# Bank Linkages and International Trade

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**Abstract**

We show that bank linkages have a positive effect on international trade. We construct the global banking network (GBN) at the bank level, using individual syndicated loan data from Loan Analytics for 1990-2007. We compute network distance between bank pairs and aggregate it to country pairs as a measure of bank linkages between countries. We use data on bilateral trade from IMF DOTS as the subject of our analysis and data on bilateral bank lending from BIS locational data to control for financial integration and financial flows. Using gravity approach to modeling trade with country-pair and year fixed effects, we find that new connections between banks in a given country-pair lead to an increase in trade flow in the following year, even after controlling for the stock and flow of bank lending between the two countries. We conjecture that the mechanism for this effect is that bank linkages reduce the risk exporters face and present four sets of results that supports this conjecture.

JEL classification: F10, F15, F34, F36

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# 1 Introduction

Global financial crisis demonstrated that connections between banks can be fragile and dangerous. Not surprisingly, much of recent literature on banking linkages or networks focused on the risk and contagion aspects of such connections,[1] with hardly any attention devoted to the benefits of bank linkages beyond the obvious risk-sharing effects. In this paper we demonstrate that there are positive externalities associated with bank linkages by showing that, even when controlling for actual financial flows and financial integration, we find a positive effect of bank linkages on international trade. We conjecture that bank linkages, which are formed through bank to bank lending, reduce the asymmetry of information and the resulting risk the exporters or their funders face, and provide four pieces of evidence supporting this conjecture.

The main goal of the paper is to show that bank linkages have a positive impact on trade that goes beyond the immediate effect of bank lending and to explain the mechanism behind this effect. In particular, we argue that export risk that arises due to information asymmetry or payment enforcement difficulties can be mitigated through bank linkages. Bank linkages can help enforce or guarantee payments, as in Olsen (2013). In addition, banks are likely to have access to the information on creditworthiness of potential importers and may pass this information to banks they are connected to in exporting countries, to be in turn passed on to exporting firms.

We proxy for the tightness of bank linkages for each country pair using individual loan-level data from Loan Analytics database. We construct a global network of banks in which relationships are formed when banks extend syndicated loans to each other.[2] The Loan Analytics database provides

[1] Battiston et al. (2012); Castiglionesi & Navarro (2007); Chan-Lau et al. (2009); Cocco et al. (2009); Craig & von Peter (2010); Delli Gatti et al. (2010); Elliot et al. (2012); Garratt et al. (2011); Giannetti & Leaven (2012); Haldane (2009); Haldane & May (2011); Imai & Takarabe (2011); Kalemli-Ozcan et al. (2013); May & Arinaminpathy (2010); Mirchev et al. (2010); Nier et al. (2007); Sachs (2010) and von Peter (2007).

[2] In this we differ from Garratt et al. (2011); Kubelec & Sá (2010); Minoiu & Reyes (2011); von Peter (2007), who construct banking networks at aggregate level, using BIS data. See Hale (2012) for the discussion of advantages of the bank-level approach. We also ignore ownership-based bank linkages, information on which was recently put together by Claessens & Van Horen (2013), and which could be an alternative proxy. We do conduct robustness tests with respect to this measure.

information on syndicated banks loans, including those extended to financial institutions. For our purposes, syndicated loans are a good proxy for bank relationships because they tend to be of much longer maturities than interbank loans and thus represent a larger commitment and the potential for information flows.[3] In fact, anecdotal evidence suggests that establishing relationships is one of the main purposes of bank to bank syndicated lending on some occasions.[4] In constructing the network we take into account the direction of the lending, but we ignore the amounts lent to avoid results being driven by trade financing.

We test our hypothesis that bank linkages have an impact on trade using standard gravity model with country-pair and year fixed effects in our benchmark specification. Our sample includes 29 largest industrialized and developing countries and extends from 1991 to 2009.[5] We use trade data from the IMF Direction of Trade Statistics (DOTS), which is a standard source, and show that in our sample the gravity model has the same fit as in the literature. We also show that measures of financial integration and financial flows, which we proxy for by BIS locational data on bilateral stocks and flows of bank assets, are correlated with international trade.

Controlling for measures of financial flows and financial integration, along with other standard variables, as well as country pair and year fixed effects, we find that trade is higher between country pairs in which banks have established new connections in the previous year. The magnitude of this effect is economically significant, but not very large: doubling the change in the intensity of bank linkages due to new banking connections, increases trade in subsequent year by about 2 percent. We analyze the effect of bank linkages on exports over time and find that this result is very robust. Moreover, while the effect of bank linkages did become larger during the crisis of 2008-09, our main

[3]The bank-to-bank syndicated loan market is relatively large — in the late 1990s syndicated bank loans extended to banks and reported in Loan Analytics amounted to over 30 percent of total bank claims on banks as reported by the BIS. This ratio fell to below 20 percent by the end of our sample as interbank lending ballooned prior to the global financial crisis. In 2007 alone 4.7 trillion USD worth of syndicated loans extended to banks are reported in Loan Analytics.

[4]See, for example, the media coverage of a syndicated loan to Turkish Garanti Bank in 2010, such as "Banks on Parade," IFR Turkey 2010.

[5]Countries included in the sample are listed on Figure 1.

results are not driven by these two years. We also find that the effect of bank linkages became more important towards the end of our sample.

Next we show the evidence that the mechanism by which bank linkages affect trade is through reduction of export risk. To conduct these test we gather additional data, namely, industry-level trade data from Comtrade, export insurance premia from the U.S. EXIM bank, and insured export credit exposure from the Berne Union. All our tests support the export risk channel of the effect of bank linkages on exports. First, we show that bank linkages matter much more for exports of differentiated goods, for which export risk tends to be higher (Rauch & Trinidade, 2002; Ranjan & Lee, 2007). Second, we show that bank linkages are significantly more important for exports to countries where export risk is higher. Third, we show that the effect of bank linkages on exports is significantly smaller if the importing country has better access to export insurance, which would make bank linkages a secondary avenue of mitigating export risk. Fourth, we show that bank linkages are twice more important for exports to non-OECD countries, where contract enforcement tends to be worse, than for exports to OECD countries.

While we emphasize the importance of bank linkages in reducing export risk and contract enforcement, our results can also be interpreted in the spirit of the literature on social network in international trade surveyed by Rauch (2001).[6] Bank linkages can be similar to social network linkages in that they may provide channels of information flows and help match seller to buyers in different countries. This interpretation is partially encompassed in our main interpretation of bank linkages as reducing export risk in that banks are particularly good at providing information on creditworthy buyers. Thus, they may not only facilitate matching of sellers to buyers, but in doing so they may be reducing asymmetric information that leads to payment enforcement problem in international transactions.

In addition to showing the benefits of bank linkages, our paper contributes to the literature on

[6]Since the survey, the importance of social and information network has been further shown in Combes et al. (2005), and Baston & Silva (2012), among others.

trade and financial globalization in a number of important ways. First of all, it adds to the body of evidence showing the connection between globalization of goods and capital markets. The rapidly growing body of literature shows the importance of finance in trade.[7] We show, that beyond the direct effect of financial flows on trade, there is an externality that arises from bank linkages. Another strand of literature is focusing on opening the black box of the border effect by uncovering mechanisms that put a wedge between home and foreign price of goods.

