.*

Healthcare System A pandemic is primarily a public health issue. Thus, the level of development of the public healthcare system can prove indicative of a country's ability to cope with the coronavirus pandemic and its economic consequences. Further, there are two sub-groups of variables: (i) the sources and magnitudes of financial expenditures spent on health; (ii) quality of service estimated by variables *Hospital beds per capita*, *Physicians per capita*, and the *UHC service coverage index*, which measures the coverage of essential health services on a unitless scale of 0 to 100 (WHO, 2020d).

Trade Not only the decline in production but also the extensive international border closures and the above-described supply and demand shocks have affected the international flows of goods and services. To capture the different effects of countries' trade positions, two sub-groups of data were included: (i) trade openness - exports, imports and total trade to GDP; and (ii) the composition of trade.

Governance and Digitization The last group of variables describes the strength of the policy and institutional framework as well as the levels of digitization of the society. The strength of the institutional framework is represented by Worldwide Governance Indicators (WGI), which is a set of governance perception indicators constructed by the World Bank from 31 various underlying data sources (Kaufmann, Kraay Mastruzzi, 2010). We use 5 of the 6 indices included in WGI - Political Stability and Absence of Violence/Terrorism, Government Effectiveness, Regulatory Quality, Rule of Law, and Control of Corruption. To capture country's level of digitization, we use: (i) World Bank's Digital Adoption Indices (DAI), which estimate digital adoption in three sections of the economy: people, government, and businesses (World bank,2020); (ii) United Nations' E-Government Development Index (EDGI), which consists of another three components: the scope and quality of online public services, the level of development of telecommunication infrastructure, and the status of human capital (United Nations, 2020).

4.3 Dataset

The final dataset, which was compiled from the above-mentioned data, is a cross-sectional dataset. It captures 149 WEO-defined regions with 35 explanatory variables. Appendix [TO BE ADDED] provides the full list of included regions as well as summary statistics of the included variables.

5 Methodology

In this section, we first introduce the intuition behind the use of Bayesian model averaging (BMA) in model uncertainty situations. After that, the theoretical foundation of BMA is described. Lastly, the Markov Chain Monte Carlo Model Composition algorithm - through which BMA is carried out - is explained.

5.1 Bayesian Model Averaging

Imagine a researcher who might be interested in the effect religion has on economic growth. In order to analyze such a relationship, he would normally have various regression models connecting religion and varying combinations of other explanatory variables (education, mortality rate, etc.). Let M_r for $r = 1, ..., R$ denote the R different models under consideration. Each of the models depends upon a vector of parameters Φ_r and it is characterized by prior $p(\Phi_r|M_r)$, likelihood function $p(y|\Phi_r, M_r)$, and posterior $p(\Phi_r|y, M_r)$. Let Φ be a vector of parameters that has a common interpretation in all models. It comes naturally, that the coefficient $\mathit{\Phi}$ would be the point of interest in all the regression models. Bayesian logic implies that all the known information about the coefficient Φ is summarized in its posterior $p(\Phi|y)$ and the rules or probability further establish

$$p(\phi|y) = \sum_{r=1}^{R} p(\Phi|y, M_r)p(M_r|y) \tag{1}$$

Similarly, the conditional expectation rules imply that for a function of Φ, $f(\Phi)$,

$$E\left[f(\Phi)|y\right] = \sum_{r=1}^{R} E\left[f(\Phi)|y, M_r\right] p(M_r|y) \tag{2}$$

holds. Simply put, the Bayesian inference logic states one should collect results of every considered model and average them, where the individual weights in the averaging are the posterior model probabilities. Conceptually, Bayesian model averaging is quite straightforward. However, its implementation can prove difficult since R — the number of considered models — is often massive. Incorporating every possible model in averages such as (2) is not feasible for many applications. Consequently, various algorithms that do not require the researcher to be dealing with all the models have been developed with the MC^3 model being one of the most commonly used (Koop, 2010).

