CHAPTER 28

NETWORKS IN INTERNATIONAL TRADE

THOMAS CHANEY

This chapter is organized as follows. In Section 28.1, I review theoretical work on the diffusion of information in networks, with a particular application on the geographic expansion of firm level trade. In Section 28.2, I review empirical evidence on the role of ethnic and social networks in international trade. In Section 28.3, I review theoretical and empirical work on production networks and firm to firm trade.

The theoretical models described in Sections 28.1 and 28.3 of this chapter are meant to address mostly macroeconomic questions. As such, those models do not go into great details about the interaction between agents connected through a network. The network itself is complex, but the interactions inside this network are rather simple. Several chapters in this handbook describe much more elaborate models of games and interactions within a network: Daniele Condorelli and Andrea Galeotti analyze models of intermediation within networks; Matt Eliott and Mihai Manea present models of bargaining within networks; and Ana Mauleon and Vincent Vannetelbosch study network formation games.

28.1 Information Networks in Trade

Introducing the notion of networks in international trade poses two main theoretical challenges. The first is conceptual, the second technical.

First, the empirical literature on networks in international trade identifies one key dimension along which networks matter for trade, the transmission of information. Information exchanges are inherently different from the exchange of physical goods: once someone knows something, that person can share this information with whomever they know and are willing to communicate with. So information has a tendency to diffuse along network connections.

Second, networks are inherently complex objects. The description of the properties of the network that connect together, say, importers and exporters from various countries, the characterization of the dynamics of this network, all require new analytical tools. So the second challenge for modeling networks in trade is technical: one has to develop new analytical tools to study those complex objects.

I now describe several theoretical contributions that address both of those challenges: modeling the concept of information, and modeling the complex dynamics of large-scale networks. Along both dimensions, new theoretical insights are gained from the study of networks. Note that while informational frictions do not necessarily imply that networks matter, conversely it is necessary to have a clear idea of what information frictions entail before introducing them into a model of information diffusion within a network.

28.1.1 Information Frictions

Two recent contributions introduce the notion of information frictions explicitly in international trade. Allen (forthcoming) uses a search and matching model to analyze the role of informational frictions in trade, and estimates that model using trade between islands in the Philippines. Dasgupta and Mondria (2014) model explicitly the cost of processing information for individual traders into an otherwise classical Ricardian trade model.[1]

Information frictions are prevalent in economics. They are arguably more severe in the context of international trade, where buyers and sellers are by construction far from each other. They are probably even more severe in developing countries where infrastructures that facilitate the flow of information are less developed. This is the context for Allen's (forthcoming) study of information friction in trade between islands in the Philippines. Allen models explicitly the cost for a potential buyer (exporter) to learn about demand conditions in remote markets (destinations). Formally, Allen models a costly sequential search by heterogenous producers. Heterogenous producers of a homogenous good are located in various islands. Because producers are heterogeneous in terms of productivity, there are potential gains from trade. Because these islands are far from each other, trade is costly. Moreover, because these islands are far from each other, information does not flow freely between them, and information about prices and quantities in other islands is not readily available to potential traders.

[1] The Ricardian trade model is a simple model where trade arises because countries differ in the technologies they have access to. In such a model, and even if one country is more efficient at producing all goods, and even in the presence of trade frictions between countries, trade will happen because of comparative advantages. Dornbusch, Fisher, and Samuelson (1977) extend David Ricardo's classic model to allow for a continuum of goods traded between two countries. Eaton and Kortum (2002) further extend this model to allow for any finite number of countries trading a continuum of goods, using a probabilistic approach to characterize the equilibrium.

Allen documents a series of stylized facts that would be incompatible with a model where only traditional trade costs exist, but that are consistent with a model that features information frictions. First, transportation costs cannot fully account for the negative impact of distance on trade. To the extent that information frictions increase with distance, they can explain the strong negative impact of distance on trade flows. Second, it is frequent two regions both import and export commodities. Again, in the case of the homogenous commodities considered here, a traditional model with only physical trade costs could not explain two-way trade. Information frictions can reconcile those facts with the theory. Moreover, the introduction of cell phones, which arguably lower information search costs, decrease the incidence of two-way trade. Third, the pass-through of price shocks between provinces declines when cell phones are introduced, again giving credence to the information friction channel. Fourth, larger farmers are more likely to "export" their output to other islands, but this size premium declines (small farmers start exporting) when cell phones are introduced. Fifth and last, the more heterogeneous the producers are in an origin island, the more elastic trade flows are to destination island prices. A conventional model with only physical trade frictions would predict the opposite (more heterogeneous producers, less elastic trade flows).

Note while networks do not play an explicit role in Allen's work, the joint presence of physical and informational trade frictions gives rise to two interesting networks: on the one hand, the conventional network of trade linkages between locations (in that case, islands in the Philippines); on the other hand, the information network of which farmer knows about prices in which set of locations. Those two networks, the observable network of trade linkages, and the notional network of information flows interact with each other in a subtle fashion: trade costs and prices affect which farmer learns about which market; this in turn determines the patterns of supply in each market, and hence equilibrium prices; equilibrium prices in turn affect trade flows and the incentives to acquire information.

Dasgupta and Mondria (2014) take the notion of information frictions in a somewhat different direction. Instead of assuming a direct cost for acquiring information, they model the cognitive cost of processing information. One interesting feature of such a model is that the cost of information becomes endogenous, as traders optimally choose how much information to process. Dasgupta and Mondria offer a simple and tractable model of trade with information frictions and rationally inattentive traders (importers in their case). As in Allen (forthcoming), the presence of information frictions allows for two-way trade even in a Ricardian trade model. In their model of rational inattention, Dasgupta and Mondrian can even explain why importers buy the very same good from different sources (and at different prices), as they optimally choose to randomly buy from different sources, not knowing exactly what price they will ultimately pay.

A nice feature of Dasgupta and Mondria is that they explicitly solve for a gravity equation type prediction for bilateral aggregate trade flows. Exports from country i to country j depend (mechanically) on the sizes of i and j, and on an index of the combined information and transportation frictions that are preventing the free flow of goods between countries. This index for the cost of trade has two components. The first one is exogenous, and depends essentially on the physical cost of trading goods between countries. The second component is more interesting: it is the endogenous outcome of the decision of rationally inattentive traders to acquire information or not. The presence of this second component generates subtle and nonstandard predictions.

First, in the presence of information frictions and rationally inattentive traders, the impact of changes in physical trade costs on trade flows is magnified: a small reduction in bilateral (physical) trade costs induces traders to optimally reallocate their attention. They will typically do so by paying more attention to markets where they are ex ante more likely to find profitable trading opportunities. If the cost of trading with one country decreases (keeping other costs constant), the likelihood of finding profitable trades with that country increase, and traders will optimally reallocate part of their (limited and hence costly) attention towards that country. Doing so, they de facto reduce the *informational* cost of trading with that country, and trade more with that country. The elasticity of trade with respect to physical trade costs is magnified.

