Very Preliminary!

# Airline Services Agreements:<br>A Structural Model of Network Formation

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July 2016

**Abstract**

Airline services agreements are necessary for direct flights between countries and consequently they are central to the operation of the commercial airline market. These agreements are bilateral in nature but their coverage is far from universal. To gain insight into why some agreements are signed but other links go unrealized, we study a new data set on airlines services agreements from the perspective of strategic network formation. We develop a structural model based on moment inequalities that uses the concepts of pairwise stability to generate estimating equations and also introduce methods to implement refinements of pairwise stability. The network structure is found to be important in determining the choices of countries to form agreements, and that the jointly optimal network of agreements would be substantially different than the observed outcome.

# 1 Introduction

Air services agreements govern the international airline market. In order to have a commercial flight between two countries, there must be some form of agreement between them, almost always an airline services agreement (ASA). Thus, the existing network of ASAs provide structure for the pattern of international flights. Given the importance of direct links for international trade and global commerce more generally, it is somewhat surprising that the coverage of ASAs is relatively incomplete. For example, for the largest 58 countries, less than half of potential bilateral agreements are realized by an ASA. In contrast, we observe that almost all of these countries are engaged in bilateral trade. What factors explain the pattern of agreements we observe? Is the realized set of agreements desirable in some broad sense?

In this paper, we address these questions by studying the incentives to form ASAs. We take the perspective of the economic literature on strategic network formation, which models the utility-maximizing choices of agents to form links between each other. In this framework, we interpret countries as nodes (or agents) and ASAs as links that allow communication between nodes. Our most basic question is whether countries account for the link structure in choosing whether to form agreements. Do countries account for the agreements that potential partners have signed, or do countries just focus on bilateral characteristics? We further ask what elements of the link structure are important, which then implies what externalities are prevalent in the network of agreements. For instance, are countries particularly interested in connecting to countries that are well-connected, or are countries primarily interested in serving as hubs between unconnected countries (or both)? Finally, we compute the globally optimal network of agreements, and compare that to the observed network.

In order to estimate the payoff function of countries and perform counterfactual experiments, we estimate a structural model of the network formation process. Our model follows closely the theoretical literature on strategic network formation, such as discussed in Goyal (2007) and Jackson (2008). In our model, there are no transfers between countries, so a link is formed only if both agents derive positive payoff from the link. Nash equilbirum in simultaneous choices is often of limited use in network formation contexts, so we follow the theoretical literature and instead study *pairwise stable* allocations. Pairwise stability places conditions on how observed choices must generate higher payoffs than unobserved choices, which leads to inequality conditions. Still, predicting outcomes is problematic since for any given set of parameters, there will often be multiple stable allocations. This problem is common in estimating games with strategic interactions, which often face multiple equilibria. Instead of predicting outcomes, we map these inequalities directly into empirical counterparts, and estimate based on the recent literature on estimation with moment inequalities, such as Pakes et al. (2015). In practice, we follow a version of the method of Andrews & Barwick (2012) for constructing confidence intervals in partially identified models. Inspired by refinements to pairwise stability, such as Nash pairwise stability, we develop additional moment inequalities, and we study how much information these concepts provide in the sense of providing more precise estimates of parameters.

In our model, the country-level payoff to an agreement is a reduced-form function of bilateral characteristics and network structure. The bilateral characteristics are similar to those found in the literature on estimating gravity equations (see Head & Meyer, 2013), such as the distance between countries, and in our preferred specification, we use predictions from a gravity equation model directly as an explanatory variable. An important element of our paper is to develop useful measures of network structure for capturing the issues of interest. We are motivated by the externalities studied in the theoretical literature in network formation, particularly Jackson & Wolinsky (1996). They discuss the *coauthor externality* and the *information flow* externality, which we interpret in our context as the incentive to be a hub between otherwise unconnected countries, and the incentive to connect to well-connected countries. For empirical measures of these features, we turn to the vast literature on social networks (see Prell, 2011; Kolaczyk, 2009). We further discuss this literature below, but it provides a wide variety of measures of network features. We rely on *betweenness centrality* to measure hubbing incentives and *eigenvector centrality* to measure the desire for connected partners. For instance, if we observe countries form links that increase their betweenness centrality, we conclude that the desire to be a hub is important. We view developing a relationship between theoretical concepts of externality and empirical measure of network features to be a contribution of our paper.

Our central data set is called the World Air Services Agreements (WASA) database, and is published by the International Civil Aviation Organization (ICAO), an agency of the United Nations. The WASA data base aims to catalog all ASAs. Although we focus only on the existence or non-existence of ASAs, the WASA database contains data on ASAs features, such as whether the ASA is an Open Sky Agreement (which we discuss further below). The WASA database has significant drawbacks, such as the fact that it is missing data on a substantial number of agreements, and that it is difficult to use the data on how long an agreement has been in effect. We discuss these issues and our response below, but surely, WASA is the best database that we are aware of for studying ASAs. We match WASA up to trade and characteristic data on country pairs. In order to reduce heterogeneity, we select a list of 58 countries that are big, wealthy, or both. An advantage of air services agreements is that they are almost all negotiated bilaterally rather than multilaterally, which makes them similar to existing network theoretical models. A major exception is the European Union, which functions as a large multilateral agreement. We impose various adjustments to address this issue. We use data from 2005. Afterwards, a number of new multilateral agreements appear, which would complicate our analysis.

We find that network structure plays a substantial role in determining choices. In particular, countries form agreements that increase their role as a hub between otherwise unconnected countries. That is, countries form agreements that raise their betweenness centrality. Additional moments generated from an empirical analog of Nash pairwise stability play a limited role in identifying parameters, but are important in some circumstances.

Our computation of the globally optimal network of agreements addresses two externalities. The first is pairwise, and results from the fact that some agreements do not form even if the sum of payoffs from the agreement is positive because we do not allow side payments between countries. The second is more global, and arises from the preference to be a hub. If we address only the first issue, we would raise the percentage of agreements from 40% of potential agreements to 70%. Further addressing the network issue causes the social planner to reduce the number of agreements (to increase the number of hubs) from 70% to 65%. In general, the social planner adds links where the gravity model predicts high trade but there is no agreement, and deletes links between countries that have low “gravity scores” but have an agreement.

To be clear, our research has several caveats. We derive the payoffs to countries from revealed prefence about how the countries form agreements, and use this payoff function in calculating counterfactual payoffs. Thus, we ignore political economy concerns, such as in CITE, that might cause countries to maximize something other than the welfare of their citizens. In addition, we do not currently address potential endogeneity or omitted variable bias. For instance, a country may have many links for some unobserved reason, and failing to account for this may lead a researcher to falsely conclude that countries want to link to countries that have many links. Although our specific results are difficult to explain with endogeneity or omitted variable bias, we are currently working on a technique using trade data drawn from a earlier time period, when commercial air traffic was less important, to control these unobservable factors.

## 2 Literature Review

The study of *social networks* is a vast field, stretching across psychology, sociology, anthropology, economics, statistics and even physics. See Prell (2011) for an excellent overview and a history of the field, and Kolaczyk (2009) for an overview of statistical issues. The literature is largely empirical, with substantial effort devoted to collecting data, describing data and creating better measures of network position, such as the measures of centrality described above. There are many examples in economics, such as Alatas et al. (2014). An interesting recent example in the field of industrial organization is Fershtman & Gandal (2011), which studies information spillovers in the context of networks of open-source computer programmers. An overview of research using exogenous matching to provide identification appears in Sacerdote (2014), and a more general overview of the econometric study of networks appears in **?**)

We distinguish between the literature on social networks, and the literature on *strategic network formation.* The social networks literature typically takes the formation of a network as exogenous, or as a reduced-form function of network variables, whereas the strategic network formation literature arises from economics and studies the incentives of agents to form links. Thus, it provides micro-structural models of the formation of networks, and emphasizes stability concepts, and efficiency issues. An early contribution is Jackson & Wolinsky (1996). Two recent overviews are Jackson (2008) and Goyal (2007). Naturally, there is substantial overlap between the literatures on social networks and strategic network formation, in terms of concepts, notation, and empirical examples, and even authors.

