"The effect of health and economic costs on governments' policy responses to COVID-19 crisis, under incomplete information"

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Abstract

COVID-19 outbreak has become an unprecedented health, economic and social crisis. We build a theoretical model, based on which we develop an empirical strategy to analyze the drivers of the agility of policy response to the outbreak. Our empirical results show that government overconfidence in its own country capacity of health services and the intensity of expected economic costs from hard measures to manage the crisis delayed policy response. Contrarily, being a game against nature with incomplete information, increased knowledge and reduced uncertainty on other countries' policy responses and on the epidemic development increased the agility of the country's policy response.

JEL classification: D81, H12, I18.

Keywords: COVID-19, Crisis management, Public policy, Policy response.

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Introduction

The coronavirus outbreak has produced an unprecedented health, economic, and social crisis, becoming a transboundary crisis as characterized in Boin (2019). As of mid-June 2020, more than 8 million cases have been diagnosed and more than 400,000 people have died, according to The Johns Hopkins COVID-19 tracker. Global leaders, such as Antonio Guterres (Secretary General of United Nations) or Angela Merkel (Chancellor of Germany), have compared its impact to the World War II.

In a crisis, authorities must engage in coherent analysis under limited time, uncertainty, and intense pressure, searching for a proper response (Boin et al, 2005), and this has been the case for COVID-19 (van Dooren, forthcoming). In this vein, the rapid spread of the pandemic has forced countries to take unprecedented measures. More than 90% of the world's population live in countries with restrictions on people arriving from other countries who are neither citizens nor residents, such as tourists, business travelers, and new immigrants, and many of them live in countries with borders completely closed to non-citizens and non-residents, according to the Pew Research Center (see Connor, 2020). Quarantine, social distancing, and isolation of infected populations can contain the epidemic. However, there is no clear consensus on the specific impact of each measure in terms of propagation mitigation (see, among others, Anderson et al., 2020; Prem et al., 2020; Koo et al., 2020), and few policy analyses related to COVID-19 are available in the literature so far. Among these, Moon (2020) analyzes the policy response in Korea; Gupta et al (2020) analyze behavioral responses to policies mandated in the US. Policy analysis related to COVID-19 is restricted given the provisional character and limitations of existing data (Stock, 2020; Rusell et al., 2020). Nonetheless, there is a widespread consensus among researchers and international organizations that early prevention and response are critical (Grasselli, Pesenti, and Cecconi, 2020).

However, already available information allows analyzing what made some countries react sooner than others. This is a relevant public policy issue, as the time dimension is central to crisis management, and policies applied by governments to deal with COVID-19 have followed distinct national rather than consensual international standards, as it happened with policy responses to previous epidemic crisis (Vallgårda 2007; Baekkeskov, 2016).

In this paper we present a model to characterize the drivers of the reaction time to coronavirus, namely, the number of known diagnosed cases per million population (incidence rate) when the government approved hard contention measures (partial or complete lockdown). Our base model considers a rational government that cares about the population welfare and is conditioned by the level of information about the pandemic. Hence, the model includes three main factors: expected capacity of the health system to deal with the outbreak, expected economic costs of hard measures, and government's level of information. We extend our analysis to account for emotional beliefs and biases affecting the assessment of the risk of the pandemic, and policy survival factors.

We estimate an equation derived from our modeling. Using data from OECD and European countries, we find that the three of them are statistically relevant. First, the confidence of the government in its capacity to fight the outbreak, measured as the total healthcare expenditure per capita (PPP), is a significant delaying factor of policy response, and its weight is very important, as it accounts for a 30.5% of total delay. The higher the expenditure on healthcare, the more likely the government feels that can handle the outbreak; hence the longer the delay in response. According to our empirical estimation, each additional point of GDP spent on healthcare delayed hard measures up to increase by 16.91 the incidence rate when hard measures are announced.

Regarding the prevention of economic costs, the more a country is exposed to globalization and international trade, the more it is (relatively) affected by implementing hard measures, such as border closures. We use total trade (% GDP) and total travel and tourism contribution to GDP as proxies for the expected cost of hard measures. Both are highly significant and together account for 45.8% of the total predictive power of the model. As expected, the higher the cost, the slower the reaction: on average, a 10% increase in trade and tourism contribution increased by 26.79 the incidence rate at the time of hard measures adoption.

To represent the level of information, we use the number of countries that have taken hard measures before the pandemic started in the government's own country. As expected, countries whose first case was after other countries implemented lockdowns, anticipated their responses. Level of information shows important influence, being responsible for 18.6% of the explanatory power of the model. Regarding emotional or perception factors, proximity bias -represented by the distance from Wuhan to the capital city of the country- accounts for 5.2% of the total explanation of the delay in response, although its statistical significance is weak. Finally, we extend our analysis by testing several variables related to values and ideological biases, and the political survival hypothesis, but we do not find any systematic role for these factors.

The rest of the paper is organized as follows. First, we outline a theoretical framework to model the velocity of response to the COVID-19 outbreak and formulate empirical predictions expected according to our model. In section three we discuss the data. Section four presents the empirical results from our base equation. Section five extends the analysis by considering several additional hypotheses. Next we conduct robustness checks. Finally, we draw the main conclusions and discuss some policy implications.

Modeling the decision of the policy response to the crisis outbreak

Next we present a theoretical model that builds the foundations of the empirical strategy that we follow later to analyze the drivers of the agility of policy response.