Second, in the presence of information frictions, a reduction in the cost of processing information may have a non-monotone impact on trade flows with some countries. This is due to the endogenous decision of inattentive traders to allocate between different markets. When the cost of information increases, traders search for information less aggressively. There is an overall negative impact of information costs on the overall amount of information collected. But in addition to this global effect, there is a more subtle reallocation effect. Not only do traders reduce the overall amount of information they process, but they will also tend to allocate disproportionately more of their limited attention towards a priori more profitable markets. If this composition effect is strong enough, an increase of information processing costs may cause an *increase* in the amount of trade from some nearby countries, at the detriment of more remote countries. This result very much has a network flavor, where a shock in one part of the network has a very heterogeneous impact on other parts of the network.

Finally, Dasgupta and Mondria's model can easily explain the presence of zeros in bilateral trade matrices, the fact that many country pairs do not trade at all. When information processing costs become high, the expected gain from trade may not be able to compensate traders for the cost of processing information. As a consequence, for high information costs, traders endogenously decide not to trade (potentially not to trade with any foreign countries), even though they are fully aware that profitable trading opportunities exist.

A key takeaway from these models is that information frictions matter for trade. A direct corollary not explored in those papers is that due to the specific nature of information (once acquired, transmitting information is very cheap), information will tend to percolate along individual connections. In other words, the network of potential importers and exporters will evolve dynamically.

28.1.2 Information Diffusion in a Network of Traders

I now turn to the description of papers that explicitly take into account the network dimension of informational linkages, Chaney (2013) and Chaney (2014). If information is costly to acquire, then traders will optimally choose to have information only about a small number of trading partners. Subsequently, information will tend to diffuse among connected traders. The web of contacts that connect individual traders to each other can be described as a network. To understand the patterns of trade that emanate from the sharing of information among connected traders, one must describe how information diffuses along these connections between traders, as well as how this network endogenously evolves over time.

The diffusion of information about foreign trading partners shares many features of the propagation of financial crises, or financial contagion, described by Antonio Cabrales, Douglas Gale, and Petro Gottardi in this handbook.

In the case of international trade, one key information traders want to acquire is "*where* are potential trading partners located?". "Where" in international trade typically refers to which country those potential trading partners are located in, or even which city within a country. I present below a simple model of traders (exporting firms) gradually acquiring trading partners (customers) in various remote locations. But a priori, this "where" could represent their location in other spaces, such as a space of attributes, a space of cultural/linguistic/ethnic proximity, a space of prices. The technical tools I propose below can be used to model dimensions other than the geography of trade.

I now present a simple model of a dynamic network of importers and exporters. This model combines together elements of the models in Chaney (2013) and Chaney (2014). For simplicity, an individual exporter only sells to importers it knows. The question I seek to answer with the model is: "where are the firms an exporter sells to located?" I assume that the exporter gets to know importers in two ways: it can either search for importers at random (random search); alternatively, that exporter can meet the contacts of its existing contacts (remote search). Information about new trading partners percolates along existing connections. This model resembles the dynamic social network model in Jackson and Rogers (2008), where individuals meet new friends either at random, or via friends of friends. A key difference is that I characterize not only how many trading partners a firm has, but also where those trading partners are. Bramoulle, Currarini, Jackson, Pin, and Rogers (2012) propose an extension of Jackson and Rogers (2008) where they allow for agents of different types. Those types would correspond to what I call geographic location in my model. The model I propose shares many features of Bramoulle et al. (2012), but extends to as many as a continuum of types (geographic locations in the trade application), and offers further characterization of the aggregate properties of this dynamic network.

Consider a simplified setup with a continuum of locations along the real line, indexed by $x \in \mathbb{R}$. In each location, there is a continuum of firms. Time is continuous. When a firm is born, it randomly connects with a measure K of contacts, located in various locations of the real line. Consider a firm born at time $t=0$ in the origin location $x=0$. As the model is symmetric, this is without loss of generality. When the firm is born, the density of firms it is connected to located at coordinate x is given by $f(x)$, where f is symmetric, integrable, has a finite second moment, but is otherwise an arbitrary function that sums to K. After it is born, the firm meets new contacts through two channels. First, with a Poisson arrival rate ρ, it meets firms at random, according to the same density f: over a short time interval dt, it meets ρdtK firms overall, and $\rho dtf(x)\,dx$ firms in a neighborhood dx of location x. Second, with Poisson arrival rate β, any of the existing contacts of the firm reveals one of their own contacts.

Let us call f_t the function that describes the location of the firm's contacts at age t, so that at age t, the firm is in contact with $\int_a^b f_t(x)\,dx$ in an interval $\left[a,b\right]$; and $K_t = \int_{\mathbb{R}} f_t(x)\,dx$ the total measure of the firm's contacts at age t. The total measure/number of a firm's contacts evolves recursively according to the simple Ordinary Difference Equation,

$$\frac{\partial K_t}{\partial t} = \rho K + \beta K_t \tag{28.1}$$

with initial condition $K_0 = K$. This ODE admits a simple solution. The location of the firm's contacts (i.e., the function f_t) evolves recursively according to the more complex Partial Differential Equation,

$$\frac{\partial f_t(x)}{\partial t} = \rho f(x) + \beta \int_{\mathbb{R}} \frac{f_t\left(x-y\right)}{K_t} f_t\left(y\right) dy \tag{28.2}$$

with initial condition $f_t = f$. The first term on the right corresponds to random searches: with a Poisson arrival rate ρ, new contacts are formed in locations given by the exogenous density f. The second term corresponds to meeting the contacts of a firm's contacts: with Poisson arrival rate β, any contact in any potential location y (there are $f_t\left(y\right)$ of them in each $y \in \mathbb{R}$) reveals the name of one of her contacts, which happens to be in location x with a (density of) probability $f_t\left(x-y\right)/K_t$.

While the ODE (28.1) governing the dynamics of the number (measure) of contacts is simple, the PDE (28.2) governing the dynamics of the location of those contacts is more complex. How many contact a firm gains in any single location x depends on how many firms it knows in each and every locations in the world (i.e., on the entire function f_t). In mathematical terms, the complexity appears in equation (28.2) through the integral term, where the function $f_t\left(y\right)$ multiplied by $f_t\left(x-y\right)$ is integrated over all $y \in \mathbb{R}$: the entire function f_t becomes a state variable for the recursive evolution of $f_t(x)$ evaluated at any x.