The papers that analyze the impact of information and contract enforcement in international trade are closely related to our analysis. In particular, Rauch & Trinidade (2002) show the importance or ethnic networks, Guiso et al. (2009) show the role of trust in explaining international trade patterns and Cristea (2011) and Poole (2012) show the importance of business relations. More generally, we contribute to the understanding of border effects by suggesting that asymmetric information generates export risk and showing that such risk is likely reduced through bank linkages between the countries. By relating bank linkages to trade, our paper also contributes to the literature on the role of financial flows in international business cycles. While Imbs (2006) shows a positive cross-country correlation between financial flows and business cycle comovements, a recent paper by Kalemli-Ozcan et al. (2013) finds a negative within correlation. Potentially, a more precise understanding of mechanisms through which financial flows affect economic relationships between countries can shed further light on this issue.

In the next section we present the theoretical background for our analysis, describe our data, and present our empirical model. In section 3 we describe and discuss our results. Section 4 concludes.

[7]See survey by Contessi & de Nicola (2012) as well as Manova (2008); Ahn et al. (2011); Amiti & Weinstein (2011); Minetti & Zhu (2011); Chor & Manova (2012) and references therein. Paravisini et al. (2011), however, find that in case of Peru credit shortage affects production rather than export-specific activities.

# 2 Theoretical background, data, and empirical approach

Our analysis fits well in the general framework of the gravity model of trade. To show this, it is worth recapping the basic microfoundations of the model.

## 2.1 Theoretical underpinnings of the gravity model and export risk

Following Feenstra (2004), assume that preferences of a representative consumer are isoelastic (CES) and that consumers in each country $j$ consume good produced in all other countries $i \in (i, C)$ so that utility function is

$$U^j = \sum_{i=1}^{C} N^i (c^{ij})^{\frac{\sigma-1}{\sigma}},$$

where $N^i$ is the number of goods produced in country $i$ and $c^{ij}$ is country $j$'s consumption of goods made in $i$, which also corresponds to the volume of exports from $i$ to $j$, $\sigma > 1$ is elasticity of substitution. We assume that all goods produced in country $i$ are sold in country $j$ for the same price $p^{ij}$. We also assume balanced trade, which implies that the budget constraint for country $j$ is given by its total output $Y^j$ as

$$Y^j = \sum_{i=1}^{C} N^i p^{ij} c^{ij}.$$

The optimization yields

$$c^{ij} = \frac{p^{ij}}{P^j}^{-\sigma} \frac{Y^j}{P^j},$$

where $P^j$ is the CES price index

$$P^j = \left( \sum_{i=1}^{C} N^i (p^{ij})^{1-\sigma} \right)^{\frac{1}{1-\sigma}} .$$

The value of exports is then

$$X^{ij} = N^i Y^j \left( \frac{p^{ij}}{P^j} \right)^{1-\sigma} .$$

Assuming labor to be the only input and full employment (Krugman, 1979), zero-profit condition implies that $Y^i = yN^i p^i$, where $y$ is the labor productivity, $N^i$ is the labor supply in country $i$ and $p^i$ is the price of domestically produced output in country $i$. Further assume that there is a wedge $T^{ij}$ between the price of the good made in country $i$ sold domestically, $p^i$, and the same good sold in country $j$, $p^{ij} = T^{ij} p^i$, with $T^{ii} = 1$, $T^{ij} > 1$.

Combining all of the above, we can express the value of exports from $i$ to $j$ in each period $t$ as

$$X_t^{ij} = \frac{Y_t^i Y_t^j}{(p_t^i)^\sigma y} \left( \frac{T_t^{ij}}{P_t^j} \right)^{1-\sigma} .$$

The wedge between domestic and foreign prices has been given many interpretations in the literature, including transportation costs, trade barriers, as well as information costs. Here we will focus of what we believe are two important components: geographical distance and export risk. Our specific interpretation of export risk is related to the cost of payment, or contract, enforcement in cross-border deals, the importance of which is well documented in Anderson & Marcouiller (2002). This cost is likely to be increasing with distance because of longer shipping time and will also be affected by the relative quality of institutions in countries $i$ and $j$ and by how differentiated is the good traded (which we don't model explicitly). Assume that this cost can be reduced if banks in country $i$ are closely linked with banks in country $j$, either through direct payment enforcement and guarantees as in Olsen (2013) or through selection of creditworthy counterparties by banks in country $j$. Thus we assume

$$T_t^{ij} = D^{ij} \left(R_t^{ij}\right)^{(1-a_t^{ij})},$$

where $D^{ij}$ is constant distance between countries $i$ and $j$, $R_t^{ij}$ is the cost of contract enforcement in country $j$ relative to country $i$ in the absence of bank linkages and in case of unit elasticity, and $a_t^{ij}$ is the strength of bank linkages between countries $i$ and $j$. We use relative cost of contract enforcement because the assumption is that firms in country $i$ can always sell their output in domestic markets, which can also be subject to contract enforcement problem. That is, we continue to interpret $T^{ij}$ as the wedge between export price and domestic price of goods.

Combining the above and taking logs, we obtain

$$\ln X_t^{ij} = \ln Y_t^i + \log Y_t^j - (\sigma-1)\ln D^{ij} - (\sigma-1)\ln R_t^{ij} + (\sigma-1)\ln R_t^{ij} a_t^{ij} - \sigma \ln p_t^i - \ln y + (\sigma-1)\ln P_t^j.$$

From this equation we can draw two main testable implications with respect to bank linkages:

**Testable implications.** *a) exports are an increasing function of bank linkages; b) the effect of bank linkages is stronger the higher is the export risk in country $j$ relative to country $i$, $R_t^{ij}$.*

In what follows, we will put these predictions to the test.

## 2.2 Data

We collect three main types of data. First, our trade data comes from the IMF Direction of Trade Statistics (DOTS). Second, we use BIS locational banking statistics for bilateral data on *stocks* of claims of banks on all sectors, to proxy for the degree of financial integration of each country pair, and data on valuation-adjusted bank *flows* from the same source to proxy for financial flows within each country pair. Third, we construct a measure of bank linkages using the data on banks' syndicated lending to each other, at the loan level, using Dealogic Loan Analytics Database (a.k.a. Loanware). In addition, we use industry-level trade data from Comtrade, as well as a number of additional sources described below. GDP and population data are from WDI.

### 2.2.1 International Trade

We use the measure of bilateral exports from country $i$ to country $j$ reported in USD, deflated by the U.S. CPI, $EX_{ij}$. Our sample covers 30 countries for the period of 1990-2009 at annual frequency, a strictly balanced panel. We conduct our analysis using the logarithmic transformation of the data

$$ex_{ij} = \log(1 + EX_{ij}),$$

which allows us to preserve the zeros. Since our sample is limited to 29 countries that are actively engaged in international goods and capital markets and thus available in BIS data sets, we don't have many zeros in our data set.[8] Out of 16240 observations (812 country pairs for 20 years), only 126 are zeros. Appendix Figure A.1 shows the distribution of $ex_{ij}$ in the beginning of our sample, in 2007, and in 2009. While there is a small mass point at and near zero, especially in the early part of our sample, it is not substantially large to influence our results, as we will show in robustness tests.

