THE MORE WE DIE, THE MORE WE SELL? A SIMPLE TEST OF THE HOME-MARKET EFFECT*

ARNAUD COSTINOT
DAVE DONALDSON
MARGARET KYLE
HEIDI WILLIAMS

The home-market effect, first hypothesized by Linder (1961) and later formalized by Krugman (1980), is the idea that countries with larger demand for some products at home tend to have larger sales of the same products abroad. In this article, we develop a simple test of the home-market effect using detailed drug sales data from the global pharmaceutical industry. The core of our empirical strategy is the observation that a country's exogenous demographic composition can be used as a predictor of the diseases that its inhabitants are most likely to die from and, in turn, the drugs they are most likely to demand. We find that the correlation between predicted home demand and sales abroad is positive and greater than the correlation between predicted home demand and purchases from abroad. In short, countries tend to be net sellers of the drugs they demand the most, as predicted by Linder (1961) and Krugman (1980). *JEL* Codes: F1, O3.

I. INTRODUCTION

Do countries with larger domestic markets for some products tend to sell more of those same products in foreign markets? The idea that local demand may stimulate exports is an old one. First hypothesized by Linder (1961) and later formalized by Krugman (1980), the so-called home-market effect has become a central

*We are very grateful to Manon Costinot, Maya Durvasula, Masao Fukui, Ryan Hill, Anton Popov, Juan Rios, Oliver Salzmann, Mahnum Shahzad, and Sophie Sun for excellent research assistance, as well as to Daron Acemoglu, Pol Antràs, David Atkin, Keith Head, David Weinstein, three anonymous referees, and seminar audiences at many institutions for comments that have improved this work. We thank Pierre Azoulay, Joshua Graff Zivin, Danielle Li, and Bhaven Sampat for sharing advice and data on the NIH subsidy analysis presented in this article. The construction of some of the data analyzed in this publication was supported by the National Institute on Aging and the NIH Common Fund, Office of the NIH Director, through Grant U01-AG046708 to the National Bureau of Economic Research; the content is solely the responsibility of the authors and does not necessarily represent the official views of the NIH or NBER. Financial support from NSF Grant no. 1151497, the Hoover IP^2 working group, and the Intellectual Property and Markets for Technology Chair at MINES ParisTech is also gratefully acknowledged. Kyle thanks Pfizer for access to the IMS data.

The Quarterly Journal of Economics (2019), 843–894. doi:10.1093/qje/qjz003.
Advance Access publication on January 21, 2019.

tenet of the new trade theory (Helpman and Krugman 1985, 1989) and the new economic geography literature (Fujita, Krugman, and Venables 2001). In terms of policy, it implies that import protection may be used as export promotion, a view often more popular in business communities than among economists (Krugman 1984).

To establish the empirical validity of the home-market effect, one must overcome a key challenge. While theory predicts that the cross-sectional variation in demand causes the pattern of international specialization, observable demand shifters are rarely available in practice. National accounts, for instance, may report how much a country spends on a particular good. But expenditures depend on prices, which themselves depend on supply, not just on demand conditions.

In this article, we propose a simple test of the home-market effect that uses variation in disease burdens across countries as a way to address this empirical challenge. Our starting point is the observation by Acemoglu and Linn (2004) that demographic groups who are more likely to die from particular diseases—because of exogenous characteristics—are also more likely to demand pharmaceutical treatments that target those diseases. In their original article, Acemoglu and Linn (2004) exploit such demographic variation over time within the United States to estimate the impact of market size on innovation. Here, we employ the spatial analog of this strategy, drawing on cross-sectional variation in the demographic composition of different countries in a given year, to explore how exogenous variation in demand may shape the pattern of trade.

Intuitively, our empirical strategy exploits the facts that disease burdens vary by demographic groups and that countries vary in their demographic composition to construct a "predicted disease burden" measure for each disease in each country in a given year, which measures the average country-level disease burden that would be expected given a country's demographic structure. Using this measure, we can then test for the existence of the home-market effect by estimating (i) whether higher (predicted) disease burdens at home tend to increase the sales of domestic drugs treating those diseases abroad (what we call the weak home-market effect), and if so, (ii) whether they tend to increase them by more than the sales of foreign drugs at home (our strong home-market effect).

To take a concrete example, consider the drug famotidine (known as Pepcid® in the United States). Famotidine is used to

treat peptic ulcers and gastroesophageal reflux and was discovered in Japan (Hara 2003)—a country known for particularly high incidence rates of peptic ulcers. In our data, individuals in Japan are nearly twice as likely to die from digestive disorders than are individuals in the rest of the world (0.266 deaths per 1,000 population annually in Japan, relative to 0.170 on average in other countries). Looking at data on Japan's exports and imports, sales of Japanese drugs targeting peptic ulcers and gastroesophageal reflux diseases outside Japan account for 10.35 % of world sales, compared to an average of 4.54 % for all other disease categories. More strikingly, Japan is a net importer in the pharmaceutical sector as a whole, but is a net exporter of drugs targeting peptic ulcers, reflux, and related digestive diseases.

While the previous observation is consistent with the potential existence of the home-market effect, building an empirical study around such examples is challenging for many reasons. In this particular case, Cleave (1962) conjectures that Japan has higher rates of peptic ulcers due to differences in dietary consumption (namely, higher consumption of salty foods), but cross-country variation in diets could at least partly reflect differences in relative prices and hence supply considerations. Our empirical strategy, based on the type of demographic variation exploited by Acemoglu and Linn (2004), is designed to address such endogeneity issues.[1]

The rest of our article is organized as follows. After discussing the related literature in Section II, we present a flexible model of the supply and demand for pharmaceutical drugs in Section III. For expositional purposes, we first study a perfectly competitive environment. In this context, we introduce a simple test of the weak and strong home-market effects based on a log-linear approximation of our model around a symmetric equilibrium and characterize the conditions for such effects to arise. We then show that the same test remains valid in a range of imperfectly competitive environments, including the one considered in Krugman (1980). Our theoretical analysis highlights the role of sector-level economies of scale, while clarifying that their particular determinants may be irrelevant for the validity of our test.

Section IV describes our data. Our empirical analysis draws on a linkage between two data sets. The first one documents sales

1. Other applications of this strategy can be found in DellaVigna and Pollet (2007) and Jaravel (2019).

in 56 countries of more than 20,000 molecules by roughly 2,650 firms, which we convert to a data set of bilateral sales at the disease level, by matching each firm to the country in which it is headquartered and each molecule to the disease that it targets.[2] The second data set documents the demographic composition of and disease burdens in the same 56 countries, which we use to compute predicted disease burdens by country and disease.

Section V presents our main results. Our simple test focuses on a log-linear specification where bilateral sales of drugs targeting different diseases are allowed to depend on (i) disease burdens in the destination country, that is, the country where drugs are sold; (ii) disease burdens in the origin country, that is, the country where firms selling those drugs are headquartered; and (iii) a full vector of disease indicator variables and destination-and-origin indicator variables. Everything else equal, we document that countries tend to sell relatively more of the drugs for which they have higher disease burdens, in line with the existence of a weak home-market effect. Furthermore, the elasticity of sales towards foreign countries tends to be higher than the elasticity of purchases from foreign countries, consistent with the existence of a strong home-market effect.

Section VI analyzes further the economic determinants of the home-market effect. Although the previous results provide empirical support for the notion of a home-market effect in the global pharmaceutical sector, the existence and magnitude of this phenomenon depend, according to our model, on both demand and supply elasticities. Our last results point toward the home-market effect being driven by substantial economies of scale at the sector-level rather than low elasticities of demand. Quantitatively, the sector-level economies of scale that we estimate in the pharmaceutical industry are about 25% smaller than those that Krugman's (1980) monopolistically competitive model predicts.

II. Related Literature

The literature on the home-market effect is large and varied. As we explain below, the variation derives in part from the use

2. Our data set does not contain information about location of production. Thus, we cannot shed light on whether the home-market effect ultimately operates through exports, foreign direct investment, or a mixture of both. We come back to this point when discussing the related literature in Section II.

of related but distinct definitions of "the" home-market effect by different authors.

Whereas Linder's (1961) and Krugman's (1980) original works emphasize the consequences of cross-country differences in demand for the pattern of trade, Helpman and Krugman (1985) focus instead on whether larger countries tend to specialize in sectors with larger economies of scale.[3] Subsequent work by Davis (1998), Head, Mayer, and Ries (2002), Holmes and Stevens (2005), and Behrens et al. (2009) provide additional conditions on the nature of trade costs and the number of goods and countries under which the latter pattern may or may not arise. Amiti (1998), in turn, studies whether larger countries should have a comparative advantage in sectors with higher trade costs. Motivated by the theoretical predictions of Helpman and Krugman (1985), Hanson and Xiang (2004) show that high-GDP countries tend to sell disproportionately more in sectors with larger transportation costs and lower elasticities of substitution, a measure of sector-level economies of scale under monopolistic competition. In related work, Feenstra, Markusen, and Rose (2001) document that high-GDP countries tend to be net exporters of differentiated goods, which they also interpret as evidence of a home-market effect in such industries.[4]

A number of more recent theoretical papers have extended the work of Krugman (1980) to study the implications of nonhomothetic preferences for the pattern of trade and foreign direct investment; see Fajgelbaum, Grossman, and Helpman (2011, 2015) and Matsuyama (2015). A key prediction of these models is that in the presence of economies of scale, rich countries that have larger demand for high-quality goods will tend to specialize in those goods. As a result, they will trade more with, or invest more in, other rich countries, as also emphasized by Linder (1961). In these models, exogenous differences in income across countries play the same role as differences in preferences in

3. Ethier (1982) discusses similar issues in a perfectly competitive model with external economies of scale.

4. Provided that the economy is subject to increasing returns to scale, one would also expect larger countries to have higher wages. In their survey of the literature, Head and Mayer (2004) refer to this prediction as the "price" aspect of the home-market effect. Though our analysis implicitly allows for such effects to be active, it focuses exclusively on the relationship between economies of scale, cross-country demand differences, and international specialization. This is what Head and Mayer (2004) refer to as the "quantity" aspect of the home-market effect.

Krugman (1980). In line with the previous models, Caron, Fally, and Fieler (2015) document that the sectors on which high-GDP countries spend more also tend to be the sectors in which high-GDP countries export more. Dingel (2016) also offers empirical evidence consistent with the previous mechanism using information about shipment prices from different U.S. cities and the income composition of neighboring cities.

Our analysis is most closely related to the early empirical work of Davis and Weinstein (1996) and later studies by Davis and Weinstein (1999, 2003), Lundback and Torstensson (1998), Head and Ries (2001), Trionfetti (2001), Weder (2003), Crozet and Trionfetti (2008), and Brulhart and Trionfetti (2009). Like ours, the aforementioned papers focus on the impact of differences in demand on the pattern of international specialization. In their review of the literature, Head and Mayer (2004) conclude that this type of empirical evidence on the home-market effect is highly mixed.[5] While empirical specifications and data sources vary across studies, the previous studies share a key characteristic: data on expenditure shares are used as proxies for demand differences. As argued earlier, one nontrivial issue with such proxies is that differences in local supply conditions may also affect expenditure shares through their effects on local prices. This makes earlier tests of the home-market effect hard to interpret.

Compared to earlier work on the home-market effect, we view the approach in this article as having both costs and benefits. Since the home-market effect emphasized by Linder (1961) and Krugman (1980) is about the causal effect of demand differences across countries, any test of this effect ultimately requires exogenous demand variation. Although we have no silver bullet to deal with endogeneity issues, and we discuss the challenges associated with our approach later in the article, we believe that using (predicted) disease burdens as observable demand shifters, rather than expenditure shares, is a significant step forward.

5. Given our focus on the pharmaceutical industry, it is worth noting that Trionfetti's (2001) sector-level test for the home-market effect is rejected for "chemical products." Fabrizio and Thomas (2012) provide another estimate that is specific to the pharmaceutical industry. They document that pharmaceutical firms' patenting is more correlated with home sales (and cultural proxies for home sales) than with foreign sales, thus suggesting a systematic relationship between home demand and firm-level innovation.

A first drawback of our empirical strategy is that its scope is restricted to an important, but single industry.[6] Another limitation of our data set is that it does not allow us to distinguish between exports and foreign direct investment: we only observe total sales by firms headquartered in a particular country. Thus, the home-market effect we identify may operate through both exports and foreign direct investment, not just exports, as has been emphasized in the previous literature. The previous observation notwithstanding, it is not clear that if the only choice were to study either exports or the sum of exports and sales by foreign affiliates, one should prefer the former to the latter because the same economic forces are likely to be at play for both types of sales.

III. The Simple Economics of the Home-Market Effect

We begin with a theoretical analysis that is split into two steps. First, we consider a world economy with perfect competition (Section III.A) and develop a test of the home-market effect in this environment (Section III.B). This allows us to describe the logic of the home-market effect in the simplest possible way using supply and demand analysis. Second, we demonstrate how our test of the home-market effect and its economic interpretation may carry over to industries with imperfect competition, endogenous innovation, and price regulations (Section III.C). This illustrates the broader applicability of our empirical strategy and justifies using data from the pharmaceutical industry to implement our test in subsequent sections.

III.A. Perfectly Competitive Benchmark

1. Demand. To facilitate the connection between our theoretical and empirical analysis, we focus on an economy where individuals consume drugs that target multiple diseases, indexed by n, as well as other goods, which we leave unspecified. Empirically, each disease n will correspond to a broad disease class

6. According to the World Trade Organization, global exports in the pharmaceutical industry grew faster between 1995 and 2014 than in any other industry besides fuel, surpassing $500 billion (or approximately 3% of global merchandise trade) by 2014. The pharmaceutical sector has also received considerable attention in recent trade agreements, particularly the Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS) and the Trans-Pacific Partnership (TPP).

like "cardiovascular diseases." We assume that the aggregate consumption of drugs targeting disease n in country j can be expressed as

$$D_j^n = \theta_j^n D_j D\left(\frac{P_j^n}{P_j}\right), \tag{1}$$

where $D(\cdot)$ is a strictly decreasing function; P_j^n depends on the prices of drugs targeting disease n in country j, as described below; D_j and P_j are endogenous country-specific demand shifters that are common to all drugs in country j; and θ_j^n is an exogenous disease-and-country-specific demand shifter, which we later proxy for using data on disease burdens.