Let ρ be the transmission rate of the virus under no contention measures and d its death rate. The strategies to fight the outbreak can be modelled as a sequential decision process with incomplete information. In every time period, the government can decide either to take hard measures to contain the virus or to take soft measures. If the government takes soft measures (SM) at time t, transmission rate is reduced to $\rho_t = \delta^S \rho$. If it takes hard measures, then it loses π units of utility (lost production) but reduces transmission rate to $\delta^H \rho$, with $\delta^H < \delta^S < 1$. Let n_{t-1} be the number of infected people at the end of time t − 1. At the beginning of period t, they infect $\rho_t n_{t-1}$ people, and then they are treated. Let us note by c the capacity of the healthcare system. If $n_{t-1} < c$, then no infected population die at t and all get cured. Otherwise, the number of fatalities at t is $f_t = d(n_t - c)$, and the rest get cured.

Let us consider a 4-period process, as the one represented in Figure 1. At t = 0, nature determines an initial number of infected people n_0 and the transmission rate ρ. At t = 1, infected people transmit the virus to others and then get treated. Therefore, $n_1 = \rho n_0$, and the number of dead people at t = 1 is $f_1 = d \max\{n_0 - c, 0\}$. The government gets an estimation of the transmission rate $\rho_1 = \hat{\rho}$ and of the total number of infected people, $\widehat{n_1}$. Based on that information, the government estimates the expected transmission rate, death rate and capacity for the following periods ($\hat{\rho}_{t+1} = E_t(\rho_{t+1})$, $\hat{d}_{t+1} = E_t(d_{t+1})$, $\hat{c}_{t+1} = E_t(c_{t+1})$) and decides whether to take soft or hard contention measures. The process goes like this until t = 4, where a vaccine is discovered, and propagation goes to 0. Figure 1 represents how the government expects that the pandemic will evolve, at t = 1.

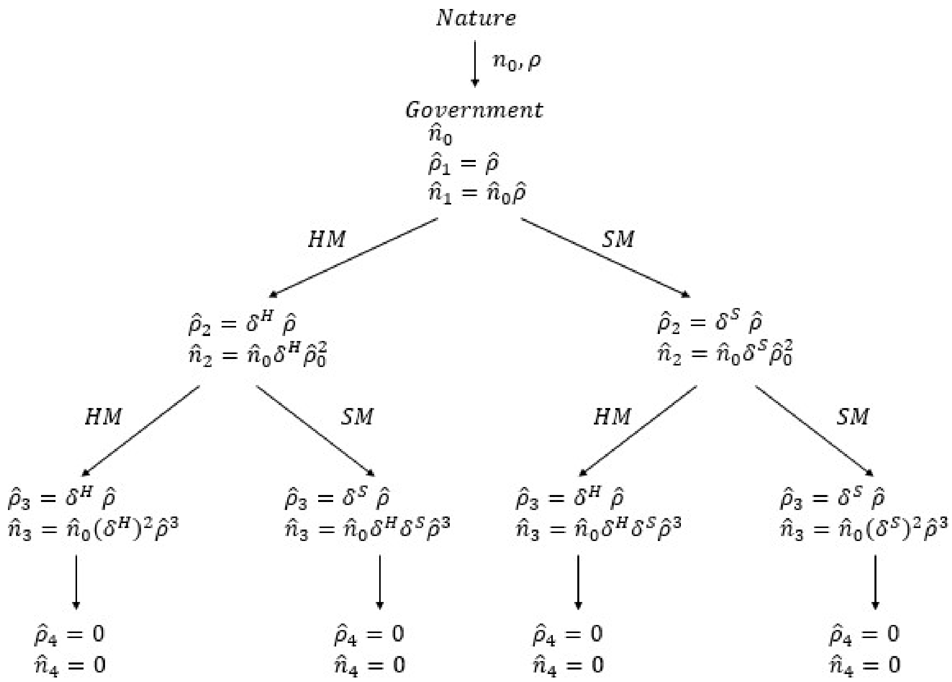

Figure 1: Representation of the 4-periods decision process with government expectation of transmission rates and number of infected people at t = 1.

Let us note by $\hat{f}_{t+i}(\hat{n}_t) = \hat{d}_{t+i}\max\{\hat{n}_t - \hat{c}_{t+1}, 0\}$ the expected fatalities at time *t+i,* given the expectations of the death rate and the capacity, and by *l* the cost per fatality. Then, the expected cost at *t = 1* of the different strategies that the government can take are:

$$EC(HM,HM) = l\{\hat{f}_1(\hat{n}_0) + \hat{f}_2(\hat{\rho}\hat{n}_0) + \hat{f}_3(\hat{\rho}^2\delta^H\hat{n}_0) + \hat{f}_4(\hat{\rho}^3(\delta^H)^2\hat{n}_0)\} + 2\pi \quad (1)$$

$$EC(HM,SM) = l\{\hat{f}_1(\hat{n}_0) + \hat{f}_2(\hat{\rho}\hat{n}_0) + \hat{f}_3(\hat{\rho}^2\delta^H\hat{n}_0) + \hat{f}_4(\hat{\rho}^3\delta^H\delta^S\hat{n}_0)\} + \pi \quad (2)$$

$$EC(SM,HM) = l\{\hat{f}_1(\hat{n}_0) + \hat{f}_2(\hat{\rho}\hat{n}_0) + \hat{f}_3(\hat{\rho}^2\delta^S\hat{n}_0) + \hat{f}_4(\hat{\rho}^3\delta^S\delta^M\hat{n}_0)\} + \pi \quad (3)$$

$$EC(SM,SM) = l\{\hat{f}_1(\hat{n}_0) + \hat{f}_2(\hat{\rho}\hat{n}_0) + \hat{f}_3(\hat{\rho}^2\delta^S\hat{n}_0) + \hat{f}_4(\hat{\rho}^3(\delta^S)^2\hat{n}_0)\} \quad (4)$$

First, notice that *EC(HM, SM) ≤ EC(SM, HM),* with strict inequality if under soft measures the healthcare system collapses. Delaying the adoption of hard measures is a weakly dominated strategy if the government expects a collapse. Therefore, under the assumption of rationality, the only reason for governments that took hard measures not to take them before was a risk underestimation or an overconfidence in their capacity. The latest reasoning is consistent with the offsetting behavior hypothesis, put forward by Peltzman (1975), which implies that risk is compensated: agents adjust behavior in response to the perceived level of risk, and behave less carefully if they feel more protected. This hypothesis has been tested frequently, for instance, in car safety analysis (Chirinko and Harper, 1993; Peterson, Hoffer and Millner, 1995).