We also use Comtrade to obtain industry level trade data at 4-digit SITC level of aggregation in order to compute exports by Rauch (1999) categories of product differentiation. Rauch (1999) sorts SITC codes into three categories of goods: homogeneous (those traded on international exchanges or reference prices) or differentiated (goods for which branding information precludes them from being traded on exchanges or reference priced).

[8] See Figure 1 for the list of countries in the sample.

### 2.2.2 Financial Integration and Financial Flows

We use bilateral data on banks' claims on all sectors from BIS locational banking statistics including all types of claims. BIS reports both stocks and valuation-adjusted flows of these variables, for both assets and liabilities. We use stocks of claims outstanding, in real USD, to represent the degree of financial integration between the countries in the pair. We use flows of bank credit to proxy for financial flows. Since trade credit extended by banks to firms is frequently backed up by credit lines the banks obtain in larger financial institutions, flows of bank claims also provide a proxy for the availability of trade credit.

There are many missing values in BIS series for the 812 country-pairs we have in the data. We replaced, when possible, missing values of assets of $i$ in $j$ with reported value of liabilities of $j$ to $i$, for both stocks and flows. In addition, some stocks of claims are negative. We replaced both remaining missing values of stocks and flows and negative values of stocks with zeros. There reason we make such choice is because we believe small stocks of claims are more likely to be missing than the large ones. As a result, about 5000 out of 16240 observations for which stock and flow measures are zero, with the larger share of zeros in the first half of the sample.

For the regressions we make the following logarithmic transformation of the stocks $BS_{ij}$

$$bs_{ij} = \log(1 + BS_{ij}).$$

Since flows $BF_{ij}$ can be negative, we compute

$$bf_{ij} = \log(1 + BF_{ij})\ , BF_{ij} >= 0\ ; \quad bf_{ij} = -\log(1 - BF_{ij})\ , BF_{ij} < 0.$$

The distribution of these variables for 1990, 2007, and 2009, including the zeros, is shown on Appendix Figure A.2.

#### 2.2.3 Bank Linkages

We obtain deal–level data on syndicated international and domestic bank loans from Dealogic's *Loan Analytics* database (also known as Loanware). As our goal is to capture bank-to-bank lending activity, we download all loans extended to public and private sector banks between 1 January 1980 and 31 December 2009. To get a sense of how representative our data are, consider just one pre-crisis year, 2006. During this year about 4 trillion USD worth of new loans were extended to public and private sector banks. In December of that same year, 2006, BIS reports total amount of banks' claims on banks, domestic and international, to be about 18 trillion USD. While these numbers are not directly comparable because Loan Analytics reports amounts of loans originated and BIS reports amounts of loans outstanding, they give a sense of the relevance of the syndicated loan market.

Ideally, we would like to ensure that each of the loans in our sample is a bank-to-bank loan, but the Dealogic database only allows us to constrain borrowers' type (which we constrain to be either public or private sector bank); it does not allow us to place the same constraints on lenders.[9] Among the loans in our sample over 60% are term credit, revolving loans or CD's while only about 15% are various credit facilities. We replicate syndicated loans as many times as there are lenders in the syndicate on the signing date of the loan.

The vertices (nodes) of our network, each representing a bank, are indexed by $m = 1, ..., I$. The edges (direct connections) between each pair of nodes $m$ and $n$, loans in our case, are denoted by $c_{mn}$, which is binary $\{0, 1\}$. Not every pair of nodes is connected by edges. The edges are directed so that $c_{mn} \neq c_{mn}$. We will denote $c_{mn}$ as connections going from node $m$ to node $n$, i.e. a link generated by bank $m$ lending to bank $n$. We will refer to it sometimes as a *lending* connection or connection through lending; we will refer to $c_{nm}$ as a *borrowing* connection or connection through

[9] As such, some of the lenders within a syndicate may not be banks. We find that the non-bank lenders account for roughly 29% of all lenders in our sample and consist mostly of insurance companies and special purpose vehicles.

borrowing.

For our purposes, the *length* of a path is the number of edges that comprise that path. A *geodesic path* is a path between two given nodes that has the shortest possible length. We denote the *length* of the geodesic path from node $m$ to node $n$ as $g_{mn}$. Note that each pair of nodes $m$ and $n$ can have more than one geodesic path which will, by definition, have the same length. Because the network is directed, there are pairs of nodes for which there is a path in one direction, and not in the other.

For each of the years in our sample, we construct a cumulative global banking network (GBN), where for each year $t$ all the loans between 1990 and $t$ are included.[10] Thus, cumulative GBN expands every year through the addition of new connections as loans between bank pairs that have to engaged in lending previously. By the end of our sample, we have 5942 banking institutions as lenders and 3646 banking institutions as borrowers. For further detail on the data and the network construction, see Hale (2012).

For each year for each pair of banks and for each year we compute their *proximity* $p_{mn}$ as an inverse of the length of the geodesic path, that is $p_{mn} = 1/g_{mn}$. The interpretation of this measure is closer to information flows than to lending because our network does not account for the size of the loans extended and we assume that relationships between banks persist even after the loans mature.

We link each banking entity to a country on a locational basis,[11] and compute aggregate proximity, which is a sum of proximities for each pair of banks in a given pair of countries $i$ and $j$,

$$AP_{ij} = \sum_{m \in i} \sum_{n \in j} p_{mn},$$

so that two countries are more closely linked if there are more bank pairs between them that are

[10] While we have data going back as far as 1980, the loan coverage in Loan Analytics is substantially more sparse. The resulting network would be expanding due to expanding coverage, not increasing connectivity.

[11] Mian (2006) shows that cultural and geographical distances between headquarters and local branches play an important role.

connected at all and if these pairs of banks are connected more closely. This is our main measure of bank linkages.

In the regressions we use the logarithmic transformation of a one-period change in the aggregate proximity measure as

$$ap_{ijt} = \log(1 + (AP_{ijt} - AP_{ijt-1})).$$

This one-period change measures the increase in proximity that is due to new connections that were formed in year $t$. In our regressions we use first lag of this measure, to measure the effect of new bank linkages formed between years $t-2$ and $t-1$ on exports in year $t$.

In addition, we compute a secondary measure of bank linkages, the one that only takes into account direct connections, that is geodesic paths of length one, with all other connections set to 0. We refer to this measure as aggregate number of linkages $AL_{ij}$, and it is simply a sum of bank pairs in countries $i$ and $j$ that are directly connected. We will use the same log transformation of the one-period change in the aggregate number of linkages, which is simply a log of a number of new connections formed between countries $i$ and $j$.

$$al_{ijt} = \log(1 + (AL_{ijt} - AL_{ijt-1})).$$

The distribution of our proximity measures over years, over lenders, and over borrowers is shown on Figure 1. Left-hand side of Figure 1 shows the distribution of $ap_{ijt}$ and $al_{ijt}$. We can see that most linkages in our sample are direct. The spike in the first year of the data simply shows the formation of the network, and the results of the analysis are not sensitive to the inclusion of this year. As the differences between these two measure are rather small, we also compute the measure of indirect proximity, that is

$$aind_{ijt} = \log(1 + ((AP_{ijt} - AL_{ijt}) - (AP_{ijt-1} - AL_{ijt-1}))).$$

Right-hand side of Figure 1 shows the average of $aind_{ijt}$ over years, over lenders, and over borrowers. In the regressions we use a one-year lag of $al_{ijt}$ and of $aind_{ijt}$. Appendix Table A.3. provides summary statistics for all measures described above as well as their ingredients

#### 2.2.4 Export risk

Our main proxy for the export risk is the export insurance premia obtained from EXIM bank. Per our request, EXIM bank compiled average insurance premia they charged on export insurance contract by destination country, including the U.S. for all the years in our sample. For the U.S. the data are only available starting 1996. We merged these insurance premia to source and destination countries and computed the differential between target and source export insurance premium in each year as our proxy of relative risk measure $R_{ijt}$. Summary statistics for this measure are reported in the Appendix Table A.3.