Within each disease category n, drugs may be purchased from different countries. Any of these countries may be producing different versions of the same molecule (e.g., generic versus nongeneric), different molecules targeting the same narrow disease (e.g., angiotensin II receptor blockers and beta blockers, both treatments for high blood pressure, a risk factor for hypertensive heart disease), or different molecules targeting different diseases within the same broad category (e.g., drugs targeting hypertensive heart disease versus coronary artery disease, within the broad category of cardiovascular diseases). The previous considerations suggest imperfect substitutability between drugs from different countries, which we capture through the following specification:

$$d_{ij}^n = D_j^n d\left(\frac{p_{ij}^n}{P_j^n}\right), \tag{2}$$

where $d(\cdot)$ is a strictly decreasing function; d_{ij}^n denotes country j's consumption of varieties from country i targeting disease n, p_{ij}^n denotes the consumer price for these varieties, and P_j^n is implicitly defined by the solution to

$$P_j^n = \sum p_{ij}^n d\left(\frac{p_{ij}^n}{P_j^n}\right). \tag{3}$$

Given the level of aggregation in our empirical analysis, p_{ij}^n should itself be interpreted as a price index, aggregating prices across all

firms from country i selling drugs targeting disease n in country j. We make this aggregation explicit in Sections III.C and VI.A.[7]

2. Supply. Perfectly competitive firms produce up to the point at which drug prices are equal to marginal costs. For each disease n and country i, this leads to a supply curve,

$$s_i^n = \eta_i^n s(p_i^n), \tag{4}$$

where p_i^n denotes the producer price of drugs targeting disease n in country i and η_i^n is a disease-and-country-specific supply shifter, which may capture both technological and policy differences. Depending on whether there are external economies of scale, $s(\cdot)$ may be upward- or downward-sloping. Trade is subject to iceberg frictions. To sell one unit of a given drug to country $j \neq i$, firms from country i must ship $\tau_{ij}^n \geqslant 1$ units.[8] Without loss of generality, we set $\tau_{ii}^n = 1$ for all i and n. No arbitrage implies

$$p_{ij}^n = \tau_{ij}^n p_i^n. \tag{5}$$

3. Equilibrium. Supply equals demand for each drug,

$$s_i^n = \sum_j \tau_{ij}^n d_{ij}^n. \tag{6}$$

7. For the purposes of testing the home-market effect, we do not need the previous demand functions to be consistent with the behavior of a representative agent in country j, an assumption that may be particularly strong in a sector where demand involves physicians, pharmacists, insurers, and patients. We note, however, that equations (1)–(3) are consistent with the common assumption of nested CES utility functions, which corresponds to the special case where $D(\cdot)$ and $d(\cdot)$ are power functions.

8. Though we abstract from multinational production in our baseline model, equations (4) and (5) would still hold in a world economy with multinational activities à la Ramondo and Rodríguez-Clare (2013) and external economies of scale at the level of the headquarter country for each disease. In such an environment, τ_{ij}^n would simply correspond to the minimum cost of accessing country j from country i, either through exports or foreign direct investment; see Online Appendix A.1. Note also that while transport costs and tariffs are low in the pharmaceutical industry, drug sales exhibit significant home bias. This is partly due to local regulations that act as nontariff barriers; see Thomas (1994). For example, governments may favor domestic firms in granting approval or when negotiating prices. Iceberg trade costs in our baseline model aim to capture all the frictions involved when selling pharmaceuticals in foreign markets that appear to persist, notwithstanding the adoption of free trade agreements and international efforts to harmonize regulations.

III.B. Weak and Strong Home-Market Effects

The home-market effect is the general idea that, all else equal, countries tend to sell more abroad in sectors for which they have larger domestic markets. Here, we operationalize this idea in the context of a log-linearized version of our model around a symmetric equilibrium.

1. Defining Home-Market Effects. We start by considering the bilateral sales, $x_{ij}^n \equiv p_{ij}^n d_{ij}^n$, of drugs targeting disease n by firms from country i in country $j \neq i$. Around a symmetric equilibrium with trade costs, $\tau \geqslant 1$, and common demand and supply shocks across countries and diseases, we can express bilateral sales, up to a first-order approximation, as

$$\ln x_{ij}^n = \delta_{ij} + \delta^n + \beta_M \ln \theta_j^n + \beta_X \ln \theta_i^n + \varepsilon_{ij}^n, \tag{7}$$

where δ_{ij} is an origin-destination-specific term that captures systematic determinants of bilateral trade flows such as physical distance or whether countries i and j share the same language; δ^n is a disease-specific term that captures worldwide variation in demand and supply conditions across drugs targeting different diseases; β_M is the elasticity of trade flows with respect to demand shocks in the importing country; β_X is the elasticity of trade flows with respect to demand shocks in the exporting country j; and ε_{ij}^n is a residual that captures idiosyncratic variation in trade costs and supply conditions.

Provided that demand shocks, supply shocks, and trade costs are close enough to their values in a symmetric equilibrium, the previous elasticities can be mapped into the structural parameters of Section III.A, as we do in Online Appendix A.2. The key benefit of log-linearizing our model around a symmetric equilibrium is that we obtain elasticities, β_M and β_X, that have a structural interpretation—discussed in detail later—and are constant across origins, destinations, and diseases, which is appealing from an econometric standpoint.[9] The main drawback of our approach is that it assumes away differential effects of demand in third countries, $l \neq i, j$, on the bilateral sales of country i in country j. In

9. For instance, if we were to log-linearize around an equilibrium where trade costs are identical across diseases but allowed to vary across country pairs, $\tau_{ij}^n \equiv \tau_{ij}$, then the two elasticities in equation (7) would also vary across country pairs, that is, we would have $\beta_{M,ij}$ and $\beta_{X,ij}$.

equation (7), the effects of demand in those countries is subsumed by the disease fixed effect, δ^n, which is a function of $\sum_l \theta_l^n$. We come back to this point in Sections V.B and VI.A.

To motivate our definition of the home-market effect and help relate our analysis to earlier work in the literature, let us now go from bilateral to aggregate sales. Starting from equation (7), we can express total exports, $X_i^n \equiv \sum_{j \neq i} x_{ij}^n$, and total imports, $M_i{}^n \equiv \sum_{j \neq i} x_{ji}^n$, as

$$\ln X_i^n = \delta^n + \beta_X \ln \theta_i^n + \ln \left(\sum_{j \neq i} (\theta_j^n)^{\beta_M} \exp(\delta_{ij} + \varepsilon_{ij}^n) \right), \tag{8}$$

$$\ln M_i^n = \delta^n + \beta_M \ln \theta_i^n + \ln \left(\sum_{j \neq i} (\theta_j^n)^{\beta_X} \exp(\delta_{ji} + \varepsilon_{ji}^n) \right). \tag{9}$$

According to equation (8), a country tends to export more of the goods for which it has larger domestic demand if and only if $\beta_X > 0$. And according to equations (8) and (9), a country tends to be a net exporter of the goods for which it has a larger domestic market if and only if $\beta_X > \beta_M$.[10] Based on these two observations, we propose the following definition.

DEFINITION 1. Trade flows satisfy the weak home-market effect if $\beta_X > 0$ and the strong home-market effect if $\beta_X > \beta_M$.

This definition will be the basis of our empirical test of the home-market effect. Given data on bilateral sales, $\{x_{ij}^n\}$, and observable demand shifters, $\{\theta_i^n\}$, we estimate β_X and β_M in equation (7) and test whether the two previous inequalities hold. This simple approach differs from earlier tests of the home-market effect in three important respects.

First, our empirical test has a structural interpretation, which is discussed below. Among other things, this allows one to discuss the origin of the error term in equation (7) and the extent to which one should expect the orthogonality condition to hold; we come back to these points in Section V.B.

Second, relatedly, our empirical test focuses on elasticities with respect to demand shocks, not expenditure shares. If

10. Recall that if $\frac{X}{M}$ is increasing in θ, then $X - M = M\left(\frac{X}{M} - 1\right)$ must be positive for θ high enough and negative otherwise.

preferences across sectors are Cobb-Douglas, the two elasticities are equivalent. Away from this empirically knife-edge case, they are not. Assuming that observable demand shocks are available, a case that we make in Section IV, using these shocks alleviates concerns about "false positives"—that is, positive correlations between exports and expenditure shares driven by unobserved supply shocks that are positively correlated with both exports and expenditure shares, absent any variation in demand.

Third, our definition introduces the distinction between the weak home-market effect, which focuses on gross exports, and the strong home-market effect, which focuses on net exports. As we argue next, the weak test, which is unique to our article, provides a direct way to identify departures from the predictions of neoclassical trade models. The strong test merely puts tighter bounds on the magnitude of these departures, if any.

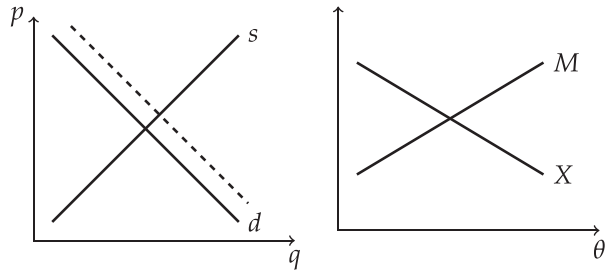
2. Economic Interpretation. The economic forces that give rise to weak and strong home-market effects are best illustrated in a world economy comprising a large number of small open economies in the sense that each country is too small to affect the price of foreign varieties, but large enough to affect the price of its own varieties, as in Gali and Monacelli (2005).[11] In this case, the two elasticities, β_X and β_M, simplify into

$$\beta_X = \frac{\lambda(1-\epsilon^x)}{\epsilon^s + \epsilon^w}, \tag{10}$$

$$\beta_M = 1 + \frac{\lambda^2(1-\epsilon^d)(\epsilon^x - \epsilon^D)}{(1-\lambda\epsilon^d - (1-\lambda)\epsilon^x)(\epsilon^s + \epsilon^w)}, \tag{11}$$

where $\lambda > 0$ is the share of expenditure, as well as revenue, on domestic drugs in the symmetric equilibrium; $\epsilon^d > 0$ and $\epsilon^x > 0$ are the lower-level elasticities of demand for domestic and foreign varieties, respectively; $\epsilon^D > 0$ is the upper-level elasticity of demand; $\epsilon^w \equiv \lambda\epsilon^d + (1-\lambda)\epsilon^x - \frac{\lambda^2(1-\epsilon^d)(\epsilon^d-\epsilon^D)}{1-\lambda\epsilon^d-(1-\lambda)\epsilon^x} > 0$ is the elasticity of world demand; and ϵ^s is the elasticity of supply, which may be

11. Formally, we obtain the small open economy limit by taking the number of countries in the world economy to infinity and adjusting trade costs, τ, to leave the expenditure share on a country's own good, λ, at a constant and strictly positive level.



(a) Price and Quantity **(b)** Exports and Imports

FIGURE I

No Home-Market Effect

positive or negative, depending on whether there are economies of scale.

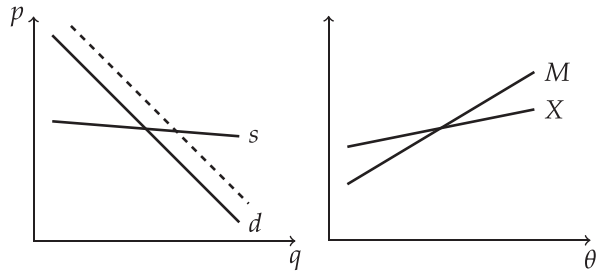
Suppose that $\epsilon^x > 1$ so that countries with lower prices tend to have higher market shares abroad, which will be the empirically relevant case. Then, according to equation (10), there can only be a weak home-market effect in the presence of economies of scale,

$$\epsilon^s < -\epsilon^w < 0.$$

In a neoclassical environment, an increase in domestic demand across sectors, that is, a positive shift in θ, raises world demand, d, and in turn, producer prices, p, as depicted in Figure I, panel (a). If the price elasticity of exports, ϵ^x, is strictly greater than 1, this necessarily lowers the value of exports, X, as depicted in Figure I, panel (b). By lowering the price of goods with larger domestic markets, economies of scale can instead create a positive relationship between exports and domestic demand, as described in Figure II.[12]

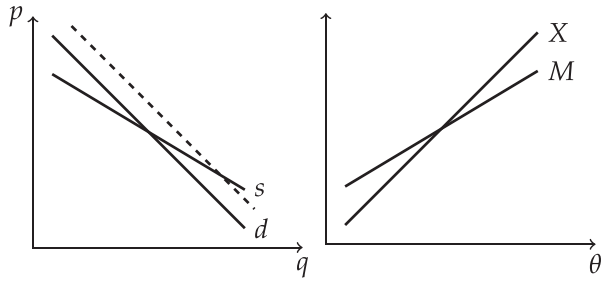
Suppose, in addition, that $\epsilon^d > 1$ and $\epsilon^x \geqslant \epsilon^D$. The second inequality is another mild restriction that requires, for example, French and U.S. drugs targeting cardiovascular diseases to be closer substitutes than drugs targeting cardiovascular and skin diseases. Under this restriction, equations (10) and (11) imply

12. Even under the assumption that $\epsilon^x > 1$, economies of scale are necessary but not sufficient for a weak home-market effect to arise. Namely, if economies of scale are so strong that the equilibrium is Marshallian unstable, with supply curves steeper than demand curves, $-\epsilon^w < \epsilon^s < 0$, then drugs with larger demand have higher prices, which leads to $\beta_X < 0$, like in a neoclassical environment.



(a) Price and Quantity **(b)** Exports and Imports

FIGURE II
Weak Home-Market Effect



(a) Price and Quantity **(b)** Exports and imports

FIGURE III
Strong Home-Market Effect

that a strong home-market effect arises if economies of scale are strong enough to dominate the direct effect of domestic demand on imports, namely, if

$$-\epsilon^w - \lambda\left[\epsilon^x - 1 + \frac{\lambda(1-\epsilon^d)(\epsilon^x - \epsilon^D)}{1-\lambda\epsilon^d - (1-\lambda)\epsilon^x}\right] < \epsilon^s < -\epsilon^w. \tag{12}$$

This situation is depicted in Figure III.

III.C. Beyond Perfect Competition

We have conducted our theoretical analysis in a stylized model with perfect competition. The goal of this subsection is to establish the broader applicability of our empirical strategy. To do so, we provide four examples that illustrate how more complex

economic environments may nevertheless generate equilibrium conditions similar to those presented in Section III.A, and, in turn, why our simple test and its economic interpretation may carry over to these environments.

The first example considers a monopolistically competitive model similar to the one studied in Krugman's (1980) original work, in which increasing returns at the sector level reflect consumers' love for variety and the positive relationship between entry and sector size. The other three examples, motivated by some key features of the global pharmaceutical industry, introduce variable markups, endogenous innovation, and price regulations. For expositional purposes, we only sketch alternative models and summarize their main implications. Details can be found in Online Appendix A.3.

1. Monopolistic Competition. Consider an economy where what we have referred to as "country i's variety" in Section III.A is itself a composite of multiple differentiated varieties, each produced by monopolistically competitive firms, as in Krugman (1980).