5.2 Bayesian model averaging in the normal linear regression model

There are numerous applications of the linear regression model with a large number of possibly significant explanatory variables. A researcher might be inclined to simply include all the potential variables in a regression. Such an approach, however, usually results in unsatisfactory outcomes since the inclusion of irrelevant variables customarily decreases estimation accuracy. Traditionally, the solution to this issue would be to conduct a sequence of tests to select the most appropriate model which omits all the irrelevant variables. However, several issues stand out with this approach. Firstly, for every time a test is made, there is a probability of the researcher making a mistake and mistakenly rejecting a superior model for an inferior one. Further, even if such sequential testing proves successful in selecting the 'best' model, it is rarely desirable to present only the results of this 'best' model and ignore all the evidence provided by the 'not so good' models. Such an approach ignores the uncertainty which is present, meaning that the researcher is not completely secure that any of the Φ coefficient estimates is completely correct. There are two reasons for that. Firstly, the researcher does not know exactly what the parameters of the model are, so *parameter uncertainty* exists, and secondly, she does not know which model is the correct one (i. e. *model uncertainty* exists). Posterior inference traditionally deals with parameter uncertainty. Bayesian econometrics logic tells us how to tackle model uncertainty (Koop, 2010).

In the case of a large set of potential explanatory variables, alternative models are defined by the inclusion or exclusion of each explanatory variable. If the number of potential explanatory variables is K, there are 2^{K} possible models. Considering the number of variables present in this thesis' data frame, where 35 explanatory variables are present, there are $2^{35} > 10^9$ models. Assuming a computer would take 0.001 seconds to analyze each model, analysis of all the models would take more than one year! Hence, explicit calculation of every term in (1) and (2) is often unobtainable and it is the reason for the development of MC^3 algorithms, which are described below (Koop, 2010).

Another issue is connected to prior information. Bayesian model averaging is often employed in a situation where a researcher is not certain about the importance of the many explanatory variables she has identified. Hence, she rarely has a significant amount of prior information. Unfortunately, the calculation of posterior model probabilities cannot be executed without proper non-informative priors and this issue has to be addressed in a BMA analysis (Koop, 2010).

5.2.1 The Likelihood Function

We have data of i= 1,..., N subjects, and the observations of the dependent variable are placed in an N-vector $y = (y_1, ..., y_T)'$. There are r = 1,..., R models, denoted as M_r. These models are all normal linear regression models which differ in their explanatory variables. Such models can be expressed as

$$y = \alpha l_N + X_r \beta_r + \epsilon \tag{3}$$

where l_N is a vector N × 1 of ones, X_r is a $N \times k_r$ matrix containing some or all columns of X. The vector of errors ϵ is assumed to be $N(0_N, h^{-1} I_T)$, where $h = \sigma^{-2}$. Because 2^K possible subsets of X exist, $R = 2^K$ (Koop, 2010).

5.2.2 The Prior

For Bayesian model averaging the choice of prior can be crucial because an appropriate prior is needed to yield meaningful posterior probabilities. The literature suggests the use of the standard noninformative prior for h,

$$p(h) \propto \frac{1}{h} \tag{4}$$

and for the intercept,

$$p(\alpha) \propto 1 \tag{5}$$

The only remaining prior from (3) which needs to be taken care of is β_r. The natural conjugate Normal-Gamma prior implies

$$\beta_r|h \sim N(\underline{\beta}_r, h^{-1}\underline{V}_r) \tag{6}$$

Further, it is a common practice to set a conservative prior such that the explanatory variables do not affect the dependent variable. Thus,

$$\underline{\beta}_r = 0_{k_r}$$

The only remaining to choose is $\underline{V}_r$, which is set to

$$\underline{V}_r = [g_r X_r' X_r]^{-1} \tag{7}$$

based on the use of *g-prior*. Zellner (1986) introduced the g-prior and it is a commonly used benchmark prior. The g-prior implies that the prior covariance of B_r is proportional to the comparable data-based quantity. There are other reasons for the use of g-prior (see Zellner, 1986), but it is reasonable to have a prior with similar properties as the data information. It is often hard to obtain prior covariance matrices such as $\underline{V}_r$ and g-prior makes this task more simple by reducing the choice to a single hyperparameter (Koop, 2010).

Hence, we set the priors for the slope coefficients as

$$\beta_r|h \sim N(O_{k_r}, h^{-1}[g_r X_r' X_r]^{-1}) \tag{8}$$

where g_r will be set in the following section.