Another way to test whether the effect of bank linkages on exports reflects mitigation of export risks is to test whether bank linkages are less important if there are alternative ways of mitigating export risks. One alternative is insured export credit that could be provided by a variety of financial institutions. Data on insured export credit exposures is provided by Berne Union and available from the Joint External Debt Hub (JEDH) for 2005-2012. Since we can't use the time- series information from just these years, we compute for each country the maximum stock of export insurance claims, in real terms, during this time period. The summary statistics for this measure are reported in the Appendix Table A.3. We then interact this measure for the exporter and the importer countries with our measures of direct and indirect bank linkages and add them to our benchmark regressions.

## 2.3 Empirical gravity model with extensions and export risk

The empirical gravity model is a direct application of the equations derived in the theoretical discussion. As a benchmark model (without the effect of bank linkages) we estimate

$$ex_{ijt} = \alpha_{ij} + \alpha_t + \mathbf{Z_{ijt}}'\delta + \varepsilon_{ijt},$$

where $ex$ is a log of exports, as described above, vector $\mathbf{Z}$ includes GDP per capita, population in both countries, as well as the ratio of GDP deflators in countries $i$ and $j$. Time fixed effects $\alpha_t$ absorb $y_t$, while time-invariant portion of $T_t^{ij}$ is absorbed by country-pair fixed effects $\alpha_{ij}$ and the time-varying portion is reflected by the error term. Measures of geographical and cultural distance between the countries that are commonly included in gravity models are absorbed by pair fixed effects, since they don't vary over time.

Appendix Table A.1 presents these benchmark regressions for our sample. Columns (1) through (3) only include fixed effects for source country $i$, target country $j$, and year, while columns (4) through (6) include country-pair fixed effects and year fixed effects as described above. All estimated coefficients have expected signs, most are statistically significant, and the fit of the regressions is similar to those found in the previous literature. We don't have data on GDP deflators for all countries in all years, therefore including the ratio of price deflators reduces our sample by about 30%, leaving the rest of the coefficients mostly unaffected.

We have to be careful that our estimates are not driven by the large plunge in global trade in the second half of 2008 and first half of 2009. Thus, in columns (3) and (6) we limit our sample to end in 2007. We find that the estimates of the effects of standard gravity variables on trade do not change much without the trade collapse years in the sample.

A number of recent papers showed the importance of financial linkages in explaining trade (Manova, 2008; Ahn et al., 2011; Amiti & Weinstein, 2011; Minetti & Zhu, 2011; Chor & Manova, 2012). For this reason, and to make sure that our main results are not driven by financial linkages, we include measures of financial linkages in our gravity regression. As discussed above, we include measures of stocks, to proxy for financial integration, and flows. Both of these measures can be thought of as reducing the wedge between domestic and foreign prices, $T^{ij}$. Since these measures are included as controls and are not central to our analysis, we did not introduce them into the model above to avoid clutter. Thus, the regression becomes

$$ex_{ijt} = \alpha_{ij} + \alpha_t + \gamma_1 bs_{ijt} + \gamma_2 bs_{jit} + \gamma_3 bf_{ijt} + \gamma_4 bf_{jit} + \mathbf{Z_{ijt}}'\delta + \varepsilon_{ijt}.$$

The results of these regressions are reported in Appendix Table A.2. All regressions include year and country-pair fixed effects, GDP per capita, population, and the ratio of GDP deflators. We find, without assigning any causality, that countries tend to export more to countries on which they have larger stocks of bank claims, while association between exports and banking flows tends to be negative. Since we do find significant effects, we will continue to include these measures as control variables in all our regressions.

As the first step of our main analysis, we estimate a reduced-form equation by including our measures of bank linkages as affecting the time-varying component of $T^{ij}$.

$$ex_{ijt} = \alpha_{ij} + \alpha_t + \beta\, L.ap_{ijt} + \gamma_1 bs_{ijt} + \gamma_2 bs_{jit} + \gamma_3 bf_{ijt} + \gamma_4 bf_{jit} + \mathbf{Z_{ijt}}'\delta + \varepsilon_{ijt}$$

with $\beta$ being our coefficients of interest which we expect to be positive. Note that we include changes in our aggregate bank proximity measures lagged by one year. Thus, we test how new connections formed between banks in year $t$ affect trade in year $t+1$.

As shown in the literature, export risks tend to be more important for more differentiated goods (Rauch, 1999; Rauch & Trinidade, 2002; Ranjan & Lee, 2007). Thus, we expect the effect of bank linkages to be higher for more differentiated goods. We will, therefore, estimate the model separately for exports of homogeneous and differentiated goods, expecting coefficient $\beta$ to be higher for differentiated goods.

As shown in the theoretical discussion, if our hypothesis of bank linkages mitigating export risk is correct, the effect of bank linkages will to vary with the export risk of country $j$ relative to country $i$

$$ex_{ijt} = \alpha_{ij} + \alpha_t + \beta_1 \, L.ap_{ijt} + \beta_2 \, R_{ijt} L.ap_{ijt} + \gamma_1 bs_{ijt} + \gamma_2 bs_{jit} + \gamma_3 bf_{ijt} + \gamma_4 bf_{jit} + \mathbf{Z_{ijt}}'\delta + \varepsilon_{ijt},$$

where $R_{ijt}$ is a proxy for relative export risk, with its main effect included in $\mathbf{Z_{ijt}}'\delta$. We expect both $\beta_1$ and $\beta_2$ to be positive.

We also test, using similar approach, whether access to export insurance reduces the importance of bank linkages, because it provides alternative ways of mitigating export risk. Moreover, we test whether the importance of bank linkages varies with the level of economic development, by splitting our sample into countries that are members and non-members of OECD.

Finally, we test whether bank linkages matter more if substitution elasticity is higher, as predicted in our theoretical discussion. To do so, we estimate the regression where we allow the effect of bank linkages to vary with average elasticity of exports from country $i$ to country $j$, $\sigma_{ijt}$:

$$ex_{ijt} = \alpha_{ij} + \alpha_t + \beta_3 \, L.ap_{ijt} + \beta_4 \, \sigma_{ijt} L.ap_{ijt} + \gamma_1 bs_{ijt} + \gamma_2 bs_{jit} + \gamma_3 bf_{ijt} + \gamma_4 bf_{jit} + \mathbf{Z_{ijt}}'\delta + \varepsilon_{ijt},$$

where the main effect of $\sigma_{ijt}$ is included in $\mathbf{Z_{ijt}}'\delta$. We expect both $\beta_3$ and $\beta_4$ to be positive.