Formally, suppose that country j's consumption of drugs targeting disease n produced by a firm ω from country i is given by

$$d_{ij}^{n}(\omega) = \left(\frac{p_{ij}^{n}(\omega)}{p_{ij}^{n}} \right)^{-\sigma} d_{ij}^{n}, \tag{13}$$

where $p_{ij}^{n} = (\int (p_{ij}^{n}(\omega))^{1-\sigma} d\omega)^{\frac{1}{1-\sigma}}$ is the CES price index and $\sigma > 1$ is the elasticity of substitution between country i's varieties. All other assumptions on the structure of demand are the same as in Section III.A. On the supply side, each firm must now pay an overhead fixed cost, $f_i^n > 0$, to produce. Once this cost has been paid, firms have a constant marginal cost, $c_i^n > 0$. All firms maximize profits taking their residual demand curves as given and enter up to the point where profits net of the overhead fixed cost are equal to 0.

At the industry level, the previous assumptions lead to a supply curve similar to equation (4). Let us define Home's aggregate

supply of drug n as the following quantity index,

$$s_i^n = \left(\int (s_i^n(\omega))^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}},$$

where $s_i^n(\omega) \equiv \sum_j \tau_{ij}^n d_{ij}^n(\omega)$ is the total quantity supplied by firm ω, regardless of whether it is ultimately sold domestically or exported. Since demand is iso-elastic, monopolistically competitive firms charge constant markups, $\mu \equiv \frac{\sigma}{\sigma-1}$, over marginal costs. Together with free entry, this leads to

$$s_i^n = (N_i^n)^{\frac{\sigma}{\sigma-1}} \frac{f_i^n}{(\mu-1)c_i^n},$$

$$p_i^n = (N_i^n)^{\frac{1}{1-\sigma}} \mu c_i^n,$$

where we let $p_i^n \equiv p_{ii}^n$ denote the price index associated with country i's varieties before trade costs have been incurred, and we let N_i^n denote the measure of firms producing drugs targeting disease n in country i. The two previous expressions provide a parametric representation of the sector-level supply curve, with the number of firms N_i^n acting as a parameter. In this case, one can eliminate N_i^n to express the supply curve explicitly as

$$s_i^n = \eta_i^n (p_i^n)^{-\sigma},$$

with $\eta_i^n \equiv f_i^n (c_i^n)^{(\sigma-1)} \sigma^\sigma (\sigma-1)^{(1-\sigma)}$. This is the counterpart of the supply equation (4). Finally, because firms charge the same markup μ in all markets, equation (5) must hold for the price indices, p_{ij}^n, of country i's varieties of drug n in any importing country j.

At this point, we have established that equations (1)–(5) continue to hold. By construction of our quantity index, equation (6) must hold as well, as shown in Online Appendix A.3. This implies that our test remains valid under monopolistic competition. The only distinction between the perfectly competitive model of Section III.A and this one is that monopolistic competition requires sector-level supply curves to be downward-sloping, with an elasticity equal to the opposite of the elasticity of substitution between domestic varieties, $\epsilon^s = -\sigma$. It is worth pointing out that the magnitude of the overhead fixed cost, f_i^n, is irrelevant for the shape of s and, in turn, irrelevant for the existence of a home-market effect. Though pharmaceutical firms are well known for

having large expenditures on research and development relative to the cost of manufacturing a drug, it does not follow, according to this monopolistically competitive model, that home-market effects should be particularly strong in that industry. The economic variable of interest for home-market effects is the magnitude of industry-level returns to scale—determined by σ under monopolistic competition—not firm-level returns to scale.

Note also that in the special case considered by Krugman (1980)—with upper-level Cobb-Douglas utility, $\epsilon^D = 1$, and lower-level CES utility, $\epsilon^x = \epsilon^d = \sigma$—the home-market effect is always strong for a small open economy. Indeed, under these parametric restrictions, inequality (12) reduces to $-\sigma - \lambda(\sigma - 1) < -\sigma < -\sigma + \lambda^2(\sigma - 1)$ which must hold for any $\lambda > 0$ and $\sigma > 1$.

2. Variable Markups. Consider the same basic environment as in the previous example, but with a finite number of firms, N_i^n, that compete à la Bertrand in each sector. To simplify the analysis, we assume that all demand functions are iso-elastic, with $D(x) = d(x) = x^{-\epsilon^d}$, and that there is an arbitrarily large number of diseases. Together these assumptions imply that while markups may vary across origins and diseases, firms from country i producing drugs that target disease n will charge the same markup across all destinations. We will relax this restriction in our final example. The rest of the model is unchanged.

In equilibrium, firms still maximize their profits taking their residual demand curves as given, albeit internalizing the effect of their decisions on the domestic price index associated with each disease. This leads to markups that now vary with the number of firms N_i^n. Formally, one can show that country i's aggregate supply of drug n and its price index now satisfy

$$s_i^n = (N_i^n)^{\frac{\sigma}{\sigma-1}} \frac{f_i^n}{(\mu(N_i^n) - 1)c_i^n},$$

$$p_i^n = (N_i^n)^{\frac{1}{1-\sigma}} \mu(N_i^n) c_i^n,$$

with $\mu(N_i^n) \equiv \frac{\left(1-\frac{1}{N_i^n}\right)\sigma + \frac{\epsilon^d}{N_i^n}}{\left(1-\frac{1}{N_i^n}\right)\sigma + \frac{\epsilon^d}{N_i^n} - 1}$ denoting the firms' markup under Bertrand competition. Though one can no longer solve explicitly for s_i^n as a function of p_i^n, the two previous expressions still provide a parametric representation of the sector-level supply curve.

Since equations (1), (2), and (5) remain unchanged, the existence of such a curve is all we need to apply our test.

Locally, the price elasticity of supply is now given by

$$\epsilon^s = -\sigma \times \frac{(\mu-1)^2 + \left(1-\frac{1}{\sigma}\right)\frac{d\ln\mu}{d\ln N}}{(\mu-1)^2\left(1-(\sigma-1)\frac{d\ln\mu}{d\ln N}\right)}.$$

Compared to monopolistic competition with constant markups, where $\frac{d\ln\mu}{d\ln N}=0$, the supply elasticity is lower in absolute value, $|\epsilon^s|<\sigma$, whenever markups are decreasing with the number of firms, $\frac{d\ln\mu}{d\ln N}<0$. This is what happens for $\sigma > \epsilon^d$. In this case, the larger aggregate output in an industry is, the more firms there are, the lower the markups that they charge, and hence the lower the price that firms are willing to accept to produce a given aggregate quantity. At the sector level, procompetitive effects act as an additional source of increasing returns.

3. Endogenous Innovation. We now consider an economy where countries only produce a single variety of each drug, but unlike in our basic environment, this variety is produced by a monopolist that can invest in R&D, as in Krugman (1984). We follow the same strategy as in the previous example and assume that demand functions are iso-elastic, with $D(x)=d(x)=x^{-\epsilon^d}$, and that there is an arbitrarily large number of drugs so that firms charge the same markup in all markets.

For each disease n, the monopolist in country i takes the residual demand curve in each market as given when simultaneously choosing its prices, p_{ij}^n, and its unit cost of production, c_i^n, in order to maximize its profits,

$$\pi_i^n = \sum_j (p_{ij}^n - \tau_{ij}^n c_i^n) d\left(\frac{p_{ij}^n}{P_j^n}\right) D\left(\frac{P_j^n}{P_j}\right)\theta_j^n D_j - \eta_i^n f(c_i^n),$$

where $\eta_i^n f(c_i^n)$ denotes the amount of R&D required to have unit cost, c_i^n, which we assume to be strictly decreasing and convex.[13] The first-order conditions associated with this maximization

13. The monopolist could be a multinational firm. That is, fixed R&D costs—equal to $\eta_i^n f(c_i^n)$—and variable production costs—proportional to $\tau_{ij}^n c_i^n$—could be incurred in different countries, with $\tau_{ij}^n c_i^n$ the minimum cost of accessing country j from country i through foreign direct investment, like in Online Appendix A.1.

problem imply the following version of the supply equation (4),

$$s_i^n = -\eta_i^n f'\left(\frac{(\epsilon^d - 1)p_i^n}{\epsilon^d}\right).$$

Under the assumption that $f(\cdot)$ is convex, drug-level supply curves are necessarily downward-sloping with local elasticity now given by

$$\epsilon^s = \frac{d\ln(-f')}{d\ln c}.$$

The critical feature of the present model is that the marginal benefit of R&D is increasing with total output, which creates a negative relationship between output and prices. Online Appendix A.3 demonstrates that the same analysis extends to environments where the monopolist needs to pay a fixed cost to sell in each destination as well as in environments where the monopolist can use R&D to increase the quality of its drugs rather than to lower their costs.

4. Price Regulations. To conclude, we focus on an economy similar to the previous one, where monopolists are free to invest in R&D to lower their production costs, c_i^n, but we now let governments, rather than firms, set prices. Formally, we relax the no-arbitrage condition (5) and assume instead that

$$p_{ij}^n = \mu_{ij}^n \tau_{ij}^n c_i^n,$$

where the markup, μ_{ij}^n, is taken as an exogenous characteristic that reflects the bargaining power of the government from country j vis-à-vis the firm from country i producing drugs that target disease n. For the same reason as in the previous example, supply satisfies

$$s_i^n = -\eta_i^n f'(c_i^n).$$

Except for equation (5), all other equations from Section III.A still hold, with the convention $p_i^n \equiv c_i^n$. As demonstrated in Online Appendix A.3, this implies that equation (7) must hold as well, with

Bilir and Morales (2018) provide evidence of productivity gains from R&D benefiting affiliates in different locations in the U.S. pharmaceutical industry.

the two elasticities, β_X and β_M, still determined by the elasticities of supply and demand. The key difference is that the exogenous markups, μ_{ij}^n, are now part of the error term in equation (7), a point to which we return in Section V.C.

5. Summary. The previous examples help clarify a number of points. First, there are many market structures, beyond Krugman's (1980) monopolistically competitive environment, that can give rise to a home-market effect. Second, the existence of a home-market effect in these examples is intimately related to the existence of increasing returns at the sector-level, that is, whether supply slopes down. Third, depending on the particular market structure, the nature of sector-level economies of scale may be very different. In our final example, it depends on the elasticity of the marginal returns to R&D; previously, it derived from Marshallian externalities, love of variety, or procompetitive effects. Fourth, independently of the nature of economies of scale, our test of the home-market effect remains valid. This suggests that our test of the home-market effect can be applied to many industries, including the global pharmaceutical industry. This is the empirical application to which we now turn.

IV. Data

Our analysis of the home-market effect rests on the correlation between a country's pattern of sales across drugs in the pharmaceutical sector and its pattern of exogenously given demand across those drugs. We therefore draw on a linkage between two data sets: one that documents sales by country at the drug level, which we convert to a data set of bilateral sales as detailed below, and one that describes the demographically driven burden of each disease in each country. In both cases we use data from one cross-section, from 2012, which suffices for testing the home-market effect since its prediction is cross-sectional in nature.

IV.A. Pharmaceutical Sales

To construct bilateral data on pharmaceutical sales, $\{x_{ij}^n\}$, we draw on the IMS MIDAS data set produced by the firm IMS Health. IMS is a market research firm that sells MIDAS and other data products to firms in the pharmaceutical and health care industries. By auditing retail pharmacies, hospitals, and other sales

channels, the raw IMS MIDAS data record quarterly revenues and quantities by country at the "package" level, for example sales of a bottle of 30 10-mg tablets of the cholesterol-lowering drug Lipitor® (atorvastatin). The data record unit sales and revenues (in local currency units) for both private and public purchasers.[14]

Our version of the IMS MIDAS data set covers sales in 56 destination countries.[15] Given the comprehensive nature of the data set, the vast majority of high-revenue drugs globally—over 20,000 unique molecules or combinations of molecules, both brand-name and generic—are included. Our sample includes sales by roughly 2,650 firms. We observe the name of the firm selling each drug in our data set and have used this name to hand-match each firm to the country in which it is headquartered.[16] We refer to this country as the origin country. Given this mapping of firms to origin countries, we then use the IMS MIDAS data on sales (for each drug) by firm in each destination country to measure bilateral sales, from origin country to destination country, for each drug.[17] We reiterate that the resulting bilateral sales data do not differentiate between exports and FDI-driven sales; they comprise the sum of all channels through which a firm in origin country i sells its product to consumers in destination country j. In addition,

14. Online Appendix B.3 describes how pharmaceutical sales from the IMS MIDAS data set compare with those from two publicly available data sources: the OECD HealthStat database and the Medical Expenditure Panel Survey (MEPS).

15. The most recent versions of the IMS MIDAS data set cover more than 70 countries. Our 56 destination countries are Algeria, Argentina, Australia, Austria, Belgium, Brazil, Bulgaria, Canada, China (mainland), Colombia, Croatia, Czech Republic, Ecuador, Egypt, Finland, France, Germany, Greece, Hungary, India, Indonesia, Ireland, Italy, Japan, Jordan, South Korea, Kuwait, Latvia, Lebanon, Luxembourg, Malaysia, Mexico, Morocco, New Zealand, Norway, Pakistan, Peru, Philippines, Poland, Portugal, Russia, Saudi Arabia, Singapore, Slovenia, South Africa, Spain, Sweden, Switzerland, Thailand, Tunisia, Turkey, United Arab Emirates, United Kingdom, United States, Uruguay, and Venezuela.

16. As the firm identifier, we use what IMS refers to as the "international corporation," representing the firm selling in any given drug-destination. This is the parent company in the case of firms with local subsidiaries or with multiple divisions with different geographic or therapeutic specialties. We have been able to ascertain the headquarters location for firms that cover 94.49% of total 2012 sales in the IMS MIDAS data set.

17. The analysis in Section V uses a sample in which origin countries are only included if they also appear as destination countries (that is, they are one of the 56 destination markets in the IMS MIDAS data set). This covers 89.04% of the total value of sales in the IMS MIDAS data set. As discussed in Costinot et al. (2016), this sample selection decision has little bearing on our results.

TABLE I
TOP 10 COUNTRIES IN TERMS OF SALES

Country	Share of world sales (%) (1)	Share of world expenditures (%) (2)	Number of firms headquartered (3)
United States	37.12	42.10	356
Switzerland	12.68	0.61	35
Japan	11.62	12.67	53
United Kingdom	10.67	2.67	80
Germany	6.77	4.68	94
France	6.51	4.34	58
India	2.29	1.61	292
China, Mainland	2.18	3.74	524
Canada	1.36	2.57	46
Italy	1.35	3.35	68

our bilateral sales data do not capture licensing. For example, if Gilead licenses a treatment to several Indian pharmaceutical makers who then sell in other markets, those sales are attributed to the licensees rather than to Gilead.