Second, let us analyze what determines whether the government decides to take hard measures or soft measures. The dynamics of governments action or inaction during crises do not imply that action is always beneficial or functional (Rosenthal and Kouzmin, 1997). Hence, governments and managers consider costs and benefits from action (Comfort, Waugh and Cigler, 2012). The government will apply hard measures (at least one time) if and only if the expected costs (economic and fatality related) are lower than those cost of soft measures. It is sufficient to compare the case when the government applies once the hard measures.

Noting by ΔC the difference between *EC(HM, SM)* and *EC(SM, SM)*, we have that:

$$\Delta C = l\{\hat{f}_3(\hat{\rho}^2\delta^H\hat{n}_0) + \hat{f}_4(\hat{\rho}^3\delta^H\delta^S\hat{n}_0) - \hat{f}_3(\hat{\rho}^2\delta^S\hat{n}_0) - \hat{f}_4(\hat{\rho}^3(\delta^S)^2\hat{n}_0)\} + \pi \tag{5}$$

The higher the lost production due to hard measures, π, the lower the incentives for the government to take hard measures, since ΔC increases as π increases. Note also that fatality costs will be positive only if the government believes that the system will collapse under soft measures. In that case, the incentive to take hard measures increases.

Third, let us notice that even if the system collapses, the government may decide not to take hard measures. Let us assume that the system will collapse under soft measures at t = 3 and t = 4 but it won't at any moment under hard measures. Then:

$$\Delta C = -l\{\hat{f}_3(\hat{\rho}^2\delta^S\hat{n}_0) + \hat{f}_4(\hat{\rho}^3(\delta^S)^2\hat{n}_0)\} + \pi \tag{6}$$

The government will take hard measures if and only if the total number of fatalities times the cost per fatality is higher than the penalty cost of the hard measures. Therefore, the larger the game (other things equal), the higher the probability of hard measures. Moreover, since the duration of the pandemic was not certain, the expectations about its duration may be itself a key parameter that modifies government reaction: the more pessimistic about the duration, the more likely to take hard measures before.

In all, the theoretical description of the decision process allows identifying two main insights. First, the decision of which strategy to follow depends on the seriousness of the pandemic and the economic and fatality costs expected by the government. Therefore, governments may behave rationally even if they decide to follow different strategies because they may be facing different expectations of associated costs. Secondly, conditioned to expecting of a healthcare collapse, anticipating hard measures is strictly better than delaying the response. Hence, governments that were forced to take hard measures once the number of diagnosed cases escalated would have been better off if they had anticipated the policy response.

Variables, data and sources

Sample

In order to ensure certain homogeneity between countries, we have considered for our model the 36 OECD countries. We also provide a robustness check increasing the sample with the five EU states that do not belong to OCDE (Bulgaria, Romania, Cyprus, Malta and Hungary) and four countries that are candidates to adhesion to EU (Albania, Montenegro, North Macedonia and Serbia). Next we explain the variables we use based on our theoretical model, how we specify them and sources from which we obtain the information.

Variables

Incidence rate at policy response: We define the incidence rate at policy response as number of cases (according to the John Hopkins Coronavirus Resource Center) adjusted per total population when the government began implementing hard measures. This variable captures the time the government waited until taking hard measures. Hard measures are those that severely restrict free movements of citizens (partial or total lockdowns): closing borders, closing schools, universities and public places, prohibiting public events and public gatherings, closing most or all non-essential shops, curfews, and forcing work at home. To establish a homogeneous criterion, at least two of these measures needed to be in place for a country to be considered as implementing hard measures. Table A-1, presents which action has been considered as the first hard action for each country. Data was obtained from the IMF database of policy response to COVID-19 (https://www.imf.org/en/Topics/imf-and-covid19/Policy-Responses-to-COVID-19), the Think Global Health timeline (www.thinkglobalhealth.org/) and complemented with official government websites and press briefings.

Fatality costs and health capacity to fight the outbreak: We use total healthcare resources per capita in 2017 (purchasing power parity - ppp), last available year, as a proxy of the level of confidence in the own capacity to overcome the outbreak, thus containing the fatality costs. Data on healthcare expenditure per capita (ppp) has been obtained from the World Bank database (https://data.worldbank.org/indicator/SH.XPD.CHEX.PP.CD). While nominal expenditure could be strongly associated to different costs, using ppp-adjusted allows controlling for cost differences. In any case, we check our results by using an alternative variable, the healthcare expenditure as a percentage of the GDP, which is a relative measure. According to the offsetting behavior hypothesis (Peltzman, 1975), we expect that a stronger capacity of the health services will be negatively associated with agile policy response.

Economic costs: Governments consider costs and benefits from policy. Hard measures to confront COVID19 crisis, due to their intrinsic characteristics, slowdown business activity thus creating damage to the economy. Trade and tourism are two activities particularly damaged by measures involving strong restrictions on mobility. Hence, we approach the relevance of economic costs with two indicators: total travel and tourism (direct and indirect) contribution, and total trade (imports and exports), both as % of total GDP in 2018. Both indicators are obtained from the World Bank Database (https://data.worldbank.org/indicator/NE.TRD.GNFS.ZS, https://tcdata360.worldbank.org/indicators/tnt.tot.contrib.gdp). Our expectation is that the higher the economic costs of adoption of hard measures the less agile is the government adopting them.