5.2.3 The Posterior and Marginal Likelihood

The posterior for β_r, the crucial parameter vectors, follows a multivariate t distribution with mean

$$E(\beta_r|y, Mr_r) \equiv \overline{\beta}_r = \bar{V}_r X_r' y \tag{9}$$

covariance matrix

$$var(\beta_r|y, M_r) = \frac{\bar{v}s_r^2}{\bar{v}-2}\bar{V}_r \tag{10}$$

and $\overline{v} = N$ degrees of freedom. Moreover,

$$\overline{V_r} = [(1+g_r)X_r'X_r]^{-1} \tag{11}$$

and

$$\overline{s}_r^2 = \frac{\frac{1}{g_r+1}y'P_{X_r}y + \frac{g_r}{g_r+1}(y-\overline{y}l_N)'(y-\overline{y}l_N)}{\overline{v}} \tag{12}$$

where

$$P_{X_r} = I_N - X_r(X_r'X_r)^{-1}X_r'$$

By using the g-prior, we obtain the marginal likelihood for model r

$$p(y|M_r) \propto \left(\frac{g_r}{g_r+1}\right)^{\frac{k_r}{2}} \left[\frac{1}{g_r+1}y'P_{X_r}y + \frac{g_r}{g_r+1}(y-\overline{y}l_T)'(y-\overline{y}l_T)\right]^{-\frac{N-1}{2}} \tag{13}$$

Accordingly, the calculation of the posterior model probabilities is

$$p(M_r|y) = cp(y|M_r)p(M_r) \tag{14}$$

with c being a constant that is the same for all the models.

Further, by setting

$$p(M_r) = \frac{1}{R} \tag{15}$$

we allocate equal prior model probability to each model.

Hence, $p(M_r)$ can be ignored and the marginal likelihood can be used for Bayesian model averaging. Thus,

$$p(M_r|y) = \frac{p(y|M_r)}{\sum_{j=1}^{R} p(y|M_j)} \tag{16}$$

The above-mentioned formulae provide further motivation for the g-prior. A perfectly non-informative prior corresponds to $g_r = 0$. On the other end, $g_r = 1$ means that the data and prior information are equally weighted in the posterior covariance matrix. Intuitively, one can imply that $g_r = 1$ would be too large (Koop, 2010). Fernandez, Ley, and Steel (2001b), recommend setting the g-prior as follows:

$$g_r = \begin{cases} \frac{1}{K^2} if N \leq K^2 \\ \frac{1}{N} if N > K^2 \end{cases} \tag{17}$$

5.2.4 Markov Chain Monte Carlo Model Composition

Theoretically, the above-mentioned calculations and results should be satisfactory to implement model averaging. In practice, however, the evaluation of 2^K models is not feasible. Subsequently, different algorithms were developed to carry out BMA without the need to evaluate every possible model. A commonly used algorithm, originally developed in Madigan et al. (1995), follows below.

It is useful to think about how posterior simulation algorithms such as Markov Chain Monte Carlo model work in order to see the intuition behind Bayesian model averaging algorithms. Such algorithms take draws from the parameter space. By making many draws from regions of the parameter where posterior probability is high and few draws from regions where the posterior probability is low, these draws are designed to mimic draws from the posterior. Since in Bayesian econometrics models are random variables, the same way parameters are, simulators drawing from the model space instead of parameter space can be derived. These simulators do not have to evaluate every model, but only focus on the models with high posterior probability. The fact that the algorithm draws from model space has motivated its name Markov Chain Monte Carlo Model Composition, or MC^3 (Koop, 2010).

The most commonly used MC^3 model space sampling algorithm is based on a Metropolis - Hastings[5] algorithm. It simulates a chain of models $M^{(S)}$ for $s = 1, ..., S.M^{(S)}$ is one of $M_1, ..., M_R$. Candidate models are then drawn from a particular distribution over model space and accepted with a certain

[5]A Markov chain Monte Carlo algorithm used for obtaining a sequence of random samples from a probability distribution.

probability by the algorithm. In the case of a candidate model not being accepted, the chain remains at the current model (i.e. $M^{(S)} = M^{(S-1)}$) (Koop, 2010).

A candidate model M^* is drawn randomly from the set of models, which includes (i) the current model, $M^{(s-1)}$, (ii) all models deleting an explanatory variable from $M^{(s-1)}$, and (iii) all models adding an explanatory variable to $M^{(s-1)}$. The acceptance probability of such candidate models is

$$\alpha(M^{(s-1)}, M^*) = min\left[\frac{p(y|M^*)p(M^*)}{p(y|M^{(s-1)})p(M^{(s-1)})}, 1\right] \tag{18}$$

Here, the marginal likelihood (13) can be used to calculate $p(y|M^{(s-1)})$ and $p(y|M^*)$. Commonly, when equal prior weight is allocated to each model, $p(M^*) = p(M^{(s-1)})$ and they cancel out in (18). In such a case, the only quantity which must be calculated in (18) is the Bayes factor[6] comparing M^* to $M^{(s-1)}$ (Koop, 2010).

