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GLOBALIZATION AND PANDEMICS

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ABSTRACT

We propose a theory of the relationship between globalization and pandemics. We start by documenting the importance of international trade for the diffusion of infections in several pandemics throughout history. We also show that trade is closely intertwined with travel. Motivated by this evidence, we build a framework in which business travel facilitates trade according to a constant elasticity gravity equation mediated by mobility frictions. In turn, travel leads to human interactions that transmit disease, as in the Susceptible-Infected-Recovered (SIR) model. We highlight three novel interactions between these two mechanisms. First, trade-motivated travel generates an epidemiological externality across countries. Therefore, reductions in international frictions affect the evolution of the epidemic in each country, and the condition for a pandemic to occur. Second, if infections lead to deaths, or reduce individual labor supply, we establish a general equilibrium social distancing effect, whereby increases in relative prices in unhealthy countries reduce travel to those countries. Third, if agents internalize the threat of infection, we show that their behavioral responses lead to a reduction in travel that is larger for higher-trade-cost locations, and hence leads to an initial fall in the ratio of trade to GDP in the early stages of the epidemic, before a subsequent recovery.

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1 Introduction

Throughout human history, globalization and pandemics have been closely intertwined. The Black Death arrived in Europe in October 1347 when twelve trading ships from the Black Sea docked at the Sicilian port of Messina – the word *quarantine* originates from the Italian word for a forty-day period of isolation required of ships and their crews during the Black Death pandemic. Much more recently, on January 21, 2020, the first human-to-human infections of Covid-19 in Europe are presumed to have taken place in Starnberg, Germany, when a local car parts supplier (Webasto) organized a training session with a Chinese colleague from its operation in Wuhan, China. Examples of disease transmission from the travel induced by international trade abound.

In this paper, we develop a theoretical framework to analyze the relationship between globalization and pandemics. Our framework combines two core mechanisms from economics and epidemiology. First, travel between countries transmits disease through human interaction as in the Susceptible-Infected-Recovered (SIR) model. Second, international trade is facilitated by business travel between countries according to a conventional gravity equation partly mediated by mobility frictions. We show that these core mechanisms are not only empirically relevant, but they interact in systematic ways that lead to novel insights on the interaction between international trade, business travel, and the dynamics of infections during pandemics.

We begin by providing empirical evidence that international trade affects the transmission of disease. We examine the diffusion of three different infectious diseases at different points in history: (i) the medieval plague; (ii) the 1957-8 influenza; (iii) Covid-19. For all three infectious diseases, we show that the speed of diffusion of each disease increases with measures of international trade links. Furthermore, we continue to observe this positive relationship even after controlling for geographical distance from the first disease outbreak.

We next provide empirical evidence that international trade speeds the transmission of disease through the international travel that it induces. First, we use additional data that are available for Covid-19 to show that the relationship between disease diffusion and trade ceases to be statistically significant once we control for total arrivals and departures of people (including migration, tourism and business travel), as expected if the mechanism is international travel. Second, we directly examine the bilateral relationship between international travel and trade, instrumenting for trade using tariffs, as a policy measure that only directly affects trade in goods. We document that reductions in tariffs that increase trade lead to increased travel between countries.

Motivated by these empirical findings, we develop a theoretical model of globalization and pandemics that incorporates a gravity equation for trade and travel alongside a SIR model of disease diffusion. We consider a setting in which agents in each country consume differentiated varieties and choose the measure of these varieties to source from home and abroad. In our baseline model, agents must travel to source each variety from home and abroad, which involves both a fixed cost of meeting with other agents and a variable cost of shipping varieties between countries. When traveling to source varieties, agents are exposed to risk of disease transmission. If a healthy (susceptible) agent meets an infected agent, she becomes infected with a constant probability (the

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contact rate). Once infected, there is a constant probability that an agent recovers from the disease (the recovery rate). We allow these contact and recovery rates to differ across countries.[1]

We begin by abstracting from any effect on the infection on the probability of death or worker productivity, and hence from any behavioral responses, which allows us to highlight four new insights that emerge from the fact that the intensity of interactions in the SIR model is endogenous to trade costs. First, the constant elasticity gravity equation implies that domestic and foreign interactions are substitutes, in the sense that a reduction in trade costs increases foreign interactions relative to domestic interactions. Second, there is a powerful epidemiological externality between countries, such that whether a pandemic occurs depends on the disease environment in the country with the most unhealthy disease environment. Third, reductions in trade costs can either increase or decrease the range of parameter values where a pandemic occurs and the severity of the pandemic when it does occur, because of the substitutability between domestic and foreign interactions. Fourth, multiple waves of infection can occur in the open economy when a single wave of infections would occur in the closed economy. This possibility arises when the epidemic occurs at different paces across countries (perhaps due to different contact and recovery rates), in which case a country can experience a second wave of infections, even after its own wave of infections has begun to subside.

To develop these insights as clearly as possible, we keep our baseline model as stylized as possible. Later, we demonstrate the robustness of these results to a large number of extensions. For example, we relax the assumption that travel is required to source each variety by allowing agents to choose between different technologies for sourcing varieties (in-person versus remote trade), where in-person trade is assumed to involve, on average, a higher fixed cost. We show that all of our main theoretical results continue to hold in this generalization. In a further extension, we allow the productivity of these sourcing technologies to vary across sectors, where transactions that require face-to-face interaction correspond to the case in which remote trade is prohibitively costly. We also develop a dynamic extension, in which agents only need to travel to form new trading relationships, and can source varieties within existing trading relationships by remote trade, but these existing relationships break down stochastically. We show that the steady state of this dynamic specification has the same properties as the static equilibrium of our baseline model. In other generalizations, we demonstrate the robustness of our results to alternative specifications of the fixed cost of sourcing varieties, to the sourcing of intermediate inputs, and to frameworks featuring scale economies and imperfect competition.

We next allow the disease to affect the probability of death and the labor supply of infected workers, but initially continue to assume that agents remain unaware of the source of the infections, which implies no individual-level behavioral responses. Nevertheless, deaths and lower worker productivity reduce aggregate labor supply. Therefore, a country with a more unhealthy disease environment experiences a reduction in its relative supply of labor, and hence an increase in its relative wages. This increase in the country's relative wage raises the relative price of its goods,

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[1]Differences in contact and recovery rates across countries stand in for differences in local culture (e.g., mask wearing), administrative capacity (e.g., contact tracing systems) and medical technology (e.g., available medical treatments).

which reduces travel to that country, in what we term a "general equilibrium social distancing" effect. The timing of these changes in relative labor supply depends on the extent to which the disease affects mortality versus worker's labor supply while infected. Furthermore, which country has the more unhealthy disease environment can change over the course of the pandemic, if the timing of the disease outbreak differs across countries. Additionally, if the disease affects worker's labor supply, and workers self-isolate while infected, their interactions with other agents fall proportionately with their labor supply, which flattens the infection curve and reduces the total number of infections.

Finally, we consider the case in which the disease affects the probability of death, and agents internalize the threat of infection, and optimally adjust their behavior depending on the observed state of the pandemic. As in recent work (see Farboodi et al., 2021), it proves useful to assume that agents are uncertain about their own health status, and simply infer their health risk from the shares of their country's population with different health status (something they can infer from data on pandemic-related deaths). Technically, this turns the problem faced by agents into a dynamic optimal control problem in which the number of varieties that agents source from each country responds directly to the relative severity of the disease in each country.

As in recent closed-economy models of social distancing (such as Farboodi et al., 2021, or Toxvaerd et al., 2020), these behavioral responses reduce human interactions, and thereby tend to flatten the curve of infections. In contrast to these closed-economy setups, these behavioral responses now have international general equilibrium implications. In both countries, agents skew their interactions away from the relatively unhealthy country, which leads to the largest falls in the ratio of trade to income in the relatively healthier country. This redirection of interactions reduces the relative demand for the unhealthy country's goods, which in turn reduces its relative wage, thereby having the opposite effect to the reduction in its relative labor supply from greater deaths. Depending on the timing of the wave of infections in each country, which country has more infections than the other can again change over the course of the pandemic, thereby reversing this pattern of changes in trade openness and relative wages over time. We show that these behavioral responses lead to a larger reduction in travel for higher-trade-cost locations, which leads to an initially larger fall in the ratio of trade to GDP in the early stages of the pandemic, before its subsequent recovery. We document that this pattern seems to be consistent with the evolution of the trade to GDP ratio during the first wave of the Covid-19 pandemic in 2020.

Finally, we consider an extension of our dynamic framework in which there are adjustment costs of establishing the human interactions needed to sustain trade. In the presence of these adjustment costs, households react less aggressively to the pandemic and their reaction is smoother, which leads to a faster and more severe pandemic with a greater total number of deaths, but less pronounced temporary reductions in real income and trade. In deciding to accumulate contacts, households now anticipate the costs incurred in adjusting these contacts during a pandemic. In practice, we find that these anticipatory effects are quantitatively small, at least in our specification with symmetric adjustment costs. This pattern of results is consistent with the idea of a rapid recovery of economic

activity in normal times after the end of the pandemic.

Our paper connects with several strands of existing research. First, we build on an extensive empirical literature that finds that a constant elasticity gravity equation provides a good approximation to observed spatial interactions, including international trade (e.g., Anderson and van Wincoop 2003, Eaton and Kortum 2002, Arkolakis et al. 2012, Chaney 2014), migration (Kennan and Walker 2011), commuting (Ahlfeldt, et al. 2015, Monte, et al. 2018), and tourism (Morley, et al. 2014). Relative to this existing research, we incorporate a gravity equation for trade and travel alongside a SIR model of disease dynamics. Since travel and disease diffusion are endogenous to trade frictions, the gravity structure of trade determines both whether a pandemic occurs and the severity of the pandemic when it does occur.

Second, we build on the empirical literature on the role of international business travel in greasing the wheels of international trade. A large number of empirical studies find a strong correlation between international travel and international trade, including Kulendran and Wilson (2000), Cristea (2011) and Blonigen and Cristea (2015). More recently, a small number of studies have used micro data and sources of quasi-experimental variation to provide evidence of a causal impact of business travel on trade, including Bernard, Moxnes and Saito (2019), Campante and Yanagizawa-Drott (2018), Söderlund (2020), and Startz (2021). Relative to this research, we examine the role played by the link between international travel and trade in the transmission of disease.

Third, our paper also builds on the literature developing epidemiological models of disease spread, starting with the seminal work of Kermack and McKendrick (1927, 1932). More specifically, our multi-country SIR model shares many features with multigroup models of disease transmission, as in the work, among others, of Hethcote (1978), Hethcote and Thieme (1985), van den Driessche and Watmough (2002), and Magal et al. (2016).[2] A key difference is that the interaction between groups is endogenously determined by international trade frictions, which implies that trade costs affect disease dynamics in each country and the world as a whole.

The recent Covid-19 pandemic has triggered a remarkable explosion of work by economists studying the spread of the disease (see, for instance, Fernández-Villaverde and Jones, 2022) and exploring the implications of several types of policies (see, for instance, Alvarez et al., 2021, Acemoglu et al., 2021, Atkeson, 2020, or Jones et al., 2021). Within this literature, a few papers have explored the spatial dimension of the Covid-19 pandemic by simulating multi-group SIR models applied to various urban and regional contexts (see, among others, Argente et al., 2022, Bisin and Moro, 2021, Cuñat and Zymek, 2020, Birge et al., 2020, and Fajgelbaum et al., 2021). Our paper also connects with a subset of that literature, exemplified by the work of Alfaro et al. (2020), Farboodi et al. (2021), Fenichel et al. (2011), and Toxvaerd (2020) that has studied how the behavioral response of agents (e.g., social distancing) affects the spread and persistence of pandemics. Most of this research is concerned with Covid-19 and adopts a simulation approach. In contrast, we develop a theoretical framework that permits an analytical characterization of the relationship

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[2]See Hethcote (2000) and Brauer and Castillo-Chavez (2012) for very useful reviews of mathematical modeling in epidemiology, and Ellison (2020) for an economist's overview of SIR models with heterogeneity.

between globalization and pandemics. We provide empirical evidence in support of the predictions of this theoretical framework using data from a range of different infectious diseases.

Our work is also related to a large existing empirical literature in epidemiology on the role of global trade and transportation networks in the transmission of infectious disease. This body of research is summarized in Saker et al. (2004) and the National Academies of Science Conference Volume by Institute of Medicine (2006). In a related review of the existing evidence, Tatem et al. (2006) examine five human-infectious diseases (Plague, Cholera, Influenza, HIV and SARS) and four vector-borne diseases (Yellow Fever, Dengue, West Nile Virus, Malaria), and document the role played by international trade in the spread of these diseases around the globe. In the economic history literature, Benedictow (2004), Christakos et al. (2005), Boerner and Severgnini (2014), Yue et al. (2017), and Jedwab et al. (2019) all argue that international trade routes were central to understanding the transmission of the plague through medieval Europe. Kenny (2021) provides an insightful account of the effect of pandemics throughout history.

The rest of the paper is structured as follows. In Section 2, we provide empirical evidence that international trade speeds the transmission of disease and that the mechanism is through the international travel induced by trade. In Section 3, we present our baseline gravity model of travel and trade. In Section 4, we examine the implications of this model for disease dynamics, abstracting from labor supply effects from deaths or reduced worker productivity and from behavioral responses. Globalization plays a central role in shaping the course of the pandemic, because the volume of travel between countries is endogenous to trade and mobility costs. In Section 5, we incorporate labor supply responses to the pandemic, which affect the path of relative wages and thus the volume of travel between countries during the pandemic. In Section 6, we allow for individual behavioral responses motivated by agents adjusting their desired travel behavior in response to their fear of being infected by the disease. We offer some concluding remarks in Section 7. An Online Appendix presents all the proofs and extensions not included in the main text, as well as additional empirical evidence, data description, and computational algorithms.[3]

2   Motivating Evidence

We start by providing new evidence on the link between international trade and disease diffusion and the underlying mechanism connecting international travel and trade.[4] First, we provide some historical background on globalization and disease diffusion. Second, we document the speed of diffusion for three infectious diseases: the medieval plague, 1957-8 influenza, and Covid-19. Third, we provide evidence on the cross-sectional relationship between the speed of diffusion and international trade for each disease. Finally, we provide evidence on the link between international travel and trade, as the mechanism connecting disease diffusion and trade in our theoretical model.

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[3]Appendix A provides a detailed description of its contents.

[4]For additional evidence and literature reviews, see Online Appendix G on the link between trade and disease diffusion, and Online Appendix H on the link between travel and trade.