This complexity is inherent to the network structure of the model. It would be present generically in any network model where information percolates along existing connections. In other word, any model which features connections between friends of friends will naturally display this kind of complexity: to know what information an agent acquires from one period to the next, one needs to know each contact this agent already has, as information can potentially percolate via any existing connection.

Fortunately, a simple mathematical tool allows to transform this seemingly complex problem, the partial differential equation (28.2), into a much simpler problem, and use instead a more tractable ordinary differential equation. The first trick is to recognize in the integral in equation (28.2) a convolution product.[2] Using $*$ for the convolution product, the recursive equation (28.2) can be written in a compact form as

$$\frac{\partial f_t}{\partial t} = \rho f + \beta \frac{f_t * f_t}{K_t} \tag{28.3}$$

The convolution product $*$ is per se just a notation, so equations (28.2) and (28.3) are one and the same. However, once a convolution product has been recognized, one can use its many useful properties. Among them, the convolution theorem is particularly useful. This theorem says that the Fourier transform of the convolution of two functions is the simple product of their respective Fourier transforms point-wise.[3] In other words, the Fourier transform replaces the rather intractable convolution product of functions into a much more conventional multiplication of numbers. So the second trick is to take a Fourier transform of the entire partial differential equation (28.3) to transform it into the following much simpler ordinary differential equation where I denote by $\hat{f}$ the Fourier transform of f,

$$\frac{\partial \hat{f}_t(s)}{\partial t} = \rho \hat{f}(s) + \beta \frac{\hat{f}_t^2(s)}{K_t}. \tag{28.4}$$

Plugging the solution to the ODE for the number of contacts K_t, this simple ODE for the Fourier transform of the entire distribution of contact $\hat{f}_t$ can easily be solved for any s independently. Instead of solving for the entire functions f_t's all at once, one instead solves for their Fourier transform point by point, a much simpler problem. Of course, one has to check ex post that for any t, the solution for $\hat{f}_t$ is continuous in s, at least in a neighborhood of zero. This is the case for the above recursive equation.

[2] The convolution product of two functions f and g is defined as,

$$(f * g)(x) = \int_{\mathbb{R}} f(y)\, g(x-y)\, dy$$

[3] The Fourier transform of a function f, denoted $\hat{f}$ by convention, is defined as,

$$\hat{f}(s) = \int_{\mathbb{R}} e^{-isx} f(x)\, dx$$

The convolution theorem simply says,

$$\widehat{f * g}(s) = \hat{f}(s) \times \hat{g}(s)$$

Once the Fourier transform $\hat{f}_t$ is known, it is possible to recover the underlying geographic distribution of contacts f_t.[4] But the beauty of the Fourier transform $\hat{f}_t$ is that it can directly be used to compute any moments of the function f_t, without having to ever recover the function f_t directly. This is because the Fourier transform is intimately related to the characteristic function.[5] For instance, if one is interested in knowing how far on average a firm of age t exports its output, one simply evaluates the second derivative of $\hat{f}_t$ at zero,

$$\hat{f}_t"(0) = \int_{\mathbb{R}} |x-0|^2 f_t(x)\, dx,$$

which gives the average squared distance of exports. If one is interested in how much geographic dispersion there is in the exports of a firm of age t, one simply evaluates the fourth derivative of $\hat{f}_t$ at zero, and so on.

This mathematical method (the use of convolution products, of Fourier transforms to manipulate them, and derivatives of those transforms) has four main advantages.

First, it is fairly tractable. As long as a problem of information diffusion within a network can be modeled in such a way that some attributes (here geography) get added up, one can use those methods and derive very general results. Here, the additive part comes from the natural Euclidean metric of geographic space: if I am standing in location x and I want to meet someone in location z via one of my existing contacts in location y, I first need to "go" from x to y (acquire information about someone in y from x); this is represented by the vector $\overrightarrow{y-x}$; I then need my contact in y to have "gone" to z; this is represented by the vector $\overrightarrow{z-y}$; "going" from x to z via y is then represented by the vector $\overrightarrow{z-x} = \overrightarrow{y-x} + \overrightarrow{z-y}$; naturally in a Euclidian space, information diffusion is associated with adding up vectors, and Fourier transforms are then natural mathematical tools to analyze such a model.

Second, calculating moments in the data is straightforward, and the statistical properties of estimated moments are well understood. So the connection between the theory and the data can be made very tight.

[4] The inverse Fourier transform allows to recover the underlying function f from its Fourier transform $\hat{f}$,

$$f(x) = \frac{1}{2\pi} \int_{\mathbb{R}} e^{ixs} \hat{f}(s)\, ds.$$

[5] For a probability function, the Fourier transform and the characteristic functions are almost the same. If X is a random variable with p.d.f. f, the characteristic function φ_X is given by

$$\varphi_X(s) = \mathbb{E}\left[e^{isX}\right] = \int_{\mathbb{R}} e^{isx} f(x)\, dx = \hat{f}(-s).$$

The various moments of a random variable X with p.d.f. f can be calculated with the Fourier transform as easily as with the characteristic function, evaluating their successive derivatives at zero,

$$\mathbb{E}\left[X^k\right] = (-i)^k \varphi_X^{(k)}(0) = i^k \hat{f}^{(k)}(0).$$

Third, by allowing to solve for moments separately from each other, this mathematical method also allows to make sharp theoretical predictions without the need for very strong functional form assumptions. For instance, in the case of the model of international trade above, if one is interested primarily in the distance of exports of different types of firms, there is no need to characterize the exogenous function f beyond its first moment. In other words, one can simply make the reduced form assumption that firms, when they randomly look for foreign trading partners, meet partners at some average squared distance. There is no need to make any further assumption about the technology for this random search. Characterizing (and estimating) a single moment of this search technology is enough to generate rich prediction on firm-level trade.

Fourth, there exist various mathematical tools to study the limiting behavior of the Fourier transforms of functions, which I will not describe in detail in this chapter. There is a readily available mathematical toolkit for analyzing many other properties of any model of information diffusion within a network that resembles the one above. For example, Chaney (2013) uses such asymptotic tools to characterize the patterns of aggregate trade. Aggregate trade is calculated by adding up firm-level trade for a large number of firms. Using asymptotic results to solve for these large sums, Chaney (2013) shows the above model naturally predicts under weak conditions aggregate bilateral trade flows are inversely proportional to distance and proportional to county size, the so called gravity equation in international trade.