Through averaging over draws, the posterior results based on the sequence of models generated from the MC[3] algorithm can be calculated. (2) can be, for example, approximated by $\hat{g}s_1$:

$$\hat{g}s_1 = \frac{1}{S_1}\sum_{s=S_0+1}^{S} E[g(\phi)|y, M^{(s)}] \tag{19}$$

As S_1 (where $S_1 = S - S_0$) approaches infinity, $\hat{g}s_1$ converges to $E[g(\phi)|y, M^{(s)}$. Finally, $M^{(0)}$ - the chain starting value - must be chosen. To eliminate the effects of the $M^{(0)}$ choice, S_0 burn-in replications should be discarded (Koop, 2010).

6 Results

We have used the BMS R library developed by Zeugner and Feldkircher (2015) to apply Bayesian model averaging to the above-described data frame consisting of 35 explanatory variables. The library's principal function, *bms*, "samples all possible model combinations via MC[3]" (Fieldkirhcer et

[6]A likelihood ratio of the marginal likelihood of two competing hypotheses.

al., 2020). Using the library's *bms* function, the baseline analysis setting is

bms(data, g= "UIP", mprior= "uniform", burn= 0.5e6, iter= 1e6, nmodel=5000)

where

1. the crucial hyperparameter g, i. e. Zellner's g-prior, is set to 'uniform information prior' (UIP). This corresponds to $g = N$, the number of observations. Thus, the prior is assigned the same weight as one data observation.

2. the *mprior* parameter defines the chosen model prior, here set to employ the uniform model prior, which gives each model equal prior probability.

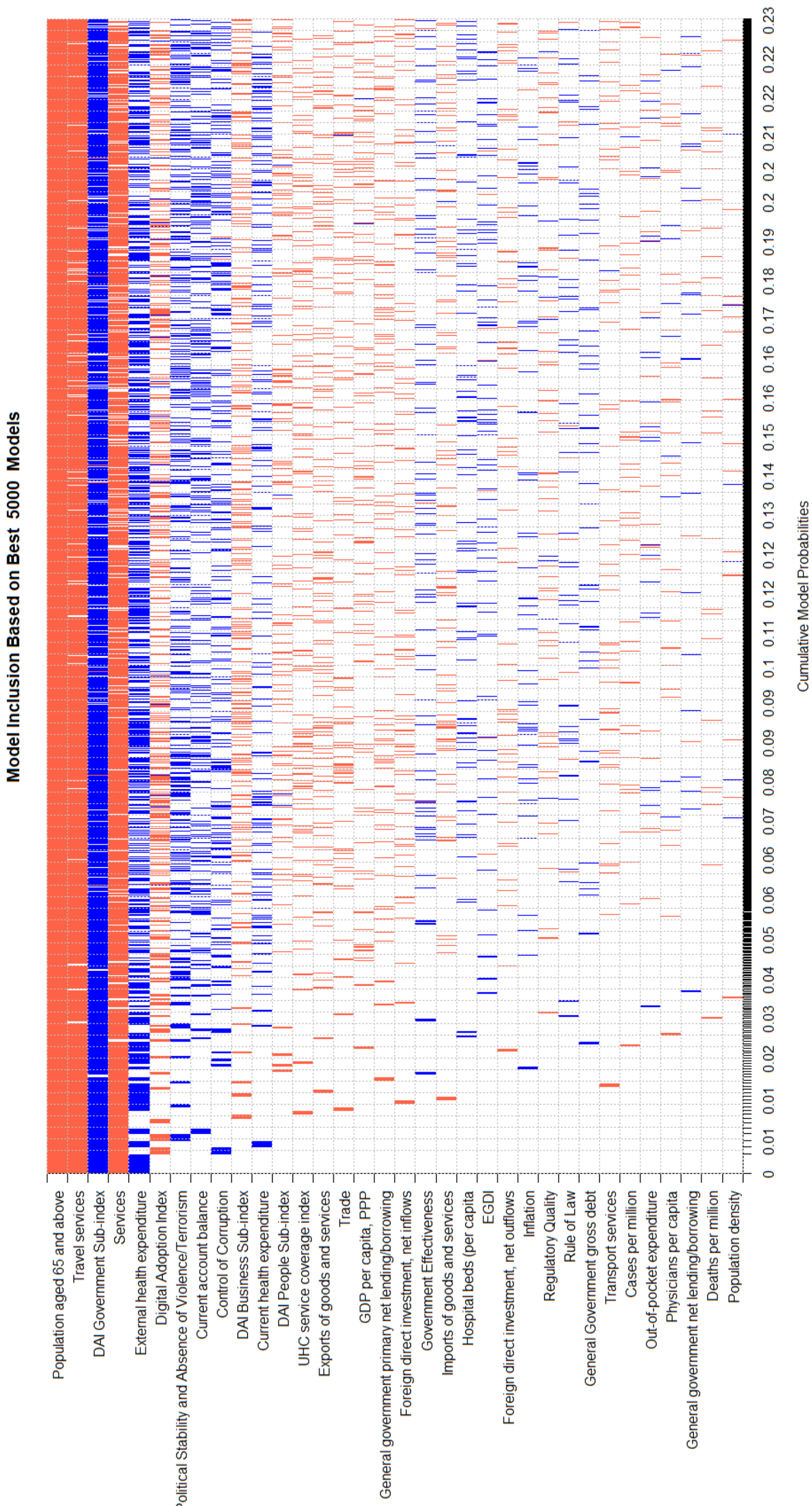
3. the *burn* parameter stands for the number of burn-in draws of the MC^3 sampler and the *iter* parameter defines the number of iteration draws to be sampled, excluding burn-ins.