Our project fits into a growing number of papers that attempt to structurally estimate a model of strategic network formation.[1] A seminal contribution is Ho (2009), who estimates a model of hospitals joining insurance networks, which is motivated by the solution concept of stability to generate moment inequalities, in the spirit of Pakes et al. (2015). This case is two-sided, in the sense that hospitals match to insurance companies rather than to other hospitals. Several other papers discus methods or applications for estimating matching games – see Sorensen (2007), Fox (2010) and Agarwal (2013).

The last few years have seen rapid growth in methods for estimating strategic network formation models. Graham (2015) discusses this literature. Imbens & Kalyanaraman (2010), Goldsmith-Pinkham & Imbens (2013) and Mele (2013) present related methods based on Bayesian statistical estimators that require repeatedly solving for the choice of each agent. These papers solve their model by assuming that players make decisions according to an exogenous or random ordering, with myopic decision-making. Thus, their solution concept does not correspond to a standard solution concept in the theoretical literature, although Mele (2013) repeatedly cycles through the set of players, which can be shown to converge to a stable outcome. Hsieh & Lee (2012) also use a Bayesian method and the concept of a potential game in order to avoid issues of multiple equilibria. All three of these papers are motivated by friendship networks in surveys of elementary schools in the AddHealth data.

Sheng (2012) and Miyauchi (2014) use a technique that bears a similarity to the approach of

[1] Note that it is possible to model network formation without modeling what we refer to as strategic network formation. Exponential Random Graph Models are a popular tool outside of economics for modeling network formation, typically as a reduced-form function of network features. Chandrasekhar & Jackson (2014) do in fact provide micro-foundations for a broad class of related models, although their specific assumptions, based on random meetings between groups of agents, probably does not describe our setting.

Ciliberto & Tamer (2009) in the entry literature. For a given set of parameters, Sheng (2012) computes the maximum and minimum of the probability of observing a given link structure, and uses these with the observed probabilities to form moment inequalities. To lower the computational complexity of this problem, the paper holds most decisions constant at their observed outcome, focusing on one "sub-network" at a time. Miyauchi (2014) similarly takes a strategy of bounding moments from the data, in this case focusing on the case of non-negative externalities across nodes (which is not satisfied in our model) to simplify the problem.

Leung (2015) models agents in a game of imperfect information, and recommends a two-step estimator that addresses endogeneity and multiple equilibria in a way similar to Bajari et al. (2007). Boucher & Mourifié (2015) develops a likelihood framework, focusing on the case of no externalities between agents. Currarini et al. (2009) develop an estimator based on an underlying model of search and matching between agents. Badev (2013) does as well, and further studies the choice of smoking and how it interacts with friendship formation. The vast majority of these papers study friendship pattern in surveys of school students.

The paper by de Paula et al. (2014) presents a model for aggregate data of populations that meet and match. Graham (2014) studies network formation in a model with transferable utility, and is particularly concerned with the issue of omitted variables. While the paper focuses on the case in which links are formed just on bilateral characteristics, he introduced network structure into the problem using a conditioning argument similar to the solution of Chamberlain (1980) for the fixed-effects logit.

The paper most similar to ours in terms of methods is Uetake (2014), who also uses the concept of stability to generate moment inequalities drawn directly from the consumer's utility functions. Unlike our method, Uetake (2014) simulates the error terms in the agent utility function, and focuses on the case where the researcher observes many networks. The paper focuses on the propensity of venture capitalists to work with similar venture capitalists (similar in terms of observable characteristics), and less-so on network structure. Note that all of the papers discussed are written for cross-sectional data. Fong & Lee (2013) present a method for studying matching in a dynamic context.

Relative to all of these papers, our project makes several contributions. Our method relies directly on theoretical stability concepts and so is attractive from the perspective economic theory, and we are the first to exploit the idea of Nash pairwise stability, which would be difficult to do in other approaches. Our method can handle large numbers of agents and our method is fast – we obtain confidence intervals on 12 parameters using 1,400 pairs of agents in under a minute. Our project emphasizes the use of network variables such as centrality, and the link to theoretical concepts such as the co-author externality that we discuss below. Our goal of characterizing externalities and comparing the optimal network to the observed network is central to the theoretical goals of the literature on strategic network formation. Furthermore, our application to agreements between countries is substantially different from other papers, and the resulting conclusions that we can reach are thus quite different as well. Our empirical approach requires strong assumptions on error terms, as in Pakes et al. (2015) and related papers. But as can be seen, all methods require important restrictions in order to make progress. We believe that our project represents an important contribution to the discussion of appropriate methods for this area, and is complementary to existing work in this area.

Our project also bears on the field of international trade. Some previous theoretical work studies treaties, typically free-trade agreements, through the prism of network formation games, such as Goyal & Joshi (2006), and Furusawa & Konishi (2007). There is also a related empirical literature on the determinants of free-trade agreements, such as Baier & Bergstrand (2004) and Egger et al. (2011). A small empirical literature studies air services agreements, primarily on the topic of Open Sky Agreements. The existing empirical literature largely takes the air services agreements as an explanatory variable that can be used to predict outcomes, such as trade, whereas our project treats the air services agreements as the endogenous variable to be explained. Naturally, the extent to which air services agreements affect economic outcomes is an important justification for our study of the formation of agreements, so we view this literature as highly complementary. Cristea et al. (2012) study the impact on trade of US Open Sky Agreements, using panel-data techniques. Micco & Serebrisky (2006) also look at this issue. There is a substantial literature on air services agreements that exists outside of mainstream economics journals, primarily in fields such as operations research, engineering, and transportation research. One example is Dresner (2008). A recent report commissioned by the Department of State also finds large benefits to agreements (Intervistas, 2015).

## 2.1 Industry and Data

Recognizing the importance of the nascent air services industry, a large group of countries met in Chicago in 1944 to work out an international agreement on how the industry should be managed.[2] The so-called Chicago Convention failed to reach a comprehensive international agreement, but instead led to a treaty that established a framework under which subsequent bilateral agreements would follow, essentially establishing a template for subsequent ASAs. ASAs determine what rights partner-country airlines have, such as whether to pick up passengers or cargo, and also determine issues such as what routes are allowed, how many airlines are allowed on the routes, and whether price changes require government approval.[3]

Open Sky Agreements are perhaps more widely known than air services agreements, although formally, Open Sky Agreements are a subset of air services agreements. Open Sky Agreements are a particularly liberal version of air services agreements. While the Chicago Convention provides a formal definition of Open Sky Agreements, few agreements today live up to that definition.[4] Open Sky has come to mean agreements that have relatively few restrictions on routes, cities, airlines and prices. We observe an indicator of whether an agreement is considered Open Sky, although we do not make use of it in this paper. While Open Sky Agreements are particularly important between the biggest countries, they appear to be less important outside of that group, which is the source of most of the variation in our data.

The Chicago Convention envisioned only bilateral agreements, which is helpful for our purposes since multi-lateral agreements are more difficult to model, particularly in the context of

[2] Odoni (2009) provides an excellent discussion of the institutional background for air services agreements.

[3] Note that these deals are termed international *agreements* rather than *treaties*. Agreements are typically easier to negotiate. For instance, in the United States, agreements do not require congressional approval whereas treaties do.

[4] For instance, formally, Open Sky would mean allowing domestic cabotage, which is allowing foreign airlines to pick up and drop off passengers flying within a country. While the US would say that it has signed many Open Sky agreements, none of them allow that.

strategic network formation. In practice, there is one multilateral air services agreement, which is between members of the European Union. Since 1992, EU members have participated in a multi-lateral, very liberal agreement. However, up until 2002, EU countries continued to sign bilateral agreements with non-EU countries, rather than having the EU negotiate as a whole.[5] We address this issue in the construction of our data. Since 2005, several more multi-lateral air services agreements have arisen or have been proposed, particularly in Asia, and so we use 2005 data in order to avoid this issue.

The Chicago Convention also established ICAO (named as such later, when it became part of the United Nations), which coordinates international standards on flight and airport regulations. ICAO maintains a data set of all ASAs, the World Air Services Agreements (WASA) Database, that is the centerpiece of our data set. At this stage, we make use of only the existence of an agreement, and we model whether countries form an agreement or not.[6] The WASA database also lists the date that the agreement was signed, and any amendments, but we found this difficult to use. If countries signed an agreement and then signed a new agreement, we see only the most recent agreement, and we have no indication of the existence of the earlier agreement. Whereas some countries that have liberalized air services have amended the agreement they originally signed in the 1940's, others have started over with a new agreement.[7] Thus, we ignore the time dimension of our data set, and treat our data as a cross-section of existing agreements.