One should also note that as with any stylized model, mathematical elegance comes at the cost of strong simplifying assumptions. For instance, the tools described above are inappropriate when the model is not symmetric: in equation (28.2), if firms in location y have a different distribution of their own contacts than a firm located at the origin—in other words, if $f_{t,y}(x) \neq f_{t,0}\left(x-y\right)$ where $f_{t,y}$ is the distribution of contacts at time t for firms located in y and $f_{t,0}$ that for firms located at the origin—then the integral in equation (28.2) can no longer be treated as a convolution product, and most of the analytical tractability is lost. Numerical simulations can be useful in such cases to explore how differently the simplified (symmetric) model behaves compared to a more complex and analytically intractable asymmetric model. Chaney (2014) uses such numerical explorations to assess the robustness of a simplified model to relaxing some of the strong simplifying assumptions. Of course, numerical simulations offer only a partial and informal assessment of the robustness of this type of model, but they remain a useful complement to the formal study of simplified models.

It should be noted to conclude this section that similar mathematical tools, convolution products, and Fourier transforms to manipulate them have been used in other contexts to study similar problems of information diffusion. In particular, several works by Darrell Duffie and Gustavo Manso with various coauthors study problems of information percolation within financial markets. Since the questions asked are similar (how does information percolate within a network of traders?), it should not be surprising the same analytical tools are used.

Duffie and Manso (2007) study information percolation in a decentralized market with a large number of traders. Using the same tools, convolution products and Fourier transforms, they provide explicit analytical solutions at each point in time for the distribution of posteriors regarding some underlying asset value among market participants with diffused information that randomly meet each other.

Duffie, Malamud, and Manso (2009) study a similar setup and provide welfare analysis for various types of policy intervention: a subsidy to search costs (potentially welfare enhancing), or the provision of public signals (potentially welfare reducing).

Duffie, Giroux, and Manso (2010) characterize the speed of convergence towards a common posterior in a decentralized market where information percolates through random meetings, and provide an explicit formula for this speed of convergence.

Finally, Duffie, Malamud, and Manso (2015) study the dynamics of auctions taking place in over-the-counter markets. Over-the counter-markets differ from centralized markets in that trades occur between connected traders. This is therefore a natural network environment, where information about some underlying traded asset will gradually percolate as agents engage in bilateral trades and learn from each other. In this paper, unlike in the earlier ones, Duffie, Malamud, and Manso (2014) explicitly allow for a more interesting network structure: they consider cases where some agents are more connected than others; they even allow for traders to endogenously seek to trade with better connected agents.

All those papers use the same analytical tools as the one described in this section: convolution products (to describe the evolution over time of some attribute, in their case information about some underlying relevant payoff), and Fourier transforms to manipulate those convolution products and derive analytical solutions. In any setup where information diffuses gradually within a network of connected agents, such mathematical tools are natural candidates for deriving elegant and relatively simple solutions and characterizations of various equilibrium outcomes. I believe those tools are fairly easy to use, and can profitably be applied to a range of economic environments where networks play a central role.

28.2 Ethnic Networks and the Patterns of International Trade

In a seminal paper, Rauch and Trindade (2002) show that the presence of ethnic Chinese networks facilitates trade between countries, particularly so for differentiated goods. While this paper is not the first to look at the impact of migrant networks on international trade, the magnitude of the effects, as well as the relative precision with which the authors are able to quantify the ethnic proximity between two countries, explain why this paper has had a large and lasting impact on the study of networks in international trade. Even though the paper does not claim to address potential issues of endogeneity or reverse causality, it stands as a de facto benchmark in the study of the impact of social networks on international trade flows.

In this section, I review several empirical papers that have documented the quantitative impact of social networks on the patterns of international trade. Most of those use ethnic migrants to proxy for the presence of social ties. Few explicitly address concerns of endogeneity. After a brief description of the theoretical motivation behind those empirical studies, I describe in more details their empirical procedure and main findings.

There are two main reasons why social networks may affect the patterns of international trade: informal trade barriers and contract enforcement.

Impediments to trade take many forms, few of which are easy to measure. While transportation costs, explicit tariffs, or quotas are simple to quantify, and their impact on the cost of international transactions well understood, many other trade frictions hinder the flows of goods and services between countries. One indication informal barriers exist over and beyond traditional barriers to trade such as transportation costs, tariffs, and quotas is the fact that geographic distance has a strong negative impact on bilateral flows between countries, even after controlling for any measurable barrier to trade.

The first main category of informal trade barriers has to do with informational frictions: information about foreign products may be hard to acquire; the tastes of foreign consumers may differ significantly from domestic ones; in the case of trade in highly differentiated and customized intermediates, the precise instructions for customizing inputs according to an importer's specific needs may be hard to communicate. I collect all those informal trade frictions under the label of informational barriers.

The second main category of informal trade barriers has to do with contract enforcement. The inability of buyers and sellers to fully commit to pre-established contracts ex ante, and the inability of the justice system to perfectly enforce existing contracts ex post is not unique to international trade. However, it is arguably more salient for international trade than for domestic trade: differences in legal systems between countries, ambiguity of the extent of the jurisdiction of the national court system, and the mere distance between trading partners all contribute to making contract enforcement even harder for international than domestic trade. Greif (1989, 1993) shows that ethnic networks can mitigate the negative impact of incomplete contracts, by providing a punishment mechanism for traders that default on their promises.

For both categories the presence of migrant networks tends to mitigate informal trade frictions and facilitate trade. Migrant networks have the added advantage for the researcher of being relatively easy to identify, while other types of social networks are harder to quantify.

Kaivan Munshi in this handbook further describes community networks and migrations.

28.2.1 Ethnic Chinese Networks

Rauch and Trindade (2002) offer a reduced form test of the hypothesis that ethnic networks facilitate trade. They focus their attention on ethnic Chinese networks for three reasons. First, ethnically Chinese names are relatively easy to identify, and to distinguish from the names of other ethnic groups. Second, and more importantly, ethnic Chinese represent a large population, having penetrated countries all over the world. Third, Chinese emigration is both relatively recent, so that ties between ethnic Chinese may remain relatively strong, and not too recent, so that the determinants of ethnic Chinese migrations can plausibly be assumed to be independent of the contemporaneous barriers to international trade (even though Rauch and Trindade do not offer any direct test of that hypothesis).