4. *nmodel* defines the number of models for which information is stored. By default, this number is 500 and we have purposely increased it to 5000 in order to increase the cumulative model probabilities captured by the best sampled models.

Eicher et al. (2011) recommend the above-mentioned combination of g- and model prior due to its strong performance in predictive exercises.

The BMA results are depicted in Figure 2. Each column represents a single regression model. On the vertical axis, the variables are sorted by posterior inclusion probability in descending order (i. e. the uppermost variable is included in the largest amount of sampled models). If the variable is included and its estimated sign is positive, it is shown in blue color. Red color, on the contrary, corresponds to a variable that is included and its estimated sign is negative. The cells with no color suggest that the variable

Figure 2: Model Inclusion Based on Best 5000 models



is excluded from the model. The cumulative posterior model probability is measured on the horizontal axis and the best models are shown on the left.

The numerical results of BMA are reported in the left-hand panel of Table 1. According to Kass & Raftery (1995), variables with posterior inclusion probability above 0.5 have a *non-negligible* impact on the dependent variable. There are five such variables in our results: *Population aged 65 and above, Travel services (% of exports), DAI Government Sub-index, Services (% of GDP), and External health expenditure (% of health expenditure).* Additionally, a frequentist check was made for the *non-negligible* variables by running a simple OLS. Its results are shown on the right-hand side of the table. Hence, the right-hand side of the table shows a combination of BMA and OLS estimations. The moments for BMA shown in Table 1 are unconditional, meaning that even the models in which a variable is not included are used to compute the posterior means and the posterior standard deviations reported. For important variables with a high enough posterior inclusion probability, such as *Population aged 65 and above or Travel services (% of health expenditure)* in our results, there is very little difference between conditional and unconditional moments because such variables are included in almost all of the best regression models (Havranek & Sokolova, 2020).

6.1 Results interpretation and discussion

It can be seen in Figure 2 that the best regression model, according to BMA, includes 5 explanatory variables: *Population aged 65 and above, Travel services (% of exports), DAI Government Sub-index, Services (% of GDP), and External health expenditure (% of health expenditure).*

Population aged 65 and above as a share of total population is the most important variable due to its posterior inclusion probability of 0.999 meaning that it is included in almost all of the sampled models. The estimated sign of the variable is negative and the interpretation seems quite intuitive since the majority of fatalities amongst COVID-19-related deaths falls within this demographic group, as was mentioned in Section 3. However, Rio-Chanona

Table 1: Why do projected 2020 GDP growth revisions differ?