Uncertainty and information: We use as main indicator for the level of information of a government, the total number of countries that have announced or are already implementing hard measures when the government starts dealing with the pandemic (first case diagnosed within the country). We also use an alternative proxy: the number of days between the first lockdown (Hubei, 23th January 2020) and the first case within each country. More time elapsed since the eruption of the crisis allows governments to adjust responses and reduce the risk of problems such as cognitive overload or panic (Moynihan, 2008). Hence, countries whose first case occurred later should have had more accurate information and more cognition of the risk. This allows policymakers to lessen the gap between planning and practice (Comfort, 2007). Therefore, we expect them to act relatively faster, because they had available more and better signals calling for urgent action before reaching higher level of criticality (Farazmand, 2007).

Table 1 displays the description of the variables and their sources. Table 2 shows the descriptive statistics. Table A-2, in appendix, displays the correlation matrix.

Table 1. Variables: Description and sources

	Description	Source	Hypothesis
Dependent variable			
Incidence rate	The number of cases adjusted per total population when the government began implementing hard measures.	IMF & Think Global Health	
Covariates			
Health Expenditure per capita (ppp)	Logarithm of total healthcare expenditure per capita in 2017 (ppp).	World Bank	αj > 0
Tourism	Logarithm of total travel and tourism contribution to GDP.	World Bank	αj > 0
Trade	Logarithm of total trade (imports and exports) as % GDP.	World Bank	αj > 0
Previously locked countries.	Total number of countries that had begun to have implement hard measures when the pandemic hits the country.	Own elaboration	αj < 0
Alternative covariates			
Health Expenditure % GDP	Logarithm of the health Expenditure as % GDP	World Bank	αj > 0
Days since Hubei lockdown	Number of days between the first lockdown (Hubei, 23th January) and the first case within each country.	Own elaboration	αj < 0

Table 2: Descriptive statistics

	Min	Max	Mean	St Dev
Incidence rate at policy response	0.0121	379.9037	68.1322	89.5308
Healthcare expenditure (ppp) (LN)	6.9990	9.2790	8.2200	0.5231
Tourism (LN)	1.4590	3.5440	2.2270	0.4751
Trade (LN)	3.3140	5.9590	4.5250	0.5365
LockedCountries	0.0000	8.0000	1.0280	1.4038
Healthcare expenditure % GDP	1.4398	2.8367	2.1388	0.2728
Days since Hubei lockdown (LN)	-7	48	25.0556	17.0192

Empirical model and results

Our empirical analysis follows a three-step procedure. Firstly, we estimate a base model according to the theoretical model presented in Section two. Then, we discuss potential extensions of the model, by introducing new variables to capture additional effects, such as emotional and political biases. Lastly, we estimate a final model, present some robustness checks, and the interpretation of the results.

Our base empirical model is grounded on the theoretical model presented. The agility to take action (cases adjusted by total population when hard measures are implemented) is affected by the capacity of the healthcare system to avoid fatalities and reduce transmission rate, the costs of hard measures, and the information available to the government with respect the expected deaths of the pandemic and the transmission rate. As explained in the previous section, in order to capture these drivers, we use the following variables: healthcare expenditure per capita, tourism, trade, and previously locked countries. Therefore, we estimate a base model of the form:

$$Cases = f(population, healthcare, tourism, trade, locked\ countries) \quad (7)$$

Due to the non-negative discrete nature of the problem, a discrete modeling approach is the most suited. Thus, our empirical approach is done by using a GLM with Negative Binomial distribution. The negative binomial allows us to capture over and under dispersion, and therefore provides more robust estimates of the parameters and the standard errors than a Poisson distribution. We also adjust an alternative specification of the model by using OLS. In order to do so, we transform the target to the logarithm of the incidence rate. Although for a general discrete problem this approach may lead to non-normality of residuals and may not solve the relationship between variance and mean associated with counting problems (see, for instance, Long, 1997; Lindsey, 2000), in this case, after the transformation residuals can be considered normal (p-value for the Shapiro-Wilk test is 0.2020 and for the Anderson-Darling test is 0.1364) and homoscedastic (White test for heteroscedasticity yields p-value = 0.3346). The average variance inflation factor (VIF) is 1.34 and no individual VIF is above 2.

Table 3 presents the results using the two modeling techniques. Both methods yield similar estimation of the parameters. In both cases, the theoretical hypotheses cannot be rejected for all parameters. Confidence on health capacity to deal with the crisis is associated with a higher incidence rate and, therefore, negatively associated with the agility of policy response. In this regard our result is consistent with the offsetting behavior hypothesis. Expectations of economic impact if hard measures are delayed are as well negatively related to the agility of policy response. On the contrary, increased information and reduced uncertainty as long as more countries have adopted hard measures are associated with a more agile policy response.

Table 3: Estimated parameters of the models

	Negative Binomial (1)	**OLS Robust (2)**
Intercept	-35.9934***	-24.9476***
	(3.2792)	(3.9831)
Healthcare capacity	1.9031***	1.9908***
	(0.3228)	(0.3815)
Tourism	1.7829***	2.1120***
	(0.3093)	(0.3863)
Trade	1.4726***	1.6882***
	(0.2763)	(0.3976)
Locked countries	-0.6344***	-0.6611***
	(0.1362)	(0.2382)
N. Observations	36	36
R-Squared		0.8167
F-Test		5.188e-11***
Residual/Null deviance	0.6830	

Standard errors in brackets. Level of Significance: *** p<0.01, ** p<0.05, * p<0.1

The negative binomial distribution avoids any transformation of the target and guarantees a proper fitting for a counting outcome without the assumption of normality of the residuals. Therefore, we take it as our base model. Next, we check what are the results when using the alternative specifications for health capacity (expenditure in % GDP) and level of information (days since Hubei lockdown). Table 4 shows the results.