## 3 Effects of bank linkages on exports

Our reduced-form results are presented in Table 1, where we test whether changes in our measure of new bank linkages formed during the year $t-1$ affect exports in year $t$. The first four columns report regressions with changes in aggregate proximity *ap*, and last four columns split this measure into changes in direct linkages *al* and changes in indirect proximity *aind*. In each of these sets, first regression does not include controls for BIS stocks and flows, the second regression does include them, the third regression includes all controls but limits the sample to years prior to the trade collapse of 2008-2009, the fourth regression goes back to the full sample and excludes the ratio of GDP deflators to increase the sample. All regressions include country pair and year fixed effects and are reported with robust standard errors.

We can see that in all specifications we find a positive effect of newly formed bank linkages on exports. We find that both direct and indirect lending linkages have a positive effect on exports, but only the effect of direct linkages is statistically significant. The coefficient on bank linkages, total or direct, remains unchanged whether or not we control for BIS stocks and flows of foreign bank claims, indicating that the measure of newly formed bank linkages we use is pretty much orthogonal to actual banking flows in the following year. Since some of the BIS measures enter significantly, we continue to include them in all our regressions. The effect of banks' lending linkages becomes smaller if we exclude 2008 and 2009, the years of the global trade collapse, from the sample (columns (3) and (7)). This indicates that bank linkages became especially important for trade during the global financial crisis, the hypothesis we will explicitly test next. Finally, the effect of bank linkages on exports increases slightly if we expand the sample by excluding the ratio of GDP deflators, as in columns (4) and (8), which become our benchmark regressions.

Since in the regressions all variables are in logs, it is easy to interpret the magnitudes of the coefficients. Most of our results suggest that doubling the change in intensity of bank linkages due to new banking connections is associated with 2-2.5 percent increase in exports in the following year — this impact is not very large, but it is not negligible either. In other words, when banks in country $i$ extend loans to twice as many banks that they previously did not have a relationship with in country $j$ as in country $k$, other things being equal, exports from $i$ to $j$ increase in the following year by 2-2.5 percent more than exports from $i$ to $k$. Note that this is likely to be a lower bound on the effect of bank linkages on trade, because our measure captures only a subset of bank relationships, those through the syndicated loan market.

Table 2 present the results of our further investigation of the effects of time and of the financial crisis and global trade collapse in 2008-2009. To this end we include in our benchmark regressions an indicator of "crisis" (years 2008 and 2009) and linear trend, both interacted with our variables of interest. We continue to include country pair and year fixed effects. To make sure we carefully control for financial integration and financial flows, the effects of which could also have changed during the crisis and over time, we interact the crisis indicator and the linear trend with the measures of stocks and flows of bank claims as well.

In columns (1) through (3) we use our aggregate proximity measure, while in columns (4) through (6) we again decompose it into direct and indirect linkages. As we expected, we find that bank linkages, including indirect linkages, became more important during the crisis years, when global trade and bank lending have shrunk substantially — this is indicated by positive and statistically significant interaction terms in columns (1) and (4). The increased importance of overall and direct bank linkages during crisis remains statistically significant even if we allow for increasing importance of bank linkages over time, as in columns (3) and (6). We can see, however, that indirect linkages became gradually more important over time, and once we allow for this trend, the effect of the crisis is no longer significant.

Columns (2) and (5) of Table 2 show that all bank linkages became more important over time. While the coefficients on main effect and the interaction of our bank linkage variables with linear trend are not statistically significant (except for the indirect linkages), we can compute the threshold year for which the sum of the main effect and the effect of the interaction with trend is statistically significant at the 10% level according to the F-test. We find that, depending on whether we allow for the level shift during the crisis years, overall and direct bank linkages became important for trade in 1992-94 and 1990-93, respectively, while indirect connections became statistically important in 2003 if we do not allow for the level shift in 2008-09. We also tested whether the slope of the trend has changed during crisis years, but found no evidence for that.[12]

To sum up, we find that effects of bank linkages are positive and statistically significant, and that they are driven predominantly by direct bank linkages. Moreover, we find that bank linkages, including indirect ones, became more important in the last years of the sample, due to both positive trend and financial crisis. We next turn to the tests of our hypothesis that this effect of bank linkages on exports represents the role of bank linkages in reducing export risks that are due to payment enforcement and other problems arising from asymmetric information.

### 3.1 Export risk and bank linkages

As we discussed earlier, existing literature suggests that export risks are higher for goods that are more differentiated (Rauch & Trinidade, 2002; Ranjan & Lee, 2007). This implies that for more differentiated goods the effects of bank linkages will be larger, because there are more risks to mitigate. We test this hypothesis by estimating our benchmark regressions for exports of differentiated, exchange traded, and reference priced goods, using Comtrade data at the 4-digit SITC level sorted into Rauch (1999) categories.[13] The results are presented in Table 3, where the first three columns test this hypothesis with respect to our benchmark bank linkages measure, and the last three columns split this measure into direct and indirect linkages. As before, all regressions include country pair and year fixed effects as well as controls for BIS measures of stocks and flows of international banking claims, and gravity measures.

[12] In the interest of space, we are not reporting these results.

[13] Since the totals across all SITC4 categories in Comtrade data are not identical to IMF DOTS data, and there is no data for one of our countries, Panama, we verify that our benchmark results hold for the total exports computed from Comtrade data. This is indeed the case with the coefficient on bank linkages slightly larger with Comtrade data. We also verified that our benchmark result is unchanged if we use IMF DOTS export data, but reduce the sample to be identical to that with Comtrade data.

Columns (1) and (4) of Table 3 report the results of the regression for the exports of differentiated goods. We find that the coefficients on overall proximity and direct linkages are substantially higher for differentiated goods than for the full sample. Comparing to columns (2)-(3) and (5)-(6) we can see that the coefficient on differentiated exports is almost double that for homogeneous goods, whether they are traded on an exchange or are reference priced. The differences between these coefficient are statistically significant. We do not find such difference for indirect linkages. These results also hold if we exclude crisis years.[14] Thus, bank linkages are more important for exports of differentiated goods, which is consistent with the interpretations of our results as bank linkages reducing export risk.

A more direct test of our hypothesis that bank linkages alleviate export risks is a regression with measures of bank linkages interacted with a proxy for bank risk. Are proxy for export risk is export risk premium differential between the target and the source country. The regressions are presented in Table 4, where again, first two columns estimate regressions for overall measure of bank linkages, while second two columns split the measure into direct and indirect linkages. As before, all regressions include country pair and year fixed effects as well as controls for BIS measures of stocks and flows of international banking claims, and gravity measures.

First of all, across all columns in Table 4, we find that the effect of our export risk proxy is as expected. An increase in the difference between cost of export insurance in the target country and that in the source country tends to lower exports. Note that this result is obtained in the regression with country pair fixed effects and therefore should be interpreted in dynamic terms. Columns (1) and (3) of Table 4 show that simply introducing this control in our regression does not affect our benchmark results.[15] Columns (2) and (4) show that the effect of bank linkages, overall and direct ones, is substantially higher for country pairs with larger export risk in the destination country

[14]In the interest of space we do not report these regressions.