Historical Background   For most of human history, regional and continental populations were relatively isolated from one another. Large-scale improvements in land, sea, and air transportation technologies over the centuries have dramatically increased the globalization of the world economy and the associated movement of people and goods around the world.[5] Perhaps the most dramatic example of international trade spreading infectious disease comes from Christopher Columbus's discovery of the New World in 1492, during his search for a more direct trade route with China and the Spice Islands. Since the natives of the New World had no accumulated immunity to Old World infectious diseases, such as smallpox, measles, and influenza, the subsequent epidemics of these infectious diseases resulted in mortality rates of up to 80-90 percent.[6]

Disease Diffusion over Time   We provide empirical evidence for three quite different diseases at different points in history: (i) The medieval plague; (ii) The 1957-8 influenza; (iii) The Covid-19 pandemic. Both the influenza virus and Covid-19 are spread through airborne transmission between people in close proximity. Although debate continues about the exact origin and mode of transmission of the plague, the consensus is that the plague is initiated by the flea-borne bacterium *Yersina pestis*, which circulates between mammal hosts.[7]

We use data on plague outbreaks across European cities from 1347-1760 and outbreaks of influenza from 1957-8 and Covid-19 from 2019-2020 across countries. The medieval plague first arrived in Europe at Messina in 1347 and then spread along Old World trading routes. The first cases of both 1957-8 influenza and Covid-19 were in China, before spreading around the world. For each disease, we compute an *arrival time* for each location, as the difference in time between the first outbreak of the disease in that location and its first outbreak anywhere.[8]

In the left panel of Figure 1, we show the distribution of these arrival times in years for the plague across European cities. Given the relatively low economic integration in the medieval period, some cities were infected by the plague early on, whereas others escaped earlier epidemics, only to be infected in a later outbreak. In the right panel of Figure 1, we show the distribution of these arrival times in days for the 1957-8 influenza and Covid-19 pandemics across countries. Again we find that it takes time for each infectious disease to diffuse across countries. But the arrival times are substantially more rapid for the 1957-8 influenza and Covid-19 pandemics, consistent with the much greater integration of the world economy in more recent decades.[9]

Trade and Disease Diffusion   We next provide empirical evidence that the speed of diffusion of each infectious disease is shaped by international trade (see also Online Appendix G.1). We

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[5]For a historical discussion of the relationship between globalization and disease diffusion, see Kenny (2021).
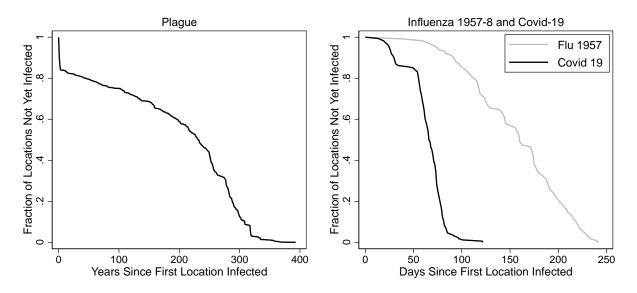
[6]See for example Diamond (1998) and Nunn and Qian (2010). We focus on the relationship between globalization and the speed of diffusion of infectious diseases rather than mortality, because mortality can be heavily influenced by public health improvements, as discussed for example in Chapters 6 and 7 of Kenny (2021).

[7]Traditionally, it was thought that this bacterium was mainly spread by rat fleas. More recent research suggests that it also can be spread by human and cat fleas, or through infected meat, or oral transmission between humans.

[8]For the case of Covid-19, in Online Appendix G.1.4, we also provide evidence on the *intensive margin* growth of infections (and how it is shaped by infections in other countries) once the first infection has occurred.

[9]These findings are consistent with the epidemiological literature that argues that global transport networks have accelerated disease diffusion, as reviewed in Tatem et al. (2006), and discussed in Online Appendix G.2. Although, of course, one also needs to account for differences in infection rates across diseases.

Figure 1: Arrival Times for the Plague, 1957-8 Influenza and Covid-19

Note: Arrival time defined as the difference in time between the first outbreak of a disease in a location and its first outbreak anywhere; left panel shows arrival times in years for the plague across European cities from 1347-1760; right panel shows arrival times in days for 1957-8 influenza and Covid-19 across countries.

focus on the initial diffusion of each disease, and use measures of international trade from before the outbreak of each disease, in order to abstract from public policy interventions and behavioral responses.

In our baseline specification, we regress the arrival time of each disease on these pre-existing trade measures. Much of the variation in these pre-existing trade measures is driven by bilateral geographical distance. But one potential concern is that there could be omitted variables that affect disease diffusion and are correlated with geographical distance (e.g., movements of animals that can act as reservoirs for the disease). To address this concern, we also report specifications, in which we control separately for geographical distance. In each specification, we standardize variables to have a mean of zero and a standard deviation of one, such that the estimated coefficients correspond to β-coefficients. In Column (1) of Table 1, we report the estimation results for the plague. Since data on bilateral trade between European cities during the medieval period are unavailable, we follow the existing historical literature on the plague in measuring trade access using the inverse of distance from the nearest Old World trade route. Even after controlling for log geographical distance from the first European plague outbreak in Messina, we find a negative and statistically significant coefficient on log trade access, implying that the plague diffused faster to cities with better trade access.

In Column (2) of Table 1, we report the results for the 1957-8 influenza, where there are only 52 countries for which we observe both influenza arrival times and positive bilateral trade (exports plus imports in 1956) with China, as the country with the first outbreak. Despite the relatively small sample, we find a negative and statistically significant coefficient on log trade with China,

implying shorter arrival times for the influenza for countries that trade more intensively with China, even after controlling for log geographical distance.[10]

Table 1: Arrival Times for Plague, Influenza 1957-8 and Covid-19

	(1) Log Arrival Plague	(2) Log Arrival Influenza 1957-8	(3) Log Arrival Covid-19	(4) Log Arrival Covid-19	(5) Log Arrival Covid-19
Log Trade Access	-0.218*** (0.0349)				
Log Trade		-0.176* (0.1048)	-0.525*** (0.0742)	-0.238*** (0.0804)	0.0195 (0.1012)
Log Distance	0.108*** (0.0302)	0.560*** (0.0867)	0.301*** (0.0819)	0.227*** (0.0819)	0.0665 (0.0897)
Log Migrant Stock				-0.440*** (0.0920)	-0.279*** (0.0945)
Log Arrivals-Departures					-0.512*** (0.1259)
Observations	1,149	52	172	152	149
R-squared	0.072	0.439	0.462	0.538	0.576

Note: Observations in Column (1) are European cities; Observations in Columns (2)-(5) are countries; All variables are standardized to have a mean of zero and a standard deviation of one; Arrival is the difference in time between the first outbreak of a disease in a location and the first outbreak anywhere; Trade Access is the inverse of the shortest distance to an Old World Trade Route; Trade is the sum of the value of each country's exports and imports with China (the country with the first outbreak of Influenza 1957-8 and Covid-19); trade is measured in the year before each of these pandemics (1956 and 2019, respectively); Distance is geographical distance from the location of the first outbreak; Migrant stock is the total number of immigrants in a country from China plus the total number of ex-patriots in China from that country; Arrivals-Departures is the total number of people arriving in a country from China plus the total number of people arriving in China from that country (including migrants, business travellers and tourists); heteroskedasticity robust standard errors in parentheses; *** denotes significance at the 1 percent level; ** denotes significance at the 5 percent level; * denotes significance at the 10 percent level.

In Column (3) of Table 1, we show that we find the same pattern of results for Covid-19, with a negative and statistically significant coefficient on log trade with China (in 2019), even after controlling for log geographical distance, where again China is the country with the first outbreak.[11] The natural mechanism through which trade affects disease diffusion is international travel. For Covid-19, we can provide further evidence on this mechanism, by including as controls other measures of international linkages between countries for which data are available.

In Column (4), we include the log stock of migrants in China from each country (including both immigrants and ex-patriots). Consistent with the idea that disease can be transmitted through

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[10]If we include zero trade flows by estimating the equation in levels rather than logs, we have 117 countries for which we observe arrival times, and find an estimated coefficient (standard error) of -0.135 (0.0145). We find similar results for the 1968-9 influenza, with negative and statistically significant trade coefficients in both levels and logs.

[11]These results are again consistent with a large historical literature that emphasizes the role of international travel and trade in disease diffusion, as discussed in Fauci (2005) and Online Appendix G.2.

people movements associated with both migration and trade, we find negative and statistically significant coefficients for both variables. In Column (5), we further augment this specification with the log total number of arrivals and departures between each country and China (including migration, business travel, and tourism). Consistent with trade affecting disease diffusion through travel, we find that the estimated trade coefficient is no longer significant once we control for total arrivals and departures. We continue to find a negative and statistically significant coefficient on the log migrant stock, which could reflect measurement error in total arrivals and departures, such that the migration stock is proxying for unobserved people flows associated with migration.[12]

In sum, for all three infectious diseases, we find that the speed of diffusion of the disease is systematically related to international trade, even after controlling for distance. Additionally, for Covid-19, we find that this effect of international trade operates through movements of people, which is consistent with the scientific mechanism through which Covid-19 is transmitted (which requires exposure to infectious respiratory fluids through face-to-face interactions). While we focus here in the main text on the extensive margin of disease diffusion, in Online Appendix G.1.4 we use our additional data for Covid-19 to provide evidence on the intensive margin of the rate of growth of infections once the first infection has occurred. We show that countries that trade more with partners with high relative levels of infections experience more rapid rates of growth of infection, even after controlling for the time since their own first infection.

International Travel and Trade We now provide additional evidence in support of international travel as the mechanism through which trade affects disease diffusion (see also Online Appendix H.1). We use tariffs as a source of variation in trade costs to provide evidence of a causal impact of trade on international travel. We show that reductions in tariff barriers that increase international trade lead to greater travel between countries, which is the key mechanism through which trade affects disease diffusion when human contact is required for disease transmission.[13]

We measure international travel using data on the bilateral number of air passengers from the Origin and Destination (OFOD) Database of the International Civil Aviation Organization (ICAO) from 1982-2019. We begin by examining the correlation between international travel and trade. We regress the log of bilateral air passengers on the log of bilateral trade (exports plus imports), including origin-destination and year fixed effects. The inclusion of the origin-destination fixed effects implies that the estimated coefficient is identified from the relationship between changes in international travel and changes in international trade over time. As reported in Column (1) of Table 2, we find a positive and statistically significant correlation between international travel and trade, with a one percent increase in the value of bilateral trade associated with a 0.217 percent increase in bilateral air passengers.

Clearly, this positive correlation need not have a causal interpretation, because travel and trade

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[12]As a further specification check, we report placebo specifications in Online Appendix G.1 in which we show that a range of measures of international financial linkages are statistically insignificant once we control for total arrivals and departures, consistent with the travel-based mechanism in the model.

[13]For a review of the existing empirical literature on the role played by business travel in international trade, see Online Appendix H.2.

Table 2: International Travel and Trade

	(1) Log Air Passengers	(2) Log Air Passengers	(3) Log Air Passengers	(4) Log Air Passengers	(5) Log Air Passengers
Log Trade	0.217***	0.399**	0.452***		
	(0.0111)	(0.1574)	(0.1423)		
Log Trade Land/Sea				0.498***	
				(0.1594)	
Log Tariff					-1.088***
					(0.3682)
Estimation	OLS	IV	IV	IV	OLS
Sample	All	All	> 3,000 km	All	All
Origin-Destination FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Observations	124,597	68,734	34,889	65,967	71,376
R-squared	0.763	–	–	–	0.790
First-stage F-statistic	–	100.8	129.7	122.7	–

Note: Panel of origin-destination-year observations; Air passengers is total number of airline passengers from an origin to a destination in a given year; Trade is the average of exports and imports for each origin and destination in a given year; Trade Land/Sea is the average of exports and imports for Harmonized System (HS) 6-digit products for which air transport accounts for less than 20 percent of the value of trade; Log tariff is the average of the *ad valorem* bilateral tariff in the origin and destination countries; Origin-Destination FEs are origin-destination fixed effects; Year FEs are year fixed effects; In Columns (3)-(4), Log trade is instrumented with log tariff; Sample in Column (4) is restricted to origin-destination pairs with bilateral distances greater than 3,000 km; First-stage F-statistic is the F-statistic for the statistical significance of the instrument in the first-stage regression; the R-squared for the second-stage regression is not reported in the IV specifications, because it does not have a meaningful interpretation; Standard errors in parentheses are clustered by origin-destination pair; *** denotes significance at the 1 percent level; ** denotes significance at the 5 percent level; * denotes significance at the 10 percent level.

are both jointly determined by trade and travel frictions. Therefore, we instrument log bilateral trade with the average of the log bilateral tariff in the origin and destination countries. We find that tariffs are a powerful determinant of trade in the first-stage regression, with the first-stage F-statistic reported at the bottom of the column well above the conventional threshold of 10. Our identifying assumption is that tariffs only affect international travel through international trade, using the fact that tariffs are a policy measure that only directly affects trade in goods.

As reported in Column (2), in the IV specification we continue to find a positive and statistically significant coefficient on bilateral trade. Hence, reductions in trade costs that raise international trade lead to increased travel between countries. We find that the IV coefficient is larger than the OLS coefficient. In general, the OLS coefficient could be either upward or downward-biased, depending on whether bilateral routes with high idiosyncratic growth in international travel tend to have high or low growth in international trade. Economies of scale on bilateral routes would induce an upward bias in the OLS coefficient, as increases in international travel for idiosyncratic reasons reduce the costs of trading costs, and hence lead to increased international trade. Diseconomies of scale (or congestion effects) on bilateral routes would have the opposite effect, and thus induce a

downward bias in the OLS coefficient. More generally, the error term is likely to include increased demand for tourist travel over time. If locations with greater growth in tourism tend to be those with lower growth in tradable production (e.g., pristine beaches), this would generate a negative correlation between idiosyncratic changes in international travel in the error term and changes in international trade, and hence would induce a downward bias in the OLS coefficient, as we find in Column (2).

Our results are robust to a range of alternative specifications. One potential concern is that air passengers could underestimate bilateral travel, because it abstracts from travel by land or sea. In Column (3), we find similar results if we restrict attention to origin-destination pairs more than 3,000 kilometers apart, for which air travel is likely to be the dominant mode of transport. Another potential concern is that aircrafts are used to transport both people and goods, which could introduce a mechanical correlation between air travel and trade. In Column (4), we find similar results if we restrict attention to trade in goods for which air transport accounts for less than 20 percent of the value of trade, confirming that our findings are not driven by such a mechanical correlation.[14] Finally, in Column (5), we report the corresponding reduced-form regression of international travel on tariffs for our baseline specification from Column (2). Consistent with the predictions of our theoretical model below, we find a negative and statistically significant coefficient on tariffs, such that increases in tariffs lead to reductions in travel between countries.[15]

Motivated by these empirical findings on disease diffusion, international trade and international travel, we now turn to develop our baseline theoretical framework.

3   Baseline Economic Model

In this section we develop a stylized model of the global economy in which international trade is sustained by face-to-face interactions. Our main goal is to develop the *simplest* model in which both international trade and face-to-face interactions are jointly determined in general equilibrium. With that in mind, we focus on a baseline static one-sector, two-country world in which individuals use labor to produce differentiated goods that are exchanged exclusively via face-to-face interactions in competitive markets. Although this specification is intentionally stylized, we show in Section 3.3 how our model can be generalized to a wide range of settings while preserving its main insights.

3.1   Environment

Consider a world with two locations: East and West, indexed by i or j. We denote by $\mathcal{J}$ the set of countries in the world, so $\mathcal{J} = \{East, West\}$. Location $i \in \mathcal{J}$ is inhabited by a continuum of

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[14]COMTRADE data are not reported by origin-destination-product-mode of shipment. Therefore, we combine trade data by origin-destination-product with separate information on the importance of air trade for each product.

[15]A number of recent empirical studies have used sources of quasi-experimental variation in the costs of business travel to provide evidence of a causal impact of business travel on trade. In particular, Söderlund (2020) uses the liberalization of airspace in the Soviet Union in the mid-1980s, and Campante and Yanagizawa-Drott (2018) uses the technological limitations of air travel beyond 6,000 km, as discussed in Online Appendix H.2.

measure L_i of households, and each household is endowed with the ability to produce a differentiated variety using labor as the only input in production. We denote by w_i the wage rate in country i. We abstract from intertemporal borrowing and lending and hence income equals expenditure.

Trade is costly. There are iceberg bilateral trade cost $\tau_{ij} = t_{ij} (d_{ij})^{\delta}$, when shipping from j back to i, where $d_{ij} \geq 1$ is the symmetric distance between i and j, and t_{ij} is a man-made additional trade friction imposed by i on imports from country j. We let these man-made trade costs be potentially asymmetric reflecting the fact that one country may impose higher restrictions to trade (e.g., tariffs, or delays in goods clearing customs) than the other country. For simplicity, there are no man-made frictions to internal shipments, so $t_{ii} = 1$ and $\tau_{ii} = (d_{ii})^{\delta}$, where $d_{ii} < d_{ij}$ for $j \neq i$ can be interpreted as the average internal distance in country $i = East, West$.

Each of the L_i households in country i is formed by two individuals. One of these individuals – the *seller* – is in charge of producing and selling the household-specific differentiated variety from their home, while the other individual – the *buyer* – is in charge of procuring varieties for consumption from other households in each of the two locations. We let all households in country i be equally productive in manufacturing varieties, with one unit of labor delivering Z_i units of goods. Goods markets are competitive and sellers make their goods available at marginal cost.