Table 4: Estimated parameters of the models with alternative specifications

	Base model (1)	**Negative Binomial (3)**	**Negative Binomial (4)**
Intercept	-35.9934***	-28.375***	-38.8726***
	(3.2792)	(3.2480)	(3.2280)
Healthcare capacity	1.9031***	-	2.1684***
	(0.3228)	-	(0.3399)
Tourism	1.7829***	1.4700***	1.8666***
	(0.3093)	(0.3563)	(0.3389)
Trade	1.4726***	2.1681***	1.5858***
	(0.2763)	(0.3646)	(0.3507)
Locked countries	-0.6344***	-0.8000***	-
	(0.1362)	(0.1776)	-
% GDP health (LN)	-	2.7408***	-
	-	(0.8381)	-
Days since Hubei [b]	-	-	-0.0006**
	-	-	(0.0003)
N. Observations	36	36	36
Residual/Null deviance	0.6830	0.4333	0.6301

Standard errors in brackets. Level of Significance: *** p<0.01, ** p<0.05, * p<0.1

Both estimations using alternative specification for health capacity and level of information yield almost identical results as those we obtained with the base model -estimation (1)- (and the same happens if we run OLS Robust estimations, which results are available upon request). When the health capacity is measured in relative terms (estimation 3), goodness of fit is a bit lower, revealing that it is more relevant the absolute level of healthcare resources (adjusted by PPP) than the relative. When the level of information is measured as the days since Hubei's lockdown (estimation 4), the level of significance goes to $p<0.05$ from $p<0.01$. Thus, governments incorporated more information by knowing other governments' strategies than by any other means.

Extension of the model: emotions, beliefs and policy survival

Starting from our base model estimated with the negative binomial distribution (which avoids any transformation of the target and guarantees a proper fitting for a counting outcome without the assumption of normality of the residuals), in this section we test several additional hypotheses on emotional and political biases. Table 5 shows the results.

Emotions

Decision-making is highly influenced by emotions, especially when there is a lack of information (Kahneman, 2011), and Akerloff and Shiller (2009) pointed out that emotions play a relevant role in economics and are a key driver of market failures and financial crisis. Regarding emotional biases, two main indicators are considered. First, the greater the geographic proximity of the crisis, the greater its impact in terms of the incentives for policy action, including increased fear and attention (Nohrstedt and Weible, 2010). Hence, we consider the distance *kilometers from Wuhan* to the capital city of each country (source Google Maps API), as a proxy for geographic proximity bias, and we expect that the closer the country to Wuhan, the more agile the policy response. The variable is included as the logarithm of the distance to capture a concave dissipation effect.

The second indicator corresponds to the gender of the Prime Minister. The discussion of whether female prime ministers have taken faster, and more executive action has been widely discussed (e.g. *CNN,* April 16, 2020; *The Guardian*, 25 April 2020). A possible explanation is that women are more risk averse than men, and place heavier weight on safety, which is consistent with Barnes and Beaulieu's (2018) survey experiment on women and risk aversion. We specify the variable *Gender PM* as a dummy that takes value 1 for women and 0 otherwise (source official countries' web pages). We expect female prime minister to be more agile in policy response.

Results show that the distance to Wuhan is a significant factor in the agility of policy response (estimation 5). The more distant to Wuhan the slower the reaction, consistent with the geographic proximity hypothesis. On the contrary, our variable for gender prime minister (estimation 6) does not make a significant difference in the agility of policy response. This result is consistent with that in Pondorfer, Barsbai and Schmidt (2017), who do not find actual gender differences on risk preferences, but find that this perception is rather based on stereotypes.

Table 5: Estimations of extensions of the base model

	Base (1)	**(5)**	**(6)**	**(7)**	**(8)**
Intercept	-35.9934***	-40.8394***	-36.7422***	-36.2375***	-39.4017***
	(3.2792)	(3.5442)	(3.6301)	(3.2534)	(3.0522)
Healthcare capacity	1.9031***	1.9096***	1.9949***	1.8996***	1.9630***
	(0.3228)	(0.3127)	(0.3587)	(0.3218)	(0.2976)
Tourism	1.7829***	1.7696***	1.8231***	1.8861***	1.7910***
	(0.3093)	(0.3007)	(0.3298)	(0.3103)	(0.2891)
Trade	1.4726***	1.4029***	1.4540***	1.4897***	1.3906***
	(0.2763)	(0.2710)	(0.2759)	(0.2748)	(0.2571)
Locked countries	-0.6344***	-0.6317***	-0.6156***	-0.6949***	-0.5721***
	(0.1362)	(0.1326)	(0.1361)	(0.1449)	(0.1197)
Km from Wuhan		0.5734**			
		(0.2555)			
Gender PM			-0.1627		
			(0.3947)		
Ideology				0.1650	
				(0.1559)	
Days to election					0.4766*
					(0.2756)
Num. observations	36	36	36	36	36
Residual/Null deviance	0.6830	0.7085	0.6842	0.6982	0.7042

Note: Standard errors in brackets. Level of Significance: *** p<0.01, ** p<0.05, * p<0.1

Beliefs

We consider the possibility that different ideologies or beliefs on the role of government can influence how crisis are viewed and managed (Dror, 1994). The effects of ideological and partisan differences in the management of COVID-19 crisis in the US have been extensively studied (see Barrios and Hochberg, 2020, for a review). We have specified a variable *Ideology*, in which we give a score from -1 (left) to 1 (right). Center parties are scored 0 (Main sources are the World Bank Database of Political Institutions https://datacatalog.worldbank.org/dataset/wps2283-database-political-institutions, and international alliances to which parties in government belong). We expect that left-wing parties will be more prone to agile policy response. From results of estimation (7) we observe that *ideology* has no significant influence on the agility of policy response to COVID-19 crisis.