Because of the size of ethnic Chinese networks, Rauch and Trindade do not only focus on trade to and from China, but also between third countries with varying ethnic Chinese populations. Their empirical strategy is straightforward: they estimate a conventional gravity equation[6] (the volume of bilateral trade between two countries is explained by their respective sizes, measured as GDP, and the bilateral distance between them), using as an additional control the product of the share of the population that is ethnic Chinese in the importing and exporting countries. In order to distinguish between the impact of ethnic Chinese networks on contract enforcement and reducing informational barriers, they estimate their model separately for trade in different industries. They use Rauch's classification (1999) of industries in three categories: commodities traded on organized markets, commodities with a reference price, and differentiated commodities. They argue that while contract enforcement via ethnic Chinese networks ought to be similar across all commodity types, informational barriers are likely to be mostly prevalent for differentiated commodities. Formally, they estimate via maximum likelihood the following equation separately for each commodity category,

$$V_{ijk} = controls_{ijk} \times \exp\left(\cdots + \psi_k CHINSHARE_{ij} + u_{ijk}\right)$$

where V_{ijk} is the volume of trade (imports plus exports) of type k commodities between countries i and j, and $CHINSHARE_{ij}$ is the product of the share of the population that is

[6] The gravity equation in international trade corresponds to the empirical regularity, first uncovered by Jan Tinbergen (1962), that relates the volume of bilateral trade $X_{A,B}$ between two countries A and B to their respective sizes, measured as GDP_A and GDP_B, and the bilateral distance between them $Distance_{A,B}$, according to a log-linear relationship:

$$X_{A,B} = constant \times \frac{GDP_A^{\alpha} GDP_B^{\beta}}{Distance_{A,B}^{\delta}}$$

Most estimates for the elasticities α, β and δ are close to 1. Since the early work of Tinbergen, empirical trade researchers have added a series of additional explanatory variables, such as tariffs, the existence of a trade agreement, the volatility of the exchange rate, colonial linkages etc. The measure of ethnic proximity used by Rauch and Trindade (2002) is one more example.

ethnic Chinese in i and j. This simple product of shares can be interpreted as a measure of the probability that if one selects at random an individual in each country, both will be ethnic Chinese.

Rauch and Trindade present three main results of interest. First, the presence of ethnic Chinese networks facilitates trade, raising trade by as much as 60% when one compares country pairs with Chinese networks as large as those prevailing in Southeast Asia to a counterfactual world without those networks. Second, ethnic Chinese networks facilitate trade significantly more for differentiated goods than for goods traded on organized exchanges. Rauch and Trindade interpret this difference as suggesting that ethnic Chinese networks not only improve contract enforcement (they do so for all categories of goods), but also serve as a conduit for information flows (which matter disproportionately more for differentiated goods). Third, Rauch and Trindade find that the trade enhancing effect of ethnic Chinese networks exhibits decreasing returns to scale: the marginal effect on trade of increasing the likelihood that two individuals are ethnic Chinese decreases with the size of the ethnic Chinese population.

While this paper does not attempt to deal with potential endogeneity or reverse causality issues (the same unobserved variables that facilitate trade between i and j may also encourage migrations of ethnic Chinese to those countries), it stands as a seminal contribution in the study of informal trade barriers, and in particular on how to use data on migrants to proxy for those informal barriers. I now turn to a series of papers that have used essentially the same idea to assess the impact of informal barriers on trade and investment flows both between and within countries.

28.2.2 Migrant Networks and Trade within Countries

While international migrants can act as facilitators of international trade, international migrations are far less frequent than migrations within countries. And while trade within countries is arguably subject to fewer frictions than international trade, within country trade frictions do exist as well: the negative impact of geographic distance, for instance, is about equally strong between as within countries (see the evidence starting with McCallum 1995). Interestingly, census data provides detailed information about the internal migrations within countries at least once a decade.

Combes, Lafourcade, and Mayer (2005) explore the hypothesis that networks may facilitate trade in their study of trade between regions within France. They offer two quantitative measures of the network of contacts that connects regions. The first one is similar to Rauch and Trindade's ethnic Chinese network: it is a measure of the number of people currently working in region j that were born in region i. The second one is a measure of the network of business linkages between regions, and it is formally close to the definition of ethnic Chinese networks in Rauch and Trindade. For each business group that owns plants in both regions i and j, Combes et al. take the product of the number of plants in i and in j, and then add up this product for all business groups with plants in i and j. Using an analogy to Rauch and Trindade's measure of ethnic Chinese networks, it is as if each business group represented a separate "ethnic" network, and Combes et al. simply add up all possible networks. This second measure is meant to capture the flow of information that transits within the boundaries of firms, but across geographic space, as well as the flows of workers between firms. Both measures of social and business linkages are expected to have a positive impact on trade flows.[7]

Combes et al. estimate again a simple gravity equation for bilateral trade flows between French regions, adding as control their measures of social and business networks. They use a somewhat more elaborate, or rather more theoretically founded, econometric procedure than Rauch and Trindade, either including importer and exporter fixed effects, or using ratios of trade flows to control for unobserved price effects.

Their main finding is in line with Rauch and Trindade. For two regions with a degree of either social or business connections equal to the average among French region pairs, migrants networks increase bilateral trade between 70% and 100% compared to a counterfactual world without migrant networks, and business networks increase trade by about 300% compared to a counterfactual world without business networks. Part of the reason why business networks have such a large impact is that, at least within France, the number of multi-plant firms and business groups is large. In other words, a counterfactual world with business networks is one where a very large fraction of business linkages would be severed.

Combes et al. perform an interesting decomposition of the impact of social and business networks on the traditional proxies for trade frictions. They find that accounting for this measure of informal trade barriers, proxied by social and business networks, reduces the estimated impact of all traditional measures of trade frictions: the estimated border effect (a measure of how much more trade happens within than between regions) is reduced by about 50%, the estimated negative effect of transportation costs (proxied by geographic distance) is reduced by about 60%, and the estimated positive effect of contiguity is reduced by about 20%. The estimated contiguity effect is also reduced, with all the reduction accounted for by social networks and not by business networks. This is mostly due to the fact that migrations typically occur over much shorter distances than business connections.

As is the case with the work of Rauch and Trindade, the interpretation of those numbers is subject to potential endogeneity issues. Combes et al. offer one attempt to deal with the problem of endogeneity or reverse causality: they instrument the stock of migrants in 1993 by the stock of migrants in 1978. This instrumentation strategy leaves the main results unchanged, or even slightly stronger.

[7] Note that contrary to Rauch and Trindade, Combes et al. do not directly control for the impact of size when building their proxies for the prevalence of social and business networks, as they use simple counts (of migrants or plants) instead of shares. They use a log specification which alleviates this concern partially. But instead of using $\ln\left(Migrants_{ij}\right)$ to measure migrants networks, they use the nonhomogenous function $\ln\left(1 + Migrants_{ij}\right)$. The use of $\ln(1 + \cdot)$ allows to deal with zeros, but it introduces a nonhomogeneity that makes the results unit dependent.

28.2.3 The Causal Impact of Migrant Networks on Trade

I now turn to several papers that deal with endogeneity concerns more forcefully. Migrations (as well as ownership of plants) is most often an endogenous decision. The same forces that determine the decision to migrate may also have a direct impact on trade flows. Several recent contributions offer solutions to this endogeneity problem.