The 10 largest firms in our data set in terms of sales (with origin country in parentheses) are, in descending order, Novartis (Switzerland), Pfizer (United States), Merck & Co. (United States), Sanofi-Aventis (France), Roche (Switzerland), AstraZeneca (United Kingdom), GlaxoSmithKline (United Kingdom), Johnson & Johnson (United States), Eli Lilly & Co. (United States), and Abbvie (United States, a spin-off of Abbott Laboratories).[18] While these top firms are headquartered in just 4 countries, firms in our data set are headquartered in a total of 55 (out of a possible 56) different origin countries. Table I reports the distribution of global sales for the 10 largest countries in terms of share of world sales, along with the number of firms that are headquartered in each of those countries.[19] There is a clear skewness in both

18. All comparisons across local currency units in this section use average 2012 exchange rates from the World Bank's World Development Indicators database. Due to the inclusion of destination fixed effects, the home-market effect tests in Section V and the parameter estimates in Section VI do not require a conversion across local currency units.

19. "World sales" in column (1) refers to total sales in MIDAS to the 56 countries in our sample, and analogously for "world expenditures" in column (2). The number of firms in column (3) refers to firms making strictly positive sales in 2012 to at least one of the 56 countries in our sample.

variables, so we conduct our tests of the home-market effect in a wide range of subsamples designed to explore potential heterogeneity across large and small countries, as well as countries (such as India and China) where the large number of headquartered firms reflects a relatively large share of generic drug producers.

IMS uses a standard industry classification known as ATC codes, from the Anatomical Therapeutic Classification System, to classify molecules into approximately 600 different therapeutic classes based on the main disease the drug is designed to treat.[20] To link back to the example in our introduction, "acid pump inhibitors", which are commonly used to treat peptic ulcers, correspond to the ATC code A2B2.

The resulting data set can be reshaped to describe, within each therapeutic class, the bilateral sales between any origin country and any of 56 destination countries in 2012.

IV.B. Disease Burden

We isolate a plausibly exogenous source of demand-side variation for each drug, in each country, by isolating the apparent extent to which drugs have a demographic bias in their relevance, as well as the extent to which countries differ in the demographic composition of their populations. This is the spatial analog of the identification strategy in Acemoglu and Linn (2004), who use changes in the age distribution of the United States over time to estimate the relationship between market size and innovation in the pharmaceutical industry.

To construct this demand shifter, we draw on two data sets. The first, the World Health Organization (WHO)'s Global Burden of Disease (GBD) data set (Global Burden of Disease Collaborative Network 2014), measures the burden of each disease, based on WHO-assigned disease codes,[21] in each country

20. IMS's ATC classification is maintained by the European Pharmaceutical Market Research Association, and should not be confused with the WHO Anatomical Therapeutic Chemical classification.

21. The underlying WHO data are provided in a tree structure that includes both "aggregate" codes and "root" codes. For example, that file records disease burden data for "infectious and parasitic diseases," "childhood cluster diseases" and "pertussis." In the tree structure of the file, "pertussis" is contained within "childhood cluster diseases," which in turn are contained in "infectious and parasitic diseases." "Pertussis" has no further subcategories (which we refer to as an example of a root code), whereas the other two are aggregates of other subcategories. We focus our analysis on the root codes to avoid double counting.

and year (again, we focus on 2012). Although there may be local variation in the collection of vital statistics that underpin these measures, the WHO ensures that these data are valid for cross-country and cross-disease comparisons. Importantly, these country-year-disease measures of burden are further broken down into six different demographic groups: three age groups (0–14, 15–59, and 60+) for each gender. The provided disease burden measure on which we draw is the number of lost disability-adjusted life years (DALYs)—combining data on the mortality and morbidity caused by each disease.

We have hand-coded a many-to-one linkage from each of the 600 therapeutic classes (ATC codes) in IMS MIDAS to its corresponding WHO disease code. For example, the ATC code A2B2 for "acid pump inhibitors" is linked to the WHO code for "peptic ulcer disease." Using the most disaggregated WHO disease codes for 2012 for which we have disease burden data and a corresponding ATC code in the IMS sales data, we match 60 of the GBD 2012 codes to the ATC codes in the IMS.[22] The full crosswalk can be found in Online Appendix B.4. In practice, 2 of the 60 WHO disease codes have no recorded global sales in our sample in 2012, implying that our actual analysis sample includes 58 diseases.[23] Each of the WHO disease codes is the empirical counterpart of a disease n in the model of Section III.

Table II describes the top 10 diseases (broken down by WHO codes) in terms of global sales of their corresponding drugs in the IMS MIDAS data set. For each disease, there are many origin countries participating in the sale of drugs treating that disease. As illustrated in the last column, the typical destination country in our data is served by an extremely unconcentrated set of firms, even within each disease class.

The second input into the construction of our demand shifter is the population of each country in each of the six demographic groups in 2012. We obtain this data from the U.S. Census Bureau's International Database.

Using the data described above, we exploit the twin facts that disease burdens vary by demographic groups and that countries vary in their demographic composition, to construct a "predicted

22. One GBD code, U047 for "abortion," is missing disease burden data; we impute the disease burden to be 0 in this case.

23. Around 89% of our ATC4 codes were linked to WHO GBD codes. The main reason for nonmatches is that certain ATC4 codes are too broad to be matched to a single GBD disease code.

TABLE II
TOP 10 DISEASES IN TERMS OF SALES

Disease class (WHO system)	Share of world sales (%) (1)	Number of origin countries (2)	Average Herfindahl index across destinations (3)
Other infectious diseases	8.62	55	0.08
Hypertensive heart disease	6.56	55	0.10
Other cardiovascular diseases	6.30	55	0.13
Ischemic heart disease	5.99	54	0.14
Other neoplasms	5.80	52	0.12
Diabetes mellitus	4.75	54	0.15
Rheumatoid arthritis	4.55	49	0.23
Other genitourinary system diseases	3.97	52	0.14
Chronic obstructive pulmonary dis.	3.50	49	0.27
Schizophrenia	3.27	52	0.17

disease burden," for disease n in country i in 2012 as:

$$(PDB)_i^n = \sum_{a,g} \left[\text{population}_{iag} \times \left(\frac{\sum_{k \neq i} \text{disease burden}_{kag}^n}{\sum_{k \neq i} \text{population}_{kag}} \right) \right]. \tag{14}$$

The ratio $\frac{\sum_{k \neq i} \text{disease burden}_{kag}^n}{\sum_{k \neq i} \text{population}_{kag}}$ measures the average disease burden per capita from disease n for gender g and age group a in 2012, calculated excluding the country of interest (that is, summing over all countries k except for country i).[24] This ratio is then weighted by the population for that gender g and age group a, and summed across age and gender groups, for a given country i in 2012.

We can illustrate the basic sources of variation exploited in our empirical analysis in two figures. Figure IV provides an illustration of how population age profiles vary across countries. We plot the share of the population under age 60 by country. This share varies from just under 70% in Japan to just below 100%

24. The fact that firms from country i are better at treating disease n may cause a lower burden for that disease in country i. Leaving out country i from the average disease burden per capita addresses this endogeneity issue. However, in practice, we obtain very similar results when including country i's disease burden in the construction of $(PDB)_i^n$. The same is true when using a simple average of country-specific per capita disease burdens, rather than the population-weighted average that appears in equation (14).

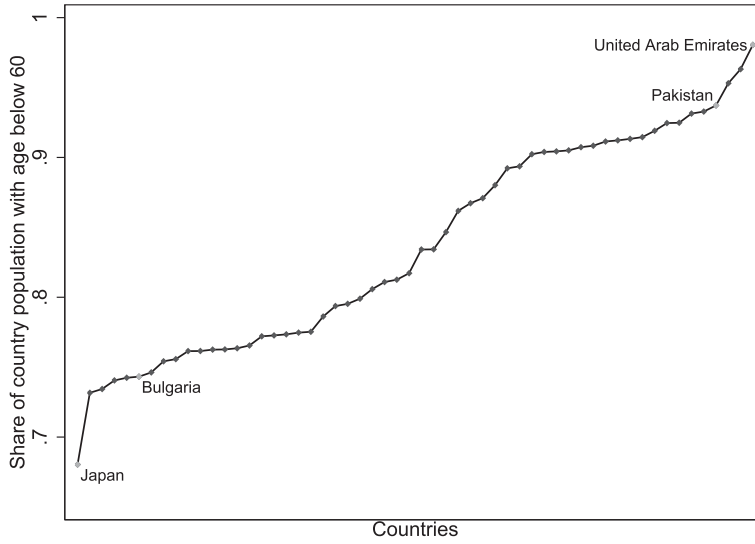


FIGURE IV

Population Age Profiles across Countries

in the United Arab Emirates. Both Japan and the United Arab Emirates are relatively rich countries by many measures, yet apparently they differ quite dramatically in the demographics of their populations.[25]

Our empirical strategy exploits the demographic variation illustrated in Figure IV together with the fact that diseases vary dramatically in the age profiles of the populations they affect. Figure V provides an illustration of how disease burden age profiles differ across diseases. We plot the share of the global disease burden, within each disease, borne by those under the age of 60. This share varies from around 10% for Alzheimer's disease (code U087)

25. Consistent with that example, Online Appendix Figure B.1 splits our sample of countries by those with above-median levels of GDP per capita ("rich") and below-median levels of GDP per capita ("poor"). The variation within this sample of rich countries spans the same range as does the full sample of countries in Figure IV. The variation within this sample of poor countries is also quite wide—ranging from around 75% below age 60 in Bulgaria to around 95% in Pakistan—although somewhat more compressed than in the rich country sample. This implies that even conditional on a country's level of development, there exists variation in our demographic shifters; this is also consistent with the results in Tables VI and VIII that document insensitivity to including flexible controls for per capita GDP.

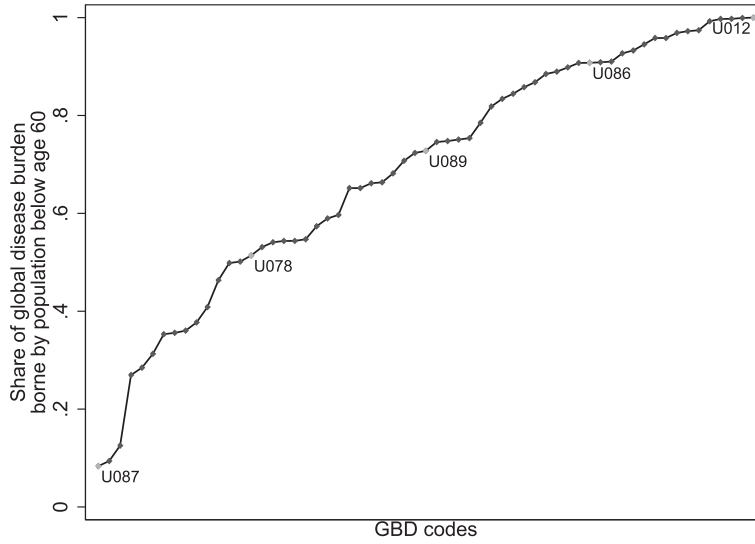


FIGURE V

Global Disease Burden Age Profiles across Diseases

The labeled global burden of disease (GBD) codes correspond to the following diseases: U087: Alzheimer's disease and other dementia; U078: other neoplasms; U089: multiple sclerosis; U086: alcohol use disorders; and U012: whooping cough.

to nearly 100% for whooping cough (code U012), with other diseases such as "other neoplasms" (U078), multiple sclerosis (U089), and alcohol use disorders (U086) lying in between as shown.

V. TESTING FOR THE HOME-MARKET EFFECT

V.A. Baseline Results

To test whether bilateral sales in the pharmaceutical industry satisfy the weak and strong home-market effects, we use $(PDB)_i^n$ as an empirical proxy for the demand shifter θ_i^n in equation (1). That is, we assume that up to a first-order approximation,

$$\ln \theta_i^n = \gamma \ln(PDB)_i^n + \gamma_i^n, \tag{15}$$

where γ is strictly positive and γ_i^n captures other determinants of the demand shifter θ_i^n for drugs targeting disease n in country i that are uncorrelated with $(PDB)_i^n$. Online Appendix B, Table B.1 establishes that the variable $(PDB)_i^n$ is a strong predictor of the

TABLE III
TEST OF THE HOME-MARKET EFFECT (BASELINE)

	Log (bilateral sales)		
	(1)	(2)	(3)
Log (PDB, destination)	0.520		0.545
	(0.097)		(0.107)
Log (PDB, origin)		0.947	0.928
		(0.174)	(0.123)
p-value for $H_0 : \tilde{\beta}_X \leqslant 0$		.000***	.000***
p-value for $H_0 : \tilde{\beta}_X \leqslant \tilde{\beta}_M$			.018**
Origin × disease FE	√		
Destination × disease FE		√	
Disease FE			√
Adjusted R^2	0.630	0.563	0.540
Observations	18,756	18,905	19,150

Notes. OLS estimates of equation (16). Predicted disease burden (PDB_i^n) is constructed from an interaction between the global (leaving out country i) disease burden by demographic group in disease n, and the size of each demographic group in country i. All regressions omit the bilateral sales observation for home sales (i.e., where $i = j$) and control for origin-times-destination fixed effects. The number of observations differs across columns due to omission of observations that are completely accounted for by the included fixed effects. Standard errors in parentheses are two-way clustered at origin and destination country levels. p-values are based on the F-test of the stated H_0. *** $p < .01$, ** $p < .05$. A p-value of ".000" refers to one below .0005.

actual burden that any country i is likely to suffer from for disease n. That is, the simple demographic predictor of disease burden in equation (14) is a useful empirical proxy for θ_i^n, despite the myriad other reasons for countries to differ in their demand for drugs targeting any particular disease.[26] Our results in Table III demonstrate that this proxy is also a strong predictor of expenditure.

To estimate β_X and β_M, one could use either the cross-sectional variation in bilateral sales, that is, equation (7), or the cross-sectional variation in total exports and imports, that is, equations (8) and (9). Like in recent empirical tests of other sources of comparative advantage (e.g., Chor 2010; Costinot, Donaldson, and Komunjer 2012), we prefer to use the former. The

26. The 2SLS specification that we would ideally estimate would instrument for our demand shifter θ_i^n with our predicted disease burden measure. However, in practice θ_i^n is unobserved. In Online Appendix Table B.1, we show that our predicted disease burden measure is correlated with the actual disease burden at the country-disease level. However, actual disease burden is not equivalent to θ_i^n, so the first-stage "scaling" provided by the estimates in Online Appendix Table B.1 is not the conceptually correct scaling from the perspective of estimating a 2SLS regression.

advantage of this strategy is that it lets us control for variation in trading frictions and demand across destination countries when estimating the impact of a given source of comparative advantage across origin countries, here their own demand. In contrast, even around a symmetric equilibrium, total exports, X_i^n, do not only depend on a country's own demand, but also on its access to foreign buyers, $\ln(\sum_{j\neq i}(\theta_j^n)^{\beta_M}\exp(\delta_{ij}+\varepsilon_{ij}^n))$. If demand shocks are spatially correlated across countries, estimates of β_X obtained from equation (8) would therefore be biased. Under the same assumptions, estimates of β_X obtained from equation (7) are not.