The benefit of an agreement is that it allows for direct flights between countries. Travel between countries would otherwise require connecting flights, which can exist only if connecting countries have signed ASAs. The effects of an ASA can easily expand beyond air travel. If air travel supports communication between executives at trading companies, the impacts of an

[5]The use of bilateral agreements was subject to a lawsuit filed by the European Commission against member countries. The court found that member countries had the right to negotiate bilateral agreements under the Treaty of the European Union, but that member countries did not have the right to restrict the benefits only to their own national airlines. While some EU countries have updated their bilateral agreements accordingly, bilateral agreements hold little appeal without this last element, and agreements since then have tended towards multi-lateral agreements between an outside country and all EU countries simultaneously. See http://ec.europa.eu/transport/modes/air/international_aviation/external_aviation_policy/horizontal_agreements_en.htm.

[6]WASA also contains a list of indicator variables describing the agreement, so it is possible to utilize more information about agreements in the future. An strand of the strategic network formation literature analyzes the intensity of a link, and these indicator variables could be understood along these lines.

[7]For example, our data would indicate that the US and Canada have had an agreement only since 1992, but it is well known that there was air travel between these two countries long before then.

ASA may be much larger in shipping than air. One question is why countries do not sign ASAs with every other country. Signing agreements has a cost in terms of administration and negotiator's time. Furthermore, a country may be opposed to an ASA in some cases. If one country believes that its airlines will not be competitive on a particular route with the airlines of another country, that country may be reluctant to open up that route. In the United States, the State Department has an Aviation Negotiation division that is dedicated to negotiating ASAs. Their website highlights the number of Open Sky Agreements they have signed over the last several years. Naturally, we are not privy to how the division decides with which countries to negotiate.

Although agreements are public documents, they are surprisingly difficult to observe for the purpose of creating a database. ICAO relies on countries to self-report any new agreements, but has recently engaged in a more proactive approach to learn about agreements. Even so, ICAO representatives believe that the WASA database contains only a subset of existing agreements.[8] In order to address this problem, we have obtained another database from ICAO, the TFS database. For our purposes, the TFS database indicates which pairs of countries had direct flights at an annual level, either for people, cargo or mail. ICAO representatives argue that this can be useful since any direct flight requires some kind of agreement between the two countries in advance. Note that this database does not allow us to study the details of the agreement, it only determines the existence of an agreement. The TFS database provides an alternative way to construct the network of agreement. In general, the network drawn from the TFS database has substantially more links than WASA, but one is not perfectly contained in the other. In what follows, we provide results based on the WASA database. We plan to use the TFS data as a robustness check.

We start with the CEPII data set created for Head et al. (2010), which contains several useful bilateral variables, such as distance and indicators for a common border and a common language. There are several matching issues that we address, further described elsewhere. For variables that

[8] In private communication, an ICAO representative guessed that WASA has between one-half and two-thirds of agreements, although it is difficult to know. Also, agreements are kept in the database until the participating countries indicate that they have a new agreement. Thus, WASA contains a number of agreements between countries that no longer exist. Furthermore, the database contains a number of agreements between EU countries, which we know are superseded by EU legislation.

vary over time, such as GDP and population, we use the average of 2000-2006. Check this!

To keep our data reasonably homogenous and in order to keep our estimation tractable, we do not include every country in the world in our data set. In order to choose countries, we take the top 50 countries by population and the top 50 by GDP and form the union. From this, we drop countries with population less than 500,000 as well as Puerto Rico and Taiwan, whose freedom to negotiate agreements is unclear.[9] We add back in Iceland although its population is less than 500,000 because Iceland has a prominent national airline. Overall, we have a list of 58 countries from 6 continents. That creates a list 3,306 country-pairs.

From the perspective of the social networks literature, we term the countries as *nodes* and the agreements as *links*. The *degree* is the number of links to a node. In our computations, we count links from EU countries to outside countries but not EU countries to other EU countries.[10] In our definition of "EU," we include the 25 states that joined by 2005 (Bulgaria and Romania joined in 2007) plus Norway, Lichtenstein, Iceland and Switzerland, which signed the Common Aviation Area (CAA) agreements by 2005 (see European Commission, 2010). Note that Lichtenstein is dropped from our final data set because it has low population. We do not count Western Baltic states, which signed CAA agreements in 2010. We assume Russia inherits all of the agreements of the Soviet Union. The only other post-Soviet state in our sample is Estonia. We assume Estonia does not inherit these agreements. We assume the Czech Republic and Slovenia inherit all of the agreements of Czechoslovakia. Since we drop all EU pairs, we end up with 1400 pairs of countries, or 2,800 decisions by potential partners.

In our empirical work, we ask how a country values connectedness. We focus on three measures of connectedness. The first is degree, the number of links a country has. While straightforward, the literature on social networks has recognized that this measure if often too simple to capture issues of interest, and has developed a number of other measures, broadly termed *centrality measures*. Centrality measures capture more complete measures of the location of a node in a network. For instance, we might be concerned not just with how many links a node has, but

[9]Dropping countries with low populations eliminates Antigua, the Bahamas, Barbados, Brunei, Equitorial Guinea, Iceland, Luxemborg, Macau, Malta, St. Kitts, and the Seychelles.

[10]This reflects the state of the EU in the early 2000s, which we believe best describes our 2005 data. Keep in mind that non-EU countries have an opportunity for a higher number of links than EU countries, since EU-to-EU links are deleted.

also with whether those links are to nodes that themselves have many links. Similarly, we might care whether those links are to nodes that are connected amongst each other, or whether a given node is the sole pathway between sets of nodes.

Some notation aids in developing these concepts. Let the set of countries be $\mathcal{N} = \{1, \ldots, n\}$. Let $\Lambda$ be an $n \times n$ matrix. Element $\{i, j\}$ of matrix $\Lambda$ equals 1 if countries $i$ and $j$ have an ASA, and 0 otherwise. Thus, $\Lambda$ represents the set of links between nodes. The diagonal of $\Lambda$ is 1 by assumption. Let the function $s_i(\Lambda)$ return the set of countries that are linked to $i$ in network $\Lambda$. That is, $s_i(\Lambda) = \{j : \Lambda_{ij} = 1\}$. *Degree* is defined as the cardinality of $s_i(\Lambda)$.

We would also like an index that reflects not only how many links a country has, but also how many links the partner countries have, and the partners of those partners in turn. Labeling this vector of indices as $C^{eig}$, we wish to solve:

$$aC^{eig} = \Lambda C^{eig}$$

where $a$ is a proportionality factor. Thus, $C^{eig}(\Lambda)$ is an eigenvector of $\Lambda$, and $a$ is the corresponding eigenvalue. The convention is to use the highest eigenvector, and term $C_i^{eig}(\Lambda)$ the *eigenvector centrality* for node $i$.

Next, we consider the sense in which a node sits between other nodes. A *geodesic* is a shortest path between two nodes. There may be multiple geodesics between any two nodes. For instance, in our data, countries that do not have a link can almost always reach each other in two links, but there may be multiple paths by which to do so. Let $P(k, j)$ be the number of geodesics between nodes $k$ and $j$. Let $P_i(k, j)$ be the number of geodesics between $k$ and $j$ that pass through $i$. *Betweenness centrality* is:

$$C_i^{betw}(\Lambda) = \sum_{\{k,j:k\neq i,j\neq i,k\neq j\}} \frac{P_i(k,j)}{P(k,j)}.$$

To see how these two measures differ, consider Figure 1. The figure has 5 nodes, $A - E$, and 5 links. The figure displays the nodes and links, as well as the resulting measures of eigenvector and betweenness centrality.[11] We do not display degree, but it is clear: node C has degree 3, node

[11] For clarity, we display $P_i(kj)$ instead of $C_i^{betw}$.