Perhaps the most convincing evidence so far that social networks have a causal impact on economic outcome in general, and on trade in particular, is Burchardi and Hassan (2013). The authors show social ties that existed between East and West Germany pre-1989 can explain the unevenly distributed impacts of the German reunification on West German towns. West German towns where a large fraction of the population had lived in East Germany and kept social ties with the East benefited disproportionately from the German reunification, in the sense that income per capita rose relative to other towns following the fall of the Berlin wall. Part of income gains can be directly explained by increased entrepreneurial activity and increased investment of West German firms into East Germany.

Burchardi and Hassan address the two most salient issues of endogeneity related to the impact of social networks on economic outcome. First, social links can be formed among others for economic reasons: I become friends with Mr. X because I expect to do business with Mr. X in the future. Second, social links can be denser in some regions for the same reasons that trade towards those regions is large. To establish causal impact of social networks on economic outcomes, one must find social links that are not formed because of expected economic benefits, and plausibly exogenous variations over space of the density of the social network. Using the specificities of German post–World War II history, Burchardi and Hassan address both. First, they identify social ties between East and West Germany; until about the last minute, it was not expected that the Berlin wall would fall. People in the West who kept social links with the East did not expect any economic benefits from ties. Second, Burchardi and Hassan cleverly use the tumultuous history of Germany during World War II to identify plausibly exogenous variations in migrations from East to West. In particular, when a large number of ethnic German refugees and expellees arrived from Eastern Europe at the end of World War II, large swaths of Germany had been destroyed during battles, so that they had no choice but to temporarily relocate to the eastern parts of Germany. Those refugees and expellees formed social connections in the places where they settled. Many of those refugees eventually kept moving west, ultimately settling down in places that would become part of West Germany. To identify exogenous variations in the migrants that moved from East Germany to West Germany before the construction of the Berlin wall and the iron curtain (between 1945 and 1961), Burchardi and Hassan use as an instrument the bombing campaign of the Western Allies, and the uneven destruction of the housing stock in the western part of Germany that resulted from these bombing campaigns.

Having identified plausibly exogenous variations in the intensity of network connections between East and West Germany, Burchardi and Hassan assess the impact of those (exogenous) social connections on growth and investment post-reunification: following the German reunification, East Germans had access to relevant information about local demand conditions and the quality of the local productive assets, but no access to finance; West Germans on the other hand had the capacity to invest into the East, but a priori no good information about where valuable investment opportunities were. Those West Germans with social ties to East Germany were in a privileged situation to fully take advantage of the opportunities offered by investing in the East.

The quantitative effect of those social ties on macro-economic outcomes is sizable. A one standard deviation increase in the share of East German expellees settling in a West German region is associated with a 4.6% rise in income per capita in the years immediately after the fall of the Berlin wall (1989–1995), or a 0.7 percentage point higher growth. A one standard deviation increase in the share of East German expellees was also associated with a 3.4% increase in the likelihood that firms from that West German region would acquire a subsidiary in East Germany. This effect on investment persists at least until 2007. Finally, at the household level, the income of households with at least one relative in the East rises 4.9% in the years immediately after the fall of the Berlin wall (1989–1995). Overall, Burchardi and Hassan find a substantial *causal* impact of social networks on aggregate economic outcomes.

Several other papers have documented a *causal* impact of social networks on aggregate economic outcomes, and on the patterns of international trade in particular. Two papers in particular use innovative instrumental variable strategies to tease out this causal impact. Both Cohen, Gurun, and Malloy (2014) and Burchardi, Chaney, and Hassan (2014) evaluate the causal impact of migrants networks on U.S. trade and investment. Both papers study how the composition of ethnic migrants in different locations within the United States affect the pattern of trade of U.S. states (Burchardi et al. 2015), and the patterns of foreign investment of U.S. firms (Cohen et al. 2014 and Burchardi et al. 2015). To the extent that those papers look at trade and investment originating from the same country, the United States, some of the concerns of reverse causality are mitigated: the regulatory environment, most direct barriers to trade and investment, as well as the ease with which migrants from different countries can emigrate are all relatively uniform. Those two papers therefore isolate one single channel, the presence of ethnic migrant networks locally and the social network connection they bring with them, on the patterns of trade and investment.

Cohen et al. (2014) use the forced relocation of Japanese immigrants and Japanese Americans into internment camps during World War II to identify arguably exogenous variations in the local ethnic composition. They then assess the impact of those exogenous variations in the ethnic composition on the export performance of local U.S. firms. They find the local ethnic network affects the likelihood that a firm exports; firms that exploit this local network outperform other importers and exporters, they grow faster, and their (risk-adjusted) stock returns are 5–7% higher than other firms.

Burchardi, Chaney, and Hassan (2014) instead use the history of subsequent waves of migrants into the United States for over 150 years to instrument the current ethnic composition of U.S. states. They use decennial censuses to identify both the existing composition of migrants in different U.S. states at different times, and the arrival of new migrants from abroad. Under the assumption that new migrants from a given ethnic group are more likely to settle down in U.S. counties where there already exists a significant community from the same ethnic group, they predict for each decade the local ethnic composition using only past migrations. Doing so recursively from 1860 onward, they predict the local ethnic composition in 1990 taking as exogenous only the initial ethnic composition in 1860 and the size of inflows into the United States as a whole (not in any state in particular). Again, they find that the local composition of ethnic networks within the United States have a *causal* impact on the patterns of international trade of U.S. states, as well as the patterns of foreign investment of individual U.S. firms. This instrumentation strategy is data intensive, as it requires collecting data on migrations going back at least several decades, or even centuries. It is, however, very general and easy to replicate. As such, it differs from other instrumentation strategies that rely on specific historical accidents unlikely to be repeated.

Both papers isolate a *causal* impact of social networks (here proxied by ethnic networks) on the patterns of international trade and investment of the United States. These empirical contributions shed new light on the nature of some of the informal barriers to trade. They open up new questions on the role of various nonconventional policy instruments in reaping the gains from international trade and investment. By offering new empirical facts, they also open up new avenues for theoretical research on the dynamics of international trade and investment, international migrations, and the role of information frictions and contract enforcement. In the next section, I review recent theoretical advances in networks and international trade.

28.3 Production Networks and Firm-to-Firm Trade

I conclude this chapter with a description of recent work in macroeconomics and international trade on the role of production networks and firm-to-firm trade. Modern economies are characterized by complex production processes. Firms combine inputs with capital and labor to produce output; their output is often used as input by more downstream firms. Most firms have only a relatively small number of upstream suppliers and downstream customers, so that most of these firm-to-firm interactions are local in the sense they take place among a small number of firms. In other words, production is achieved by combining gradually more elaborate intermediate inputs along vertical production chains. Those chains form a complex network of input-output linkages. Understanding the aggregate properties of this web of input-output linkages requires a careful network analysis.