Combining equations (7) and (15), we have the following baseline estimating equation:

$$\ln x_{ij}^n = \delta_{ij} + \delta^n + \tilde{\beta}_M \ln(PDB)_j^n + \tilde{\beta}_X \ln(PDB)_i^n + \tilde{\varepsilon}_{ij}^n, \tag{16}$$

with $\tilde{\beta}_M \equiv \gamma\beta_M$, $\tilde{\beta}_X \equiv \gamma\beta_X$, with δ_{ij} and δ^n represented by origin-destination and disease fixed effects, respectively, and with the error term given by $\tilde{\varepsilon}_{ij}^n \equiv \varepsilon_{ij}^n + \beta_X\gamma_i^n + \beta_M\gamma_j^n$. Under the assumption that $\gamma > 0$, a positive test of the weak home-market effect therefore corresponds to $\tilde{\beta}_X > 0$, whereas a positive test of the strong home-market effect corresponds to $\tilde{\beta}_X > \tilde{\beta}_M$. Under the assumption that $\ln(PDB)_i^n$ is a pure demand shifter—such that it is uncorrelated with the supply shifter η_i^n and hence the error $\tilde{\varepsilon}_{ij}^n$—both $\tilde{\beta}_X$ and $\tilde{\beta}_M$ can be estimated using OLS, as we do below.[27]

Several details of the estimation procedure used in this section are worth mentioning. First, we estimate equation (16) on a sample of ij observations for which $i \neq j$, in line with the derivation of equation (7). This ensures that the trivial correlation between home's demand shifter and sales from home to itself does not enter the analysis (however, as we show in Table VII, incorporating this variation does little to change our findings). Second, in our baseline estimates we drop observations for which $x_{ij}^n = 0$, but we return to this aspect of the variation in Table VIII. Finally, because the predicted disease burden regressors vary at

27. We stress at this point that the coefficient estimates of $\tilde{\beta}_M$ and $\tilde{\beta}_X$ are valid for testing the weak and strong home-market effects, and have a structural interpretation as discussed in Section III.B. But they are not sufficient for conducting comparative statics analyses of the effects of *PDB* on bilateral sales because of the fact that the disease fixed effect δ^n is also a function of each country's *PDB*, as established in Online Appendix A.2. The same observation applies to other comparative statics exercises, like the introduction of import tariffs in the pharmaceutical sector.

the origin and destination levels (but not at the bilateral level) we provide standard errors that are two-way clustered at both the origin and destination levels throughout.

Table III presents OLS estimates of equation (16). We begin in column (1) with a specification designed to estimate $\tilde{\beta}_M$ as accurately as possible. To do so we control for an origin-disease fixed effect (rather than including the origin country's predicted disease burden). While the estimate of $\tilde{\beta}_M > 0$ seen there should not be surprising—a demand shifter in the destination country is positively correlated with greater purchases by that destination—this can be thought of as a check on the validity and power of demographic variation for predicting drug expenditure. Column (2) proceeds with an analogous specification designed to estimate $\tilde{\beta}_X$ alone, as accurately as possible, while controlling for a destination-disease fixed effect. The estimated value of $\tilde{\beta}_X$ is clearly positive and statistically significant. This result (and the accompanying p-value for the one-sided t-test of $\tilde{\beta}_X \leqslant 0$) provides a resounding rejection of the absence of a weak home-market effect.

Finally, column (3) estimates $\tilde{\beta}_M$ and $\tilde{\beta}_X$ simultaneously in the true spirit of equation (7). This is our preferred specification. We first note that the estimates of $\tilde{\beta}_M$ and $\tilde{\beta}_X$ in column (3) are very similar to those in columns (1) and (2), so evidence for the weak home-market effect remains firm. The p-value on the F-test for $\tilde{\beta}_X \leqslant \tilde{\beta}_M$ is .018, implying that the absence of a strong home-market effect can be rejected at the 5% level.[28] That is, it seems likely that the strong home-market effect is at work in the pharmaceutical sector.[29]

V.B. Why Does Home Demand Matter?

The foregoing results demonstrate a reduced-form relationship between a country's home demand for a drug category and foreign sales. But why does home demand matter in this way? Section III described a range of theoretical settings in which the industry-level supply curve is downward-sloping, and it is this

28. With standard errors that are clustered three-way at the origin country, destination country, and disease levels (following Cameron, Gelbach, and Miller 2011) the standard errors on $\tilde{\beta}_M$ and $\tilde{\beta}_X$ are (0.218) and (0.232), respectively. The p-values for the tests of $\tilde{\beta}_X \leqslant 0$ and $\tilde{\beta}_X \leqslant \tilde{\beta}_M$ are .000 and .115, respectively.

29. This is equally true when we estimate equation (16) on IMS MIDAS data from 2004, the earliest year for which comparable data are available. In that case the estimates (and standard errors) of $\tilde{\beta}_M$ and $\tilde{\beta}_X$ are 0.582 (0.076) and 0.910 (0.166), respectively.

feature, and only this feature, that explains why home demand matters for export success. We now discuss two alternative explanations that could, in principle, provide equally plausible answers to the question of why home demand matters.

1. Alternative I: Home Demand Is Positively Correlated with Supply-Side Considerations Driving the Pattern of International Specialization. As discussed, equation (16) describes the pattern of equilibrium drug expenditure around the world due to fundamental demand-side (PDB_i^n and PDB_j^n) and supply-side (η_i^n, a component of $\tilde{\varepsilon}_{ij}^n$) considerations. If PDB_i^n and $\tilde{\varepsilon}_{ij}^n$ were positively correlated, our OLS estimates of $\tilde{\beta}_X$ would be biased upward, potentially generating the appearance of a home-market effect, when other forces are at play.

One possible reason for such a positive correlation is that a common factor explains both variables. For example, in Vernon's (1966) theory of the product cycle, drugs would initially be produced in high-income countries and eventually be produced in poorer countries. Because one might expect the demographic ingredients of *PDB* to be equally distinct across high- and low-income countries, it is possible that per capita GDP is a common factor that affects both demand and supply in a manner that would confound estimation of $\tilde{\beta}_X$.

To assess this possibility, column (2) of Table IV tests for the two home-market effects in a specification that also simultaneously controls for per capita GDP as a source of comparative advantage, that is, for the interaction between the origin country's per capita GDP and disease fixed effects, as well as for the analogous variable on the destination country side. Compared to our baseline estimates in Table III, reported in column (1) for the sake of comparison, the null of no weak home-market effect can still be rejected at standard confidence levels, whereas this is no longer true for the null of no strong home-market effect. Reassuringly, however, the point estimates of $\tilde{\beta}_M$ and $\tilde{\beta}_X$ have not changed much in comparison with the estimates in column (1). This suggests that although there may be some systematic tendency for poor countries to produce certain drugs—in line, for instance, with Vernon (1966)—these drugs do not happen to treat the diseases associated with poor country demographics.

Symmetrically, column (3) reports a specification that controls for interactions between country (origin and destination)

TABLE IV
TEST OF THE HOME-MARKET EFFECT (SENSITIVITY ANALYSIS I)

	Log (bilateral sales)		
	(1)	(2)	(3)
Log (PDB, destination)	0.545	0.533	0.405
	(0.107)	(0.102)	(0.099)
Log (PDB, origin)	0.928	0.740	0.865
	(0.123)	(0.166)	(0.113)
p-value for $H_0 : \tilde{\beta}_X \leqslant 0$	.000***	.000***	.000***
p-value for $H_0 : \tilde{\beta}_X \leqslant \tilde{\beta}_M$	.018**	.122	.003***
Disease FE × origin p.c. GDP		√	
Disease FE × dest. p.c. GDP		√	
Origin FE × disease decile			√
Dest. FE × disease decile			√
Adjusted R^2	0.540	0.555	0.560
Observations	19,150	19,150	19,105

Notes. OLS estimates of equation (16). All specifications control for origin-destination fixed effects and disease fixed effects. "Disease decile" in column (3) represents the decile of the worldwide distribution, based on total disease burden, in which a given disease falls. See Table III for details on construction of variables, sample restrictions, and calculation of standard errors (reported in parentheses) and p-values. *** $p < .01$,** $p < .05$.

fixed effects and a measure of disease intensity (the decile in which a disease falls in the worldwide distribution, based on its disease burden). This allows some countries to have a comparative advantage in the most severe diseases, due to some unobserved country-specific characteristic that may be different from per capita GDP. Again, the stability of the key coefficients, $\tilde{\beta}_M$ and $\tilde{\beta}_X$, implies that they are being identified from the intended demographic-related component of disease burden, rather than some other pattern related to disease burden more generally. In contrast to column (2), the p-value on the F-test for $\tilde{\beta}_X \leqslant \tilde{\beta}_M$ also implies that the absence of a strong home-market effect can be rejected at the 1% level. In short, Table IV implies that potential common contributors to both demand-side and supply-side determinants of international specialization based on countries' income levels or diseases' overall severity may exist, but not in a way that appreciably affects our estimates.

A second possible source of correlation between demand (PDB_i^n) and supply ($\tilde{\varepsilon}_{ij}^n$) could be more direct. For example, government funding of medical research may reflect, at least in part, the needs of the local population; see Lichtenberg (2001).

Similarly, clinical trials may be cheaper to conduct in countries with a large pool of potential subjects. If so, one would expect the supply shifter η_i^n, and hence the residual, $\tilde{\varepsilon}_{ij}^n$, to be an increasing function of $\ln(PDB)_i^n$,

$$\tilde{\varepsilon}_{ij}^n = \psi \ln(PDB)_i^n + \nu_{ij}^n, \tag{17}$$

with $\psi > 0$ and ν_{ij}^n uncorrelated with $\ln(PDB)_i^n$. In such cases, it is important to note that our empirical test of the home-market effect would remain valid in the sense that we could still estimate equation (16) using OLS to test whether an increase in domestic demand, as proxied by $\ln(PDB)_i^n$, tends to raise exports. The structural interpretation of the estimated elasticities, however, would change. For instance, in the case of a small open economy discussed in Section III.B, the OLS estimate of the elasticity of $\ln x_{ij}^n$ with respect to $\ln(PDB)_i^n$ would now be equal to the sum of $\gamma\lambda\frac{1-\epsilon^x}{\epsilon^s+\epsilon^w}$ and ψ.

To separate out the economic mechanism described in Section III from the potential confounders discussed here, the most direct empirical strategy would be to control for these supply-side determinants, the same way we have controlled for per capita GDP and disease severity in Table IV. Unfortunately, we lack systematic information about subsidies and the cost of clinical trials at the disease-country level. What is available is data on subsidies from the U.S. National Institutes of Health (NIH). Using data from Azoulay et al. (2019) on subsidies paid from each NIH subinstitute, we derive a measure of how exposed each disease group in our data is to NIH subsidies.[30] Table V, column (2) reports the counterpart of our baseline results for diseases aggregated up to this NIH institute level, with the United States as the only origin country. Because this new specification lacks the analog of a disease fixed effect that can only be included in a sample which includes multiple origin countries, the estimates cannot be compared directly with those from our baseline specification (again,

30. The Azoulay et al. (2019) data on NIH subsidies is available from 1980 to 2005. To remain consistent with the cross-sectional nature of our empirical exercise, we only work with the latest year, 2005. We merge the 17 NIH subinstitutes into our 58 disease codes by hand. For three disease codes (abortion, maternal conditions, and poisoning) we deemed the merge indeterminate and drop those codes from our subsequent analysis. Six NIH subinstitutes (e.g., National Human Genome Research Institute) were also unmatched, leaving us with 11 aggregated disease categories that cover 55 of our original disease codes.

TABLE V
TEST OF THE HOME-MARKET EFFECT (SENSITIVITY ANALYSIS II)

	Log (bilateral sales)				
	(1)	(2)	(3)	(4)	(5)
Log (PDB, destination)	0.545	0.361	0.346	0.510	0.671
	(0.107)	(0.187)	(0.183)	(0.217)	(0.234)
Log (PDB, origin)	0.928	1.056	1.018	0.398	0.638
	(0.123)	(0.185)	(0.197)	(0.144)	(0.161)
p-value for $H_0 : \tilde{\beta}_X \leqslant 0$	.000***	.000***	.000***	.004***	.000***
p-value for $H_0 : \tilde{\beta}_X \leqslant \tilde{\beta}_M$	.018**	.033**	.040**	.668	.542
USA only origin		✓	✓		
Control for NIH subsidies			✓		
Generic drugs only				✓	
Drop richest 1/3 origins					✓
Adjusted R^2	0.540	0.778	0.778	0.472	0.446
Observations	19,150	597	597	8,700	5,461

Notes. OLS estimates of equation (16). Columns (1), (4), and (5) control for origin-destination fixed effects and disease fixed effects. Columns (2) and (3) use only the United States as an origin country, aggregate disease-level variation to the NIH institute level, and control for destination fixed effects. Column (3) additionally controls for the log of the value of NIH subsidies within each NIH institute. See Table III for details on construction of variables, sample restrictions, and calculation of standard errors (reported in parentheses) and p-values. *** $p < .01$,** $p < .05$.

included in column (1) for reference). It is nevertheless noteworthy that the results resoundingly reject the absence of a strong home-market effect on this U.S. sample. More importantly, column (3) demonstrates that controlling for (log) NIH spending has little impact on our point estimates.[31]

As an alternative, we return to our baseline specification but restrict the sample of drugs and countries to those for which we expect government subsidies and the costs of clinical trials to be minimal. Table V, column (4) looks only at drug sales for generic drugs (where the original molecule is no longer subject to intellectual property protection and hence is free to be produced by any firm), dropping sales of branded drugs (on which intellectual property rights still apply). The fact that we continue to reject the lack of a weak home-market effect in column (4) suggests that our baseline estimates are not caused entirely by a correlation between demographic-driven demand and demographic-driven supply (i.e., $\psi > 0$). It is notable, however, that within this generics subsector

31. The coefficient (and standard error) on the NIH log spending variable in this specification is 0.124 (0.103).

of the pharmaceutical industry, it appears that economies of scale are not strong enough to generate the strong home-market effect. As an alternative approach, we can focus on countries that we expect are more likely to solely produce generics (namely, poorer countries): as column (5) demonstrates, we continue to reject the lack of a weak home-market effect when using a sample that excludes the richest third of origin countries (in terms of GDP per capita).