Households have CES preferences over differentiated varieties, with an elasticity of substitution $\sigma > 1$ regardless of the origin of these varieties, and they derive disutility from the buyer spending time away from home. More specifically, a household in country i incurs a utility cost

$$c_{ij} (n_{ij}) = \frac{c}{\phi} \mu_{ij} (d_{ij})^{\rho} (n_{ij})^{\phi}, \tag{1}$$

whenever the household's buyer secures n_{ij} varieties from location j, at a distance $d_{ij} \geq 1$ from i. The parameter μ_{ij} captures travel restrictions imposed by country j's government on visitors from i. The parameter c governs the cost of travel and we assume it is large enough to ensure an interior solution in which $n_{ij} \leq L_j$ for all i and $j \in \mathcal{J}$. We assume that whenever $n_{ij} < L_j$, the set of varieties procured from j are chosen at random, so if all households from i procure n_{ij} from j, each household's variety in j will be consumed by a fraction n_{ij}/L_j of households from i.

Welfare of households in location i is then given by

$$W_i = \max_{n_{ii}, n_{ij}, q_{ii}(\cdot), q_{ij}(\cdot)} \left[\left(\sum_{j \in \mathcal{J}} \int_0^{n_{ij}} q_{ij} (k)^{\frac{\sigma-1}{\sigma}} dk \right)^{\frac{\sigma}{\sigma-1}} - \frac{c}{\phi} \sum_{j \in \mathcal{J}} \mu_{ij} (d_{ij})^{\rho} (n_{ij})^{\phi} \right], \tag{2}$$

subject to the household's budget constraint

$$\sum_{j \in \mathcal{J}} \int_0^{n_{ij}} p_{ij} (k) q_{ij} (k) dk = w_i, \tag{3}$$

where $p_{ij} (k)$ and $q_{ij} (k)$ denote the price and quantity consumed in i of the variety produced in j by household k, and w_i is household income.

3.2 Equilibrium

Let us first consider the consumption choices of a representative household in country i for a given n_{ij}. The problem in (2), yields

$$q_{ij} = \frac{w_i}{(P_i)^{1-\sigma}} \left(\frac{\tau_{ij}w_j}{Z_j}\right)^{-\sigma}, \tag{4}$$

where w_j/Z_j is the common free-on-board price of all varieties produced in location j, τ_{ij} are trade costs when shipping from j to i, and P_i is a price index given by

$$P_i = \left(\sum_{j \in \mathcal{J}} n_{ij} \left(\frac{\tau_{ij}w_j}{Z_j}\right)^{1-\sigma}\right)^{1/(1-\sigma)}. \tag{5}$$

In order to characterize each household's choice of n_{ij}, we first plug equations (4) and (5) into equation (2) to obtain

$$W_i = \max_{n_{ii}, n_{ij}} w_i \left[\left(\sum_{j \in \mathcal{J}} n_{ij} \left(\frac{\tau_{ij}w_j}{Z_j}\right)^{1-\sigma}\right)^{\frac{1}{(\sigma-1)}} - \frac{c}{\phi} \sum_{j \in \mathcal{J}} \mu_{ij} (d_{ij})^{\rho} (n_{ij})^{\phi}\right]. \tag{6}$$

From the first-order condition for n_{ij}, we obtain the following gravity equation for face-to-face interactions that is log-separable in origin and destination terms and bilateral frictions:

$$n_{ij} = (c(\sigma-1)\mu_{ij})^{-1/(\phi-1)} (d_{ij})^{-\frac{\rho+(\sigma-1)\delta}{\phi-1}} \left(\frac{t_{ij}w_j}{Z_jP_i}\right)^{-\frac{\sigma-1}{(\phi-1)}} \left(\frac{w_i}{P_i}\right)^{1/(\phi-1)}. \tag{7}$$

Evidently, natural and man-made barriers to trade (d_{ij}, t_{ij}) and to travel (μ_{ij}) tend to reduce the number of interactions sought by agents from country i in country j. As we show in Online Appendix B.1, for the second-order conditions to be satisfied for all values of μ_{ij}, d_{ij}, and t_{ij}, we need to impose $\phi > 1/(\sigma-1)$ and $\sigma > 2$. Bilateral imports satisfy an analogous gravity equation, namely,

$$X_{ij} = n_{ij}p_{ij}q_{ij}L_i = (c(\sigma-1)\mu_{ij})^{-\frac{1}{\phi-1}} (d_{ij})^{-\frac{\rho+\phi(\sigma-1)\delta}{\phi-1}} \left(\frac{t_{ij}w_j}{Z_jP_i}\right)^{-\frac{\phi(\sigma-1)}{\phi-1}} \left(\frac{w_i}{P_i}\right)^{\frac{1}{\phi-1}} w_iL_i. \tag{8}$$

Therefore trade shares can be written as the following constant elasticity import demand system,

$$\pi_{ij} = \frac{X_{ij}}{\sum_{\ell \in \mathcal{J}} X_{i\ell}} = \frac{(\Upsilon_{ij})^{-\varepsilon} (w_j/Z_j)^{-\frac{\phi(\sigma-1)}{\phi-1}}}{\sum_{\ell \in \mathcal{J}} (\Upsilon_{i\ell})^{-\varepsilon} (w_\ell/Z_\ell)^{-\frac{\phi(\sigma-1)}{\phi-1}}}, \tag{9}$$

where we have defined the composite trade friction as

$$(\Upsilon_{ij})^{-\varepsilon} \equiv (\mu_{ij})^{-\frac{1}{\phi-1}} (d_{ij})^{-\frac{\rho+\phi(\sigma-1)\delta}{\phi-1}} (t_{ij})^{-\frac{\phi(\sigma-1)}{\phi-1}}, \tag{10}$$

which encompasses travel frictions (μ_{ij}), transport costs (d_{ij}), and trade frictions (t_{ij}). Note that

the distance elasticity is affected by the standard substitutability σ, but also by the traveling cost elasticity ρ, and by the convexity ϕ of the traveling costs. It is clear that both $\rho > 0$ and $\phi > 1$ increase the distance elasticity relative to a standard Armington model (in which the distance elasticity would be given by $\delta(\sigma - 1)$). The other man-made bilateral frictions also naturally depress trade flows.[16]

Finally, from the equality between country i's income and expenditure on the goods that it produces, we obtain the following system of equations that determines equilibrium wages:

$$\pi_{ii}(w_i, w_j) w_i L_i + \pi_{ji}(w_i, w_j) w_j L_j = w_i L_i, \tag{11}$$

where $\pi_{ii}(w_i, w_j)$ and $\pi_{ji}(w_i, w_j)$ are given by equation (9). This pair of equations (one per country) allow us to solve for w_i and w_j as a function of the unique distance d_{ij}, the pair of travel restriction parameters μ_{ij} and μ_{ji}, the pair of man-made trade barriers t_{ij} and t_{ji}, and the parameters ϕ, σ, δ, and ρ. Setting one of the country's wages as the numéraire, the general equilibrium only requires solving one of the non-linear equations in (11). Once one has solved for this (relative) wage, it is straightforward to solve for trade flows and for the flow of buyers across locations, as well as for the implied welfare levels.

Note that the general-equilibrium condition in (11) is identical to that obtained in standard gravity models, so from the results in Alvarez and Lucas (2007), Allen and Arkolakis (2014), or Allen et al. (2020), we can conclude that:[17]

Proposition 1 *As long as trade frictions Υ_{ij} are bounded, there exists a unique vector of equilibrium wages $\mathbf{w}^* = (w_i, w_j) \in \mathbb{R}_{++}^2$ that solves the system of equations in (11).*

Using the implicit-function theorem, it is also straightforward to see that the relative wage w_j/w_i will be increasing in L_i, Υ_{ii}, Υ_{ji}, and Z_j, while it will be decreasing in L_j, Υ_{jj}, Υ_{ij}, and Z_i.

Given the vector of equilibrium wages $\mathbf{w} = (w_i, w_j)$, we are particularly interested in studying how changes in trade frictions (d_{ij}, t_{ij}, or μ_{ij}) affect the rate of human-to-human interactions at home, abroad and worldwide. Note that, combining equations (4), (8), and (9), we can express

$$n_{ij}(\mathbf{w}) = \left(\frac{t_{ij}(d_{ij})^\delta w_j}{P_i(\mathbf{w}) Z_j} \right)^{\sigma-1} \pi_{ij}(\mathbf{w}), \tag{12}$$

where $\pi_{ij}(\mathbf{w})$ is given in (9) and $P_i(\mathbf{w})$ in equation (B.1) in Online Appendix B.2. Studying how $n_{ii}(\mathbf{w})$ and $n_{ij}(\mathbf{w})$ are shaped by the primitive parameters of the model is complicated by general equilibrium effects on wages, but we show in Online Appendix B.3 that:

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[16]An implication of this constant elasticity gravity equation representation is that our model falls within the class of models discussed in Arkolakis et al. (2012), in which the domestic trade share is a sufficient statistic for welfare, as shown in Online Appendix B.2.

[17]In Alvarez and Lucas (2007), uniqueness requires some additional (mild) assumptions due to the existence of an intermediate-input sector. Because our model features no intermediate inputs, we just need to assume that trade frictions remain bounded.

Proposition 2 *A decline in any international trade or travel friction $(d_{ij}, t_{ij}, t_{ji}, \mu_{ij}, \mu_{ji})$ leads to: (a) a decline in the rates (n_{ii} and n_{jj}) at which individuals will meet individuals in their own country; and (b) an increase in the rates at which individuals will meet individuals from the other country (n_{ij} and n_{ji}).*

Therefore, despite the fact that changes in trade and travel frictions impact equilibrium relative wages, the more open are economies to the flow of goods and people across borders, the larger will be international interactions and the lower will be domestic interactions.

We can also study the effect of reductions in international trade and travel frictions on the *overall* measure of varieties consumed by each household, which also corresponds to the number of human interactions experienced by each household's buyer (i.e., $n_{ii} + n_{ij}$), and on the total number of human interactions carried out by each household's seller (i.e., $n_{ii} + n_{ji}$).[18] General equilibrium forces complicate this comparative static, but we show in Online Appendix B.4 that:

Proposition 3 *Suppose that countries are symmetric, in the sense that $L_i = L$, $Z_i = Z$, and $\Upsilon_{ij} = \Upsilon$ for all i. Then, a decline in any (symmetric) international trade frictions leads to an overall increase in human interactions ($n_{ii} + n_{ij}$) experienced by both household buyers and household sellers.*

The assumption of full symmetry is extreme, but the result of course continues to hold true if country asymmetries are small and trade frictions are not too asymmetric across countries. In fact, exhaustive numerical simulations suggest that the result continues to hold true for arbitrarily asymmetric declines in trade frictions, as long as countries are symmetric in size ($L_i = L$) and in technology ($Z_i = Z$).

Reverting back to our general equilibrium with arbitrary country asymmetries, we can also derive results for how changes in the labor force in either country affect the per-household measure of interactions at home and abroad. More specifically, from equation (11), the relative wage w_j/w_i is monotonic in the ratio L_i/L_j. Using this property, we show in Online Appendix B.5 that:

Proposition 4 *A decrease in the population of country i relative to that in country j leads to a decrease in the rates n_{ii} and n_{ji} at which individuals meet in country i, and to an increase in the rates n_{jj} and n_{ij} at which individuals meet in country j.*

We use this result in Section 5 below, where we study how reductions in labor supply from deaths and/or lower worker productivity while infected affect face-to-face interactions and trade.

3.3 Generalizations

We have intentionally developed a stylized model of international trade and face-to-face interactions, which allows us to derive our predictions for the relationship between globalization and pandemics

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[18]Note that despite us modeling a frictionless labor market, the assumed symmetry of all households implies that no household has any incentive to hire anybody to buy or sell goods on its behalf.

as transparently and sharply as possible. But we now show that the main predictions of our theoretical framework are not sensitive to these stylized features and continue to hold under a wide range of generalizations. We briefly summarize these generalizations here and report the mathematical derivations in Online Appendix C.

Our baseline model 'hardwires' the need for face-to-face interactions with the assumption that agents must travel to obtain consumption goods from abroad. In reality, many transactions are executed remotely and human interactions may only be necessary for certain types of transactions (such as tourism services or merchandise transactions for which face-to-face interactions are key) or at specific times in a trade relationship (e.g., at their onset). Furthermore, in reality only a small set of a country's population is involved in international business travel.

In Online Appendix C.1, we work out an extension of our framework in which households have access to two alternative technologies for procuring consumption goods, one involving travel, and the other one involving importing goods remotely. To introduce a trade off between these two options, we let the fixed utility cost of sourcing from each location depend on which of these two technologies is used. Naturally, sourcing a variety through travel is more costly, *on average*, than doing so remotely, but for certain buyers, personal contacts with foreign sellers may be particularly important (see Startz, 2021), so we capture this by introducing agent-specific idiosyncratic shocks to these sourcing costs. We show that the resulting generalized model is isomorphic to our baseline specification, except that the measure of varieties sourced depends on the expected costs of the two sourcing technologies, and that only a fraction of varieties are sourced through face-to-face interactions, with the remaining fraction sourced through remote trade. All theoretical results continue to apply in this generalization. In Online Appendix C.1, we also develop further generalizations of this specification, in which the shares of varieties sourced varies across households, and potentially features full segmentation between 'jet setters' (buyers who only travel) and 'homebodies' (buyers who only buy remotely).

In a similar vein, in Online Appendix C.2 we develop a dynamic version of our framework in which face-to-face interactions are only necessary to *initiate* a commercial link between a buyer and a seller. The stock of buyer-seller links is thus increased by personal contacts, but we also let it depreciate at some constant rate δ. In the steady state of this generalization, the number of country j varieties consumed by households in i $(n_{ij}^*(t))$ takes the same value as in our baseline model up to a constant. Therefore, all of our comparative static results for our baseline model hold as comparative steady-state results in this generalization. We focus on steady-state comparisons, because the transition dynamics of face-to-face interactions during a pandemic are likely to be heavily influenced by behavioral responses, and we provide a characterization of transition dynamics in the presence of behavioral responses in Section 6.

In Online Appendix C.3, we also develop a multi-sector version of the model in which the number of international face-to-face interactions varies across sectors, and is shaped by trade costs, travel costs, and also the relative advantage of in-person versus remote interactions. Our main comparative statics become more involved in that case, but we show that as long as sectoral

asymmetries in primitive parameters are small, proportional declines in trade frictions continue to generate effects on human interactions analogous to those described in Propositions 2 and 3.

In Online Appendix C.4, we consider an extension to multiple countries. We show that all of the equations above apply to that multi-country environment (with $\mathcal{J}$ re-defined to include multiple countries), except for the labor-market clearing condition, which is now $\sum_{j \in \mathcal{J}} \pi_{ij}(\mathbf{w}) w_j L_j = w_i L_i$, where $\pi_{ij}(\mathbf{w})$ is defined in (9).[19] In Online Appendix C.5, we consider an alternative specification of travel costs in terms of labor rather than utility. We show that this specification is isomorphic to our baseline specification, except for a slightly different expression for the equilibrium price index P_i. Therefore, Propositions 1 through 4 apply. In Online Appendix C.6, we show that it is straightforward to re-interpret the differentiated varieties produced by households as intermediate inputs, which all households combine into a non-traded homogeneous final good.

Finally, we explore two alternative environments with a distinct market structure from the one in our baseline model. Instead of our Armington framework in which goods are differentiated at the household level, Online Appendix C.7 considers an environment à la Eaton and Kortum (2002), in which the measure of final good varieties is fixed at one, and all households worldwide compete to be the least-cost supplier of those goods to other households. Assuming that household- and variety-specific labor productivity is Fréchet distributed, the equilibrium conditions of our model are isomorphic to those derived in our baseline model, and thus they carry the same implications. In Online Appendix C.8, we explore a final variant of our model featuring scale economies, monopolistic competition and fixed cost of exporting, as in the literature on selection into exporting emanating from the seminal work of Melitz (2003). In that variant, it is the household's seller rather than the buyer who travels to other locations, paying a fixed cost that is a function of the measure of buyers reached in a destination market. Again, Propositions 1 through 4 continue to hold in such an environment.