Policy survival and electoral competition

The application of the logic of political survival (Bueno de Mesquita et al, 2003) to disaster management suggests that since voters punish governments for improper crisis response, risk-averse governments will implement proactive policies, especially within highly competitive contexts and close to elections (Baekkeskov and Rubin, 2014). Among the expectations that these authors state, one is of especial interest for our research: the relationship of the policy response with the electoral cycle, suggesting that the closer the next election the most comprehensive the policy response (Bechtel and Hainmueller, 2011). Based on these insights, we have tested one additional variable: the logarithm of the *days to next election* (source National Democracy Institute database https://www.ndi.org/ and countries' official web sites), which measures the number of days between the first diagnosed case in the country and the next scheduled or expected relevant election date. The result we obtain (estimation 8) is consistent with the hypothesis than the closer the next election, the more agile the policy response, although the significance is weak.

It is worth noting that through estimations 5 to 8, all the variables in our base model keep the same sign and level of significance. Therefore, we can conclude that our basic results are very stable throughout all estimations we conducted in this section.

Robustness check and final model interpretation

In this section we conduct two robustness checks and the estimation of the final model. First, we check whether the base model and the significant extensions in sections four and five are robust to the inclusion of new countries. We introduce in the sample the five EU states that do not belong to OCDE (Bulgaria, Romania, Cyprus, Malta, and Hungary) and the four candidates to adhesion to EU (Albania, Montenegro, North Macedonia, and Serbia)

As results in Table 6 show, the base model is robust to the extension (estimation 9), as well as the proximity bias extension (estimation 10). However, the policy survival factor (estimation 11) is not significant when including additional countries.

Table 6: Robustness check including additional countries in the sample

	Base (1)	**(9)**	**(10)**	**(11)**
Intercept	-35.9934***	-34.0238***	-38.8302***	-33.9575***
	(3.2792)	(2.6918)	(3.3258)	(2.6767)
Healthcare capacity	1.9031***	1.8557***	1.8740***	1.7595***
	(0.3228)	(0.2724)	(0.2656)	(0.2877)
Tourism	1.7829***	1.3832***	1.3855***	1.3655***
	(0.3093)	(0.2675)	(0.2617)	(0.2685)
Trade	1.4726***	1.3172***	1.2481***	1.3233***
	(0.2763)	(0.2671)	(0.2639)	(0.2658)
Locked countries	-0.6344***	-0.6313***	-0.6195***	-0.6310***
	(0.1362)	(0.1211)	(0.1179)	(0.1191)
Km from Wuhan			0.5531*	
			(0.2751)	
Days to election				0.1119
				(0.1519)

Num. observations	36	45	45	45
Residual/Null deviance	0.6830	0.6900	0.7067	0.6935

Note: Standard errors in brackets. Level of Significance: *** p<0.01, ** p<0.05, * p<0.1

Second, we present an additional robustness check by conducting a Bayesian estimation of the model. Low sample size can lead to less robust estimation of parameters and standard errors, thus compromising the significance test of GLM, which relies on asymptotic properties of the estimators (Western and Jackman, 1994). We perform the Bayesian estimation using the *brms package* available in R (Bürkner, 2017), and using no prior to avoid introducing any bias. Since the *days to election* variable is not robust to the inclusion of additional countries, we only include the *kilometers from Wuhan* extension. As can be seen in Figure 2, all parameters are robust to the Bayesian estimation, but *kilometers from Wuhan* exhibits weak significance (p-value 0.1234), due to certain skewness of the distribution.

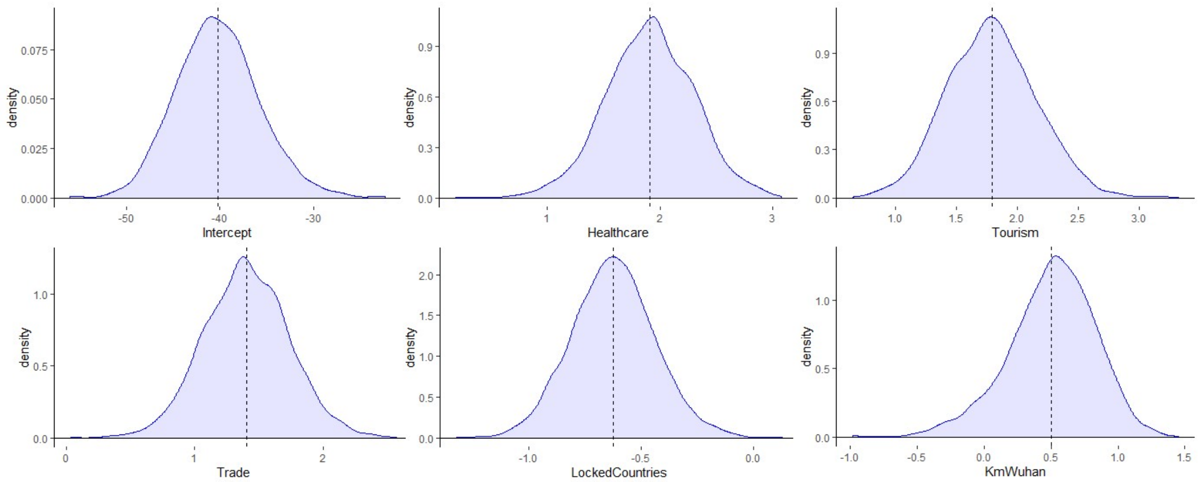

Figure 2: Distribution of the parameters of the model using a Bayesian estimation