2. Alternative II: Home Demand is Positively Correlated with Demand in Neighboring Countries. A different explanation for the importance of home demand documented in Table III comes from the potential for a country's own home demand to be correlated with demand conditions abroad in ways that are not accounted for in equation (16). Around a symmetric equilibrium, we have shown that our test of the home-market effect does not require any restriction on the spatial correlation of demand shocks across countries. As already mentioned in Section III.B, demand in countries different from the origin and the destination should simply be absorbed by a disease fixed effect. In general, however, even if all the assumptions of Section III.A are satisfied, a country's pattern of specialization may reflect not only the variation in its own demand but also the variation in its neighbors' demand, through the direct effect on the quantities they consume and the indirect effect on the price of the drugs they produce, the variation in the demand of its neighbors' neighbors, and so on.

Theoretically, it is unclear under which conditions, if any, the previous considerations should lead to a generalization of equation (7) in which the two elasticities, β_M and β_X, remain constant and a country's "home market" becomes the distance-weighted sum of its neighbors' demand or some more general function of demand around the world. For this reason, we prefer to stick to the issue of whether a country's own demand, that is, literally its home market, provides a source of comparative advantage and treat the variation in demand from neighboring countries as another potential source of omitted variable bias. Empirically, the question of interest is whether there is evidence in the data for strong multilateral effects, beyond those already absorbed by our disease fixed effect.

Table VI explores this issue. Again, column (1) repeats our baseline estimate for the purpose of comparison. Columns (2) and (3) show that restricting sales to a "donut" of destination

TABLE VI
TEST OF THE HOME-MARKET EFFECT (SENSITIVITY ANALYSIS III)

	Log (bilateral sales)			
	(1)	(2)	(3)	(4)
Log (PDB, destination)	0.545	0.537	0.610	0.542
	(0.107)	(0.115)	(0.087)	(0.107)
Log (PDB, origin)	0.928	0.941	0.843	0.928
	(0.123)	(0.147)	(0.166)	(0.127)
p-value for $H_0 : \tilde{\beta}_X \leqslant 0$	.000***	.000***	.000***	.000***
p-value for $H_0 : \tilde{\beta}_X \leqslant \tilde{\beta}_M$	.018**	.033**	.134	.019**
Sample of only ij obs. with $dist_{ij} \geqslant$	–	1,000 km	2,000 km	–
Control for $\sum_{k \neq j} \ln PDB_k^n \cdot dist_{kj}^{-1}$				√
Control for $\sum_{k \neq i} \ln PDB_k^n \cdot dist_{ik}^{-1}$				√
Adjusted R^2	0.540	0.540	0.551	0.540
Observations	19,150	16,405	13,141	19,150

Notes. OLS estimates of equation (16). All specifications control for origin-destination fixed effects and disease fixed effects. See Table III for details on construction of variables, sample restrictions, and calculation of standard errors (reported in parentheses) and p-values. *** $p < .01$,** $p < .05$.

countries, located at either more than 1,000 km or more than 2,000 km from the home market, has little effect on the economic magnitude of our estimates, although the statistical significance of the strong home-market effect weakens in the 2,000 km specification.[32] The same is true in column (4) when we control for the average disease burdens in all other countries, weighted by their distance to the origin and destination country; formally, we estimate a version of equation (16) that also includes the regressors $\sum_{k \neq i} \ln PDB_k^n \cdot dist_{ik}^{-1}$ and $\sum_{k \neq j} \ln PDB_k^n \cdot dist_{kj}^{-1}$. Put together, these results imply that multilateral considerations, at least according to the proxies used here, do not appear to be a source of quantitatively meaningful departures from our log-linearization around a symmetric equilibrium.

In this final regression, we note that the coefficients (and standard errors) on $\sum_{k \neq j} \ln PDB_k^n \cdot dist_{kj}^{-1}$ and $\sum_{k \neq i} \ln PDB_k^n \cdot dist_{ik}^{-1}$ are 0.591 (1.576) and −0.772 (3.623), respectively. The fact that the latter coefficient (while imprecisely estimated) is negative is consistent with the possibility that neighboring countries may

32. Data on bilateral country pair distance (calculated from population-weighted averages of bilateral major city pair distances) are from the CEPII Gravity data set; see Head and Mayer (2010).

benefit disproportionately more from an increase in their own demand, thereby reducing the price of their drugs relative to country i's and, in turn, lowering the residual demand faced by country i.[33]

V.C. Further Sensitivity Checks

We assess the robustness of our results to a miscellany of alternative specifications and modeling assumptions.

1. Pricing-to-Market. One potential concern is that firms in our setting can engage in substantial pricing-to-market, due to prohibitions on international resale, and hence the no-arbitrage equation (5) may not apply. Although we have already demonstrated in Section III.C that our empirical test may remain theoretically valid in the absence of this equation, we revisit this issue empirically. Specifically, in Table VII, column (2), we limit the sample of destination markets to those within the EU, a free trade area where parallel trade makes pricing-to-market difficult to sustain; see Scott Morton and Kyle (2012) for further discussion.[34] If one thought that pricing-to-market had a significant effect on the relationship between drug sales and home demand, then one would expect different elasticities, $\tilde{\beta}_X$ and $\tilde{\beta}_M$, in the EU sample. For instance, if governments were able to negotiate lower drug prices for diseases with greater burdens in their populations, there would be a negative correlation between $\tilde{\varepsilon}^n_{ij}$ and $\ln(PDB)^n_j$ in equation (16), driven by the lower markup μ^j_{ij} in destinations with high PDB^n_j. This would lead to larger estimates of $\tilde{\beta}_M$ in those countries compared with those within the EU, for which markups are more likely to be constant across destinations. Although the

33. This finding is reminiscent of "agglomeration shadows" (e.g., Arthur 1990; Matsuyama 2017). The idea is that countries surrounded by larger neighbors may face lower demand for their products, in spite of the fact that having larger neighbors tends to mechanically raise demand. We note, however, that a negative coefficient on $\sum_{k \neq i} \ln PDB^n_k \cdot dist_{ik}^{-1}$ does not imply that the total effect of larger neighbors is to reduce demand. In our regression, we already control for the size of demand PDB^n_j at any given destination j. Hence, the mechanical effect of demand in larger neighbors is not being picked up by $\sum_{k \neq i} \ln PDB^n_k \cdot dist_{ik}^{-1}$. A negative coefficient merely suggests that countries surrounded by larger neighbors face tougher competition in otherwise bigger markets.

34. More precisely, we focus here on the set of countries in our sample that were members of the European Single Market as of 2012, which includes Norway and Switzerland as well as EU members.

TABLE VII
TEST OF THE HOME-MARKET EFFECT (SENSITIVITY ANALYSIS IV)

	Log (bilateral sales)				
	(1)	(2)	(3)	(4)	(5)
Log (PDB, destination)	0.545	−0.007	0.573	0.547	0.514
	(0.107)	(0.460)	(0.265)	(0.102)	(0.104)
Log (PDB, origin)	0.928	0.726	0.823	0.785	0.843
	(0.123)	(0.285)	(0.201)	(0.104)	(0.098)
p-value for $H_0 : \tilde{\beta}_X \leqslant 0$	.000***	.010**	.000***	.000***	.000***
p-value for $H_0 : \tilde{\beta}_X \leqslant \tilde{\beta}_M$	.018**	.098*	.198	.061*	.023**
EU destinations only		√			
Below median FDI share			√		
PDB with 1996 demographics				√	
Home sales (X_{ii}^n) obs. incl.					√
Adjusted R^2	0.540	0.538	0.459	0.539	0.563
Observations	19,150	7,223	5,081	19,150	21,291

Notes. OLS estimates of equation (16). All specifications control for origin-destination fixed effects and disease fixed effects. See Table III for details on construction of variables, sample restrictions, and calculations of standard errors (reported in parentheses) and p-values. *** $p < .01$,** $p < .05$, * $p < .1$.

effect of destination *PDB* for the EU sample is imprecisely estimated (so it remains within the 95% confidence interval of our baseline estimate, repeated again in column (1) for comparison), the lower point estimate of $\tilde{\beta}_M$ gives some support to that view.[35] For our purposes, the main take-away from this sensitivity check is that the estimated value of $\tilde{\beta}_X$ is again quite similar to that in previous specifications. Hence, the weak home-market effect remains operational within the EU sample.

2. Foreign Direct Investment. As discussed already, a limitation of the MIDAS pharmaceutical data set used throughout our

35. In addition, this result implies that predicted disease burdens are not a strong predictor of demand among these destinations. However, in an analogous specification that instead restricts attention to EU origin countries only we estimate (with standard errors in parentheses) $\tilde{\beta}_M = 0.366$ (0.123) and $\tilde{\beta}_X = 0.875$ (0.715). One possible reason for the larger correlation between *PDB* and exporting success, relative to demand, among this set of countries is the fact that exporting success is likely to reflect lagged demand, and intra-EU pharmaceutical resale is a relatively recent phenomenon. For example, according to the European Medicines Agency's Parallel Distributor Register, 20 licenses had been granted for the resale of 20 different drugs in 2000, but these figures had risen to 1,799 licenses for 257 drugs as of 2012.

empirical analysis is that it does not provide information about where a firm's final product is made. We only know where a firm sells its products and where it is headquartered. Accordingly, the economies of scale underpinning the home-market effect that we have documented earlier could have multiple roots. For instance, it could be the case that there are local economies of scale at the production site and the headquarter location is a good proxy for the location of production sites (which would be the case if multinational production is not widespread); or there could be local economies of scale at the R&D site and the headquarter location is a good proxy for the location of R&D sites; or there may be economies of scale across affiliates from the same firm in a given headquarter country.

We are unaware of any data set that could be used to disaggregate total sales x_{ij}^n into FDI and export sales at the country pair-disease level. But publicly available (OECD) data on international trade flows record the value of exports by country pair for the pharmaceutical sector as a whole. By comparing total OECD exports to total MIDAS foreign sales, we can obtain an estimate of the importance of trade relative to FDI for a given origin country.[36] Using such information, column (3) estimates our baseline specification on the subset of country pairs for which the ratio of total OECD exports to total MIDAS foreign sales is above the median. If economies of scale were primarily operating at the level of the production sites, we would expect a stronger home-market effect in this subsample since foreign sales are more likely to occur through exports from a single origin country. The stability of our estimated coefficients to this subsample is suggestive of the notion that in our context, this type of economies of scale is unlikely to be prevalent.

36. We draw on OECD BTDIxE data (Zhu, Yamano, and Cimper 2011) for 2012, corresponding to the industry activity category "Basic pharmaceutical products and pharmaceutical preparations" and the end use category "total trade in goods," as reported by the importing country. It should be clear that beyond the presence of bilateral FDI, which is what we are interested in, there are multiple reasons to expect imperfect alignment of MIDAS bilateral (all-disease) foreign sales and OECD bilateral pharmaceutical export data. These include exports occurring as platform FDI, intermediate inputs, or uncorrected re-exporting; differing pricing concepts (retail versus border prices); differing sets of products included in pharmaceuticals (notably the OECD data's inclusion of veterinary drugs); and data-reporting issues (e.g., misreporting in either data set, miscoding of headquarter locations, timing of exporting versus sales within the calendar year, and confidentiality restrictions in OECD data). Reassuringly, the correlation between the two sources is 0.595 (or 0.628 in logs).

3. Endogenous Demographics. Another possibility is that our baseline results are biased because a country's demographic composition could itself be shaped by its disease environment. To assess this, we compare the effect of constructing our predicted disease burden (*PDB*) regressors from countries' lagged demographic composition (in column (4), based on 1996 demographics) relative to our baseline estimate (column (1), based on 2012 demographics).[37] That the estimates of $\tilde{\beta}_M$ and $\tilde{\beta}_X$ are similar suggests that this form of reverse causation is not quantitatively plausible in our setting.

4. Estimation Sample and the Extensive Margin. The estimates presented so far have been obtained from a sample that uses all bilateral sales observations x_{ij}^n for which $i \neq j$, and for which $x_{ij}^n > 0$. We now assess the importance of these two sample decisions.

First, Table VII, column (5) confirms that including home sales observations (those for which $i = j$) has little effect on our estimates of the home-market effect. Second, Table VIII concludes with estimates of the home-market effect along the extensive margin—that is, whether a foreign market is penetrated at all. Given that our previous results (in Tables III–VII above) used the log of bilateral sales (x_{ij}^n) as the dependent variable, any country pair-disease observations with zero bilateral sales were omitted from the estimation sample. Therefore, for completeness, we present in column (2) results from Poisson pseudo-maximum likelihood (PPML) estimation, a standard alternative estimation approach to gravity-like estimation in the presence of zeroes in the dependent variable (see, for example, Head and Mayer, 2013). While the (two-way clustered) standard errors on this estimate are larger than their OLS analogs (in column (1), our baseline estimate), we still reject the lack of a weak and a strong home-market effect (at the 1% and 10% levels, respectively). Columns (3) and (4) go on to estimate a specification in which the dependent variable is no longer the (log) level of x_{ij}^n but a dummy variable for whether bilateral sales take place (i.e., $x_{ij}^n > 0$) or not. For

37. This specification draws on demographic data (in the PDB variable) from 1996, the earliest year for which data are available on the demographic composition spanning a wide set of countries.

TABLE VIII
TEST OF THE HOME-MARKET EFFECT (EXTENSIVE MARGIN)

	Log (bilateral sales)	Bilateral sales	$\mathbb{1}$(bilateral sales > 0)	
	(1)	(2)	(3)	(4)
Log (PDB, destination)	0.545	0.382	0.009	0.009
	(0.107)	(0.148)	(0.004)	(0.004)
Log (PDB, origin)	0.928	1.300	0.054	0.061
	(0.123)	(0.534)	(0.013)	(0.013)
p-value for $H_0 : \tilde{\beta}_X \leqslant 0$	.000***	.008***	.000***	.000***
p-value for $H_0 : \tilde{\beta}_X \leqslant \tilde{\beta}_M$	.018**	.066*	.001***	.000***
PPML estimator		√		
Disease FE × origin GDP/capita				√
Disease FE × dest. GDP/capita				√
Adjusted R^2	0.540	0.421	0.486	0.499
Observations	19,150	64,728	178,640	178,640

Notes. Column (1) reports OLS estimates, column (2) pseudo-maximum likelihood (PPML) estimates, and columns (3) and (4) linear probability model estimates, based on equation (16). Pseudo-R^2 reported in column (2). All specifications control for origin-destination fixed effects and disease fixed effects. See Table III for details on construction of variables, sample restrictions, and calculations of standard errors (reported in parentheses) and p-values. *** $p < .01$,** $p < .05$,* $p < .1$.

simplicity, we estimate this as a linear probability model. There is strong support in these two sets of results—whether a full set of disease fixed effect interactions with country living standards as in Table IV is included or not—for the idea that home demand shocks also lead to more exports abroad along the extensive margin.