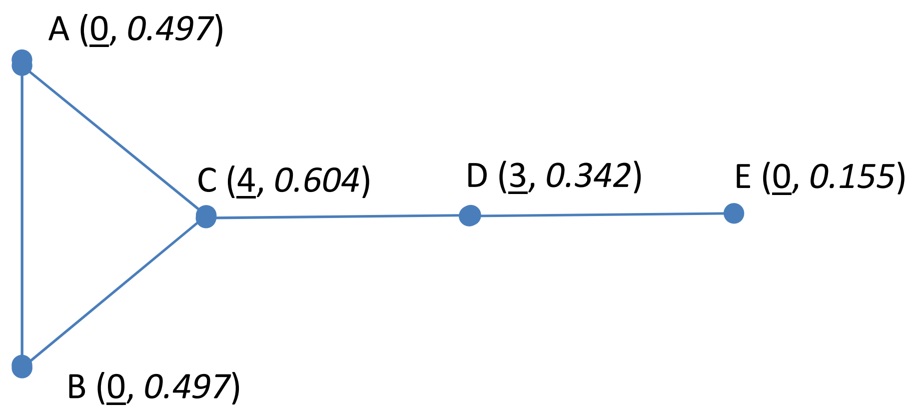


Figure 1: An example of a network. Betweenness centrality is underlined, Eigenvector centrality is in italics.

E has degree 1, and the rest have degree 2. Node C is central in this network, and has the highest score in both eigenvector and betweenness centrality. However, note the differences between A, B and D. Nodes *A*, *B* and *C* make up a cluster that generates the high eigenvector scores for *A* and *B*. However, *A* and *B* are not hubs – there are no shortest paths between two nodes that run through *A* or *B*. In contrast, *D* is relatively more isolated than *A* or *B*, but is the only route to *E* from any other node. Thus, *D* is higher than *A* and *B* in betweenness centrality but lower in eigenvector centrality.[12]

Note that there are no microfoundations for these measures. That is, there is no game-theoretic model of communication across a network or formation of a network from which these measures arise. However, we believe that these statistics can be interpreted to capture some important constructs from the theoretical network formation literature. We focus on two models introduced by Jackson & Wolinsky (1996), the *co-author model* which focuses on agents that prefer links to nodes that are not linked to others, and the *connections model* which emphasizes agents that benefit from links to nodes with many links.

The model of the co-author externality recognizes that if player *A* is connected to *B* and *C*,

[12]There exists useful extensions of these measures that account for nodes that vary in importance. That is, it is more valuable to be between important nodes (say, countries with large GDP) than unimportant nodes, and centrality measures can reflect this. We are further developing this issue.

$A$ may be better off if $B$ and $C$ are not connected to each other. In the model, each player has a limited amount of time to devote to each link, and so the connection between $B$ and $C$ takes away time from $A$'s links. In the context of airlines, this is equivalent to saying that $A$ values being a hub between $B$ and $C$. We believe that this externality is well captured by betweenness centrality. If we observe countries forming agreements that tend to raise the country's betweenness centrality, we will say that countries prefer to be hubs, and that the coauthor externality is present. Of course, we do not restrict the sign of the coefficient on betweenness centrality. It may be that the link between countries $B$ and $C$ raises growth so much for those countries that traffic to $A$ actually increases, in which case there is still an externality, but with the opposite sign. Note that as Jackson & Wolinsky (1996) define the coauthor externality, the agent is worse off whether $B$ and $C$ form links with each other or anyone else, since any sort of links take time away from their relationship with $A$, whereas our concept of hubbing would mean that it is particularly the link between $B$ and $C$ that hurts $A$. In this sense our concept of hubbing differs from the coauthor externality. We believe that betweenness centrality better captures hubbing than the coauthor externality in this sense.

The connections model recognizes that if player $A$ is connected to $B$ but not $C$, then $A$ gains when $B$ connects to $C$ because now $A$ can reach $C$. This set-up has a natural interpretation in the airlines context, where more connected paths between any two countries provide more options for that country-pair market. We believe that this measure is well captured by eigenvector centrality, which measures the overall connectedness of any given node. In either the co-author or connections case, if $B$ and $C$ make their decision without accounting for $A$, we have an externality. Thus, we look for countries that create agreements to increase their eigenvector or betweenness centrality in order to infer which of these issues are present.

Now we turn to some simple statistics. The US, Russia and Singapore have the highest degrees (numbers of links), with 50, 44 and 42 respectively. The highest degrees within the EU are Switzerland, the Netherlands and the UK, with 34, 32 and 31.[13] The mean number of links per

[13] If we counted agreements in the data between EU countries, the most linked country overall would be Switzerland, and EU countries would make up most of the top 10.

country is 22.44, the standard deviation is 11.1, the median is 22 and the 25th percentile is 13. Thus, there is substantial variation in the number of links.

Our network is highly connected. Connected paths exist between every node, usually requiring only one or two links. We find that 39.4% of country-pairs are directly connected, and 58.9% of country-pairs require only one intermediate node to reach each other. The remaining 1.8% of country-pairs require two links to reach each other, and no country-pair requires more.

Table 1 presents the network statistics that we are interested in. The table is ordered by degree and presents the top 12 countries. It also presents betweenness centrality and eigenvector centrality, along with the rank of each country in these statistics. For instance, we see in the first row that the United States has 50 agreements and has the highest values for both betweenness and eigenvector centrality. The top 4 of each statistic is held by the US, Singapore, Russia and China almost exclusively. Interestingly, Japan is the 5th in number of agreements and 4th in eigenvector centrality but only 13th in betweenness. That is, although Japan is well connected, it rarely provides an intermediate travel point for countries that are not otherwise connected. Hong Kong is similar, which ranks 8th in eigenvector centrality but only 18th in betweeness. In contrast, Switzerland is tied with Hong Kong for number of agreements (at 10th) and is 11th for eigenvector centrality but is substantially higher for betweenness at 5th. The Netherlands is similar, being only 14th for eigenvector centrality but 8th for betweeness. While clearly correlated, the measures of centrality capture different issues, and our project uses these differences to gain insight into the nature of externalities that govern the structure of ASAs.

One concern we might have is that our measures just count links, as if all links were equal. We might prefer a measure of betweenness centrality that reflects not only the number of paths that pass through a node, but also whether those paths are important. For instance, being between two countries that are close together should matter more than being between countries that are far apart, or being between countries that trade a lot should matter more than being between countries that do not. CITE discusses the concept of *weighted network statistics*, and we use those ideas to construct weighted versions of betweenness centrality and eigenvector centrality. For weights, we use both trade and (the inverse of) distance. We discuss the exact calculation in

| Country | Degree | | Betweenness Centrality | | Eigenvalue Centrality | |
|---|---|---|---|---|---|---|
| | Value | Rank | Value | Rank | Value | Rank |
| United States | 50 | 1 | 123.0 | 1 | 32.7 | 1 |
| Russia | 44 | 2 | 104.1 | 2 | 28.7 | 3 |
| Singapore | 42 | 3 | 45.2 | 4 | 30.1 | 2 |
| China | 40 | 4 | 99.2 | 3 | 27.5 | 5 |
| Japan | 38 | 5 | 27.7 | 13 | 28.2 | 4 |
| India | 37 | 6 | 32.8 | 9 | 27.0 | 6 |
| Canada | 35 | 7 | 37.5 | 6 | 24.5 | 10 |
| South Africa | 35 | 7 | 36.5 | 7 | 24.9 | 9 |
| Thailand | 35 | 7 | 31.9 | 10 | 25.8 | 7 |
| Hong Kong | 34 | 10 | 19.0 | 18 | 25.6 | 8 |
| Switzerland | 34 | 10 | 39.4 | 5 | 24.0 | 11 |
| Netherlands | 32 | 12 | 33.6 | 8 | 23.1 | 14 |

Table 1: Comparing centrality statistics.

Appendix A, but ultimately we find that our results are robust to using weighted statistics.

## 2.2 Model

This section presents our model of network formation, from which we derive estimating equations. Let the vector $x_{ik}$ describe observable characteristics of $i$ and $k$, such as GDP and population, and bilateral characteristics, such as the product of GDPs, distance, and perhaps bilateral trade flows. In our preferred specification, we use only two variables for $x_{ik}$, a constant term and what we term the *gravity score*, the prediction from a gravity equation model that we estimate on trade data, that we discuss below. The function $\psi_i(\Lambda, \alpha)$ captures the profit to $i$ from a given link structure $\Lambda$, parameterized by $\alpha$. In our approach, it is a statistic such as betweenness centrality, i.e., $\psi_i(\Lambda, \alpha) = \alpha C_i^{betw}(\Lambda)$. The payoff to country $i$ from the network of links $\Lambda$ is:

$$\Pi_i(\Lambda) = \psi_i\left(\Lambda, \alpha\right) + \sum_{k \in s_i(\Lambda)} x_{ik}\beta + \varepsilon_{ik}.$$

In this expression, the first term represents the overall network benefit whereas the second term captures the sum of bilateral benefits.