4 Trade, Travel and Disease Diffusion

We now embed our gravity model of trade and travel into a model of disease dynamics. We interpret our model as describing a standard "day" in the household. In the morning the buyer in each household in i leaves the house and visits n_{ii} sellers in i and n_{ij} sellers in j, procuring goods from each of those households. For simplicity, we assume that buyers do not travel together or otherwise meet each other. While the buyer visits other households and procures goods, the seller in each household sells its own goods to visitors to their household. There will be n_{ii} domestic visitors and n_{ji} foreign visitors. In the evening, the two members of the household reunite.

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[19]Similarly, the model is also easily adaptable to the case in which there is a continuum of locations $i \in \Omega$, where Ω is a closed and bounded set of a finite-dimensional Euclidean space. The equilibrium conditions are again unaltered, with integrals replacing summation operators throughout.

4.1   Preliminaries

With this background in mind, consider now the dynamics of contagion. As in the standard epidemiological model, we divide the population at each point in time into **S**usceptible households, **I**nfectious households, and **R**ecovered households (we will incorporate deaths in the next section). We think of the health status as being a household characteristic, implicitly assuming a perfect rate of transmission within the household (they enjoy a passionate marriage), and also that recovery is experienced simultaneously by all household members. For simplicity, we ignore the possibility that a vaccine puts an end to an epidemic before herd immunity is achieved.

Throughout this section, we focus on the role of trade and travel in shaping disease dynamics through the intensity of domestic and foreign interactions. In particular, we abstract from any impact of the disease on the ability to work and trade, or on mortality. Therefore, there are no general equilibrium effects of the pandemic on labor supply, and there is also no incentive for agents to change their individual behavior. As a result, domestic and foreign interactions are time-invariant throughout the course of the pandemic.

Even with these simplifications, the endogeneity of domestic and foreign interactions to trade and travel costs implies that the gravity model of trade and the SIR model of disease dynamics interact in a number of subtle ways. First, we establish an epidemiological externality between countries, such that the condition for a pandemic to occur depends on the health environment in the most unhealthy country. Second, the constant elasticity gravity equation implies that domestic and foreign interactions are substitutes, in the sense that a reduction in trade costs increases foreign interactions relative to domestic ones. Therefore, reductions in trade costs can either increase or decrease the range of parameters where a pandemic occurs, and the severity of the pandemic when it does occur, depending on the relative levels of infections at home and abroad. Third, we show that multiple waves of infection can occur in the open economy, even though a single wave of infection would occur in the closed economy.

In Section 5, we generalize the analysis to allow the disease to affect the ability to work and trade, as well as mortality. But we assume that agents are unaware of the source of the infection, and hence have no incentive to change their individual behavior. In this case, there is a further interaction between trade and disease dynamics, because changes in relative labor supplies give rise to a form of general equilibrium social distancing. In Section 6, we further enrich the analysis to allow agents to become aware of the source of the infection, and to adjust the intensity of their interactions based on the threat of infection. This introduces yet another interaction between trade and disease dynamics, because of individual-level social distancing in response to the threat of infection.

4.2 The Dynamic System

The share of households of each type in country i evolves according to the following laws of motion (we ignore time subscripts for now to keep the notation tidy):

$$\dot{S}_i = -2n_{ii}\alpha_i S_i I_i - n_{ij}\alpha_j S_i I_j - n_{ji}s\alpha_i S_i I_j \tag{13}$$

$$\dot{I}_i = 2n_{ii}\alpha_i S_i I_i + n_{ij}\alpha_j S_i I_j + n_{ji}\alpha_i S_i I_j - \gamma_i I_i \tag{14}$$

$$\dot{R}_i = \gamma_i I_i. \tag{15}$$

To better understand this system, focus first on how infections grow in equation (14). The first term $2n_{ii}\alpha_i S_i I_i$ in this equation captures newly infected households in country i. Sellers in i receive (in expectation) n_{ii} domestic buyers, while buyers meet up with n_{ii} domestic sellers. The household thus jointly has $2n_{ii}$ domestic contacts. In those encounters, a new infection occurs with probability α_i whenever one of the agents is susceptible (which occurs with probability S_i) and the other agent is infectious (which occurs with probability I_i).[20] The second term of equation (14) reflects new infections of country i's households that occur in the foreign country when susceptible buyers from i (of which there are S_i) visit foreign households with infectious sellers. There are n_{ij} of those meetings, leading to a new infection with probability α_j whenever the foreign seller is infectious (which occurs with probability I_j). Finally, the third term in (14) reflects new infections associated with susceptible sellers in country i receiving infectious buyers from abroad (country j). Each susceptible domestic buyer (constituting a share S_i of i's population) has n_{ji} such meetings, which cause an infection with probability α_i whenever the foreign buyer is infectious (which occurs with probability I_j). The final term in equation (14) simply captures the rate at which infectious individuals recover (γ_i), and note that we assume that this recovery rate only depends on the country in which infected agents reside, regardless of where they got infected.

Once the equation determining the dynamics of new infections is determined, the one determining the change of susceptible agents in (13) is straightforward to understand, as it just reflects a decline in the susceptible population commensurate with new infections. Finally, equation (15) governs the transition from infectious households to recovered households.

We allow the epidemiological parameters (α_i, γ_i) to differ across countries, which is consistent with the very different experiences of countries during the Covid-19 pandemic. One source for these differences is culture. For example, Japan was relatively less affected by Covid-19, because of its culture of mask wearing in public. Another source is differences in public health technology, including administrative capability and medical resources. For example, South Korea was relatively less affected by Covid-19, because of an effective contact tracing scheme. In contrast, India was relatively severely affected, because of a lack of hospital capacity and available treatments.[21]

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[20] In summing the buyer and seller domestic contact rates to obtain a domestic contact rate of $2n_{ii}$ for the household, we use the continuous time property that there is zero probability that the buyer and seller are simultaneously infected at exactly the same instant.

[21] See Kang et al. (2021) on South Korea's contact tracing and the New York Times article "The Night the Oxygen Ran Out" (June 28, 2021) for an account of India's problems with hospital capacity.

4.3 The Closed-Economy Case

Our model reduces to a standard SIR model when there is no movement of people across countries, namely, $n_{ij} = n_{ji} = 0$. In such a case, the system in (13)-(15) reduces to

$$\begin{aligned}
\dot{S}_i &= -\beta_i S_i I_i \\
\dot{I}_i &= \beta_i S_i I_i - \gamma_i I_i \\
\dot{R}_i &= \gamma_i I_i
\end{aligned}$$

where $\beta_i = 2n_{ii}$ is the so-called contact rate.

The dynamics of this system have been studied extensively since Kermack and McKendrick (1927, 1932). Suppose that at some time t_0, there is an outbreak of a disease, which leads to a small initial infection: $I_i(t_0) = \varepsilon > 0$. Since ε is small, $S_i(t_0)$ is close to 1. Therefore, from the second equation, we obtain the standard result that the initial infection quickly dies out if the *basic reproduction number* $\mathcal{R}_{0i} = \beta_i / \gamma_i$ is less than one: $\dot{I}_i(t) < 0$ for all $t > t_0$. In other words, when $\mathcal{R}_{0i} = \beta_i / \gamma_i < 1$, an *epidemic-free* equilibrium is globally stable. In contrast, if $\mathcal{R}_{0i} = \beta_i / \gamma_i > 1$, the number of new infections necessarily rises initially. As a result, the share of susceptibles declines until the system reaches a period t^* at which $S_i(t^*) = \gamma_i / \beta_i$, after which infections decline and eventually go to 0. The steady-state value of $S_i(\infty)$ in this *epidemic* equilibrium is determined by the solution to the following non-linear equation (see Online Appendix D.1):

$$\ln S_i(\infty) = -\frac{\beta_i}{\gamma_i}(1 - S_i(\infty)), \tag{16}$$

which admits a unique solution with $1 > S_i(\infty) > 0$.[22]

4.4 The Open-Economy Case

We now return to the two-country system in (13)-(15). We first explore the conditions under which a pandemic-free equilibrium is stable, and infections quickly die out worldwide, regardless of where the disease originated. For that purpose, it suffices to focus on the laws of motion for (S_i, S_j, I_i, I_j) evaluated at the pandemic-free equilibrium, in which $S_i = S_j \simeq 1$ and $I_i = I_j \simeq 0$.

In parallel to the closed economy case, in the two-country system we can define $\mathcal{R}_0$ as the expected number of secondary cases produced by a single (typical) infection starting from a completely susceptible world population. The pandemic-free equilibrium is necessarily stable if $\mathcal{R}_0 < 1$ (see Online Appendix D.3 for a proof).[23] In order to compute $\mathcal{R}_0$, we follow the approach in Diekmann et al. (1990), and write the system of equations determining the dynamics of infections in

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[22] Equation (16) is also satisfied when $S_i(\infty) = 1$, but this equilibrium is not stable when $\mathcal{R}_{0i} > 1$.

[23] Because our model maps directly to multi-group models of disease transmission, we can invoke (and verify in Online Appendix D.3) results from that literature to provide an analysis of the stability of the pandemic-free equilibrium in our two-country dynamic system. See Hethcote (1978), Hethcote and Thieme (1985), van den Driessche and Watmough (2002), and Magal et al. (2016).

each country, given by equation (14), as

$$
\begin{bmatrix} \dot{I}_i \\ \dot{I}_j \end{bmatrix} = \underbrace{\begin{bmatrix} 2\alpha_i n_{ii} S_i & (\alpha_j n_{ij} + \alpha_i n_{ji}) S_i \\ (\alpha_j n_{ij} + \alpha_i n_{ji}) S_j & 2\alpha_j n_{jj} S_j \end{bmatrix}}_{F} \begin{bmatrix} I_i \\ I_j \end{bmatrix} - \underbrace{\begin{bmatrix} \gamma_i & 0 \\ 0 & \gamma_j \end{bmatrix}}_{V} \begin{bmatrix} I_i \\ I_j \end{bmatrix}.
$$

The so-called next generation matrix is given by FV^{-1} (evaluated at $t = t_0$, thus $S_i(t_0) = S_j(t_0) \simeq 1$). The results in Diekmann et al. (1990) then imply that $\mathcal{R}_0 = \rho(FV^{-1})$, where $\rho(FV^{-1})$ is the spectral radius of the next generation matrix. In our case, this is given by

$$
\mathcal{R}_0 = \frac{1}{2}\left(\frac{2\alpha_i n_{ii}}{\gamma_i} + \frac{2\alpha_j n_{jj}}{\gamma_j}\right) + \frac{1}{2}\sqrt{\left(\frac{2\alpha_i n_{ii}}{\gamma_i} - \frac{2\alpha_j n_{jj}}{\gamma_j}\right)^2 + 4\frac{(\alpha_j n_{ij} + \alpha_i n_{ji})^2}{\gamma_i \gamma_j}}. \tag{17}
$$

Clearly, $\mathcal{R}_0$ is nondecreasing in n_{ij} and n_{ji}, and thus

$$
\mathcal{R}_0 \geq \mathcal{R}_0|_{n_{ij}=n_{ji}=0} = \max\left\{\frac{2\alpha_i n_{ii}}{\gamma_i}, \frac{2\alpha_j n_{jj}}{\gamma_j}\right\}. \tag{18}
$$

A key implication of this result in (18) is that our open economy SIR model features a powerful *epidemiological externality* between countries. Even if one country has the disease under control (a reproduction number $\mathcal{R}_{0i}$ based only on its domestic interactions of less than one), it will necessarily participate in a global pandemic if there is positive trade between the countries, and the other country does not have the disease under control.[24]

If the global reproduction rate satisfies $\mathcal{R}_0 > 1$, there exists a unique asymptotically stable 'pandemic' equilibrium. Following a small initial infection, the share of *worldwide* infected households necessarily increases for a period of time, and then declines to a point at which infections vanish and the share of susceptible households in the population in each country $(S_i(\infty), S_j(\infty))$ takes a value strictly between 0 and 1. In Online Appendix D.3, we show that the steady-state levels of infections in the two countries satisfy the following system of non-linear equations

$$
\ln S_i(\infty) = -\frac{2\alpha_i n_{ii}}{\gamma_i}(1 - S_i(\infty)) - \frac{\alpha_j n_{ij} + \alpha_i n_{ji}}{\gamma_j}(1 - S_j(\infty)) \tag{19}
$$

$$
\ln S_j(\infty) = -\frac{2\alpha_j n_{jj}}{\gamma_j}(1 - S_j(\infty)) - \frac{\alpha_j n_{ij} + \alpha_i n_{ji}}{\gamma_i}(1 - S_i(\infty)). \tag{20}
$$

Totally differentiating this system of equations, the steady-state values of S_i and S_j are decreasing in n_{ii}, n_{jj}, n_{ij}, and n_{ji}, as shown in Online Appendix D.2, where we determined these bilateral interactions in terms of bilateral travel and travel frictions in the previous section. We summarize the results in this section with the following proposition (see Online Appendix D.3 for a proof):

Proposition 5 *Assume that there is trade between the two countries (i.e., $\alpha_j n_{ij} + \alpha_i n_{ji} > 0$). If*

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[24]In Online Appendix D.4, we compute the largest positive eigenvalue of the Jacobian of the system around $S_i = S_j \simeq 1$ and $I_i = I_j \simeq 0$ and show that, consistent with equation (18), a pandemic-free equilibrium can only be locally stable whenever $2\alpha_i n_{ii}/\gamma_i \leq 1$ and $2\alpha_j n_{jj}/\gamma_{jj} \leq 1$.

$\mathcal{R}_0 \leq 1$, *the no-pandemic equilibrium is the unique stable equilibrium. If $\mathcal{R}_0 > 1$, the no-pandemic equilibrium is unstable, and there exists a unique stable endemic equilibrium with a steady state featuring no infections ($I_i(\infty) = I_j(\infty) = 0$) and shares of susceptible agents $S_i(\infty) \in (0,1)$ and $S_j(\infty) \in (0,1)$ that satisfy equations (19) and (20).*

In Figure 2, we illustrate these analytical results by holding the infection rate in Country 1 (α_1) constant and varying the infection rate in Country 2 (α_2). The starting point is two identical countries with a common infection rate of $\alpha_1 = \alpha_2 = 0.04$. The rest of the parameter values are described in Online Appendix K. For this initial common infection rate, the global reproduction number is $\mathcal{R}_0 = 0.75$, and the open economy domestic reproduction rates are $\mathcal{R}_{01} = \mathcal{R}_{02} = 0.46$. As a result, the initial infection quickly dies out and there is no global pandemic. The fraction of recovered agents in the long run, $R_i(\infty)$, which is equal to the cumulative number of infected agents in the absence of deaths, is essentially zero in both countries.

The left panel of Figure 2 plots $R_i(\infty)$ as a function of $\mathcal{R}_0$ as we progressively increase α_2 from 0.04 to 0.10. The value of $\mathcal{R}_0$ is monotone in α_2 and increases from 0.75 to 1.46. Hence, as the exogenous infection rate of Country 2 increases, the global reproduction rate increases beyond the critical value of 1, and the world experiences a global pandemic. Note how the fraction of the cumulative number of recovered agents rises rapidly once $\mathcal{R}_0$ increases beyond 1 and both countries go through increasingly severe pandemics. Note also the importance of cross-country contagion in the open economy. Even though nothing is changing in the domestic characteristics of Country 1, it is dramatically affected by the worsening conditions in Country 2 through the epidemiological externality. The right panel shows the evolution of the pandemic in Country 1 for different levels of severity of the disease environment in Country 2.[25] The most severe and rapid pandemics are associated with the highest values of α_2 (the lightest curve in the graph). As α_2 declines and $\mathcal{R}_0$ falls and crosses the value of 1, the evolution of infections flattens and becomes longer, until the pandemic eventually disappears.