28.3.1 Theoretical Models of Production Networks

To gain intuition on the complexity of production processes with input-output linkages, consider the following simplified set-up, taken from Chaney (2013). Intermediates producers combine input from upstream suppliers with equipped labor, and sell their output to downstream customers. Formally, intermediate producer i combines equipped labor L_i with intermediates $q_{k\to i}$ ($q_{k\to i}$ stands for the sales from k to i) from a continuum of suppliers $k \in \mathcal{S}_i$ and sells its output to a continuum of customers $j \in \mathcal{C}_i$ using a constant returns to scale technology approximated by the following nested Cobb-Douglas-CES production function,

$$Q_i = \frac{1}{\alpha^\alpha (1-\alpha)^{1-\alpha}} \left(\int_{k\in\mathcal{S}_i} q_{k\to i}{}^{\frac{\sigma-1}{\sigma}} dk \right)^{\alpha \frac{\sigma}{\sigma-1}} L_i^{1-\alpha}. \tag{28.5}$$

Firms face the same iso-elastic demand from any customer $j \in \mathcal{C}_i$, $p_{i\to j} q_{i\to j} = \frac{p_{i\to j}{}^{1-\sigma}}{\int_{k\in\mathcal{S}_j} p_{k\to j}{}^{1-\sigma} dk} X_j$ with $p_{i\to j}$ the price charged by i to customer j, $q_{i\to j}$ the units sold by i to j, and X_j the total spending on intermediates by j. Given these iso-elastic demands, firm i charges all its customers the same constant mark-up, $\frac{\sigma}{\sigma-1}$, over its marginal cost,

$$p_{i\to j} = p_i = \frac{\sigma}{\sigma-1} w^{1-\alpha} \left(\int_{k\in\mathcal{S}_i} p_k{}^{1-\sigma} dk \right)^{\frac{\alpha}{1-\sigma}} \tag{28.6}$$

with w the competitive wage rate.

Equation (28.6) sheds light on the complex interactions between firms in a network of input-output linkages. The price firm i charges to any of its clients (p_i) depends on both the prices it pays to its suppliers (the p_k's) and the diversity of its suppliers (the set $\mathcal{S}_i$). With iso-elastic demand, prices are simply proportional to a firm's productivity. So from equation (28.6), a firm with either more efficient suppliers (lower p_k's) or with a more diverse set of suppliers (a larger measure for $\mathcal{S}_i$) will have a lower marginal cost of production. The productivity of each of firm i's suppliers in turn depends on the efficiency of their suppliers, so that the structure of the entire upstream production chain matters for firm i's efficiency.

Generically, given that the price set by any firm depends on the prices set by other firms, finding an equilibrium set of prices requires to jointly solve for all prices, taking as given the network of input-output linkages given by all the sets of suppliers and customers, the $\mathcal{C}_i$'s and $\mathcal{S}_i$'s. Generically, solving for prices in a complex network is hard. One should note that the expression $\int_{k\in\mathcal{S}_i} p_k{}^{1-\sigma} dk$ in equation (28.6) corresponds to the $(\sigma-1)^{th}$ moment of the prices of firm i's suppliers. Using the same analytical tools as those described in the previous section, Fourier transforms and the related moment generating function allow some insights into the solution to this problem. It is possible, however, to further simplify the problem to derive explicit solutions.

Chaney (2013) assumes the input-output network can partitioned in such a way that a given firm only competes with similar firms. Under this symmetry assumption, he solves explicitly for the equilibrium of this model, and further endogenizes the entire network of input-output linkages by explicitly modeling the choice of individual producers to seek suppliers and customers.

Oberfield (2013) goes a different route and assumes inputs are perfectly substitutable ($\sigma \to \infty$), so that in equilibrium, a firm only sources inputs from a unique supplier. He further allows firms to differ in their individual Total Factor Productivity, adding a firm-specific multiplicative term z_i to the production function in equation (28.5): $Q_i = \frac{1}{\alpha^{\alpha}(1-\alpha)^{1-\alpha}} z_i \left(\int_{k \in \mathcal{S}_i} q_{k \to i}^{\frac{\sigma-1}{\sigma}} dk \right)^{\alpha \frac{\sigma}{\sigma-1}} L_i^{1-\alpha}$. Under those two assumptions, Oberfield proposes an elegant fixed point solution concept for the endogenous structure of the network of input-output linkages. This network emerges semi-endogenously: Oberfield assumes that firms can *potentially* trade with an exogenously given set of firms (buy inputs from, sell their output to); among that exogenously given set, they decide endogenously to *actually* trade with only one of them. In other words, the actual flow of inputs along vertical production chains comes both from the exogenous distribution of potential network connections between suppliers and customers, and from the endogenous choice of each firm to pick only the best among its potential suppliers. Formally, the techniques used by Oberfield are related to the techniques used for the study of information percolation in the previous section. The one difference is instead of characterizing the behavior of the sums of random variables, Oberfield characterizes the maximum of random variables.

On this last note, I want to briefly comment on a series of recent work in macroeconomics that study the diffusion of knowledge, or of technologies, in a random network of firms. Luttmer (2007 and 2012); Alvarez, Buera, and Lucas (2008); Lucas (2009); Ghiglino (2011); Konig, Lorenz, and Zilibotti (2012); and Perla and Tonetti (2014) study the gradual diffusion of best techniques among firms that randomly meet each other. Lucas and Moll (214) and Luttmer (2014) further endogenize the choice of how intensively to seek information from other firms. Luttmer (2014) characterizes the long run growth rate in such an economy where information about technologies gradually diffuse among firms. All those models develop formal tools to study the asymptotic behavior of the maximum of many draws from a random variable (the best technique available after many meetings with other entrepreneurs).

In this handbook, Daron Acemoglu, Asuman Ozdaglar, and Alireza Tahbaz-Salehi describe the origins of systemic risk in a network model of input-output linkages. The model they describe shares some resemblance with the model above. They are interested in particular in the second moment properties of such a model, namely the variation of aggregate output emanating from local idiosyncratic shocks hitting each node in the input-output network.

28.3.2 The Empirics of Firm-to-Firm Trade

Few recent papers in international trade rigorously analyze the empirics of firm-to-firm trade.