We assume that the agent measures one of the elements of $x_{ik}$ with error, which is captured by $\varepsilon_{ik}$. That is, we break up $x_{ik}$ into $\{x_{ik1}, x_{ik2}\}$ where $x_{ik1}$ is the first variable in the vector $x_{ik}$, and $x_{ik2}$ is the remaining vector of variables. Suppose the measurement error is over the first variable, $x_{ik1}$. There is some $\tilde{x}_{ik1}$ such that $\tilde{x}_{ik1} = x_{ik1} + \varepsilon_{ik}$. The country makes its decisions based on $E[x_{ik1}|\tilde{x}_{ik1}]$, which is just $\tilde{x}_{ik1}$. Conditional on the agent's information set, the expectation of $\varepsilon_{ik}$ is 0. That is $E[\varepsilon_{ik}|\tilde{x}_{ik1}, x_{ik2}, \Lambda] = 0$. That is because the country's decision depends only on $\tilde{x}_{ik1}$, $x_{ik2}$, not on $\varepsilon_{ik}$. In fact, conditioning on any subset of the agent's information leads to the same result. Pakes et al. (2015) and Dickstein & Morales (2013) further discuss how $\varepsilon_{ik}$ can be interpreted either as expectational on the part of the agent, or measurement error. The implication is that we can assume that $E[\varepsilon_{ij}|x_{ij2}, \Lambda] = 0$. Although we cannot condition on $x_{ik1}$ in this statement, the conditioning on $\Lambda$ is key to developing moment inequalities.

It is certainly a reasonable assumption that the country cannot predict its payoff from an agreement exactly, because it faces this measurement error. In different specifications, we use the gravity score or the product of GDPs as $x_{ik1}$, but any country has difficulty measuring these variables accurately, and moreover, their mapping into the benefits from an ASA are also uncertain. However, it differs from the usual treatment of discrete choice variables, which assumes there is a structural error term that explains why observationally identical agents make different choices, and would not assume that $\varepsilon_{ik}$ is mean independent of the outcome $\Lambda$. Below, we discuss adding an error term that is known to the country.[14] [15]

Thus, the payoff to $i$ from linking to $j$ is:

$$\Pi_{ij} = \psi_i \left(\Lambda \cup \{i,j\}, \alpha\right) + \sum_{k \in s_i(\Lambda \cup \{i,j\})} x_{ik}\beta + \varepsilon_{ik}.$$

Here, $\Lambda \cup \{i,j\}$ represents the network $\Lambda$ including a link between countries $i$ and $j$. If $i$ and $j$ are already linked in $\Lambda$ (i.e., $\Lambda_{ij} = 1$), then $\Lambda \cup \{i,j\} = \Lambda$. The payoff to not linking to $j$ is:

$$\Pi_{i-j} = \psi_i \left(\Lambda - \{i,j\}, \alpha\right) + \sum_{k \in s_i(\Lambda - \{i,j\})} x_{ik}\beta + \varepsilon_{ik}.$$

Naturally, $\Lambda - \{i,j\}$ indicates network $\Lambda$ with $\Lambda_{ij} = 0$, and if $\Lambda$ does not contain a link between $i$ and $j$, then $\Lambda - \{i,j\} = \Lambda$.

Thus, country $i$ benefits from a link with $j$ if:

$$\begin{aligned} \pi_{ij} &= \Pi_{ij} - \Pi_{i-j} \\ &= \psi_i \left(\Lambda \cup \{i,j\}, \alpha\right) - \psi_i \left(\Lambda - \{i,j\}, \alpha\right) + x_{ij}\beta + \varepsilon_{ij} \geq 0. \end{aligned} \tag{1}$$

Since the country cannot observe $\varepsilon_{ij}$, the countries instead expects the payoff from an agreement

[14] Dickstein & Morales (2013) suggest using an instrument for the mismeasured variable, in a context with a structural error term with a normalized variance. As discussed below, we instead normalize the parameter on the mismeasured variable to 1 in a context with no structural error term.

[15] We do not take a position on whether $\Pi_i(\Lambda)$ represents true welfare for the country, or is manipulated by issues of political economy. We regard it as the country's objective function, no matter its source. Naturally, we can include variables representing political economy concerns in $x_{ik}$.

to be positive if:

$$E[\pi_{ij}] = \psi_i\left(\Lambda \cup \{i,j\}, \alpha\right) - \psi_i\left(\Lambda - \{i,j\}, \alpha\right) + x_{ij}\beta \geq 0$$

One approach to solving the game might be to specify strategies and then solve for a Nash equilibrium. However, this approach tends to generate unrealistic equilibria, such as when no players link with anyone (Myerson, 1977, considers such a game). Instead, the literature has focused on pairwise stability:

**Definition** A network $\Lambda$ is *pairwise stable* if:

1. $E[\pi_{ij}] \geq 0 \quad \forall \quad \{i,j : \Lambda_{ij} = 1\}$.
2. $\min\{E[\pi_{ij}], E[\pi_{ji}]\} \leq 0 \quad \forall \quad \{i,j : \Lambda_{ij} = 0\}$.

The expectation is taken over $\varepsilon_{ij}$, which is assumed to be orthogonal to decision-making. Note that point 1 is a cooperative concept. A network fails pairwise stability if *two* players would like to form a link that have not done so. Point 2 considers only a unilateral deviation. That is, a link does not survive pairwise stability if either player wishes to sever the link.

This formulation implicitly assumes that utility is non-transferable between agents. If one agent does not benefit from a link, the agent deletes the link and there is no opportunity for the partner to use his surplus from the link to pay the agent to maintain the link. We find a model with non-transferable utility more natural in this environment.[16]

We now turn to estimation. We exploit the definitions of pairwise stability to generate moment inequalities, following Pakes et al. (2015). Thus, we can use moment inequalities based on the definition of pairwise stability:

$$\begin{aligned} E\left[\psi_i\left(\Lambda, \alpha\right) - \psi_i\left(\Lambda - \{i,j\}, \alpha\right) + x_{ij}\beta | \Lambda_{ij} = 1, x_{ij}\right] &\geq 0 \\ E\left[\min_{k \in \{i,j\}} \psi_k\left(\Lambda \cup \{i,j\}, \alpha\right) - \psi_k\left(\Lambda, \alpha\right) + x_{kj}\beta | \Lambda_{ij} = 0, x_{ij}\right] &\leq 0 \end{aligned}$$

[16] Estimating under a model with transferable utility is feasible. With transferable utility between pairs of agents, the definition would be 1) $E[\pi_{ij} + \pi_{ji}] \geq 0$ for all $\{i,j : \Lambda_{ij} = 1\}$ and $E[\pi_{ij}] + E[\pi_{ji}] \leq 0$ for all $\{i,j : \Lambda_{ij} = 0\}$. If we instead allowed transfers between any agents, so for instance, agent $i$ could pay $j$ and $k$ based on whether $j$ and $k$ form a link, then the network would be at its social optimum. We could still form inequalities based on whether the sum of all payoffs went up or down with each link that we observe or do not.

These equations capture that for any pair with an agreement, we know that both countries prefer an agreement to no agreement, but that for each pair without an agreement, we know only that one of the two countries prefers no agreement. We can further interact elements of these conditions with $x_{ij}$ and network statistics to generate more moments.

### 2.3 K-stability

One criticism of pairwise stability is that it allows for over-connected networks. A set of links can satisfy pairwise stability if agents do not want to sever any single link, even if agents would wish to sever multiple links. This idea leads to a refinement of pairwise stability called *Nash pairwise stability*, and is discussed in Jackson & Wolinsky (1996).[17] We provide a method for utilizing the ideas of Nash pairwise stability in order to develop additional moments that we can impose on our estimation. This is particularly attractive because moment inequalities frameworks lead to partial identification and thus wide ranges for parameter estimates. The extra information embedded in Nash pairwise stability could be a valuable source of identification. However, we observe players with more than 30 links, so it is difficult to consider every possible deletion strategy numerically. Instead, we consider limited deletion strategies, where players are allowed to delete some finite set of links.