4.5   Trade Integration and Pandemics

We now turn to the relationship between trade integration and the incidence and severity of the pandemic. In terms of the stability of a pandemic-free equilibrium, inspection of equation (18) might lead one to infer that avoiding a pandemic is always more difficult in a globalized world. First, for given positive values of n_{ii} and n_{jj}, if the ratio α_i/γ_j is sufficiently high in *any* country in the world, a global pandemic affecting *all* countries cannot be avoided, even though the country with the lower ratio α_i/γ_j might well have avoided it under autarky. Second, even when $\alpha_i = \alpha_j$ and $\gamma_i = \gamma_j$, the max operator in (18) may seem to imply that the pandemic-free equilibrium is less likely to be stable in the open economy.

However, this reasoning does not take into account that the intensities of bilateral interactions $(n_{ii}, n_{jj}, n_{ij}, n_{ji})$ are endogenous to trade integration. On the one hand, if countries are symmetric,

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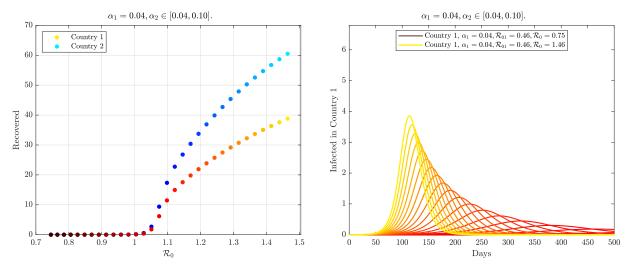[25] The color of each curve corresponds to the colors of the points in the left panel.

Figure 2: The Impact of Changes in the Exogenous Infection Rate in Country 2, α_2

Note: See Online Appendix K for further details on the parameters and algorithms used in the numerical simulations.

lower trade costs increase the overall number of interactions (domestic plus foreign), as shown in Proposition 3. This increase in overall interactions acts to promote disease diffusion. On the other hand, domestic and foreign interactions are substitutes for one another in the constant elasticity gravity equation, which implies that lower trade costs induce substitution from domestic to foreign interactions, as shown in Proposition 2. This substitution could either increase or decrease disease diffusion, depending on the disease environment in each country (α_i, α_j, γ_i, γ_j), as determined by local culture, administrative capacity, and medical technology.

We now show formally that trade integration can either increase or decrease the range of parameters where a pandemic occurs and the severity of the pandemic if it does occurs. We begin by considering a fully symmetric world in which all primitives of the model (population size, technology, trade barriers, recovery rates, etc.) are common in both countries, so that we have $n_{dom} \equiv n_{ii} = n_{jj}$, $n_{for} \equiv n_{ij} = n_{ji}$, $\alpha_i = \alpha_j = \alpha$, and $\gamma_i = \gamma_j = \gamma$. In such a case, $\mathcal{R}_0$ simplifies to

$$\mathcal{R}_0 = \frac{2\alpha\left(n_{dom} + n_{for}\right)}{\gamma},$$

and it thus follows immediately from Proposition 3 that a decline in any (symmetric) international trade friction increases $\mathcal{R}_0$, and thus decreases the range of parameters for which a pandemic-free equilibrium is stable. Furthermore, in this same symmetric case, the steady-state share of susceptible households in the population is identical in both countries and implicitly given by

$$\ln S_i\left(\infty\right) = -\frac{2\alpha\left(n_{dom} + n_{for}\right)}{\gamma}\left(1 - S_i\left(\infty\right)\right).$$

Thus, not only the frequency but also the severity of the pandemic is higher the lower are (symmetric) trade frictions. We summarize these results as follows:

Proposition 6 *Suppose that countries are symmetric, in the sense that $L_i = L$, $Z_i = Z$, $\Upsilon_{ij} = \Upsilon$, $\alpha_i = \alpha_j$, and $\gamma_i = \gamma$ for all i. Then, a decline in any (symmetric) international trade friction: (i) increases $\mathcal{R}_0$, thus decreasing the range of parameters for which a pandemic-free equilibrium is stable, and (ii) increases the share of each country's population that becomes infected during the pandemic when $\mathcal{R}_0 > 1$.*

Although we have so far focused on a fully symmetric case, the main results in this Proposition continue to hold true even if countries are not perfectly symmetric. More generally, a necessary condition for the pandemic-free equilibrium to be stable is $\mathcal{R}_0 < 1$, and thus what matters for the effects of reductions in trade and travel frictions is whether $\mathcal{R}_0 < 1$ increases or decreases with those reductions in barriers.

Figure 3 illustrates Proposition 6 for a case in which we introduce an asymmetry in the exogenous infection rate across countries but $\mathcal{R}_0$ is still decreasing in international trade frictions. We let $\alpha_1 = 0.04$ and $\alpha_2 = 0.07$, and study the cumulative number of recovered agents when we increase symmetric international trade frictions (t_{ij}, left panel) and travel frictions (μ_{ij}, right panel). The first point on both graphs, when $t_{12} = t_{21} = \mu_{12} = \mu_{21} = 1$, is one of the cases we studied in Figure 2. The large infection rate in Country 2 generates a pandemic in both countries. Globalization is essential to generate this pandemic. As both graphs illustrate, as we increase either tariffs or travel restrictions, global interactions decline, and the total number of recovered agents decreases. Eventually, when the world is sufficiently isolated, the pandemic disappears and the pandemic-free equilibrium becomes stable. In both graphs, the value of $\mathcal{R}_0$ (plotted in orange and measured in the right axis) declines smoothly with frictions. The vertical line in the figure indicates the value of tariffs or travel frictions, respectively, corresponding to $\mathcal{R}_0 = 1$.[26]

Although, in most cases, $\mathcal{R}_0$ increases as one lowers trade and travel frictions, we now show that lower trade costs can also *reduce* the risk of a pandemic if there are differences in the disease environment across countries (e.g., due to culture, administrative capacity or medical technology). Suppose, in particular, that country j is a much lower risk environment, in the sense that α_j is very low – so infections are very rare – and γ_j is very high – so infected households quickly recover in that country. In the limiting case $\alpha_j \to 0$, the condition that $\mathcal{R}_0 < 1$ reduces to [27]

$$\frac{2\alpha_i n_{ii}}{\gamma_i} + \frac{1}{\gamma_j} \frac{(\alpha_i n_{ji})^2}{\gamma_i} < 1.$$

For a high value of γ_j, it is then straightforward to see that the fall in country i's domestic interactions n_{ii} associated with a reduction in international barriers makes this constraint laxer,

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[26]Note that the value of $R_i(\infty)$, does not become zero for either country right at the point where tariffs or travel frictions lead $\mathcal{R}_0$ to become greater than one. The reason is that even though one of the countries necessarily avoids a pandemic, it lingers close to its initial value of infections for a long time, which accumulates to a positive cumulative number of recovered agents.

[27]It is straightforward to show that a necessary condition for $\mathcal{R}_0 < 1$ is

$$\frac{2\alpha_i n_{ii}}{\gamma_i} + \frac{2\alpha_j n_{jj}}{\gamma_j} - \frac{2\alpha_i n_{ii}}{\gamma_i} \frac{2\alpha_j n_{jj}}{\gamma_j} + \frac{(\alpha_j n_{ij} + \alpha_i n_{ji})^2}{\gamma_i \gamma_j} < 1.$$
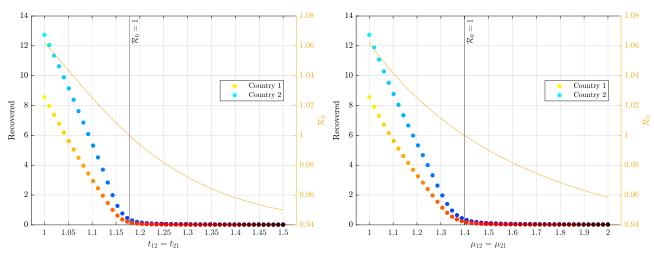
Figure 3: The Impact of Changes in Trade (left) and Travel (right) Frictions

Note: See Online Appendix K for further details on the parameters and algorithms for these numerical simulations.

even if n_{ji} goes up with that liberalization. In those situations it is perfectly possible for a pandemic-free equilibrium worldwide to only be stable when barriers are low. The intuition for this result is straightforward. In such a scenario, globalization makes it economically appealing for agents from a high-risk country to increase their interactions with agents in a low-risk country, and despite the fact that overall interactions by these agents may increase, the reduction in domestic interactions in their own high-risk environment is sufficient to maintain the disease in check.
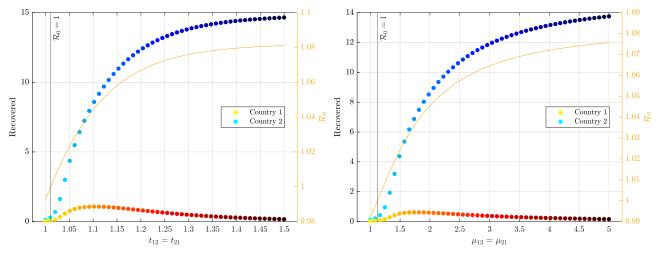
More generally, beyond this limiting case, if there are sufficiently large differences in the disease environment across countries, lower trade costs can reduce both the range of parameters where a pandemic occurs and its severity when it does occur. We summarize this result as follows:

Proposition 7 *When the contagion rate α_i and the recovery rate γ_i vary sufficiently across countries, a decline in any international trade friction (i) decreases $\mathcal{R}_0$, thus increasing the range of parameters for which a pandemic-free equilibrium is stable, and (ii) when $\mathcal{R}_0 > 1$, it reduces the share of the population in the high-risk (high α_i, low γ_i) country that becomes infected during the pandemic, and it may also reduce the share of the population in the low-risk (low α_i, high γ_i) country that become infected during the pandemic.*

Figure 4 illustrates Proposition 7 by presenting examples in which increases in trade and travel barriers eliminate the possibility of a pandemic-free equilibrium. The figure considers the case of a small infection rate in the healthy country, Country 1, of $\alpha_1 = 0.008$, and sets the infection rate in County 2 at a standard value of $\alpha_2 = 0.052$.[28] In both panels, increases in frictions now lead to increases in $\mathcal{R}_0$ (again depicted in orange and measured in the right axis). Without frictions the pandemic-free equilibrium is stable. Agents in Country 2 interact sufficiently with the healthier Country 1, which helps them avoid the pandemic. As both economies impose more

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[28]Relative to the baseline parameters the example also lowers c to 0.1 and ϕ to 1.5. These additional changes increase the overall number of domestic and foreign interactions.

Figure 4: The Impact of Changes in Trade (left) and Travel (right) Frictions with Large Differences in Infection Rates Across Countries ($\alpha_1 = 0.008$ and $\alpha_2 = 0.052$)

Note: See Online Appendix K for further details on the parameters and algorithms for these numerical simulations.

frictions, domestic interactions increase rapidly, while foreign interactions drop. This is bad news for Country 2, since its larger infection rate now leads to a pandemic. Perhaps surprisingly, it is also bad news for Country 1 since, although it interacts less with Country 2, it does so sufficiently to experience a pandemic. Larger frictions, which decrease aggregate income in both countries smoothly, also worsen the pandemic in both countries, at least when frictions are not too large; a clear case for free trade and mobility. Of course, as frictions increase further, eventually they isolate Country 1 sufficiently and so the severity of its local pandemic declines. In autarky, Country 1 avoids the pandemic completely, but at a large cost in the income of both countries. In contrast, higher frictions always worsen the pandemic in Country 2. Contacts with the healthy country are always beneficial, since they dilute interactions with locals, which are more risky.

This possibility for lower trade costs to reduce the incidence and severity of pandemics arises from the substitutability between domestic and foreign interactions. In Online Appendix I, we show that this substitutability is implied by a constant elasticity gravity equation, in the sense that reductions in trade costs increase foreign interactions relative to domestic interactions. We also show empirically that a constant elasticity gravity equation provides a good approximation to observed travel behavior. Although in practice it may be hard to find examples in which the differences in disease environment across countries are sufficiently large to imply that lower costs do indeed reduce the magnitude of pandemics, our analysis reveals and illustrates this mechanism, which is relevant for understanding the evolution of infections over the course of a pandemic and the impact of public policy interventions such as travel bans. In Section 2 above and in Online Appendix G.1, we provide empirical evidence that, on average, increased international trade speeds the diffusion of disease (the extensive margin of the arrival of the first infection) and the rate of growth of infections once a disease outbreak has occurred (the intensive margin of infection growth).

4.6 Multiple Waves of Infection

We now show that another implication of the interaction between trade and disease dynamics in our model is that multiple waves of infection can occur in the open economy, even though a single wave of infection would occur in the closed economy. Remember that for values of the global reproduction rate ($\mathcal{R}_0$) greater than one, a pandemic occurs in the open economy. Integrating the dynamics of infections in each country using the initial conditions $S_i(0) = S_j(0) = 1$ and $R_i(0) = R_j(0) = 0$, we obtain the following closed-form solutions for infections in each country at each point in time (I_{it}, I_{jt}) as a function of susceptibles in each country ($S_i(t)$, $S_j(t)$):

$$I_i(t) = 1 - S_i(t) + \frac{\log S_i(t) - \frac{\alpha_j n_{ij} + \alpha_i n_{ji}}{2\alpha_j n_{jj}} \log S_j(t)}{\frac{2\alpha_i n_{ii}}{\gamma_i} - \frac{\alpha_j n_{ij} + \alpha_i n_{ji}}{2\alpha_j n_{jj}} \frac{\alpha_i n_{ji} + \alpha_j n_{ij}}{\gamma_i}}, \tag{21}$$

$$I_j(t) = 1 - S_j(t) + \frac{\log S_j(t) - \frac{\alpha_i n_{ji} + \alpha_j n_{ij}}{2\alpha_i n_{ii}} \log S_i(t)}{\frac{2\alpha_j n_{jj}}{\gamma_j} - \frac{\alpha_i n_{ji} + \alpha_j n_{ij}}{2\alpha_i n_{ii}} \frac{\alpha_j n_{ij} + \alpha_i n_{ji}}{\gamma_j}}. \tag{22}$$

Although there is necessarily a single wave of infections in the closed economy, multiple waves of infection can occur in the open economy, because infections in each country in equations (21) and (22) depend on the stock of susceptibles in both countries. Multiple waves of infection occur when a country has a wham-bam epidemic that is over very quickly in the closed economy, whereas its trade partner has an epidemic that builds slowly in the closed economy. The first peak reflects the country's rapid explosion of infections, which dissipates quickly. The second peak, which is in general smaller, reflects the evolution of the pandemic in its trade partner.

In Figure 5 we provide an example, in which Country 1 experiences two waves of infections in the open economy, whereas Country 2 experiences a single, more prolonged and severe wave. Country 1 features a large value of α_1, but also a large value of γ_1. Thus, although the infection rate is large, people remain contagious only briefly (perhaps because of a good contact tracing program). The resulting domestic reproduction rate $\mathcal{R}_{01} = 1.08$ and the first peak of the pandemic is relatively small and quick. Since Country 1 is assumed ten times smaller than Country 2, its small initial pandemic has no significant effect on Country 2. There, the infection rate is much smaller, but the disease remains contagious for much longer, leading to a larger $\mathcal{R}_{01} = 1.66$, which also results in a global reproduction number $\mathcal{R}_0 = 1.66$.[29] The result is a more protracted but also much longer singled-peaked pandemic in Country 2. This large pandemic does affect the smaller country through international interactions. The large country amounts for many of the interactions of the small country, which leads to the second wave of the pandemic in Country 2.

Essential for this example is that countries have very different timings for their own pandemics in autarky, but also that in the open economy the relationship is very asymmetric, with the small country having little effect on the large country but the large country influencing the small country significantly. If the interactions are large enough in both directions, both countries will end up with

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[29]The parameter values used in the exercise are $\sigma = 4.5$, $L_1 = 2$, $L_2 = 20$, $d_{12} = d_{11}$, $c = 0.12$, $\alpha_1 = 0.69$, $\alpha_2 = 0.09$, $\gamma_1 = 2.1$ and $\gamma_2 = 0.18$. All other values are identical to the baseline case. See Online Appendix K for more details.

a synchronized pandemic with only one peak. This property of multiples waves of infections was observed during the Covid-19 pandemic. While these multiple waves in part reflected time-varying policies such as lockdowns, there was also much discussion of countries (or states in large countries such as the United States) becoming reinfected from one another.[30]
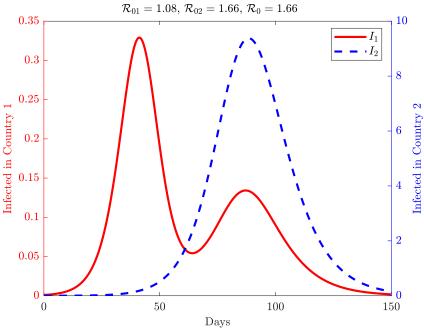
Figure 5: Multiple Waves of Infection in the Open Economy

Note: See Online Appendix K for further details on the parameters and algorithms used in these numerical simulations.