[15]Even though the sample is reduced slightly because export insurance premium data is not available for the U.S. prior to 1996.

compared to the source country. In terms of magnitude, an increase in risk premium differential by one standard deviation, 0.15, corresponds to 64 percent higher importance of overall bank linkages and 63 percent higher importance of direct bank linkages. We find no significant effect of indirect bank linkages. These results are robust to excluding crisis years.

Obviously bank linkages are not the only way to alleviate export risk, many institutions provide export insurance around the world. Thus, another way to test whether the positive effect of bank linkages on export works through alleviating export risk, is to see whether bank linkages are less important for the countries where export insurance is more readily available. We proxy for the availability of export insurance using Berne Union data on insured export credit exposures and interact this measure for the exporter and the importer countries with our measures of bank linkages. The results are presented in Table 5, where again, first two columns estimate regressions for overall measure of bank linkages, while second two columns split the measure into direct and indirect linkages. As before, all regressions include country pair and year fixed effects as well as controls for BIS measures of stocks and flows of international banking claims, and gravity measures.

In all regression in Table 5 we can see that the main effect of bank linkages, which represents the effect for country pairs with no export insurance availability, is twice as high than in our benchmark regressions. In columns (1) and (3) we show that the higher is the sum of export insurance availability in source and target countries, the lower is the effect of overall and direct bank linkages. Columns (2) and (4) show the regressions where we separate export insurance availability in exporting and importing countries. We find that the effect of export insurance availability in the country pair is entirely due to the effect of export insurance availability in the importing countries. An increase in export insurance availability in the destination country by one standard deviation, 11.1, reduces the importance of overall bank linkages by 26 percent and of direct bank linkages by 23 percent. Some of the decline in the effect of overall linkages is due to a decline in the effect of indirect bank linkages as availability of export credit in the destination country increases, as indicated by a negative and significant interaction term in column (4). Thus, the results of these regressions are consistent bank linkages helping mitigate export risk — when export insurance is ubiquitous in the import market, the risk of exporting to this country is most likely mitigated through insurance, making bank linkages less important. These results are also robust to excluding crisis year.

Another implication of the export risk interpretation of our results is that bank linkages should be more important for countries in which contract enforcement institutions are generally worse. We take a very simple approach to testing this implication and split our of importers into OECD and non-OECD countries, since by all measures of the rule of law, contract enforcement and the like, OECD countries score on average much better than non-OECD countries. The results are presented in Table 6, where first two columns estimate regressions for overall measure of bank linkages, while last two columns split the measure into direct and indirect linkages. As before, all regressions include country pair and year fixed effects as well as controls for BIS measures of stocks and flows of international banking claims, and gravity measures.

Regressions in columns (1) and (3) of Table 6 are limited to destination countries being in OECD, (2) and (4) limit the sample to non-OECD importers. We find that the effect of bank linkages is more than twice as large for the subsample of non-OECD importers. The difference between the coefficients for OECD versus non-OECD importers is statistically significant. This is consistent with our hypothesis that bank linkages will matter more if importers' institutions are less developed. These results are robust to excluding crisis years. We also find that for non-OECD importers indirect linkages have a positive effect on trade.

To sum up, we find strong support for our conjecture that bank linkages increase exports through reducing export risk that arises because of asymmetric information. We have conducted four separate tests of that mechanism and found that all result point in this direction. Moreover, we find that the effects of bank linkages are predominantly driven by direct connections, which are naturally more important in mitigating asymmetric information and enforcing payments.

### 3.2 Robustness tests

In our tests we have relied on lags to avoid effects of direct reverse causality. Persistence of the variables we consider, however, is potentially an important problem. To alleviate concerns that it is persistence in both trade and bank linkages that is driving our results, we estimate a panel regression with fixed effects and lagged dependent variable, using Arellano & Bond (1991) approach, where we treat bank stock and flow variables and GDP per capita as predetermined and bank linkages as endogenous. We present the results of this regression for our benchmark specification with two different lag configurations for full sample and sample excluding financial crisis years, in Table 7. We can see that a) our dependent variable is, indeed, rather persistent, although it is stationary; b) our main results not only survive, the coefficient on bank linkages is now higher. Overall these results suggest that the long-run effect of bank linkages on exports is also present and amounts to about 8-14 percent increase in exports in the long-run as a result of doubling the number of bank linkages.

Another important potential source of spurious correlation is general economic and financial conditions in each country. Hale (2012) shows that bank linkages are less likely to form if a country is experiencing a recession or a banking crises. Clearly, these conditions can also affect exports as well as imports. Thus, we control for GDP growth in both countries as well as for financial crises (both banking and currency) in either or both countries (Laeven & Valencia, 2012). We find that our results of benchmark as well as other regressions remain identical to those presented above, even though these controls enter our regressions significantly.[16]

Claessens & Van Horen (2013) have recently made available the data on the ownership country of

[16] We do not report the results of this and other robustness tests in the interest of space — they are available from the authors upon request.

over five thousand banks for 1995-2009. Using these data, we have computed the number of banks in country $j$ that are owned by country $i$ for each of the years in our sample. To make the analysis analogous to our benchmark, we computed the lagged change in this number of each country pair and included this variable either instead of or in addition to our measure of bank linkages. The ownership measure does not enter the regressions significantly when it is included by itself or with our measure and does not affect our results when included in addition to our measure.

Other robustness tests include controls for additional variables that may explain trade. We attempted to add controls for common currency, WTO membership and regional trade agreements between source and target,[17] time-varying transportation costs,[18], or all of these variables at once. If anything the results of our benchmark regression as well as in the analysis of export risk gain in significance and become significant at 1% in most cases.

We also attempted specifications in which we drop initial years in the sample, 1990-91, or dropping all observations in which exports are zero. These changes do not affect our results.

# 4 Conclusion

In this paper we demonstrate that connections between banks may have a positive externality. We show that when banks in a given country pair become more closely connected, it tends to increase trade between these two countries in the following year by an economically and statistically significant amount. We find this result controlling for gravity variables, financial integration, financial flows, as well as country pair and year fixed effects.

We conjecture that the mechanism for this effect is related to asymmetric information that leads to export risk. This export risk could be mitigated by bank linkages, either because they provide

[17]These variables are from Head & Mayer (2013) obtained via CEPII and are updated using the information from WTO website.

[18]Time-varying transportation costs are measured as an interaction of the Baltic Dry Index, from Bloomberg, with the distance between capitals of each country pair.

avenues for payment enforcement and guarantees, or because banks have access to information on importers' creditworthiness which they may share with other banks. We show in four separate tests that the data supports this conjecture.

We believe that this is just one example of a positive externality that arises from bank linkages, one we can easily measure. In the wake of the global financial crisis the literature on international banking is dominated by the discussion of the costs of bank linkages. We encourage researchers in the field to keep in mind potential benefits, whether direct ones, such as risk sharing and diversification, or external, such as the one we demonstrated in this paper.

## References


Ahn, J., Amiti, M., & Weinstein, D. (2011). Trade finance and the great trade collapse. *American Economic Review Papers and Proceedings*, *101*, 298–302.

Amiti, M. & Weinstein, D. (2011). Exports and financial shocks. *Quarterly Journal of Economics*, *126*, 1841–187.