Some notation is helpful. Let $k$ be a scalar and $\mathcal{S}_{ik}$ be the set of all combinations of $k$ elements of $s_i(\Lambda)$. Thus, $\mathcal{S}_{i2}$ would be all pairs of nodes that $i$ is linked to. In Figure 1, $\mathcal{S}_{C2} = \{AB, AD, DB\}$ and $\mathcal{S}_{E2} = \emptyset$. Denote each element of $\mathcal{S}_{ik}$ as $\sigma_m$, $m = 1, \ldots, \#\mathcal{S}_{ik}$. We introduce a new stability concept, motivated by Nash pairwise stability and our computational concerns:

**Definition** A network $\Lambda$ is *pairwise stable with deletion degree K*, or *K-stable* if:

1. $E[\Pi_i(\Lambda)] \geq E[\Pi_i(\Lambda - \sigma_m)] \quad \forall \quad i, k \leq K, \sigma_m \in \mathcal{S}_{ik}$:

2. $\min\{E[\pi_{ij}], E[\pi_{ji}]\} \leq 0 \quad \forall \quad \{i, j : \Lambda_{ij} = 0\}$

[17] Of course, an agent may benefit from forming links with multiple agents, which would also not be captured by pairwise stability. This concept is captured by the notion of *strong stability* (Dutta & Mutuswami, 1997). However, this requires coordinated action between multiple agents, whereas deletion of multiple links requires only unilateral actions. Thus, we focus on Nash pairwise stability, but at this point, it seems possible to extend our techniques to strong stability.

The first element of the definition rules out networks in which agents wish to delete sets of links up to size $K$. The second element is the same as in the definition of pairwise stability. K-stability rules out more networks than pairwise stability but less than Nash pairwise stability.[18]

We can generate additional moment inequalities by exploiting conditions from K-stability. In this moment, we have an observation for each pair of countries that any country is connected to. For instance, three countries that are each connected to other two generates three observations.

$$E\left[\psi_i\left(\Lambda,\alpha\right)-\psi_i\left(\Lambda-\sigma,\alpha\right)+\sum_{j\in\sigma}x_{ij}\beta|\sigma\in\mathcal{S}_{ik},x_{ij}\right]\geq 0 \tag{2}$$

This approach generates a separate moment for each value of $k \leq K$. So we add $K-1$ moments to those derived for pairwise stability (plus possible interactions with instrumental variables such as $x$).[19]

One might be tempted to implement all of the moments implied by Nash pairwise stability, rather than cutting off moments that rely on deletions of more than $K$ links. However, beyond being computationally expensive, we expect that most of the empirical value of Nash pairwise stability can be obtained for relatively low values of $K$. To take an extreme example, what would be the value of going from $K = 44$ to $K = 45$? We observe only one country with more than 44 links, so we would be forming a moment with one observation, which will have infinite variance. Moreover, we expect a very wide set of parameters to satisfy the condition that the country is better off not deleting 44 of its links, so even if there were a few more countries in this set, the moment would be of little value.

[18] There is no guarantee of existence of a Nash pairwise stable or K-stable allocation. A sequence of bilateral joins could lead to a set of links that the country would like to delete.

[19] Computationally, we implement K-stability by generating a data set that stacks all of the elements in $\mathcal{S}_{ik}$ for each country $i$. Even when a few countries have more than 30 links, this data set is not particularly large for $k = 2$, and this data set is created in advance of estimation. During estimation, checking linear profit conditions for each observation is not computationally expensive. Thus, exploring $K > 2$ appears feasible, although we have not done so yet.

## 2.4 Endogeneity

A central question in any paper on network formation should be exogeneity. For example, if we see that country A forms a link with country B that has many links, we want to know whether A was attracted to B because it has many links or because there was an unobservable feature of B that made it attractive both to A and to other countries. Technically, we can allow for an extra term $\nu_{ij}$ in Equation 1 that is unobserved to the econometrician but observed by agents and is thus endogenous to the network $\Lambda$. The unobserved term $\varepsilon_{ij}$ continues as white noise to both the econometrician and the agents. The value of a link is then:

$$\pi_{ij} = \psi_i\left(\Lambda \cup \{i,j\}, \alpha\right) - \psi_i\left(\Lambda - \{i,j\}, \alpha\right) + x_{ij}\beta + \nu_{ij} + \varepsilon_{ij}.$$

We take two approaches to addressing this endogeneity. The first is based on matching on observable variables. Following Pakes et al. (2015), we assume that $\nu_{ij}$ is constant across some observable features of countries $i$ and $j$. Then, we consider pairs of countries with similar such observable characteristics but different values of network statistics, and possibly different choices of whether to have a treaty. Covariation in these variables identifies $\alpha$ in $\psi(\Lambda, \alpha)$. The second approach to endogeneity relies on a control function. We search for a variable that proxies for unobserved features of each country. For this, we focus on older trade data – we are currently using data from the mid-1950's. This trade data is available in the data set from Head et al. (2010). Constructing centrality statistics from these data is valuable because they should be highly correlated with the intrinsic value of trading with these countries currently, but since these data largely predate the modern commercial airline industry, the statistics should not be endogenous to events in this industry (NOT IMPLEMENTED YET).[20]

[20] Naturally, there is a tradeoff between collecting older data that is less affected by the airline industry and more recent data that is more highly correlated with contemporary outcomes. Also, much older data do not exist for many country-pairs.

# 3 Estimation

This section provides sample analogs of our moments, and then discusses empirical issues with implementation. A short discussion of asymptotic properties then follows.

## 3.1 Sample analogs

In order to define the sample analog of the definition of pairwise stability, define $\mathcal{I}(\lambda_{ij} = 1)$ as the set of all pairs of countries $\{i, j\}$ that form an agreement, and $\mathcal{I}(\lambda_{ij} = 0)$ as the set of all pairs of countries $\{i, j\}$ that do not form an agreement. The number of pairs of countries that form an agreement is $n^a$ and the number that do not is $n^{na}$. We define $\mathcal{I}(\lambda_{ij} = 1)$ and $\mathcal{I}(\lambda_{ij} = 0)$ to exclude pairs of countries in which both are members of the EU. Furthermore, let $z_{ij}$ be a vector of instruments for pair $i, j$. Also, we now impose that $\alpha$ affects the network measures as a multiplicative coefficient. Then, our sample moments are:

$$\frac{1}{n^a} \sum_{\{i,j\} \in \mathcal{I}(\lambda_{ij}=1)} \Big(\alpha \left(\psi_i \left(\Lambda \cup \{i,j\}\right) - \psi_i \left(\Lambda - \{i,j\}\right)\right) + x_{ij}\beta\Big) z_{ij} \geq 0 \tag{3}$$

$$\frac{1}{2n^{na}} \sum_{\{i,j\} \in \mathcal{I}(\lambda_{ij}=0)} \min_{l \in \{i,j\}} \Big\{\alpha \left(\psi_l \left(\Lambda \cup \{i,j\}\right) - \psi_l \left(\Lambda - \{i,j\}\right)\right) + x_{ij}\beta\Big\} z_{ij} \leq 0$$

Hopefully, it is now clear why we require a model in which $\Lambda$ is exogenous to $\varepsilon_{ij}$. If not, we could not assume that $\varepsilon_{ij}$ is mean zero in each equation, in which case each equation would not hold just in observable variables, and we would not have a basis for estimation.

Moment inequalities lead to partial identification. In order to determine whether a point is in the confidence interval surrounding the identified set, we follow the algorithm presented in Andrews & Barwick (2012). Under their framework, we use the objective function that they ascribe to Pakes et al. (2015), and we use the "normal approximation" that they suggest, which assumes that moments are normal for purposes of inference rather than relying on simulation. The normal approximation substantially decreases the computational time of the estimator. Most of our parameter results are found by searching for the maximum and minimum of each parameter separately, subject to the constraint that the set of parameters must fall within the confidence intervals. We then report only these maximum and minimums, rather than the shape of the confidence intervals. Many of our specifications use only two parameters, and so we use grid searches and graphs of the confidence interval to gain a deeper understanding of our estimator. A fuller discussion of our estimation approach appears in Appendix B.

In addition to the moments in Equation 3, we utilize two more sets of moments. The first are derived from the concept of K-stability. Just as Equation 3 is an empirical counterpart to Equation 2, we develop a sample analog to Equation 2. We implement only the case for $K = 2$. That is, let $\mathcal{J}(\lambda_{ij} = 1), \lambda_{ik} = 1)$ ....