VI. DISENTANGLING DEMAND AND SUPPLY ELASTICITIES

The results of Section V provide firm support for the notion of a home-market effect in the global pharmaceutical sector. But as discussed in Section III, weak and strong home-market effects depend both on demand and supply elasticities. Thus, the structural interpretation of the previous effect remains open. We now use price data to extend our previous analysis in order to fill this gap, first by estimating the demand elasticity ϵ^x in Section VI.A and then the sector-level supply elasticity ϵ^s in Section VI.B.

VI.A. *Estimating the Elasticity of Demand*

As established in Online Appendix A.4, around a symmetric equilibrium, the demand system of equations (1)–(3), along with the no-arbitrage condition (5), can be used to express bilateral sales, up to a first-order approximation, as

$$\ln x_{ij}^n = \delta_j^n + (1-\epsilon^x)\ln p_i^n + (1-\epsilon^x)\ln \tau_{ij}^n, \tag{18}$$

where δ_j^n is a destination-disease fixed effect and p_i^n is the price index for varieties from origin i. In contrast to equation (7), it is worth pointing out that equation (18) is also valid, globally and without approximation, in the commonly applied case where the function $d(\cdot)$ in equation (2) is CES. Under this assumption, one can therefore dispense with the restriction that the observed equilibrium is close to a symmetric one as well as allow for differential effects of demand in third countries. In equation (18), such effects are implicitly captured by the disease-destination fixed effect, δ_j^n, and the origin price, p_i^n.[38]

Our aim here is to estimate the price elasticity of exports, ϵ^x. We begin by assuming that, up to a first-order approximation, trade costs τ_{ij}^n can be expressed as

$$\ln \tau_{ij}^n = \alpha \ln dist_{ij} + \nu_{ij}^n, \tag{19}$$

where $dist_{ij}$ is the physical distance between country i and country j and ν_{ij}^n is the component of trade costs not explained by distance. Combined with equation (18) this implies the following gravity equation relationship between bilateral sales and bilateral distance

$$\ln x_{ij}^n = \delta_j^n + \delta_i^n + \rho \ln dist_{ij} + \chi_{ij}^n, \tag{20}$$

with $\rho \equiv (1-\epsilon^x)\alpha$, $\chi_{ij}^n \equiv (1-\epsilon^x)\nu_{ij}^n$, and δ_i^n representing an origin-disease fixed effect.

We estimate ρ in this equation via OLS. Our estimate of ρ is reported in Table IX, column (1). As is commonly found in estimates of the gravity equation (20), bilateral distance has a negative and statistically significant impact on bilateral drug sales

38. The fact that p_i^n is not itself a log-linear function of demand shocks explains why equation (7) requires a log-linear approximation, even under the assumption that demand is CES.

TABLE IX
DEMAND ELASTICITY ESTIMATES

	Log (bilateral sales) (1)	Log (price) (2)
Log (bilateral distance)	−0.324	0.062
	(0.075)	(0.031)
Origin × disease FE	√	
Destination × disease FE	√	
Variety FE		√
Adjusted R^2	0.578	0.881
Observations	18,638	64,396

Notes. Column (1) reports OLS estimates of equation (20). Standard errors in parentheses are two-way clustered at origin and destination country levels. Column (2) reports OLS estimates of equation (22); variety fixed effects control for interactions between all combinations of active molecules, corporations, and disease classes; standard errors (in parentheses) are clustered by destination country; the sample is based on all MIDAS observations for which prices are reported. All regressions omit the bilateral sales observation for home sales (i.e., where $i = j$).

in this setting. But the estimated effect of distance on trade, $\rho = -0.324$, is about three times smaller (in absolute value) than typical estimates from trade data in other sectors. For example, Head and Mayer (2013) report a preferred distance elasticity of −0.89. This is perhaps to be expected, given the relatively low weight-to-value of pharmaceutical products and given that our data track total foreign sales (not just exports).

Because the parameter ρ captures a mixture of the demand elasticity ϵ^x and the distance-cost elasticity α, we turn to micro data on the producer prices of individual drug varieties to separate the two.[39] In particular, for any individual variety of a drug ω within the class of drugs that treat disease n, suppose that prices satisfy the variety-level analog of the no-arbitrage condition in equation (5):

$$p_{ij}^n(\omega) = \tau_{ij}^n p_i^n(\omega). \tag{21}$$

Combined with equation (19), this implies that we can obtain an unbiased estimate of α from the following specification

$$\ln p_{ij}^n(\omega) = \alpha \ln dist_{ij} + \delta_i^n(\omega) + \delta_{ij}^n(\omega), \tag{22}$$

39. Producer price (ex factory) values in the IMS MIDAS data set correspond to the prices received by manufacturing firms, as opposed to those received by wholesalers or retailers.

where $\delta_i^n(\omega)$ is a variety fixed effect and $\delta_{ij}^n(\omega)$ is an error term.[40] The basic idea here is that if a given variety sells in many destination countries, then the extent to which the prices of that variety vary across destinations j that are different distances $dist_{ij}$ from the producer's origin country i identifies α.

The result from estimating equation (22) is reported in Table IX, column (2). The estimate of $\alpha = 0.062$ implies that distance is evidently a shifter of costs at distant destination locations and is positively correlated with the producer price (for the same variety, sold from the same origin), despite the manifold reasons for producer prices to vary across consumer markets in the pharmaceutical sector.[41]

Putting together the estimates in Table IX, the identity $\rho \equiv (1 - \epsilon^x)\alpha$ implies that the demand elasticity $\epsilon^x = 6.217$, with a destination country block-bootstrapped 95% confidence interval of $[2.221, 29.656]$.[42] This implies that cross-disease demand is elastic in the present setting. As per the discussion in Section III.B, this then implies that at least for a small open economy, the tests for the weak and strong home-market effects reported in Section V.A provide bounds on economies of scale. For example, we know that the evidence for the weak home-market effect reported in Table III implies that industry-level (positive) economies of scale are at work in this setting. Naturally, such a bound is of only limited use for quantitative policy questions, so

40. By "variety" we refer, in practice, to the permutation of physiologically active molecules (since some drugs contain more than one active molecule), interacted with the disease for which the drug is intended to treat (because, in rare cases, the same molecule can be marketed in separate therapeutical classes), and interacted with the firm selling the drug.

41. We have estimated equation (22) with additional controls, such as a destination fixed effect, a destination-disease fixed effect, an indicator for whether the origin and destination countries both belong to the EU, and a measure of the absolute value of the difference in the origin and destination countries' per capita GDPs, and the estimate of α (and its standard error) ranges from 0.034 (0.015) to 0.082 (0.030) and remains statistically significant in all cases. However, when including all of these controls simultaneously the estimate of α is no longer statistically significant; in particular, $\alpha = 0.008$ (0.020) in this case.

42. We are unaware of a block-bootstrap procedure that is analogous to two-way clustering. But this does not appear to be a setting where the difference between two-way clustering (on origin and destination) is substantially different from simply clustering on either origin or destination—for example, the standard error in Table IX, column (1) is (0.053) when clustering on destination country.

we turn to a method that uses the demand elasticity estimate here to obtain a point estimate of the elasticity of supply.

VI.B. Estimating the Elasticity of Supply

We turn to a simple procedure that allows us to estimate the supply elasticity ϵ^s. Let $r_i^n \equiv p_i^n s_i^n$ denote the total sales of drugs targeting disease n by firms from country i. Around a symmetric equilibrium, up to a first-order approximation, the supply relation in equation (5) can be written as

$$\ln r_i^n = (1+\epsilon^s)\ln p_i^n + \ln \eta_i^n.$$

Using the previous expression to substitute for p_i^n in equation (18), we obtain

$$\ln x_{ij}^n = \delta_j^n + \delta_{ij} + \left(\frac{1-\epsilon^x}{1+\epsilon^s}\right)\ln r_i^n + \phi_{ij}^n, \tag{23}$$

with δ_{ij} representing an origin-destination fixed effect and $\phi_{ij}^n \equiv \chi_{ij}^n - \bar{\chi}_{ij}^n - \left(\frac{1-\epsilon^x}{1+\epsilon^s}\right)\ln \eta_i^n$ an error term. Naturally, this expression, which relates bilateral destination sales to total origin sales, involves a mixture of the demand elasticity ϵ^x in the destination and the supply elasticity at the origin ϵ^s. Armed with an estimate of the demand elasticity ϵ^x from Section VI.A, an estimate of $\left(\frac{1-\epsilon^x}{1+\epsilon^s}\right)$ from equation (23) allows us to disentangle the two.

OLS estimates of equation (23) would be biased because both the supply shock η_i^n and unobserved trade costs χ_{ij}^n in the error term ϕ_{ij}^n contribute to total sales r_i^n. But for all destination observations $j \neq i$, an exogenous shifter of demand at the origin country i (such as the predicted disease burden variable PDB_i^n introduced in equation (14)) can be used as a valid instrumental variable for r_i^n.[43] Such an IV estimation procedure identifies $\left(\frac{1-\epsilon^x}{1+\epsilon^s}\right)$.

Table X reports estimates from specification (23). We begin in column (1) by reporting the first-stage regression

43. Because $r_i^n \equiv \sum_j x_{ij}^n$, equation (23) is a log-linear analog of the canonical peer effects regression discussed in, for example, Manski (1993)—where the regressor of interest is the sum (or mean) of the dependent variable within some peer group. As is well known, identification of such peer effects is impossible without instruments that shift the actions of an agent's peers (and hence potentially also the sum of all peers' actions) but do not affect the agent's own payoff function directly. Our instrument, PDB_i^n, plays an analogous role here (given our focus on observations for which $j \neq i$).

of $\ln r_i^n$ on $\ln PDB_i^n$, conditional on origin-destination and destination-disease fixed effects. That predicted disease burden is strongly correlated with total sales (the F-statistic on this excluded instrument is equal to 128.4, the square of the t-statistic from column (1)) should come as no surprise given the results in Table III.[44] Column (2) then reports the OLS estimate of equation (23) and column (3) the corresponding IV estimate.[45] This (statistically significant) IV estimate implies that $\left(\frac{1-\epsilon^x}{1+\epsilon^s}\right) = 0.764$. Given our estimate of $\epsilon^x = 6.217$ from above, this implies that $\epsilon^s = -7.833$ (with a destination country block-bootstrapped 95% confidence interval of $[-43.744, -3.565]$). As expected, given the bounds implied by the weak home-market effect, the estimated industry-level supply curve in this setting is downward-sloping, indicating the presence of increasing returns to scale.

How does this estimate of ϵ^s compare with those in prior work? Both empirical and theoretical findings offer points of reference. From the empirical literature, one strand aims to estimate industry-level economies of scale directly, via industry-level production functions. A prominent estimate (pooled among all U.S. manufacturing sectors, so unfortunately not available for the pharmaceutical sector alone) from Basu and Fernald (1997) estimates industry-level economies of scale that generate an industry-level supply curve with $\epsilon^s = -4.45$. A second strand, initiated by Antweiler and Trefler (2002), uses patterns of comparative advantage revealed in international trade data to infer relative costs for each country-industry and then estimates the extent to which those inferred costs depend on scale. For the pharmaceutical industry, Antweiler and Trefler's (2002) estimates imply $\epsilon^s = -4.27$. Because lower supply elasticities in absolute value imply larger effects of quantity on producer prices, both estimates imply somewhat stronger economies of scale than found in our estimate of $\epsilon^s = -7.833$.[46] That said, neither estimate

44. Indeed, the test of the weak home-market effect—specifically, Table III, column (2)—is the reduced-form associated with our IV estimation procedure.

45. The fact that the OLS estimate in column (2) is smaller than the IV estimate in column (3) is consistent with downward-sloping supply curves because when $\epsilon^s < -1$ (and given elastic demand, $\epsilon^x > 1$) the error term ϕ_{ij}^n in equation (23) depends negatively on the supply shock η_i^n.

46. One possible reason for the stronger industry-level economies of scale found in these earlier studies, relative to ours, is that they are obtained from settings with more aggregate notions of an industry (a representative manufacturing sector in Basu and Fernald 1997 or the entire pharmaceutical sector in

TABLE X
SUPPLY ELASTICITY ESTIMATES

	Log (total sales)	Log (bilateral sales)	
	OLS (1)	OLS (2)	IV (3)
Log (PDB)	1.241		
	(0.110)		
Log (total sales)		0.669	0.764
		(0.052)	(0.116)
p-value for $H_0 : \left(\frac{1-\epsilon^x}{1+\epsilon^s}\right) = 1$			.048**
Adjusted R^2	0.789	0.629	0.627
Observations	18,905	18,905	18,905

Notes. Column (2) reports the OLS estimate, and column (3) the IV estimate, of equation (23). Column (1) reports the corresponding first-stage specification. The instrumental variable is log(PDB) in the origin country. All regressions omit the bilateral sales observation for home sales (i.e., where $i = j$) and control for origin-destination and destination-disease fixed effects. Standard errors in parentheses are two-way clustered at origin and destination country levels. p-value is based on the F-test of H_0. **$p < .05$.

is based on an empirical strategy that isolates variation that stems from the demand side alone and yet is powerful enough to circumvent weak instrument concerns.[47]

The influential model of Krugman (1980) also provides a clear benchmark. As discussed in Section III.C, this model is a special case in which there is a particularly stark connection between industry-level supply and demand elasticities: $\epsilon^s = -\epsilon^x$. This implies that $\left(\frac{1-\epsilon^x}{1+\epsilon^s}\right)$, the coefficient reported in Table X, column (3) should be equal to 1. Instead our IV estimate is equal to 0.764 , or

Antweiler and Trefler 2002) than that used here (a representative disease class within the pharmaceutical sector).

47. A third example of work that attempts to estimate industry-level economies of scale is due to Shea (1993), who finds that the industry-level supply curve slopes upward in the pharmaceutical industry. This approach (when applied, for example, to the pharmaceutical sector) uses input-output table information to find a downstream sector that buys a substantial share of its inputs from the pharmaceutical sector, but which sources only a small share of its other inputs from sectors that themselves are not used substantially as inputs in the pharmaceutical sector. When estimating an inverse supply curve, output in such a downstream sector can then be employed as a demand-side instrumental variable for output in the pharmaceutical sector under the assumption that the two sectors do not face correlated demand shocks. Our finding of a downward-sloping supply curve derives from a different orthogonality condition, namely, that predicted disease burden in the origin country is uncorrelated with unobserved determinants of demand in the destination, after controlling for both destination-disease and origin-destination fixed effects.

about 25% smaller. Although the reported p-value demonstrates that the particular parameter value assumed in Krugman (1980) is rejected at the 5% level, our estimate is certainly closer to this benchmark value than to the constant-returns extreme in which $\epsilon^s = \infty$ (and hence the coefficient in column (3) would be equal to 0).