Anderson, J. E. & Marcouiller, D. (2002). Insecurity and the pattern of trade: an empirical investigation. *Review of Economics and Statistics*, *84*(2), 342–352.

Arellano, M. & Bond, S. (1991). Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. *Review of Economic Studies*, *58*(2), 277–297.

Baston, P. & Silva, J. (2012). Networks, firms, and trade. *Journal of International Economics*, *87*(2), 352–364.

Battiston, S., Delli Gatti, D., Gallegati, M., Greenwald, B. C., & Stiglitz, J. E. (2012). Liaisons dangereuses: Increasing connectivity, risk sharing, and systemic risk. *Journal of Economic Dynamics and Control*, *36*(8), 1121–1141.

Castiglionesi, F. & Navarro, N. (2007). Optimal fragile financial networks. Tilburg University Center for Economic Research Discussion Paper 2007-100.

Chan-Lau, J., Espinosa-Vega, M. A., Giesecke, K., & Solé, J. (2009). *Assessing the Systemic Implications of Financial Linkages*, volume April, chapter 2. International Monetary Fund.

Chor, D. & Manova, K. (2012). Off the cliff and back? credit conditions and international trade during the global financial crisis. *Journal of International Economics*, *87*, 117–133.

Claessens, S. & Van Horen, N. (2013). Foreign banks: Trends and impact. *Journal of Money, Credit, and Banking*, *XX*(XX), XX.

Cocco, J. a. F., Gomes, F. J., & Martins, N. C. (2009). Lending relationships in the interbank market. *Journal of Financial Intermediation*, *18*, 24–48.

Combes, P.-P., Lafourcade, M., & Mayer, T. (2005). The trade-creating effects of business and social networks: Evidence from france. *Journal of International Economics*, *66*(1), 1–29.

Contessi, S. & de Nicola, F. (2012). What do we know about the relationship between access to finance and international trade. Federal Reserve Bank of St.Louis WP 2012-054B.

Craig, B. & von Peter, G. (2010). Interbank tiering and money center banks. BIS Working Paper 322.

Cristea, A. D. (2011). Buyer-seller relationships in international trade: Evidence from u.s. states' exports and business-class travel. *Journal of International Economics*, *84*(2), 207–220.

Delli Gatti, D., Gallegati, M., Greenwald, B., Russo, A., & Stiglitz, J. E. (2010). The financial accelerator in an evolving credit network. *Journal of Economic Dynamics and Control*, *34*(9), 1627–50.

Elliot, M., Goluby, B., & Jackson, M. O. (2012). Financial networks and contagion. mimeo, Department of Eocnomics, California Institute of Technology.

Feenstra, R. C. (2004). *Advanced International Trade: Theory and Evidence*. Princeton, New Jersey: Princeton University Press.

Garratt, R., Mahadeva, L., & Svirydzenka, K. (2011). Mapping systemic risk in the international banking network. Bank of England Working Paper 413.

Giannetti, M. & Leaven, L. (2012). The flight home effect: Evidence from the syndicated loan market during financial crises. *Journal of Financial Economics*, *104*(1), 23–43.

Guiso, L., Sapienza, P., & Zingales, L. (2009). Cultural biases in economic exchange. *Quarterly Journal of Economics*, *124*, 1095–1131.

Haldane, A. G. (2009). Rethinking the financial network.

Haldane, A. G. & May, R. M. (2011). Systemic risk in banking ecosystems. *Nature*, *469*, 351–355.

Hale, G. (2012). Bank relationships, business cycles, and financial crisis. *Journal of International Economics*, *88*, 312–325.

Head, K. & Mayer, T. (2013). Gravity equations: Toolkit, cookbook, workhorse. In G. Gopinath, E. Helpman, & K. Rogoff (Eds.), *Handbook of International Economics*, volume 4. Elsevier.

Imai, M. & Takarabe, S. (2011). Bank integration and transmission of financial shocks: Evidence from japan. *American Economic Journal: Macroeconomics*, *3*(1), 155–83.

Imbs, J. (2006). The real effects of financial integration. *Journal of International Economics*, *68*(2), 296–324.

Kalemli-Ozcan, S., Papioannou, E., & Perri, F. (2013). Global banks and crisis transmission. *Journal of International Economics*, *89*, 495–510.

Kalemli-Ozcan, S., Papioannou, E., & Peydró, J. L. (2013). Financial regulation, financial globalization and the synchronization of economic activity. *Journal of Finance*, *XX*, XXXX.

Krugman, P. (1979). Increasing returns, monopolistic competition, and international trade. *Journal of International Economics*, *9*, 469–79.

Kubelec, C. & Sá, F. (2010). The geographical composition of national external balance sheets: 1980-2005. Bank of England Working Paper 384.

Laeven, L. & Valencia, F. (2012). Systemic banking crises database: An update. IMF working paper 12/163, International Monetary Fund.

Manova, K. (2008). Credit constraints, equity market liberalizations and international trade. *Journal of International Economics*, *76*, 33–47.

May, R. M. & Arinaminpathy, N. (2010). Systemic risk: the dynamics of model banking systems. *Journal of the Royal Society Interface*, *7*, 823–838.

Mian, A. (2006). Distance constraints: The limits of foreign lending in poor economies. *Journal of Finance*, *61*, 1465–1505.

Minetti, R. & Zhu, S. C. (2011). Credit constraints and firm export: Microeconomic evidence from italy. *Journal of International Economics*, *83*(2), 109–125.

Minoiu, C. & Reyes, J. A. (2011). A network analysis of global banking: 1978-2009. IMF Working Paper 11/74.

Mirchev, L., Slavova, V., & Elefteridis, H. (2010). Financial system transformation — a network approach. in Proceedings of the 27th Conference Journes dconomie Montaire et Bancaire, European Research Group on Money, Banking, and Finance, Universit Montesquieu - Bordeaux IV, Bordeaux, France.

Nier, E., Yang, J., Yorulmazer, T., & Alentorn, A. (2007). Network models and financial stability. *Journal of Economic Dynamics and Control*, *31*(6), 2033–60.

Olsen, M. (2013). How firms overcome weak intrenational contract enforcement: Repeated interaction, collective punishment and trade finance. Available at SSRN: http://ssrn.com/abstract=2219243 or http://dx.doi.org/10.2139/ssrn.2219243.

Paravisini, D., Rappoport, V., Schnabl, P., & Wolfenzon, D. (2011). Dissecting the effect of credit supply on trade: Evidence from matched credit-export data. NBER WP 16975.

Poole, J. (2012). Business travel as an input to international trade. mimeo.

Ranjan, P. & Lee, J. Y. (2007). Contract enforcement and international trade. *Economics and Politics*, *19*(2), 191–218.

Rauch, J. E. (1999). Networks versus markets in international trade. *Journal of International Economics*, *48*, 7–35.

Rauch, J. E. (2001). Business and social networks in international trade. *Journal of Economic Literature*, *XXXIX*, 1177–1203.

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

Sachs, A. (2010). Completeness, interconnectedness and distribution of interbank exposures a parameterized analysis of the stability of financial networks. Deutsche Bundesbank Duscussion Paper 08/2010.

von Peter, G. (2007). International banking centres: a network perspective. *BIS Quarterly Review, December*, 33–45.