Response variable:	Bayesian Model Averaging			Frequentist check (OLS)		
Projected 2020 GDP growth revision	**Post. Mean**	**Post. SD**	**PIP**	**Coef.**	**Std. er.**	**p-value**
COVID-19-related						
Confirmed COVID-19 cases per capita	0.000	0.000	0.031			
COVID-19-related deaths per capita	0.000	0.000	0.024			
Population density	0.000	0.000	0.021			
Population aged 65 and above	-0.181	0.039	0.999	-0.186	0.031	3.13e-08
GDP & Financial structure						
Current account balance	0.008	0.018	0.208			
Primary net lending/borrowing	-0.004	0.017	0.075			
Government net lending/borrowing	0.000	0.008	0.024			
Government gross debt	0.000	0.001	0.038			
Foreign direct investment inflows	-0.002	0.009	0.071			
Foreign direct investment outflows	-0.001	0.007	0.055			
Inflation	0.000	0.000	0.051			
Services (% of GDP)	-0.045	0.023	0.893	-0.053	0.017	0.002
GDP per capita, PPP	0.000	0.000	0.075			
Healthcare system						
Physicians per capita	-0.002	0.034	0.026			
Hospital beds per capita	0.006	0.033	0.061			
Health expenditure (% of GDP)	0.011	0.035	0.135			
External health expenditure (% of health exp.)	0.019	0.021	0.520	0.038	0.011	0.007
Out-of-pocket expenditure (% of health exp.)	0.000	0.002	0.030			
UHC service coverage index	-0.003	0.011	0.095			
Trade						
Trade (% of GDP)	0.000	0.002	0.077			
Imports (% of GDP)	0.000	0.003	0.062			
Exports (% of GDP)	-0.001	0.004	0.091			
Travel services (% of exports)	-0.021	0.008	0.971	-0.019	0.006	0.002
Transport services (% of exports)	0.000	0.003	0.038			
Governance and digitization						
Control of Corruption	0.094	0.238	0.184			
Government Effectiveness	0.029	0.158	0.064			
Political Stability and Absence of Violence/Terrorism	0.134	0.252	0.280			
Regulatory Quality	-0.018	0.131	0.047			
Rule of Law	0.006	0.099	0.042			
Digital Adoption Index (DAI)	1.234e+05	1.738e+06	0.307			
DAI Business Sub-index	-4.114e+04	5.793e+05	0.157			
DAI Government Sub-index	-4.113e+04	5.793e+05	0.936	3.256	1.068	0.002
DAI People Sub-index	-4.114e+04	5.793e+05	0.101			
EDGI	0.150	0.902	0.058			
Constant	-2.560	NA	1.00	-3.588	0.925	0.000
Observations	145			145		

Notes: PIP = posterior inclusion probabiity. SD = standard deviation.

The standard errors reported for the frequentist check are heteroskedasticity-consistent White standard errors.

et al. (2020) argue that the effects of mortality and morbidity are much less significant than the economic impacts of social distancing measures put in place. Hence, it could be assumed that the policymakers of a country with a larger portion of population aged 65 and above are more inclined to enforce stricter social distancing measures in order to save lives of the elderly. The reasoning of Rio-Chanona et al. (2020) is further strengthened by the results of our analysis, according to which, the number of confirmed COVID-19 cases per capita and the number of COVID-19-related deaths per capita seem not to be even of the slightest importance in the regression models.

The interpretation of *External health expenditure as a share of health expenditure* is not intuitive either. The variable captures the share of health expenditure funded from external financial sources. These sources are composed of direct foreign transfers and other foreign transfers allocated through government, i.e. all the inflows of finances into the country's health system from outside of the country (World Bank, 2019). Naturally, one would expect even a partial dependency of country's healthcare system on external funding, i. e. a sign of weakness of the country's healthcare system, to have a negative impact on its GDP growth revisions. However, a closer inspection of the underlying data shows that this variable is null for the majority of developed countries and positive for most of the emerging and developing economies. Thus, in combination with the information conveyed in Figure 1, it can be implied that a non-zero (positive) share of external health expenditure is, generally speaking, more likely to be associated with a smaller growth revision.