VII. Concluding Remarks

Since the home-market effect hypothesized by Linder (1961) and formalized by Krugman (1980) is about the causal effect of cross-country differences in demand on the pattern of international specialization, any empirical test of this phenomenon requires exogenous demand variation. In this article, we have focused on the global pharmaceutical industry as a way to obtain such variation. Our empirical strategy builds on the basic observation that countries whose populations, because of exogenous demographic characteristics, are more likely to suffer from particular diseases are also more likely to have high demand for drugs targeting those diseases.

We have conducted tests of two different notions of the home-market effect. The first test, which is based on what we have referred to as the weak home-market effect, investigates whether countries tend to sell more abroad in sectors for which they have larger domestic markets. In the present context, this boils down to estimating whether the elasticity of a country's foreign sales with respect to its demographically predicted disease burden is positive. In line with the work of Linder (1961), the answer is a resounding yes. In short, the more we die (at home), the more we sell (abroad).

Our second test, defined by what we have referred to as the strong home-market effect, explores whether the previous effect can be important enough to turn countries with larger demand for some products into net sellers of those products, a stronger implication of Krugman's (1980) monopolistically competitive model. Our baseline results speak in favor of the strong home-market effect in the pharmaceutical sector, though in comparison with the weak home-market effect, we are not able to reject the null of no strong home-market effect in some of our specifications.

To delve further into the economic determinants of the home-market effect, we have concluded our analysis by estimating demand and supply elasticities in the pharmaceutical industry. Our estimates point toward the home-market effect being driven by

substantial economies of scale at the sector level rather than a low elasticity of demand. Quantitatively, we have estimated a supply elasticity that is about three-quarters the size of what a monopolistically competitive model, like Krugman (1980), would predict. Recent quantitative work on international trade and economic geography has typically assumed, without attempting to estimate, economies of scale that are either zero, as in Eaton and Kortum (2002), or of Krugman's (1980) magnitude. In our context, both extremes are rejected by the data. Our analysis, however, demonstrates how a single supply-side parameter can nest these two cases and how a plausibly exogenous demand shifter can let the data speak freely to this parameter's value.

Finally, we note that our results provide empirical support to the heterodox view that import protection may lead to export promotion, at least within the context of a specific but important industry. Of course, whether such promotion is welfare-improving may depend on the underlying sources of economies of scale, a matter on which our analysis remains silent.

MASSACHUSETTS INSTITUTE OF TECHNOLOGY, CENTRE FOR ECONOMIC AND POLICY RESEARCH, AND NATIONAL BUREAU OF ECONOMIC RESEARCH
MASSACHUSETTS INSTITUTE OF TECHNOLOGY, CENTRE FOR ECONOMIC AND POLICY RESEARCH, AND NATIONAL BUREAU OF ECONOMIC RESEARCH
MINES PARISTECH AND CENTRE FOR ECONOMIC AND POLICY RESEARCH
MASSCHUSETTS INSTITUTE OF TECHNOLOGY AND NATIONAL BUREAU OF ECONOMIC RESEARCH

SUPPLEMENTARY MATERIAL

An Online Appendix for this article can be found at *The Quarterly Journal of Economics* online. Data and code replicating tables and figures in this article can be found in Costinot et al. (2019), in the Harvard Dataverse, doi:10.7910/DVN/DKWB2P.

REFERENCES

Acemoglu, Daron, and Joshua Linn, "Market Size in Innovation: Theory and Evidence from the Pharmaceutical Industry," *Quarterly Journal of Economics*, 119 (2004), 1049–1090.
Amiti, Mary, "Inter-Industry Trade in Manufactures: Does Country Size Matter?," *Journal of Intermational Economics*, 44 (1998), 231–255.

Antweiler, Werner, and Daniel Trefler, "Increasing Returns and All That: A View from Trade," *American Economic Review*, 92 (2002), 93–119.
Arthur, Brian W., "Silicon Valley Locational Clusters: When Do Increasing Returns Imply Monopoly?," *Mathematical Social Sciences*, 19 (1990), 235–251.
Azoulay, Pierre, Joshua S. Graff-Zivin, Danielle Li, and Bhaven N. Sampat, "Public R&D Investments and Private-sector Patenting: Evidence from NIH Funding Rules," *Review of Economic Studies*, 86 (2019), 117–152.
Basu, Susanto, and John G. Fernald, "Returns to Scale in U.S. Production: Estimates and Implications," *Journal of Political Economy*, 105 (1997), 249–283.
Behrens, Kristian, Andrea R. Lamorgese, Gianmarco Ottaviano, and Takatoshi Tabuchi, "Beyond the Home Market Effect: Market Size and Specialization in a Multi-Country World," *Journal of International Economics*, 79 (2009), 259–265.
Bilir, Kamran, and Eduardo Morales, "Innovation in the Global Firm," NBER Working Paper No. 22160, 2018.
Brulhart, Marius, and Federico Trionfetti, "A Test of Trade Theories when Expenditure is Home Biased," *European Economic Review*, 53 (2009), 830–845.
Cameron, A. Colin, Jonah B. Gelbach, and Douglas L. Miller, "Robust Inference With Multiway Clustering," *Journal of Business and Economic Statistics*, 29 (2011), 238–249.
Caron, Justin, Thibault Fally, and Ana Cecilia Fieler, "Home-Market Effects on Innovation," Mimeo UC Berkeley, 2015.
Chor, Davin, "Unpacking Sources of Comparative Advantage: A Quantitative Approach," *Journal of International Economics*, 82 (2010), 152–167.
Cleave, T. L., *Peptic Ulcer: A New Approach to its Causation, Prevention, and Arrest, Based on Human Evolution* (John Wright and Sons, 1962).
Costinot, Arnaud, Dave Donaldson, and Ivana Komunjer, "What Goods Do Countries Trade? A Quantitative Exploration of Ricardo's Ideas," *Review of Economic Studies*, 79 (2012), 581–608.
Costinot, Arnaud, Dave Donaldson, Margaret Kyle, and Heidi Williams, "The More We Die, The More We Sell? A Simple Test of the Home-Market Effect," Mimeo, MIT, 2016.
———, "Replication Data for: 'The More We Die, the More We Sell? A Simple Test of the Home-Market Effect'," 2019. Harvard Dataverse, doi: 10.7910/DVN/DKWB2P.
Crozet, Mathieu, and Federico Trionfetti, "Trade Costs and the Home Market Effect," *Journal of International Economics*, 76 (2008), 309–321.
Davis, Donald R., "The Home Market, Trade and Industrial Structure," *American Economic Review*, 88 (1998), 1264–1276.
Davis, Donald R., and David Weinstein, "Does Economic Geography Matter for International Specialization?," NBER Working Paper No. 5706, 1996.
———, "Economic Geography and Regional Production Structure: An Empirical Investigation," *European Economic Review*, 43 (1999), 379–407.
———, "Market Access, Economic Geography and Comparative Advantage: An Empirical Test," *Journal of International Economics*, 59 (2003), 1–23.
DellaVigna, Stefano, and Joshua M. Pollet, "Demographics and Industry Returns," *American Economic Review*, 97 (2007), 1667–1702.
Dingel, Jonathan I., "The Determinants of Quality Specialization," *Review of Economic Studies*, 84 (2016), 1551–1582.
Eaton, Jonathan, and Samuel Kortum, "Technology, Geography and Trade," *Econometrica*, 70 (2002), 1741–1779.
Ethier, Wilfred J., "Decreasing Costs in International Trade and Frank Graham's Argument for Protection," *Econometrica*, 50 (1982), 1243–1268.
Fabrizio, Kira R., and L. G. Thomas, "The Impact of Local Demand on Innovation in a Global Industry," *Strategic Management Journal*, 33 (2012), 42–64.
Fajgelbaum, Pablo, Gene M. Grossman, and Elhanan Helpman, "Income Distribution, Product Quality, and International Trade," *Journal of Political Economy*, 119 (2011), 721–765.

———, "A Linder Hypothesis for Foreign Direct Investment," *Review of Economic Studies*, 82 (2015), 83–121.
Feenstra, Robert C., James R. Markusen, and Andrew K. Rose, "Using the Gravity Equation to Differentiate among Alternative Theories of Trade," *Canadian Journal of Economics*, 34 (2001), 430–447.
Fujita, Masahisa, Paul R. Krugman, and Anthony Venables, *The Spatial Economy: Cities, Regions, and International Trade* (Cambridge, MA: MIT Press, 2001).
Gali, Jordi, and Tommaso Monacelli, "Monetary Policy and Exchange Rate Volatility in a Small Open Economy," *Review of Economic Studies*, 72 (2005), 707–734.
Global Burden of Disease Collaborative Network, *Global Burden of Disease Study 2013 (GBD 2013) Age-Sex Specific All-Cause and Cause-Specific Mortality 1990–2013* (Seattle, United States: Institute for Health Metrics and Evaluation (IHME), 2014).
Hanson, Gordon H., and Chong Xiang, "The Home Market Effect and Bilateral Trade Patterns," *American Economic Review*, 94 (2004), 1108–1129.
Hara, Takuji, *Innovation in the Pharmaceutical Industry: The Process of Drug Discovery and Development* (Cheltenham: Edward Elgar, 2003).
Head, Keith, and Thierry Mayer, "The Empirics of Agglomeration and Trade," in *Handbook of Regional and Urban Economics*, vol. 4 J. V. Henderson and J. F. Thisse, eds. (Amsterdam: Elsevier, 2004).
———, "The Erosion of Colonial Trade Linkages After Independence," *Journal of International Economics*, 81 (2010), 1–14.
———, "Gravity Equations: Toolkit, Cookbook, Workhorse," in *Handbook of International Economics*, vol. 4, Gita Gopinath, Elhanan Helpman, and Kenneth Rogoff, eds. (Amsterdam: Elsevier, 2013).
Head, Keith, Thierry Mayer, and John Ries, "On the Pervasiveness of Home Market Effects," *Economica*, 69 (2002), 371–390.
Head, Keith, and John Ries, "Increasing Returns versus National Product Differentiation as an Explanation for the Pattern of U.S.-Canada Trade," *American Economic Review*, 91 (2001), 858–876.
Helpman, Elhanan, and Paul R. Krugman, *Market Structure and Foreign Trade: Increasing Returns, Imperfect Competition, and the International Economy* (Cambridge, MA: MIT Press, 1985).
———, *Trade Policy and Market Structure* (Cambridge, MA: MIT Press, 1989).
Holmes, Thomas J., and John J. Stevens, "Does Home Market Size Matter for the Pattern of Trade?," *Journal of International Economics*, 65 (2005), 489–505.
Jaravel, Xavier, "The Unequal Gains from Product Innovations: Evidence from the U.S. Retail Sector," *Quarterly Journal of Economics*, 134 (2019), 715–783.
Krugman, Paul R., "Scale Economies, Product Differentiation, and the Pattern of Trade," *American Economic Review*, 70 (1980), 950–959.
———, "Import Protection as Export Promotion: International Competition in the Presence of Oligopoly and Economies of Scale," in *Monopolistic Competition in International Trade*, Henryk Kierzkowski, ed. (Oxford: Oxford University Press, 1984).
Lichtenberg, Frank R., "The Allocation of Publicly Funded Biomedical Research," in *Medical Care Output and Productivity*, David M. Cutler and Ernst R. Berndt, eds. (Chicago: University of Chicago Press, 2001), 565–590.
Linder, Staffan B., *An Essay on Trade and Transformation* (Uppsala: Almqvist and Wiksells, 1961).
Lundback, Erik J., and Johan Torstensson, "Demand, Comparative Advantage and Economic Geography in International Trade: Evidence from the OECD," *Review of World Economics*, 134 (1998), 230–249.
Manski, Charles F., "Identification of Endogenous Social Effects: The Reflection Problem," *Review of Economic Studies*, 60 (1993), 531–542.
Matsuyama, Kiminori, "The Home Market Effect and the Pattern of Trade between Rich and Poor Countries," Mimeo, Northwestern University, 2015.
———, "Geographical Advantage: Home Market Effect in a Multi-Region World," *Research in Economics*, 71 (2017), 740–758.

Ramondo, Natalia, and Andres Rodríguez-Clare, "Trade, Multinational Production, and the Gains from Openness," *Journal of Political Economy*, 121 (2013), 273–322.
Scott Morton, Fiona, and Margaret Kyle, "Markets for Pharmaceutical Products," in *Handbook of Health Economics*, vol. 2, Thomas G. McGuire, Mark V. Pauly, and Pedro P. Barros, eds. (Amsterdam: Elsevier, 2012).
Shea, John, "Do Supply Curves Slope Up?," *Quarterly Journal of Economics*, 108 (1993), 1–32.
Thomas, Lacy Glenn, "Implicit Industrial Policy: The Triumph of Britain and the Failure of France in Global Pharmaceuticals," *Industrial and Corporate Change*, 3 (1994), 451–489.
Trionfetti, Federico, "Using Home-Biased Demand to Test Trade Theories," *Review of World Economics*, 137 (2001), 404–426.
Vernon, Raymond, "International Investment and International Trade in the Product Cycle," *Quarterly Journal of Economics*, 80 (1966), 190–207.
Weder, Rolf, "Comparative Home-Market Advantage: An Empirical Analysis of British and American Exports," *Review of World Economics*, 139 (2003), 220–247.
Zhu, Shiguang, Norihiko Yamano, and Agnès Cimper, "Compilation of Bilateral Trade Database by Industry and End-Use Category," OECD Science, Technology and Industry Working Papers, No. 2011/06, OECD Publishing, Paris, 2011, https://doi.org/10.1787/5k9h6vx2z07f-en.

CALL FOR NOMINATIONS

$300,000 Nemmers Prize in Economics

Northwestern University invites nominations for the Erwin Plein Nemmers Prize in Economics, to be awarded during the 2026–27 academic year. The prize pays the recipient $300,000. Recipients of the Nemmers Prize present lectures, participate in department seminars, and engage with Northwestern faculty and students in other scholarly activities.

Details about the prize and the nomination process can be found at **nemmers.northwestern.edu**. Candidacy for the Nemmers Prize is open to those with careers of outstanding achievement in their disciplines as demonstrated by major contributions to new knowledge or the development of significant new modes of analysis.Individuals of all nationalities and institutional affiliations are eligible except current or recent members of the Northwestern University faculty and past recipients of the Nemmers or Nobel Prize. **Nominations will be accepted until January 14, 2026.**

The Nemmers prizes are made possible by a generous gift to Northwestern University by the late Erwin Esser Nemmers and the late Frederic Esser Nemmers.

Northwestern

Nemmers Prizes • Office of the Provost • Northwestern University • Evanston, Illinois 60208
nemmers.northwestern.edu