A second set of moments that we utilize are what we refer to as the *min moments*. The moment inequality in Equation 3 averages across all pairs of agents. On average, pairs of agents that form links must be better off than if they deleted their link. However, this moment mixes together many different types of links, both those that are very valuable and those that are only marginally valuable. We might believe we learn more if we focus on those that are marginally valuable. Another way to form moments is to recognize that pairwise stability implies not just that the average link is valuable, but that the least valuable link has positive value. We can construct a moment from this insight by averaging across countries, rather than across all pairs of countries. Let $z_i^m$ be the instrument vector for the min moment applied to observation $i$. The min moment is:

$$\frac{1}{n}\sum_{i=1}^{n}\left(\min_{j\in s_i(\Lambda)} \psi_i\left(\Lambda,\alpha\right) - \psi_i\left(\Lambda - \{i,j\},\alpha\right) + x_{ij}\beta\right) z_i^m \geq 0$$

The min moment provides more information for any given country, since it states that the minimum value for that country is positive rather than the average value. However, we observe fewer countries than pairs of countries, so it is a mean over much fewer observations, and in this sense may be less informative. It is an empirical matter whether the min moment provides useful information in practice or not. We experiment with the value of the min moments and the K-stability moments in providing information about $\alpha$ and $\beta$.

### 3.2 Empirical issues

There are several more issues to be dealt with before turning to results. We let the instruments $z_{ij}$ be functions of $x_{ij2}$, $(\psi_i(\Lambda \cup \{i,j\}) - \psi_i(\Lambda - \{i,j\}))$, and $\Lambda$. Under the assumptions of our model, $x_{ij1}$ is excluded from the instrument vector since it is not exogenous. We add a constant to the instrument vector in order to ensure that each element of $z_{ij}$ is positive, since negative instruments can change the sign of the moment that they interact with.

Inspection of the estimation equations shows that if one vector of parameters satisfies the moments, any multiple will as well. Similarly, setting all parameters to zero will automatically satisfy these moments. That is, the scale of the parameters is not identified. This is standard in discrete choice models. In logit and probit models, we typically address this issue by normalizing the variance of the error term to 1. However, we do not model the distribution of the error term in this paper, so that normalization is not available. Instead, we normalize the coefficient of $x_{ij1}$ to 1. Thus, the remaining parameters should be interpreted as the importance of that variable relative to $x_{ij1}$. Normalizing the coefficient on $x_{ij1}$ is natural since our assumptions about measurement error exclude it from the instrument vector. That is, we do not estimate a coefficient for the variable that we do not include in the instrument vector.[21]

It is a challenge to implement estimation via moment inequalities in the context of many regressors. In part, this is a computational issue. Since the computational algorithm often involves something like grid search, it can be difficult to implement with many parameters. Also, this points to an inherent lack of robustness of estimation in the context of partial identification. With typical estimation based on equalities, such as estimation of a linear model via ordinary least squares, adding explanatory variables that are orthogonal to existing explanatory variables has no impact on the coefficients of the existing explanatory variables. However, with moment inequalities, we will identify only a range of parameters for this new orthogonal variable, and that

[21]Some care must be taken in choosing $x_{ij1}$ to make sure that we believe that the true coefficient is positive. If we normalize a negative coefficient to 1, we effectively change the sign of the all the other coefficients. In our case, we strongly believe that the gravity score or the product of GDPs has a positive effect on the likelihood of an agreement.

will typically expand the range of parameters that are part of the confidence interval for all of the other variables. Thus, estimation via moment inequalities is not robust to adding orthogonal variables in the same sense as standard estimation. For these reasons, it is important to choose explanatory variables carefully, and with an eye towards parsimony.

In thinking of explanatory variables, we are motivated by the literature on gravity equations used to explain trade data, since trade and ASAs are both forms of "links" between countries (see Head & Meyer, 2013). Thus, ideally, we would include all of the explanatory variables that one finds in standard estimation of gravity equations. However, in practice, this entails a great many variables, such as distance, and indicators for shared language, colonial history, and free trade agreements. Much of the gravity literature emphasizes the importance of exporter and importer fixed effects, which greatly increases the number of parameters to be estimated.

Rather than include all of these variables in our moment inequalities algorithm, we instead first estimate a gravity equation model on the list of countries we study. That is, we specify the log of unilateral trade as a linear function of exporter and importer fixed effects, and a series of explanatory variables found to be important in the gravity equation literature. More discussion and details on this estimation appear in Appendix C. We refer to the predicted value from this regression (assuming the shock in the estimation equation is equal to zero) as the *gravity score*. We use the gravity score as an important explanatory variable in our moment inequalities estimation routine. In this way, variables that are known to be important from the gravity literature are used to predict outcomes in our model of international agreement formation.

Certainly, it is possible that variables such as distance have a different effect on agreement formation than they do on trade. We can address this by including both the gravity score and variables such as distance separately as explanatory variables in our agreement formation model. That is, they can be separate values of $x_{ijk}$. We experiment with different specifications and find that these variables have little explanatory value beyond the gravity score. In much of our analysis, we use the gravity score and a constant term as the only explanatory variables, letting the gravity score take the position of $x_{ij1}$, the variable over which the countries have measurement error and with the coefficient set to 1.

## 3.3 Asymptotics

Asymptotic properties are challenging in network context such as ours, and we have no formal results, although there are a number of related formal treatments. The study of asymptotic properties in network models depends on whether one imagines observing many networks of a given number of agents, or a single network with the number of agents going towards infinity. In our context with a cross-section of data, it is more natural to think of observing a single network with an increasing number of agents. Indeed, this is the approach taken of all papers we know of that study the asymptotic properties of gravity equation estimators. See Egger & Staub (2014), Charbanneau (2014), Jochmans (2015) and Cameron & Miller (2014).

An important variable is the measure of network structure such as betweenness centrality or eigenvector centrality. One issue is that although this variable differs across observations, it still is always computed from the entire network, and we observe only one network. Menzel (2015) takes up the estimation of this type of estimator in a more general strategic framework. A second issue (pointed out to us by Antonio Mele) is that as the number of countries goes to infinity, the network structure variables go to zero. One way to imagine addressing this issue is that the network variables depend only on countries that are relatively close by in some sense, so the variables stay constant after the number of countries reaches some critical value. However, to be clear, we do not compute our network variables to reflect this notion.

## 3.4 Results

To be completed.

## References


Agarwal, N. (2013). An empirical model of the medical match. Unpublished Manuscript, MIT.

Alatas, V., Banerjee, A., Chandrasekhar, A. G., Hanna, R., & Olken, B. A. (2014). Network structure and the aggregation of information: Theory and evidence from indonesia. Unpublished manuscript, MIT.

Andrews, D. W. K. & Barwick, P. J. (2012). Inference for parameters defined by moment inequalities: A recommended moment selection procedure. *Econometrica*, *80*(6), 2805 – 2826.

Badev, A. (2013). Discrete games in endogenous network: Theory and policy. Unpublished manuscript, Board of Governors of the Federal Reserve.

Baier, S. L. & Bergstrand, J. H. (2004). Economic determinants of free trade agreements. *Journal of International Economics*, *64*, 29–63.

Bajari, P., Benkard, L., & Levin, J. (2007). Estimating dynamic models of imperfect competition. *Econometrica*, *75*, 1331–1370.

Boucher, V. & Mourifié, I. (2015). My friend far far away: Asymptotic properties of pairwise stable networks. Unpublished manuscript, University of Toronto.

Cameron, A. C. & Miller, D. L. (2014). Robust inference for dyadic data. Unpublished manuscript, University of California - Davis.

Chamberlain, G. (1980). Analysis of covariance with qualitative data. *Review of Economic Studies*, *47*, 225–238.

Chandrasekhar, A. G. & Jackson, M. O. (2014). Tractable and consistent random graph models. NBER Working Paper #20276.

Charbanneau, K. B. (2014). Multiple fixed effects in binary response panel data models. Bank of Canada Working Paper 2014-17.

Ciliberto, F. & Tamer, E. (2009). Market structure and multiple equilibria in airline markets. *Econometrica*, *77*, 1791–1828.