Finally, in order to gain a complete understanding of the model beyond the significance of the parameters, we estimate the relative importance of each variable included in the model. We use a new methodology for model interpretation suggested by Lundeberg and Lee (2017, 2019): SHAP (SHapley Additive ExPlanation) values. On synthesis, given an observation $x =$

$(x_1, \ldots, x_J)$, the SHAP value of feature j on the instance x corresponds to how the concrete value of feature j on x modifies the output of the model with respect other instances that share some of the features with x but not j. For a parametric model $F(x) = g(\sum_j \alpha_j x_j)$, where g is a function of the weighted features of x, the SHAP value corresponds to: $\varphi_j(x) = \alpha_j(x_j - E(X_j))$ where X is the set of observations and $E(X_j)$ is the average value of the j feature on X. Then, noting by N the total number of observations, we can estimate the relative importance of the feature j in the model as

$$RI_j = \frac{\sum_{i=1}^{n} |\varphi_j(x_i)|}{\sum_{k=1}^{J} \sum_{i=1}^{n} |\varphi_k(x_i)|}$$

Table 7 presents the relative importance of each variable in the final model, estimated using the Bayesian approach.

Table 7: Final model

	Bayesian estimate [a]	**Relative importance**
Intercept	-40.2217***	
	(4.4631)	
Healthcare capacity	1.9090***	30.45%
	(0.3878)	
Tourism	1.7920***	24.72%
	(0.3722)	
Trade	1.4036***	21.04%
	(0.3264)	
Locked countries	-0.6233***	18.59%
	(0.1845)	
Km from Wuhan	0.5040[+]	5.20%
	(0.3258)	
Num. observations	36	
Residual/Null deviance	0.7065	

Note: Standard errors in brackets. Level of Significance: *** p<0.01, ** p<0.05, * <0.1, [+] p<0.15

[a] The Reset test for functional form or omitted variables with a polynomial fitting of degree 4 does not reject the null hypothesis (p-value 0.3965). Therefore, the functional form is correct, and the model does not suffer from omitted variables

Conclusion and policy implications

In this research we built a theoretical model, based on which we designed and implemented an empirical strategy to analyze the drivers of the agility of policy response to the COVID-19 outbreak. We are aware that our identification strategy does not allow making strong claims of causal relations from our empirical results, which is a limitation of or research. However, we believe that our theoretical modelling provides some alleviation regarding that limitation.

The empirical results we obtained show that overconfidence in the capacity of health services and the intensity of expected economic costs from hard measures to manage the crisis delayed policy response to COVID-19. Our results are empirically robust, and are also supported by frequent public statements made by political leaders, such as those by the Spanish Prime Minister Pedro Sánchez on March 10th and the French President Macron in the same day, both praising the robustness of their respective healthcare systems as the best possible preparation to fight the pandemic. Soon after, both governments had to adopt hard measures. Indeed, this overconfidence has been stated as one of the main causes of the delay in the policy response by global healthcare experts, such as Mr. Pedro Alonso, the Director of the World Health Organization Malaria Program, who stated on May 6th that Western pride prevented most advanced countries from reacting quickly.

Increased information and reduced uncertainty on other countries' policy responses and the development of the epidemic increased the agility of the country's policy response. Being a decision process with incomplete information, variables related with additional information and valuation of risk are key and directly account for almost 25% of the total importance.

All governments have been overflowed by the pandemic and have seen themselves being forced to take hard measures to avoid the materialization of a complete health system collapse and its associated fatalities, which would have resulted in a more negative valuation of the government's policy response. According to our theoretical model, once a government has a clear expectation that it will be necessary to take hard measures, taking them immediately strictly dominates delaying them. Hence, the fact that healthcare system capacity and cost-related variables play a role in the time to reaction has a very relevant implication: they may have negatively affected the government's strategy. Because initial expectations did not match reality (otherwise governments would have had not taken hard measures), strong healthcare systems generated an over-confidence in the government's capacity to fight the outbreak. The associated economic costs created a fear of excessive economic damage. Both factors delayed hard measures, thus increasing the overall resulting cost. Estimating the actual impact on fatality and economic costs of agile versus slow policy responses is a question for future research, as required data will only be available when the COVID-19 crisis is over.

There is a wide consensus that strong healthcare capacity improves social welfare, and high levels of trade and tourism are important fuelers of economic growth. However, governments risk being biased because of these benefits, within the specific context of crisis management under incomplete information. As Ballesteros and Kunreuhter (2018, p. 9) warn when analyzing organization decision making under uncertainty shocks, "the riskification of uncertainty leads to the delusion that increasing formal insurance take-up is a sufficient mechanism to reduce vulnerability against uncertainty shocks". Thus, a relevant policy implication emerges. Increasing health expenditure as a consequence of the COVID-19 has emerged as a frequent demand. Indeed, this could improve the performance of the health system on regular day-to-day basis, provided additional capacity meets positive social cost-benefit requirements. However, it would not provide full insurance for future potential pandemics management, as it can induce riskier decisions by governments, particularly under incomplete information.