In a series of papers with various co-authors, Andrew Bernard studies the importance of production networks, firm-to-firm trade, and the role of intermediaries in the context of international trade. Bernard, Grazzi, and Tomasi (2014) study the endogenous choice of potential exporters to serve foreign markets either directly or via an intermediary (wholesaler). They confront their model to detailed Italian firm level data on manufacturing and wholesale exporters, contrasting the modes of entry into foreign markets. Using detailed data on Norwegian firm-level exports, Bernard, Moxnes, and Ulltveit-Moe (2014) describe the network structure of firm-to-firm trade: for a given exporter, the details of their transaction-level data allows them to distinguish between exports towards different importers in the same destination country. Such detailed transaction data on firm-to-firm trade gives a unique perspective on the network of linkages between firms. Finally, Bernard, Moxnes, and Saito (2014) use an exhaustive data set of buyer-seller linkages among Japanese firms to study the importance of the network structure of production of firms' efficiency. Making a clever use of the arguably exogenous impact of the high-speed train (Shinkansen) on the ease with which firms can find new suppliers, they confirm firm performance is positively affected by the diversity and quality of its suppliers.

Antras, Fort, and Tintelnot (2014) incorporate a simplified version of the model described above into a conventional model of trade with heterogeneous firms. Firms that are able to gain access to more and/or better suppliers improve their efficiency and ultimately profits. Antras et al. assume a simple fixed cost of gaining access to input sources from new countries, and they solve for the equilibrium sourcing decision of heterogeneous producers. They propose a structural estimation of their model using data on U.S. importers.

This series of papers shows taking into account the network structure of production in models of international trade generates novel predictions. This is a promising avenue for future research.

References

Allen, Treb. Forthcoming. "Information Frictions in Trade." *Econometrica*.

Alvarez, Fernando E., Francisco J. Buera, and Robert E. Lucas, Jr. (2008). "Models of idea flows." NBER Working Paper 14135.

Antras, Pol, Teresa Fort, and Felix Tintelnot (2014). "The margins of global sourcing: Theory and evidence from U.S. firms." University of Chicago, unpublished manuscript.

Bernard, Andrew, Andreas Moxnes, and Yukiko Saito (2014). "Production networks, geography and firm performance." Dartmouth, unpublished manuscript.

Bernard, Andrew, Andreas Moxnes, and Karen Helene Ulltveit-Moe (2014). "Two-sided heterogeneity and trade." Dartmouth, unpublished manuscript.

Bernard, Andrew, Marco Grazzi, and Chiara Tomasi (2014). "Intermediaries in international trade: Margins of trade and export flows." Dartmouth, unpublished manuscript.

Bramoulle, Yann, Sergio Currarini, Matthew O. Jackson, Paolo Pin, and Brian W. Rogers (2012). "Homophily and long-run integration in social networks." *Journal of Economic Theory* 147(5), 1754–1786.

Burchardi, Konrad B. and Tarek A. Hassan (2013). "The economic impact of social ties: Evidence from German reunification." *Quarterly Journal of Economics* 128(3), 1219–1271.

Burchardi, Konrad B., Thomas Chaney, and Tarek A. Hassan (2014). "Migrants, ancestors, and investments." *Toulouse School of Economics*, unpublished manuscript.

Chaney, Thomas (2013). "The gravity equation in international trade: An explanation." *National Bureau of Economic Research*, Working Paper 19285.

Chaney, Thomas (2014). "The network structure of international trade." *American Economic Review* 104(11), 3600–3634.

Cohen, Lauren, Umit G. Gurun, and Christopher J. Malloy (2014). "Resident networks and firm trade." Harvard Business School, unpublished manuscript.

Combes, Pierre-Philippe, Lafourcade Miren, and Thierry Mayer (2005). "The trade-creating effects of business and social networks: Evidence from france." *Journal of International Economics* 66(1), 1–29.

Dasgupta, Kunal and Jordi Mondria (2014). "Inattentive importers." University of Toronto, unpublished manuscript.

Dornbusch, R., S. Fischer, and P. A. Samuelson (1977). "Comparative advantage, trade, and payments in a Ricardian model with a continuum of goods." *American Economic Review* 67, 823–839.

Duffie, Darrell, Gaston Giroux, and Gustavo Manso (2010). "Information percolation." *American Economics Journal: Microeconomic Theory* 2, 100–111.

Duffie, Darrell, Semyon Malamud, and Gustavo Manso (2009). "Information percolation with equilibrium search dynamics." *Econometrica* 77, 1513–1574.

Duffie, Darrell, Semyon Malamud, and Gustavo Manso (2015). "Information percolation in segmented markets." *Journal of Economic Theory* 157, 1130–1158.

Duffie, Darrell and Gustavo Manso (2007). "Information percolation in large markets." *American Economic Review, Papers and Proceedings* 97, 203–209.

Eaton, Jonathan and Samuel Kortum (2002). "Technology, geography, and trade," *Econometrica* 70(5), 1741–1779.

Gighlino, Christian (2011). "Random walk to innovation: Why productivity follows a power law." *Journal of Economic Theory* 147(2), 713–737.

Greif, Avner (1989). "Reputation and coalitions in medieval trade: Evidence on the Maghribi traders." *Journal of Economic History* 49(4), 857–882.

Greif, Avner (1993). "Contract enforceability and economic institutions in early trade: The Maghribi traders' Coalition." *American Economic Review* 83(3), 525–548.

Jackson, Matthew O. and Brian W. Rogers (2007). "Meeting strangers and friends of friends: How random are social networks?" *American Economic Review* 97(3), 890–915.

Konig, M., J. Lorenz, and F. Zilibotti (2012). "Innovation vs. imitation and the evolution of productivity distributions." *CEPR* Discussion Papers 8843.

Lucas, Robert E., Jr. (2009). "Ideas and growth." *Economica* 76, 1–19.

Lucas, Robert E., Jr. and Benjamin Moll (2014). "Knowledge growth and the allocation of time." *Journal of Political Economy* 122(1), 1–51.

Luttmer, Erzo G. J. (2007). "Selection, growth, and the size distribution of firms." *Quarterly Journal of Economics* 122(3), 1103–1144.

Luttmer, Erzo G. J. (2014). "An assignment model of knowledge diffusion and income inequality." University of Minnesota, unpublished manuscript.

McCallum, J. (1995). "National borders matter: Canada–US regional trade patterns." *American Economic Review* 85, 615–623.

Oberfield, Ezra (2013). "Business networks, production chains, and productivity: A theory of input-output architecture." Princeton University, unpublished manuscript.

Perla, J. and C. Tonetti (2014). "Equilibrium imitation and growth." *Journal of Political Economy* 122(1), 52–76.

Rauch, J. and Trindade, V. 2002. "Ethnic chinese networks in international trade." *Review of Economics and Statistics* 84(1), 116–130.

Tinbergen, Jan (1962). "An analysis of world trade flows." In *Shaping the World Economy*, Jan Tinbergen, ed. New York: Twentieth Century Fund.