Cristea, A., Hummels, D., & Roberson, B. (2012). Estimating the gains from liberalizing services trade: The case of passenger aviation. Unpublished Manuscript, Univeristy of Oregon.

Currarini, S., Jackson, M. O., & Pin, P. (2009). An economic model of friendship: Homophily, minorities, and segregation. *Econometrica*, *77*, 1003–1045.

de Paula, A., Richards-Shubik, S., & Tamer, E. (2014). Identification of preferences in network formation games. Unpublished manuscript, Harvard University.

Dickstein, M. J. & Morales, E. (2013). Accounting for expectational and structural error in binary choice problems: A moment inequality approach. Unpublished manuscript, Princeton University.

Dresner, M. (2008). An analysis of U.S. international air transport agreements: From liberal bilaterals to the U.S.-EU multilateral accord. *Journal of Transport Research*, 115–127.

Dutta, P. & Mutuswami, S. (1997). Stable networks. *Journal of Economic Theory*, *76*, 322–344.

Egger, P., Larch, M., Staub, K., & Winkelmann, R. (2011). The trade effects of endogenous preferential trade agreements. *American Economic Journal: Economic Policy*, *3*, 113–143.

Egger, P. H. & Staub, K. E. (2014). GLM estimation of trade gravity models with fixed effects. forthcoming, *Empirical Economics*.

European Commission (2010). Common aviation area with the neighbouring countries by 2010 - progress report. Communication from the Commission of the European Commission COM/2008/0596.

Fershtman, C. & Gandal, N. (2011). Direct and indirect knowledge spillovers: The 'social network' of open-source projects. *RAND Journal of Economics*, *42*, 70 – 91.

Fong, K. & Lee, R. S. (2013). Markov-perfect network formation: An applied framework for bilateral oligopoly and bargaining in buyer-seller networks. Unpublished Manuscript, Stern School of Business, New York University.

Fox, J. (2010). Estimating matching games with transfers. Unpublished Manuscript, University of Michigan.

Furusawa, T. & Konishi, H. (2007). Free trade networks. *Journal of International Economics*, *72*, 310–335.

Goldsmith-Pinkham, P. & Imbens, G. (2013). Social networks and the identification of peer effects. *Journal of Business & Economic Statistics*, *31*, 253–264.

Goyal, S. (2007). *Connections: An Introduction to the Economics of Networks*. Princeton University Press.

Goyal, S. & Joshi, S. (2006). Bilateralism and free trade. *International Economic Review*, *47*(3), 749 – 778.

Graham, B. S. (2014). An empirical model of network formation: detecting homophily when agents are heterogeneous. Unpublished manuscript, University of California - Berkeley.

Graham, B. S. (2015). Methods of identification in social networks. *Annual Review of Economics*, *7*, 465 – 485.

Head, K., Mayer, T., & Ries, J. (2010). The erosion of colonial trade linkages after independence. *Journal of International Economics*, *81*, 1–14.

Head, K. & Meyer, T. (2013). Gravity equations: Workhorse, toolkit and cookbook. CEPR Discussion Paper, #9322.

Ho, K. (2009). Insurer-provider networks in the medical care market. *American Economic Review*, *99*, 393–430.

Hsieh, C.-S. & Lee, L.-F. (2012). A structural modeling approach for network formation and social interactions - with applications to students' friendship choices and selectivity on activities. Unpublished Manuscript, Ohio State University.

Imbens, G. & Kalyanaraman, K. (2010). An empirical model for strategic network formation. Unpublished Manuscript.

Intervistas (2015). The economic impacts of air service liberalization. U.S. Department of State, `http://www.state.gov/e/eb/tra/ata/index.htm`.

Jackson, M. O. (2008). *Social and Economic Networks*. Princeton University Press.

Jackson, M. O. & Wolinsky, A. (1996). A strategic model of social and economic networks. *Journal of Economic Theory*, *71*(1), 44 – 74.

Jochmans, K. (2015). Two-way models for gravity. Unpublished manuscript, Sciences Po.

Kolaczyk, E. (2009). *Statistical Analysis of Network Data*. Springer Series in Statistics. Springer.

Leung, M. (2015). Two-step estimation of network-formation models with incomplete information. Forthcoming, *Journal of Econometrics*.

Mele, A. (2013). A structural model of segregation in social networks. Unpublished Manuscript, Johns Hopkins University.

Menzel, K. (2015). Inference for games with many players. Forthcoming, *Review of Economic Studies*.

Micco, A. & Serebrisky, T. (2006). Competition regimes and air transport costs: The effects of Open Skies Agreements. *Journal of International Economics*, *70*, 25 – 51.

Miyauchi, Y. (2014). Structural estimation of a pairwise stable network with nonnegative externality. Unpublished manuscript, MIT.

Myerson, R. (1977). Graphs and cooperation in games. *Mathematics of Operations Research*, *2*, 225–229.

Odoni, A. (2009). The international institutional and regulatory environment. In P. Belobaba, A. Odoni, & C. Barnhart (Eds.), *The Global Airline Industry*. Wiley.

Pakes, A., Porter, J., Ho, K., & Ishii, J. (2015). Moment inequalities and their application. *Econometrica*, *83*, 315–334.

Prell, C. (2011). *Social Network Analysis: History, Theory and Methodology*. SAGE Publications.

Sacerdote, B. (2014). Experimental and quasi-experimental analysis of peer effects: two steps forward? *Annual Review of Economics*, *6*, 253 272.

Sheng, S. (2012). Identification and estimation of network formation games. Unpublished manuscript, University of Southern California.

Sorensen, M. (2007). How smart is smart money: A two-sided matching model of venture capital. *Journal of Finance,*, *62*, 2725–2762.

Uetake, K. (2014). Estimating a model of strategic network formation and its effects on performance: An application to the U.S. venture capital markets. Unpublished manuscript, Yale School of Management.

# Appendices

## Appendix A: Calculation of Weighted Network Statistics

To be completed.

## Appendix B: Computation Details of Estimation Algorithm

Our model generates $J$ moments $m_j(\theta)$, $j = 1, \ldots, J$. For instance, based on Equation 3, we have a moment $j$ defined as: $m_j(\theta) = \frac{1}{n^a} \sum_{\{i,j\}} \in \mathcal{I} \lambda_{ij} = 1 \Big( \alpha \left( \psi_i \left( \Lambda \cup \{i,j\} \right) - \psi_i \left( \Lambda - \{i,j\} \right) \right) + x_{ij}\beta \Big) z_{ij}$

We write all moments so they are expected to be positive, so that the moment corresponding to agreements that are not formed has a negative sign in front of it:

$m_j(\theta) = -\frac{1}{n^{na}} \sum_{\{i,j\} \in \mathcal{I}(\lambda_{ij}=0)} \Big(\alpha \left(\psi_i \left(\Lambda \cup \{i,j\}\right) - \psi_i \left(\Lambda - \{i,j\}\right)\right) + x_{ij}\beta\Big) z_{ij}$

We define our objective function as:

$S(\theta) = \sum_{j=1}^{J} n_j \left(\frac{\min(m_j(\theta),0)}{\sigma_j(\theta)}\right)^2$ Andrews & Barwick (2012) term this to be the objective function from Pakes et al. (2015). In order to determine if a parameter is in a particular confidence interval, we must first determine the degrees of freedom. The degrees of freedom counts the number of binding constraints at a particular parameter value:

$df(\theta) = \#\mathcal{M}(\theta) = \left[j \in 1, \ldots J \middle| \frac{\sqrt{n_j} m_j(\theta)}{\sigma_j(\theta)} < \kappa. \right]$ where # refers to the cardinality function, and $\kappa$ is a cutoff value. Finally we accept a set of parameters into the confidence interval if:

$$CS = \{\theta | \tilde{\chi}^2(S(\theta), df(\theta)) \leq 1 - \alpha\}.$$

where $\alpha$ is a confidence level. Also, $\tilde{\chi}^2$ is sum of squared half-normals.

- Step 1: Find $\theta_0$ such that $S(\theta) = 0$.
  - Gradient search works well here.
- Step 2:

$$\max_{\theta} \theta_i \;\texttt{such that}\; \chi^2(S(\theta), df(\theta)) \leq 1 - \alpha.$$

- Solve max and min for each $i$.
- Penalized simplex search here.
- If parameter hits $\pm 50$, call it unbounded.

## Appendix C: Gravity Equation Estimation

To be completed.