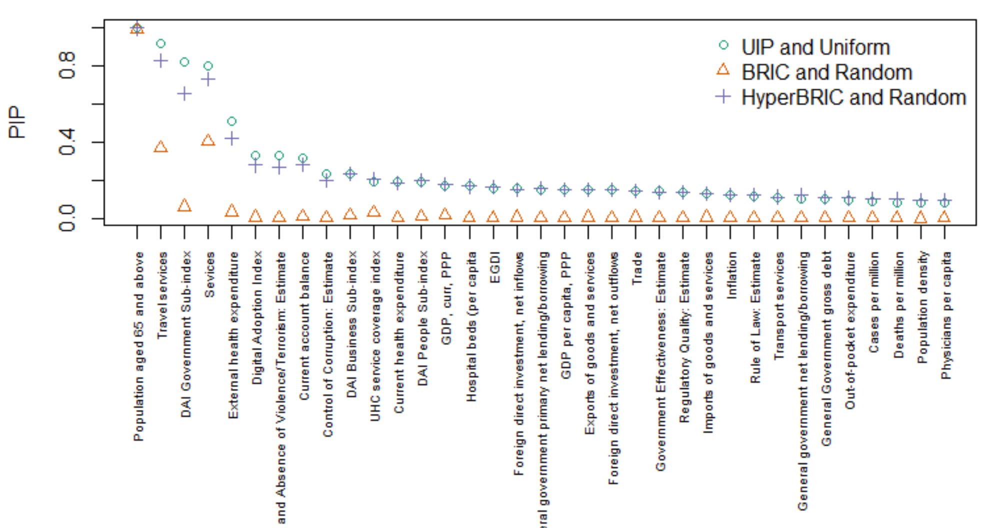
Surprisingly, the three Digital Adoption Index (DAI) sub-indexes – Business, Government, and People – have almost identical BMA Posterior Means and Posterior Standard Deviations, but only one of them – the DAI Government Sub-index – has a significantly large posterior inclusion probability. This result likely reflects the aforementioned importance of governmental policies and the effectiveness of their implementation during a pandemic.

6.2 Robustness check

To check the robustness of our BMA, we have run further BMAs with alternative priors. Fernandez et al. (2001) suggested the BRIC prior, which determines the weight of the zero prior for the regression parameters based on the number of explanatory variables. To offset the fact that the prior probability of the most common model sizes is large when each *model* has the same prior probability, we have employed the random beta-binomial model prior, which means that the probability of each *model size* is identical. The last set employs the hyper-g prior introduced by Feldkircher (2012), which is data-dependent and it should be less outlier-sensitive (Havranek & Sokolova, 2020).

Figure 3 shows the results of the robustness check. It can be seen that the change of the g-prior from the unit information prior to the data-dependent hyper-g prior combined with the change of the model prior from uniform to random beta-binomial yields results of small difference in terms of both posterior inclusion probabilities and the ranking of variables. On the other hand, the BRIC prior returns significantly lower PIPs for all variables. The ranking of the variables according to their PIP is, however, mostly sustained even for the BRIC prior. Thus, the robustness check has revealed a modest prior sensitivity. Still, all three approaches identify the same top five variables, which are the most important in describing the expected growth revisions. We can conclude that the choice of prior can slightly change the interpretation of the effects of individual variables, but it does not affect our main findings.

Figure 3: Robustness Check



7 Conclusion

Millions of individuals worldwide have contracted the COVID-19 disease, and hundreds of thousands have died of it. Furthermore, additional hundreds of millions might suffer in the near future due to the global economic recession provoked by the current coronavirus pandemic. Thus, the study of the issue at hand is of primary importance to the whole of humankind and this thesis engages in such an effort by analyzing the determinants of cross-country differences in the projected GDP growth revisions caused by the COVID-19 global pandemic.

To begin with, this work provides the reader with an introduction into the complicated topic of epidemics and pandemics. Subsequently, a general setting for an economic analysis of the current pandemic is instituted through the description of past pandemics and their economic consequences. Even though the economic impact of the coronavirus pandemic is an extremely complex phenomenon with a myriad of mutually intertwined factors involved, we have attempted to summarize the main mechanisms through which the pandemic affects both the supply side and the demand side of the economy. The analytical framework is further expanded by describing the importance and magnitude of the various policy measures being implemented by policymakers around the world.

In the empirical part, we analyze the cross-country differences in projected GDP growth revisions caused by the COVID-19 global pandemic. A considerably large data set of 34 explanatory variables describing the characteristics of 145 countries is utilized. The model uncertainty inherent to an economic analysis of such complexity is addressed through the application of Bayesian model averaging (BMA), a fairly advanced econometric method. The usage of BMA has allowed us to determine the best 5000 regression models, on the grounds of which, five determinants were identified as important in explaining the cross-country differences in the expected effect of COVID-19 on economic growth. In addition, the results of our econometric analysis were further supported by BMA robustness check and a OLS frequentist check.

To the best of our knowledge, this is the first work studying the cross-country differences in the output decline caused by the coronavirus pandemic. Despite the fundamental limitation of this analysis — which is based on growth projections instead of on actual data — we believe that it can serve as a point of reference in the future investigation of the issue. Once more data becomes available, additional research will be needed to understand the economics of the current pandemic in more detail, especially in terms of analyzing the effects of policy measures on the duration of a recession and the speed and size of the subsequent recovery in individual countries.