5   General-Equilibrium Social Distancing

In this section, we generalize our analysis to allow the disease to affect mortality and the ability to work and trade. For the time being, we assume however that agents are unaware of the source of the infection, and hence have no incentive to change their individual behavior. This generalization introduces a further interaction between trade and disease dynamics, because changes in relative labor supplies give rise to a form of general equilibrium social distancing. In Subsection 5.1, we first introduce deaths. In Subsection 5.2, we next incorporate both deaths and reduced labor supply by infected workers.

5.1   Deaths

We begin by allowing the infection to affect mortality. We assume that infected agents die with probability η_i and recover with probability γ_i, where both probabilities depend on the country in

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[30]See, for example, the discussion of U.S. regional patterns of infection in the Covid -19 pandemic in the New York Times: "What Previous Covid-19 Waves Tell Us About the Virus Now".

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which infected agents reside, and not on where they were infected.[31] Using this new assumption, the shares of households of each type evolve according to the following laws of motion (where we again ignore time subscripts to keep the notation tidy):

$$\dot{S}_i = -2n_{ii}(\mathbf{w})\alpha_i S_i I_i - [n_{ij}(\mathbf{w})\alpha_j + n_{ji}(\mathbf{w})\alpha_i] S_i I_j \tag{23}$$

$$\dot{I}_i = 2n_{ii}(\mathbf{w})\alpha_i S_i I_i + [n_{ij}(\mathbf{w})\alpha_j + n_{ji}(\mathbf{w})\alpha_i] S_i I_j - (\gamma_i + \eta_i) I_i \tag{24}$$

$$\dot{R}_i = \gamma_i I_i \tag{25}$$

$$\dot{D}_i = \eta_i I_i \tag{26}$$

There are two main differences between this dynamic system and that in equations (13)-(15). First, we now have four types of agents, as some infected agents transition to death rather than recovery. Second, we now need to make explicit the dependence of the contact rates $n_{ii}(\mathbf{w})$, $n_{ij}(\mathbf{w})$ and $n_{ji}(\mathbf{w})$ on the vector of equilibrium wages $\mathbf{w}$. As the changes in each country's population caused by deaths affect wages, this changes the intensity of bilateral interactions, which now evolve endogenously over the course of the pandemic. In particular, the equilibrium wage vector is determined by the following goods market clearing condition:

$$\sum_{j \in \mathcal{J}} \pi_{ji}(\mathbf{w}) w_j (1 - D_j) L_j = w_i (1 - D_i) L_i, \tag{27}$$

where recall that $\pi_{ij}(\mathbf{w})$ and $n_{ij}(\mathbf{w})$ are now given by equations (9) and (12), respectively.

In the special case in which $\eta_i = 0$, the system with deaths in equations (23)-(26) and equation (27) naturally reduces to the system without deaths in equations (13)-(15). Furthermore, the general equilibrium system with deaths is continuous in η_i, because (i) D_i is continuous in η_i given wages; (ii) $\pi_{ij}(\mathbf{w})$ is continuous in $\mathbf{w}$ for all ij from equation (9); (iii) $\mathbf{w}$ is continuous in D_i from equation (27); and (iv) $n_{ij}(\mathbf{w})$ is continuous in $\mathbf{w}$ for all ij from equation (12). This property of the continuity of the entire general equilibrium system in η_i ensures that all of the results established for our baseline model in the previous section necessarily hold in this generalization for sufficiently small η_i.

We now show that the impact of deaths on labor supply and equilibrium wages introduces a form of general equilibrium social distancing into the model. First, the decline in a country's labor supply from mortality leads to a change in its relative equilibrium wage (a terms of trade effect). Second, this decline in labor supply from mortality reduces the range of goods available in that country (a decline in the quantity of varieties produced). In an interior equilibrium in which agents source a subset of the varieties produced in each country, the measure of varieties sourced from each country is determined by its relative wage, as shown in the Proof of Proposition 4 in Online Appendix B.5. Therefore, the relative wage is a summary statistic for all general equilibrium effects in such an interior equilibrium where agents source a subset of varieties.

Purely through this general equilibrium force of changes in relative labor supplies, agents in the

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[31]We implicitly assume that if one of the household members dies, the other one does too.

healthy country engage in a form of endogenous social distancing, in which they skew their interactions away from the country with a worse disease environment, as summarized in the following proposition (see Online Appendix E.1 for a proof):

Proposition 8 *If country j experiences more deaths than country i, the resulting change in relative wages (w_j/w_i) leads country i to reduce its interactions with country j and increase its interactions with itself (general equilibrium social distancing).*

We provide an analytical characterization of the elasticity of a country's relative wage with respect to its own population (and hence with respect to deaths) in Online Appendix E.2. We show that this elasticity becomes larger in absolute value as the trade elasticity becomes smaller, such that a larger change in relative wages and the terms of trade is required to restore goods market equilibrium. Additionally, this elasticity becomes larger as the country's share of income derived from itself becomes smaller, such that it becomes more dependent on foreign markets. Finally, this elasticity is bounded above in absolute value by one, and converges to this largest absolute value as the trade elasticity converges to zero.

In interpreting Proposition 8, it is worth stressing that even if one of the countries has more favorable health parameters (α_i, γ_i) than the other one, which country has more infections (and hence more deaths) can change during the pandemic if the two countries' waves of infection are staggered in time. In the initial stages of the pandemic, one country may experience a larger relative reduction in its labor supply (leading to endogenous social distancing in the other country), while in the later stages of the pandemic the other country experiences a larger relative reduction in its labor supply (leading to the opposite pattern of endogenous social distancing).

Another straightforward implication of explicitly modeling deaths is that they naturally affect aggregate income in both countries. More specifically, whenever changes in trade or travel barriers affect population, aggregate real income ($w_i L_i / P_i$) and aggregate welfare ($W_i L_i$) are directly impacted by trade-induced changes in population. Because around $\mathcal{R}_0 = 1$ deaths are particularly responsive to changes in trade frictions (as evident in Figures 3 and 4), changes in trade frictions can have substantial effects on welfare through deaths relative to their conventional effects through welfare gains from goods trade.

In Figure 6, we illustrate the results in Proposition 8 with a numerical example. For illustration purposes, we consider a case with extreme differences in death rates, in which Country 1 has a death rate of 1 percent ($\eta_1/(\eta_1 + \gamma_1) = 0.01$) and Country 2 has a death rate of 50 percent ($\eta_2/(\eta_2 + \gamma_2) = 0.50$). The rest of the parameters are set to their baseline, symmetric values, across countries. We denote our generalization with deaths by 'SIRD model' and indicate our baseline specification with no deaths ($\eta_1 = \eta_2 = 0$) by 'SIR model.' The larger death rate in Country 2 leads to a fall in its relative labor supply, which increases relative wages, as shown in the top-left panel. Since the countries are otherwise symmetric, and we chose the wage of Country 1 as the numéraire, only the wage of Country 2 rises above one when deaths occur. The resulting increase in Country 2's relative wage is small (0.5%), even though about 6% of agents end up dying
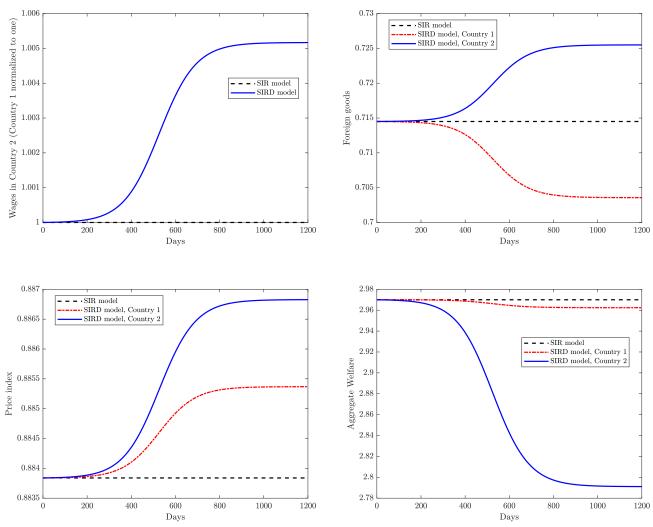
Figure 6: General Equilibrium Induced Social Distancing

Note: See Online Appendix K for further details on the parameters and algorithms for these numerical simulations.

in Country 2. Labor supply falls, but so does the aggregate demand for goods in that country and the set of varieties it produces, and the two countries here have identical size.

The rise in the relative wage of Country 2 implies that both countries tilt their consumption towards Country 1's varieties. Therefore, the consumption of foreign varieties increases in Country 2 but falls in Country 1, as illustrated in the top-right panel. We see the opposite pattern for domestic varieties, although the adjustments are smaller. Ultimately, agents in both countries consume less varieties, which increases the price index in both countries, although by more in Country 2, as shown in the bottom-left panel. Real income falls in Country 1, both per capita and in aggregate, because of this increase in the price index. In contrast, in Country 2, real income per capita rises, because the wage increases by more than the price index. Nevertheless, aggregate real income falls as result of the reduction in labor supply from deaths, as shown in the bottom-right panel.

5.2 Deaths and Reduced Worker Productivity

We now further generalize our analysis to allow the pandemic to affect a country's labor supply through both deaths and a reduction in the fraction of time that infected individuals can work. We continue to assume that agents are unaware of the source of the infection, and hence have no incentive to change their individual behavior. Specifically, we assume that infected agents only provide $1 - \varsigma_i > 0$ units of labor. Furthermore, sick individuals isolate when they do not work, and so their interactions are proportional to their labor supply. Using this assumption, the shares of households of each type evolve according to the following modified laws of motion (where, as before, we ignore time subscripts to keep the notation tidy):

$$
\begin{aligned}
\dot{S}_i &= -2n_{ii}\left(\mathbf{w}\right)\alpha_i S_i\left(1 - \varsigma_i\right)I_i - \left[n_{ij}\left(\mathbf{w}\right)\alpha_j + n_{ji}\left(\mathbf{w}\right)\alpha_i\right]S_i\left(1 - \varsigma_j\right)I_j \\
\dot{I}_i &= 2n_{ii}\left(\mathbf{w}\right)\alpha_i S_i\left(1 - \varsigma_i\right)I_i + \left[n_{ij}\left(\mathbf{w}\right)\alpha_j + n_{ji}\left(\mathbf{w}\right)\alpha_i\right]S_i\left(1 - \varsigma_j\right)I_j - \left(\gamma_i + \eta_i\right)I_i \\
\dot{R}_i &= \gamma_i I_i \\
\dot{D}_i &= \eta_i I_i
\end{aligned}
$$

Note that, since now an individual's reduced labor supply also results in reduced infections, a higher ς_i flattens the infection curve and reduces the total number of infections. In the limit, when $\varsigma_1 = 1$ in all countries, there is no pandemic since the initially infected isolate completely and infections do not spread. The modified goods market clearing condition becomes
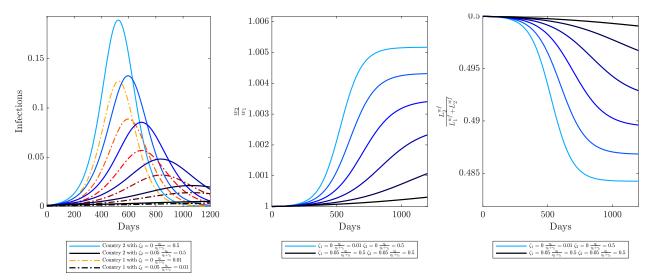
$$
\sum_{j \in \mathcal{J}} \pi_{ji}\left(\mathbf{w}\right)w_j\left(1 - D_j - \varsigma_j I_j\right)L_j = w_i\left(1 - D_i - \varsigma_i I_i\right)L_i,
$$

where $\pi_{ij}\left(\mathbf{w}\right)$ and $n_{ij}\left(\mathbf{w}\right)$ are given by equations (9) and (12), respectively.

The term $L_i^{wf} \equiv \left(1 - D_i - \varsigma_i I_i\right)L_i$ represents the total labor supply in country i, which is given by the total initial population, L_i, minus the number of deaths, $D_i L_i$, minus the time that infected agents do not work, $\varsigma_i I_i L_i$. The last term is new and implies that relatively high infections in a country will reduce its relative labor supply, which results in higher relative wages in that country. As with deaths, the larger relative wages generate a general equilibrium social distancing effect that makes individuals in the relatively healthier country interact less with those in the country with a high number of infections. A key difference is that the reduction in worker productivity while infected is only temporary for those workers who recover from the infection. Hence, these effects can be particularly large and rich when countries' waves of infections are not synchronized.

In Figure 7, we simulate the same example as in Figure 6 above, but vary ς_i from 0 to 0.05 for all i. The lightest curves present the case when $\varsigma_i = 0$ and so they reproduce the exercise in Figure 6, for comparison purposes. The three panels in Figure 7 show the wave of infections in each country, the relative wage in Country 2, and the relative labor supply in Country 2, respectively. Clearly, the main effect of an increase in ς_i is to reduce the pandemic in both countries, which reduces the labor supply effect and therefore the impact on relative wages. As people work less and isolate more, the pandemic is smaller, and so is the general equilibrium social distancing effect.

Figure 7: Evolution of Infections, Relative Wages, and Labor Supply Share with Reduced Labor Supply by the Infected

Note: See Online Appendix K for further details on the parameters and algorithms for these numerical simulations.

In Online Appendix E.3 we study a case in which the pandemic again affects labor supply through reductions in the fraction of time sick agents can work, but where the infected do not isolate, and hence keep interacting with others. A natural interpretation of this case is a reduction in the productivity of the infected. This case allows us to underscore the subtle impact of the reduction in the labor supply of the infected on relative wages and interactions, without its direct effect on the magnitude of the pandemic through the self-isolation of the infected. As with deaths, a reduced labor supply by the infected generates a general equilibrium social distancing effect, but one that evolves according to the relative number of infected agents across countries. If the health environment in one country is worse than in the other, such that the pandemic is asynchronous across countries, this leads to changes in the countries' relative labor supplies and wages. Agents buy less from the country with temporarily higher relative wages, which lowers the peak in the number of infected agents in both countries.

6   Behavioral Responses

We now consider a further generalization of our baseline open-economy SIR model, in which we assume that the infection affects mortality and agents are aware of this. This generalization introduces a further interaction between trade and disease dynamics, because agents now adjust their individual behavior to the threat of infection.

Modeling these behavioral responses in an open-economy environment is challenging. Agents in each country choose profiles of time-varying interactions for each separate market. These profiles must be individually rational, in the sense that they are consistent with the conditions for dynamic optimization at the individual level, given the aggregate SIR disease dynamics and the path of the

model's endogenous variables. But the aggregate SIR disease dynamics are themselves influenced by these individual profiles of time-varying interactions, as well as the path of the model's endogenous variables. Furthermore, the path of the model's endogenous variables is also shaped by both the aggregate SIR dynamics (through general equilibrium social distancing) and by the individual profiles of time-varying interactions (through behavioral responses). The interactions between these three sets of forces are particularly complex in the open economy, because of the much richer SIR disease dynamics with multiple countries, the more subtle general equilibrium interactions between countries, and the dimensionality of the state space at the individual level. We are not aware of any other research that analyses behavioral responses in models that feature both economic choices for spatial interactions and epidemiological disease dynamics in an open-economy setting.