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APPENDIX

Table A-1: List of date of first hard measures

Country	Date hard measures	Description
Australia	3/19/2020	Border closure; closure some non-essential shops; 4 square meter rule
Austria	3/15/2020	Nationwide lockdown, closure of all non-essential shops, ban of public gatherings
Belgium	3/12/2020	Closure of schools (but not universities), discos, cafes and restaurants, and the cancellation of all public gatherings for sporting, cultural or festive purposes
Bulgaria	3/13/2020	Closure of non-essential shops and workplaces, mandatory quarantine for all people coming from more affected countries (China, Spain, Italy, Iran, South Korea)
Canada	3/16/2020	Border closure, states of emergency including closure of non-essential shops, ban of public gathering, etc. in all Canadian states but Manitoba, New Brunswick and Nova Scotia
Chile	3/16/2020	Border closure, state of emergency, partial lockdowns in affected cities and regions, closure of schools with at least one case.
Croatia	3/17/2020	Closure of most non-essential shops, schools and universities; 14-days mandatory quarantine for people coming from affected countries, border closure
Cyprus	3/13/2020	Border closure, ban of public gatherings
Czech Rep.	3/12/2020	Border closure, nationwide curfew, schools suspended, closure of non-essential shops
Denmark	3/11/2020	Closure of schools and universities, banning of public gatherings, home-work public sector, border closure
Estonia	3/13/2020	Border closure, closure of schools, ban of public gatherings, closure of recreation and leisure shops
Finland	3/16/2020	Closure of schools and universities, banning of public gatherings, shut-down of most government-run facilities (libraries, etc.)
France	3/16/2020	Closure of most non-essential shops, ban of public gatherings, closure of schools and institutes of higher education,
Germany	3/16/2020	Closure of education institutions, ban of public gatherings, closure of non-essential shops in some states
Greece	3/13/2020	Closure of education institutions, ban of public gatherings, closure of cafes, bars, museums, shopping centers, sports facilities and restaurants, border closure with limiting countries and affected countries
Hungary	3/15/2020	Closure of education institutions, bars, restaurants, cafes, public events, border closure
Iceland	3/13/2020	Closure of educational institutions, ban of public gatherings and events
Ireland	3/24/2020	Closure of education institutions, bars and public houses
Israel	3/14/2020	Closure of education institutions, most non-essential retail, ban of public gatherings
Italy	3/8/2020	Complete lockdown north Italy, ban public gatherings
Japan	3/5/2020	Closure of education institutions and extension of the law's emergency measures for an influenza outbreak to include COVID-19
Korea	2/20/2020	Border closure with China, massive testing and surveillance, partial lockdowns on more affected areas
Latvia	3/14/2020	Closure of educational institutions, ban of public events
Lithuania	3/12/2020	Closure of educational institutions, ban public gatherings, borders closure, closure of non-essential shops

Luxembourg	3/15/2020	Closure of non-essential shops, ban of public gatherings, closure educational institutions
Mexico	3/26/2020	Closure of non-essential shops and non-essential activities, ban of public gatherings, closure educational institutions
Netherlands	3/15/2020	Closure of educational institutions; closure of cafés, restaurants, sports clubs, saunas, sex clubs and coffeeshops, museums; ban of public events
New Zealand	3/23/2020	Border closure, ban of public gatherings, closure of all venues and enforcement of telework whenever possible
Norway	3/12/2020	Closure of kindergartens, schools, universities, and some none-essential shops (bars, restaurants, pubs, clubs, among others)
Poland	3/11/2020	Closure of all schools and universities, gathering restrictions and closure of cultural institutions, such as philharmonic orchestras, operas, theatres, museums, and cinemas
Portugal	3/12/2020	State of emergency; closure of establishments in the hospitality sectors such as restaurants, pubs, bars; public gathering restrictions; closure of all education institutions (from kindergartens to universities)
Romania	3/9/2020	Border closure with affected regions; all schools, kindergartens and universities closed
Slovak Rep.	3/15/2020	Implementation of state of emergency with all non-essential stores closed, closure of all schools and 14 days quarantine for people arriving from Slovakia from Italy, China, South Korea
Slovenia	3/15/2020	Closure of all educational institutions, bars and restaurants, and gathering restriction
Spain	3/14/2020	State of emergency declared, with closure of all educational institutions, hospitality sector establishments. People are to remain locked down in their homes except for essential activities
Sweden	3/27/2020	Reunion right restriction to 50 people
Switzerland	3/13/2020	Closure of all educational institutions and gathering restriction of more than 100 people, cancelation of all sport events
Turkey	3/12/2020	Closure of all schools and universities, travel bans and border closure with affected countries
U. Kingdom	3/18/2020	Closure of all schools, restaurants, pubs, clubs, and indoor leisure facilities
United States	3/15/2020	State of emergency, >25 states with closure of education institutions, curfew population, borders closure (main affected areas, including all UE)
Serbia	3/15/2020	Closure of all education institutions from kindergartens to universities, ban public gathering, border closure
N.Macedonia	3/11/2020	Closure of all education institutions from kindergartens to universities, border closure and ban of public gatherings
Albania	3/8/2020	Closure of education institutions, gyms, bars and restaurants
Malta	3/12/2020	Closure of all schools, university and childcare, bars, restaurants and gym, mandatory quarantine to travelers from any country
Montenegro	3/13/2020	Closure of education institution, bars and borders; ban on public gatherings

Table A-2: Correlation Matrix

	Incidence rate	Healthcare capacity	Tourism	Trade	Locked Countries	Km Wuhan
Incidence rate at policy response	-					
Healthcare capacity (ppp)	45%	-				
Tourism	31%	-15%	-			
Trade	18%	-8%	-32%	-		
LockedCountries	-19%	-57%	9%	12%	-	
KmWuhan	17%	4%	7%	16%	7%	-

Note: We include Km from Wuhan because it was used in the Bayesian estimation.

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