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Appendix

Table 2: List of explanatory variables

Explanatory variable	Exp. Sign	Source
COVID-19-related		
COVID-19 confirmed cases per capita	-	World Health Organization
COVID-19 deaths per capita	-	World Health Organization
Population density	-	World Bank
Population aged 65 and above as share of total population	-	World Bank
GDP & Financial structure		
Services as share of GDP	-	World Bank
Current account balance as share of GDP	+	World Economic Outlook
General government gross debt as share of GDP	-	World Economic Outlook
Government primary net lending/borrowing as share of GDP	-	World Economic Outlook
General government net lending/borrowing as share of GDP	-	World Economic Outlook
Inflation	-	World Economic Outlook
Foreign direct investment, net outflows as share of GDP	-	World Bank
Foreign direct investment, net inflows as share of GDP	-	World Bank
Healthcare system		
Physicians per capita	+	World Bank
Hospital beds per capita	+	World Bank
Health expenditure as share of GDP	+	World Bank
External share expenditure as % health expenditure	-	World Bank
Out-of-pocket health expenditure as % of health expenditure	-	World Bank
UHC service coverage index	+	World Bank
Trade		
Imports of goods and services as share of GDP	-	World Bank
Exports of goods and services as share of GDP	-	World Bank
Trade as share of GDP	-	World Bank
Travel services as share of commercial service exports	-	World Bank
Transport services as share of commercial service exports	-	World Bank
Governance and digitization		
Digital Adoption Index (DAI)	+	World Bank
DAI Business Sub-index	+	World Bank
DAI People Sub-index	+	World Bank
DAI Government Sub-index	+	World Bank
EDGI	+	United Nations
Control of Corruption	+	Worldwide Governance Indicators
Government Effectiveness	+	Worldwide Governance Indicators
Political Stability and Absence of Violence/Terrorism	+	Worldwide Governance Indicators
Regular Quality	+	Worldwide Governance Indicators
Rule of Law	+	Worldwide Governance Indicators

Table 3: List of countries considered from WEO database

Advanced Economies	**Emerging Markets and Developing Economies**		
Greece	Afghanistan	Georgia	North Macedonia
Latvia	Algeria	Ghana	Oman
Slovenia	Angola	Grenada	Pakistan
Lithuania	Antigua and Barbuda	Guatemala	Panama
Estonia	Argentina	Guinea	Papua New Guinea
Ireland	Armenia	Guinea-Bissau	Paraguay
New Zealand	Azerbaijan	Haiti	Peru
Spain	Bahrain	Honduras	Philippines
Italy	Bangladesh	Hungary	Poland
Portugal	Belarus	India	Qatar
Israel	Belize	Indonesia	Republic of Congo
Cyprus	Benin	Iraq	Romania
Netherlands	Bhutan	Islamic Republic of Iran	Russia
Czech Republic	Bolivia	Jamaica	Rwanda
Australia	Bosnia and Herzegovina	Jordan	Saudi Arabia
Slovak Republic	Botswana	Kazakhstan	Senegal
Iceland	Brazil	Kenya	Serbia
Norway	Brunei Darussalam	Kuwait	Sierra Leone
Austria	Bulgaria	Kyrgyz Republic	South Africa
France	Burkina Faso	Lao P.D.R.	Sri Lanka
Denmark	Burundi	Lebanon	St. Lucia
Sweden	Cabo Verde	Madagascar	St. Vincent and the Grenadines
Belgium	Cambodia	Malawi	Suriname
Germany	Cameroon	Malaysia	Thailand
United States	Central African Republic	Mali	The Bahamas
Canada	Chad	Mauritania	The Gambia
Luxembourg	Chile	Mauritius	Timor-Leste
Finland	Colombia	Mexico	Togo
Switzerland	Costa Rica	Moldova	Tunisia
Malta	Croatia	Mongolia	Turkey
Japan	Democratic Republic of the Congo	Morocco	Uganda
China	Djibouti	Mozambique	Ukraine
South Korea	Dominican Republic	Myanmar	Uruguay
	Ecuador	Namibia	Uzbekistan
	Egypt	Nepal	Venezuela
	El Salvador	Nicaragua	Zambia
	Ethiopia	Niger	Zimbabwe
	Gabon	Nigeria	