To overcome these challenges, we build on the closed-economy specification of Farboodi et al. (2021), in which all infected individuals are assumed to be asymptomatic, in the sense that household behavior is independent of their specific health status, though their actual behavior is shaped by their expectation of the probability with which they are susceptible, infected, or recovered. How is that expectation formed? A natural assumption is that agents have rational expectations and that their belief of the probability with which they have a specific health status is equal to the share of the population in their country with that particular health status.[32]

We denote the individual beliefs of the probability of being infected, susceptible recovered, or dead with lowercase letters, except for their belief of the probability of being dead at time t, which we denote by $k_i(t)$ (instead of $d_i(t)$) to avoid a confusion with the notation we used for distance. The maximization problem of the individual, for known $i_i(0)$, $s_i(0)$ and $k_i(0) = 0$, is given by

$$W_i^s(0) = \max_{n_{ii}(\cdot),n_{ij}(\cdot)} \int_0^\infty e^{-\xi t} \left[\left[Q_i(n_{ii}(t),n_{ij}(t)) - C_i(n_{ii}(t),n_{ij}(t))\right](1 - k_i(t))\right] dt$$

$$\text{s.t.} \quad \dot{s}_i(t) = -s_i(t)\left[(\alpha_i n_{ii}(t) + \alpha_i n_{ii}^*(t)) i_i(t) + \left(\alpha_j n_{ij}(t) + \alpha_i n_{ji}^*(t)\right) i_j(t)\right],$$

$$\dot{i}_i(t) = s_i(t)\left[(\alpha_i n_{ii}(t) + \alpha_i n_{ii}^*(t)) i_i(t) + \left(\alpha_j n_{ij}(t) + \alpha_i n_{ji}^*(t)\right) i_j(t)\right]$$
$$\quad - (\gamma_i + \eta_i) i_i(t),$$

$$\dot{k}_i(t) = \eta_i i_i(t),$$

where ξ is the rate of time preference, and where from equation (6),

$$Q_i(n_{ii}(t),n_{ij}(t)) = w_i(t)\left(\sum_{j\in\mathcal{J}} n_{ij}(t)\left(\frac{\tau_{ij} w_j(t)}{Z_j}\right)^{1-\sigma}\right)^{\frac{1}{(\sigma-1)}},$$

---

[32] Although households do not observe their own health status, they can form rational expectations about the share of the population with each health status if they have common knowledge of the model's parameters and rational expectations about the path of the pandemic. For the latter, it suffices to assume that agents observe pandemic-related deaths at the outbreak of the disease. More specifically, at $t = 0$, notice from equation (26) that (i) I_{i0} can be obtained from $I_{i0} = D_0\eta_i$ since $D_{-1} \simeq 0$; (ii) $R_{i0} \simeq 0$; and (iii) S_{it} is then trivially $S_{i0} = 1 - I_{i0} - R_{i0} - D_{i0}$. With this initial condition, agents can solve for the future path of the pandemic using rational expectations.

and

$$C_i\left(n_{ii}\left(t\right), n_{ij}\left(t\right)\right) = \frac{c}{\phi} \sum_{j \in \mathcal{J}} \mu_{ij}\left(d_{ij}\right)^{\rho}\left(n_{ij}\left(t\right)\right)^{\phi}.$$

Note that we denote with an asterisk variables chosen by *other* households that affect the dynamics of infection of a given household.[33] Implicitly, we are assuming that agents decide their optimal path of $n_{ii}\left(\cdot\right)$ and $n_{ij}(\cdot)$ at period zero and commit to following it. Otherwise, without commitment, at some future period and conditional on being alive, agents would want to reoptimize their choices by solving the problem above but setting $k_i\left(t\right) = 0$.[34]

The Hamiltonian of the problem faced by each household is given by

$$
\begin{aligned}
&H(s, i, n_{ii}, n_{ij}, \theta^i, \theta^s, \theta^k) \\
=\ &\left[Q_i\left(n_{ii}\left(t\right), n_{ij}\left(t\right)\right) - C_i\left(n_{ii}\left(t\right), n_{ij}\left(t\right)\right)\right]\left(1 - k_i\left(t\right)\right)e^{-\xi t} \\
&- \theta_i^s\left(t\right) s_i\left(t\right)\left[\left(\alpha_i n_{ii}\left(t\right) + \alpha_i n_{ii}^*\left(t\right)\right) i_i\left(t\right) + \left(\alpha_j n_{ij}\left(t\right) + \alpha_i n_{ji}^*\left(t\right)\right) i_j\left(t\right)\right] \\
&+ \theta_i^i\left(t\right)\left[s_i\left(t\right)\left[\left(\alpha_i n_{ii}\left(t\right) + \alpha_i n_{ii}^*\left(t\right)\right) i_i\left(t\right) + \left(\alpha_j n_{ij}\left(t\right) + \alpha_i n_{ji}^*\left(t\right)\right) i_j\left(t\right)\right] - \left(\gamma_i + \eta_i\right) i_i\left(t\right)\right] \\
&+ \theta_i^k\left(t\right) \eta_i i_i\left(t\right).
\end{aligned}
$$

Hence, the optimality condition with respect to the choice of n_{ij} is

$$\left[\frac{\partial Q_i\left(n_{ii}\left(t\right), n_{ij}\left(t\right)\right)}{\partial n_{ij}\left(t\right)} - \frac{\partial C_i\left(n_{ii}\left(t\right), n_{ij}\left(t\right)\right)}{\partial n_{ij}\left(t\right)}\right]\left(1 - k_i\left(t\right)\right)e^{-\xi t} = \left[\theta_i^s\left(t\right) - \theta_i^i\left(t\right)\right] s_i\left(t\right) \alpha_j i_j\left(t\right), \quad (28)$$

while the optimality conditions associated with the co-state variables are given by:

$$
\begin{aligned}
-\dot{\theta}_i^s\left(t\right) &= -\left[\theta_i^s\left(t\right) - \theta_i^i\left(t\right)\right]\left[\left(\alpha_i n_{ii}\left(t\right) + \alpha_i n_{ii}^*\left(t\right)\right) i_i\left(t\right) + \left(\alpha_j n_{ij}\left(t\right) + \alpha_i n_{ji}^*\left(t\right)\right) i_j\left(t\right)\right], \quad (29) \\
-\dot{\theta}_i^i\left(t\right) &= \eta_i \theta_i^k\left(t\right) - \left(\gamma_i + \eta_i\right) \theta_i^i\left(t\right), \quad (30) \\
-\dot{\theta}_i^k\left(t\right) &= -\left[Q_i\left(n_{ii}\left(t\right), n_{ij}\left(t\right)\right) - C_i\left(n_{ii}\left(t\right), n_{ij}\left(t\right)\right)\right] e^{-\xi t}. \quad (31)
\end{aligned}
$$

Finally, the transversality conditions are

$$\lim_{t \to \infty} \theta_i^i\left(t\right) i_i\left(t\right) = 0, \qquad \lim_{t \to \infty} \theta_i^s\left(t\right) s_i\left(t\right) = 0, \qquad \lim_{t \to \infty} \theta_i^k\left(t\right) k_i\left(t\right) = 0.$$

In equilibrium, aggregate consistency implies that $i_i\left(t\right) = I_i\left(t\right)$, $s_i\left(t\right) = S_i\left(t\right)$, and $k_i\left(t\right) = D_i\left(t\right)$. Namely, an individual's rational expectations about their probability of being infected, susceptible, or dead in each period equal the corresponding population shares. Finally, we complete

---

[33]For instance, though the aggregate domestic rate of contact in i is $2\alpha_i n_{ii}$, a household has no control over how many buyers visit the household's seller, so the household only controls the rate $\alpha_i n_{ii}$ of contacts generated by the household's buyer.

[34]The reason for this is that the probability of deaths acts like non-exponential discounting in the value function solved by agents, and it is well-understood that non-exponential discounting creates a wedge between the solution of dynamic problems with and without commitment. Farboodi et al. (2021) bypass this issue by assuming that, instead of foregoing future utility when dying, agents pay a one-time utility cost (or value of life) at the moment they die. Note, however, that for small probabilities of death k: $(1 - kdt) \approx e^{-kdt}$. Hence, for empirically reasonable values of k, we have found that our solution under full commitment is close to the solution under the exponential approximation, which is time consistent.

our description of the general equilibrium of the model with the goods market clearing condition that determines wages

$$\sum\nolimits_{j \in \mathcal{J}} \pi_{ji}\left(\mathbf{w},t\right) w_j\left(t\right)\left(1 - D_j\left(t\right)\right) L_j = w_i\left(t\right)\left(1 - D_i\left(t\right)\right) L_i.$$

A key difference from our baseline model in Section 4, and from our generalization to incorporate changes in labor supply in Section 5, is that agents now adjust bilateral interactions $(n_{ji}(\mathbf{w},t))$ in response to the threat of the infection. Nevertheless, we are able to solve for the dynamic path of the economy numerically using a backward shooting algorithm, as discussed in Online Appendix K. This backward shooting algorithm involves a guess of the share of deaths and infections in each country in the far away future, when the pandemic is over. Given this guess, we solve for the dynamic path of the economy backward and forward, and then check that our solution is consistent with this guess. When countries are symmetric, we can simply guess a value very close to zero for infections in the far away future and make an initial guess for the steady-state number of deaths. We then iterate until we find the equilibrium value of steady state deaths in both countries. With more than one country and country asymmetries, the dynamic path of the economy not only depends on the guess of steady state deaths in each country, but is highly sensitive to the *relative* value of final infections, even if their level is very close to zero in the long run. This increases the numerical complexity of the problem significantly. Hence, it is challenging to solve the model for many parameter values or expand the number of countries in the open economy equilibrium with asymmetric countries.

From inspection of the agent's optimization problem above, when there is zero probability of death ($\eta_i = 0$ and hence $k_i(t) = 0$ for all t), the optimal choice of $n_{ii}\left(\cdot\right)$ and $n_{ij}(\cdot)$ is independent of the pandemic, given wages. Additionally, with no impact of the pandemic on labor supply, the goods market clearing condition implies that wages are time invariant. Therefore, in the special case of zero probability of death, the model here reduces to our baseline model without behavioral responses in Section 4. More generally, the Hamiltonian is continuous in η_i and concave in the controls, given the properties of $Q_i(\cdot)$ and $C_i(\cdot)$ under the maintained assumption that $\sigma > 2$ and $\phi > 1$. Using these properties, the evolution of $n_{ii}\left(\cdot\right)$ and $n_{ij}(\cdot)$ is continuous in η_i, as is the number of deaths $D_i(t)$, and hence the path of equilibrium wages. This reasoning implies that the evolution of the economy with behavioral responses when $\eta_i > 0$ approaches smoothly the one without behavioral responses as $\eta_i \to 0$. Therefore, as in the previous section, all the results in our original model without deaths or behavioral responses apply to this much more complicated model with behavioral responses when η_i is sufficiently small in each country.

With a positive probability of death $\eta_i > 0$, this is a significantly more complicated general equilibrium system, but we are able to show analytically that the solution to this problem necessarily involves individual-level social distancing. In the absence of a pandemic, households equate the marginal utility from sourcing varieties from each location to the marginal cost of sourcing those varieties. During a pandemic, households internalize that the interactions involved in sourcing varieties expose them to infection, which leads them to reduce interactions until the marginal

utility from those interactions exceeds the marginal cost, as summarized in the following proposition (proven in Online Appendix F.1).

Proposition 9 *Along the transition path, $\theta_i^s(t) - \theta_i^i(t) \geq 0$ for all t, which implies:*

$$\frac{\partial Q_i\left(n_{ii}(t), n_{ij}(t)\right)}{\partial n_{ij}(t)} > \frac{\partial C_i\left(n_{ii}(t), n_{ij}(t)\right)}{\partial n_{ij}(t)}, \qquad as\ long\ as\ I_j(t) > 0.$$

An implication of this result is that the pandemic generically has a larger impact on foreign interactions than on domestic interactions. This implication can been seen by re-arranging the optimality condition (28) and substituting for the marginal utility and marginal cost for interactions to obtain

$$\frac{1}{n_{ij}} \frac{n_{ij} q_{ij}^{\frac{\sigma-1}{\sigma}}}{\sum_{\ell \in \mathcal{J}} n_{i\ell} q_{i\ell}^{\frac{\sigma-1}{\sigma}}} Q_i = \frac{1}{n_{ij}} c \mu_{ij} d_{ij}^{\rho} n_{ij}^{\phi} + \frac{\left[\theta_i^s(t) - \theta_i^i(t)\right] s_i(t) \alpha_j I_j(t)}{(1 - D_i(t)) e^{-\xi t}},$$

where the term on the left-hand side is the marginal utility from interactions; the first term on the right-hand side is the marginal cost of interactions; and the second term on the right-hand side is the wedge capturing the threat of infection. As foreign interactions are generically a smaller share of the consumption index than domestic interactions, the fraction on the left-hand side is generically smaller for foreign interactions $(i \neq j)$. Therefore, as a pandemic emerges and the threat of infection becomes positive, a larger reduction in n_{ij} is generically needed for foreign interactions, in order to raise the marginal utility on the left-hand side until it is equal to the marginal cost plus the positive wedge capturing the threat of infections on the right-hand side.

We now illustrate some of these implications of behavioral responses for the case of symmetric countries. We use the baseline parameters with $\alpha_i = 0.1$, $\gamma_i + \eta_i = 0.2$, and $\eta_i / (\eta_i + \gamma_i) = 0.0062$ (a 0.62% death rate among those infected) for all i. We also show a specification with half the death rate of $\eta_i / (\eta_i + \gamma_i) = 0.003$ for all i, as well as the case without behavioral responses from the previous section. As we choose the wage in one country as the numéraire, with symmetric countries, the relative wage is also equal to one and constant over time. In the absence of any behavioral responses, this constant relative wage implies that both the mass of varieties and price index are constant over time. In contrast, in the presence of behavioral responses, households reduce the intensity of their interactions in response to the threat of infection, which leads to changes in the mass of varieties and the price index over time.

In the top-left panel of Figure 8, we show the percentage of individuals infected in Country 2 for all three specifications (with symmetry the figure for Country 1 is identical). Households' behavioral response of reducing interactions leads to a "flattening of the curve of the pandemic," such that the pandemic has lower peak and lower cumulative infections, but takes longer to subside. Clearly, the larger the death rate, the stronger the behavioral response and the flatter the resulting curve of infections. The top-right panel in Figure 8 presents the resulting evolution of cumulative deaths in Country 2. Behavioral responses delay and reduce total deaths, with the level (and proportional reduction) larger, the larger the death rate. Naturally, the behavioral response and the associated
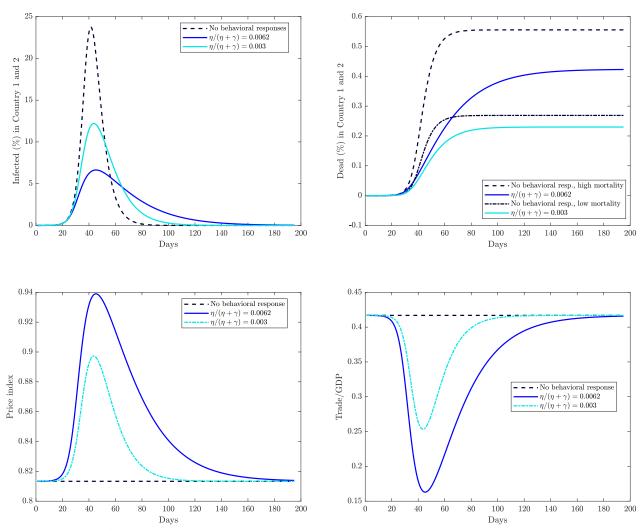
37

Figure 8: Behavioral Responses with Symmetric Countries for Various Death Rates
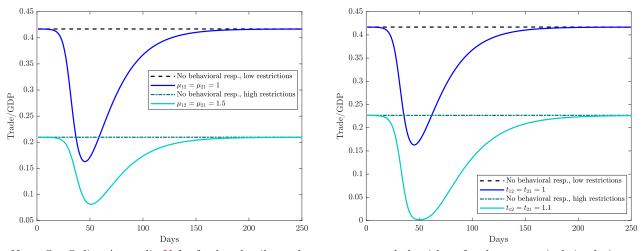

Note: See Online Appendix K for further details on the parameters and algorithms for these numerical simulations.

reductions in the number of deaths come at an economic cost for survivors. As the bottom-left panel shows, the reductions in the number of purchased domestic and foreign varieties increase the price index in each country, which results in a corresponding decline in real income. This increase in the price index, and reduction in real income, is larger the stronger the behavioral response, and hence is magnified by a higher death rate. Finally, the bottom-right panel displays the trade over GDP ratio (calculated as imports plus exports over GDP). In the example, trade/GDP falls from about 0.45 to less than 0.25 when the death rate is 0.3%, and to 0.17 when the death rate is 0.62%. Therefore, the flattening of the curve of infections and reduction in the number of deaths comes at the cost of lower trade and real income. Of course, behavioral responses are ex-ante privately optimal, so it is not surprising that they improve individual welfare.[35]

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[35]Agents' responses are not in general socially optimal, because of the externalities between agents from the transmission of the disease. Fajgelbaum et al. (2021) characterizes the socially-optimal lockdown policies of a

The value of mobility and trade frictions plays an important role in shaping the magnitude and pattern of behavioral responses. First, with symmetric countries, higher mobility and trade frictions imply a reduction in the overall volume of human interactions, which leaves less scope for behavioral responses. Second, higher mobility and trade frictions imply that more of the burden of adjustment falls on domestic rather than foreign transactions. In Figure 9, we show the evolution of the trade/GDP ratios for symmetric countries for two different levels of mobility (left panel) and trade (right panel) frictions and the baseline values of our other parameters. As discussed above, in the symmetric case without behavioral responses, all human contacts $n_{ii}(t)$ and $n_{ij}(t)$ are constant in time, which implies that mobility and trade frictions only reduce the level of the trade/GDP ratios. Once we incorporate behavioral responses, trade/GDP follows the trajectory of the pandemic. The larger value of trade frictions reduces trade openness, which dampens the absolute magnitude of the behavioral response, although trade openness can end up falling to quite low levels. In this example with 10% trade frictions, $(t_{12} = t_{21} = 1.1)$, trade essentially falls to zero in the most severe phase of the pandemic. For each level of trade frictions, behavioral responses reduce the total number of deaths, and for the parameter values considered here, higher trade and mobility frictions also reduce the total number of deaths.

Figure 9: The Effect of Mobility and Trade Frictions on Trade/GDP with Behavioral Responses

Note: See Online Appendix K for further details on the parameters and algorithms for these numerical simulations.

The evolution of the trade to GDP ratio in Figure 9 is similar to the evolution of the trade to GDP ratio in the world economy during the Covid-19 pandemic. Figure J.1 in Online Appendix J presents this ratio for the early stages of the pandemic in 2020. The figure shows a rapid decline in the trade to GDP ratio followed by an equally speedy recovery.

We next illustrate some of the implications of our model when countries are asymmetric. We focus on a case in which countries differ in their mortality rate, where remember that we assume

---

planner in a commuting model without private behavioral responses. Given the already rich interactions between globalization and disease transmission in our model with private behavioral responses, we leave the analysis of the optimal policies of the social planner in the presence of these private behavioral responses for future work.

that mortality is determined by the country in which a household lives rather than the country in which it was infected. We let Country 1 have a relatively low mortality rate of 0.3% and we leave the mortality rate of Country 2 at the higher baseline value of 0.62%. Figure 10 presents the results. The top-left panel shows the percent of infections in each country. As benchmarks, we also display the average of infections in the two countries, as well as infections in the case of two symmetric countries with an average mortality rate of 0.46% (the mean of 0.3% and 0.62%). There is a stronger behavioral response in the high-mortality Country 2 because households internalize the greater risk that infection leads to death, which results in a "flatter" curve of infections in this country. The low-mortality Country 1 ends up with about 10% higher total infections, because of its more subdued behavioral response. However, its lower mortality rate implies that it ends up with only about half the total number of deaths. This asymmetric behavioral response implies that Country 1 is a relatively dangerous destination for doing business in the early stages of the pandemic, but a relatively safe destination in the later stages of the pandemic, since it reaches herd immunity faster. Comparing the average response for the world with asymmetric countries to the response in the symmetric case with average mortality rates illustrates the implied aggregate effects from differences across countries in mortality rates. In the asymmetric case, the world's infection curve is marginally flatter than in a symmetric world with average mortality rates.

The top-right panel in Figure 10 displays Country 1's relative wage. As a result of the smaller behavioral response in this lower mortality country, there is a greater risk of infection in Country 1 in the early stages of the pandemic, which leads to a decline in demand for this country's varieties and a fall in its relative wage. Once Country 1's infection rate falls, demand for its varieties recovers, and hence so does its wage. Eventually, once Country 1's infection rate falls below that of Country 2, it becomes the relatively safe environment in which to source varieties, and its relative wage rises temporarily above one, before falling back to one as the pandemic ends. Therefore, these behavioral responses in general equilibrium with asymmetric countries lead to demand effects that reduce the relative wage of the country with a relatively higher infection rate. In addition, as shown in the previous section, there is another general equilibrium effect from changes in relative labor supply. A country with a higher death rate experiences a reduction in its relative labor supply, which leads to an increase in its relative wage. The top-right panel of Figure 10 shows the balance of these forces, and demonstrates that relative demand effects generally dominate and overturn the result in Section 5 linking higher death rates to higher relative wages.

As before, the stronger behavioral response in Country 2 as a result of its higher mortality rate comes with greater economic costs. Country 2's reduction in domestic and foreign purchases raises its price index and reduces its real income. The effect on the price index in Country 1 is more nuanced. Country 1 also reduces domestic and foreign interactions, which tends to increase its price index. However, the decline in its relative wage during the first part of the pandemic reduces the price of domestic varieties. The bottom-left panel in Figure 10 shows how these forces result in a price index with multiple peaks. Overall, the effect of the pandemic on the real income of Country 1 is negative but substantially smaller in magnitude than in Country 2. As shown in the bottom-
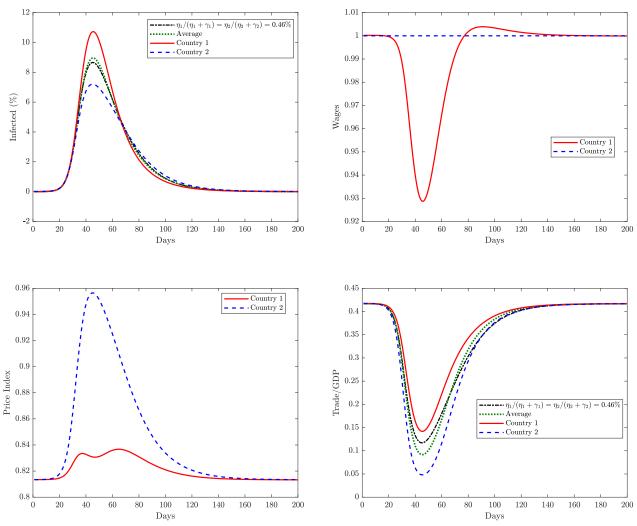
Figure 10: Behavioral Responses with Asymmetric Mortality Rates

Note: See Online Appendix K for further details on the parameters and algorithms for these numerical simulations.

right panel, the reduction in human interactions from social distancing reduces trade openness dramatically, particularly in Country 2, where behavioral responses are stronger. The asymmetry in mortality rates between the two countries initially leads to a larger reduction in trade openness than in a symmetric world with average mortality rates, in part because the behavioral response of Country 2 is particularly strong in the earlier phases of the pandemic. Later in the pandemic, the asymmetric case has higher trade openness than in a symmetric world, because the initially subdued behavioral response of Country 1 creates a more pronounced and faster wave of infections.

Adjustment Costs and the Risk of a Pandemic

Despite the potential for significant disruptions in international trade during a pandemic, a clear implication of the first-order condition (28) is that as long as $I_i(t) = I_j(t) = 0$, human interactions are at the same level as in a world without the potential for pandemics. In other words, although we

have generated rich dynamics of international trade during a pandemic, as soon as this pandemic is overcome (via herd immunity or the arrival of a vaccine), our model predicts that life immediately goes back to normal. We next explore an extension of our model that explores the robustness of this notion of a rapid V-shape recovery in economic activity and international trade flows after a global pandemic.

The main novel feature we introduce is adjustment costs associated with changes in the measures of human contacts $n_{ii}(t)$ and $n_{ij}(t)$. More specifically, we assume that whenever a household wants to change the measure of contacts $n_{ij}(t)$, it needs to pay a cost $\psi_1 |\dot{n}_{ij}(t)|^{\psi_2}$, where $\psi_1 > 0$ and $\psi_2 > 1$. An analogous adjustment cost function applies to changes in domestic interactions n_{ii}. Notice that this formulation assumes that the cost of reducing or increasing the number of contacts are symmetric. This leads to the following modified first-order condition for the choice of n_{ij} at any point in time t_0 (an analogous condition holds for n_{ii}):

$$
\int_{t_0}^{\infty} e^{-\xi t} \left[\frac{\partial Q_i(n_{ii}(t), n_{ij}(t))}{\partial n_{ij}} - \frac{\partial C_i(n_{ii}(t), n_{ij}(t))}{\partial n_{ij}} \right] (1 - k_i(t)) dt
$$
$$
= \int_{t_0}^{\infty} e^{-\xi t} \left[\theta_i^s(t_0) - \theta_i^i(t_0) \right] s_i(t_0) a_j I_j(t_0) dt + e^{-\xi t_0} \psi_1 \psi_2 |\dot{n}_{ij}(t_0)|^{\psi_2 - 1} (1 - k_i(t_0)).
$$

Since dead individuals do not pay adjustment costs, equation (31) becomes

$$
-\dot{\theta}_i^k(t) = -\left[Q_i(n_{ii}(t), n_{ij}(t)) - C_i(n_{ii}(t), n_{ij}(t)) - \psi_1(|\dot{n}_{ii}(t)|^{\psi_2} + |\dot{n}_{ij}(t)|^{\psi_2}) \right] e^{-\xi t}.
$$

The rest of the system is as before with the added feature that the values of $n_{ii}(t)$ and $n_{ij}(t)$ are now state variables, with exogenous initial conditions $n_{ii}(0)$ and $n_{ij}(0)$.[36]
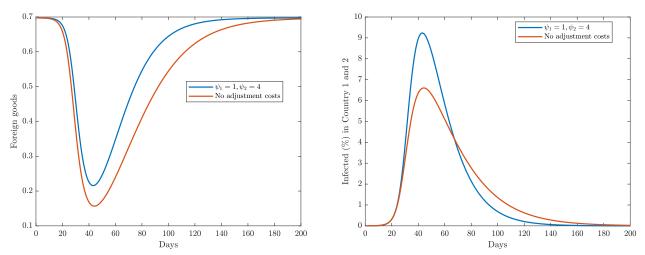
As the first-order condition makes evident, the choice of $\dot{n}_{ij}(t_0)$ now affects the values of $n_{ii}(t)$ and $n_{ij}(t)$ in the future directly and not only through its impact on the pandemic (and the corresponding co-state variables $\theta_i^s(t_0)$ and $\theta_i^i(t_0)$). This has two important implications. First, adjustment costs imply that agents will react less aggressively to a pandemic and overall their reaction will be smoother. Of course, the counterpart is that their endogenous response will attenuate the flattening of the curve of infections associated with behavioral responses. Second, if households anticipate that the probability of a future pandemic is $\lambda > 0$, the growth in the resurgence of human interactions will be slower than in the world in which the perceived probability of a future pandemic is 0, and the more so the larger is λ. As a result, if due to recency effects, households perceive a particularly high risk of future pandemics in the aftermath of a pandemic, this could slow the recovery of international trade flows after a pandemic occurs.

Figure 11 presents a numerical example of an economy with symmetric countries, behavioral responses, and adjustment costs. The figure uses the baseline parameters from the previous section for symmetric countries, together with $\psi_1 = 1$ and $\psi_2 = 4$ for the adjustment cost parameters. The left-panel shows the evolution of foreign varieties consumed, $n_{ij}(t)$, and compares it with the

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[36] Alternatively we can use terminal conditions. This is what we do in the numerical exercise below where we assume that a pandemic ends, and never happens again, after some large time period T.

case with no adjustment costs ($\psi_1 = 0$). Clearly, adjustment costs reduce the magnitude of the behavioral response. Not only do agents take longer to start the adjustment, but the adjustment is substantially smaller. In computing this example we assume that the pandemic never repeats itself. Hence, eventually the number of varieties consumed is the same as in the behavioral case without adjustment costs. We use this value as the terminal condition and compare the resulting initial $n_{ij}(1)$. Anticipatory effects, namely agents adjusting their behavior in anticipation of a pandemic, imply that the initial value should be smaller than the terminal one. Figure 11 shows no indication that these effects are significant. Although $n_{ij}(1) < n_{ij}(T)$, the effect is negligible and cannot be perceived in the graph. This is the case, even though the effect on the evolution of domestic and foreign contacts is fairly large. This pattern of results is consistent with the view that economies will quickly return to normal after the pandemic, although with the caveat that we have here assumed that adjustment costs are symmetric and that the pandemic does not affect agents' beliefs of the probability of future pandemics. The right panel of Figure 11 presents the corresponding evolution of infections with and without adjustment costs. As discussed above, the milder and delayed behavioral response in the case with adjustment costs leads to a faster increase in the number of infections. It also leads to a corresponding faster decline, since herd immunity starts reducing the number of infections earlier. The result is a faster, but more severe, pandemic with more overall deaths, but less pronounced temporary reductions in real income and trade.

Figure 11: Behavioral Responses with Adjustment Costs

Note: See Online Appendix K for further details on the parameters and algorithms for these numerical simulations.

7 Conclusions

Large-scale improvements in transportation technologies have dramatically increased the integration of the world economy and the ability of goods, people and infectious diseases to circulate around the globe. In this paper, we have developed a new theoretical framework to analyze the relationship between globalization and pandemics. Our framework incorporates two core mecha-

nisms from economics and epidemiology. First, travel between countries transmits disease, as in the Susceptible-Infected-Recovered (SIR) model. Second, international trade stimulates travel between countries, according to a constant elasticity gravity equation mediated by mobility frictions.

Although these two mechanisms had been analyzed separately, we show that they interact in rich ways when considered jointly. First, we show that trade-motivated face-to-face interactions generate a powerful epidemiological externality across countries such that whether a pandemic occurs depends on the disease environment in the country with the most unhealthy disease environment. Second, we have demonstrated that reductions in international frictions can either increase or decrease the range of parameter values for which a pandemic occurs. Third, multiple waves of infection can occur in the open economy when a single wave of infections would occur in the closed economy. Fourth, if infections lead to deaths, or reduce individual labor supply, we have established the existence of a general equilibrium social distancing effect, whereby increases in relative prices in unhealthy countries reduce travel to those countries. Finally, we have studied the case in which agents internalize the threat of infection, and we have shown that agents' endogenous social distancing leads to a reduction in travel that is larger for higher-trade-cost locations, and hence leads to an initial fall in the ratio of trade to GDP in the early stages of the epidemic, followed by a swift recovery. In the presence of adjustment costs, agents anticipate the costs incurred in adjusting contacts during a pandemic. In practice, we find that these anticipatory effects are small, at least for symmetric adjustment costs, such that economic activity rapidly recovers to its levels in normal times in the aftermath of a pandemic. This lack of sizable anticipatory effects implies that our theory can explain the role of public health improvements (that reduce mortality) in shaping globalization and the evolution of infections *during* pandemics, but it has less to say about the link between secular trends in globalization and public health improvements outside of pandemics.

Although we have argued that our results are robust to various alternative specifications of our model of international trade, our theoretical framework is still silent on a number of interesting issues. For example, although we have explored dynamic variants of our model, we have not allowed international borrowing and lending to smooth out economic fluctuations caused by a pandemic. Similarly, our analysis has been positive in nature, but it would certainly be interesting to study the normative implications of our framework in future work.

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