Figure 1: Measures of bank linkages

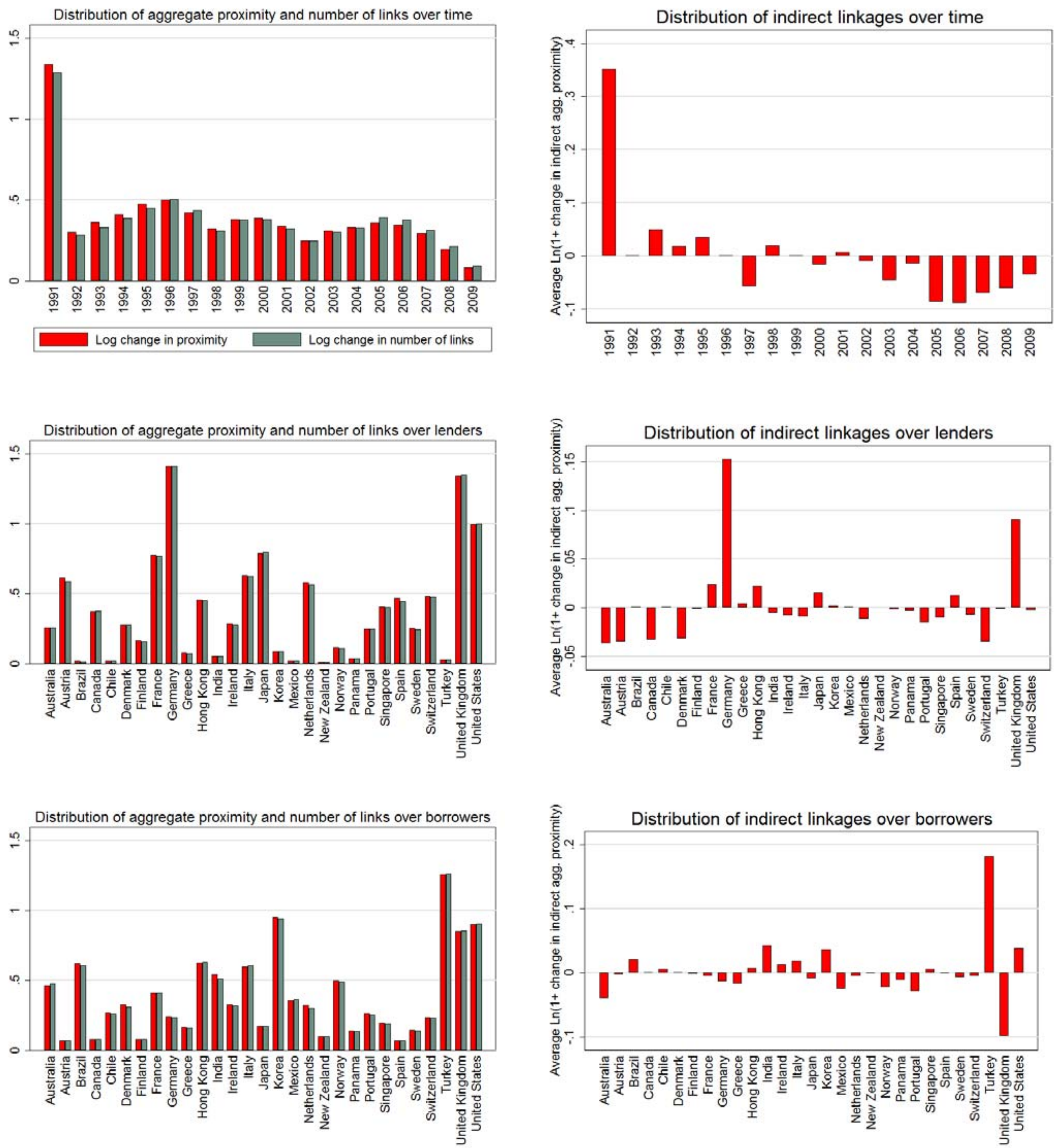

Table 1: Gravity regressions with aggregate proximity measures.

| | Full sample | Full sample | yr< 2008 | Full sample | Full sample | Full sample | yr< 2008 | Full sample |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| L.$ap_{ijt}$ | 0.0210*** | 0.0211*** | 0.0110* | 0.0257*** | | | | |
| | (0.00599) | (0.00600) | (0.00595) | (0.00562) | | | | |
| L.$al_{ijt}$ | | | | | 0.0193*** | 0.0193*** | 0.0106* | 0.0249*** |
| | | | | | (0.00562) | (0.00564) | (0.00560) | (0.00523) |
| L.$aind_{ijt}$ | | | | | 0.00640 | 0.00757 | 0.00191 | 0.00509 |
| | | | | | (0.00556) | (0.00563) | (0.00523) | (0.00516) |
| $bs_{ijt}$ | | 0.0195* | 0.0320*** | 0.0107 | | 0.0197* | 0.0320*** | 0.0107 |
| | | (0.0115) | (0.0118) | (0.0110) | | (0.0115) | (0.0118) | (0.0110) |
| $bs_{jit}$ | | 0.00703 | 0.00353 | 0.0104 | | 0.00702 | 0.00348 | 0.0103 |
| | | (0.00884) | (0.00849) | (0.00813) | | (0.00883) | (0.00848) | (0.00811) |
| $bf_{ijt}$ | | -0.00106 | -0.00419** | 0.000348 | | -0.00106 | -0.00420** | 0.000345 |
| | | (0.00165) | (0.00174) | (0.00141) | | (0.00165) | (0.00174) | (0.00141) |
| $bf_{jit}$ | | -0.00638 | -0.00741* | -0.00945** | | -0.00634 | -0.00740* | -0.00941** |
| | | (0.00459) | (0.00443) | (0.00413) | | (0.00460) | (0.00444) | (0.00412) |
| $P_j/P_i$ | 0.0217*** | 0.0219*** | 0.0196*** | | 0.0217*** | 0.0219*** | 0.0196*** | |
| | (0.00611) | (0.00611) | (0.00590) | | (0.00612) | (0.00611) | (0.00590) | |
| $N_i$ | 1.241*** | 1.298*** | 1.052** | 1.283*** | 1.239*** | 1.295*** | 1.052** | 1.282*** |
| | (0.440) | (0.431) | (0.487) | (0.351) | (0.440) | (0.431) | (0.487) | (0.351) |
| $N_j$ | 1.745*** | 1.786*** | 1.768*** | 1.454*** | 1.743*** | 1.785*** | 1.767*** | 1.452*** |
| | (0.375) | (0.375) | (0.400) | (0.326) | (0.375) | (0.376) | (0.400) | (0.326) |
| $Y_i$ | 0.762*** | 0.750*** | 0.642*** | 0.756*** | 0.762*** | 0.751*** | 0.642*** | 0.757*** |
| | (0.148) | (0.149) | (0.153) | (0.121) | (0.148) | (0.149) | (0.153) | (0.121) |
| $Y_j$ | 1.164*** | 1.152*** | 1.060*** | 1.127*** | 1.164*** | 1.153*** | 1.060*** | 1.127*** |
| | (0.153) | (0.153) | (0.166) | (0.130) | (0.153) | (0.153) | (0.166) | (0.130) |
| Observations | 10652 | 10652 | 9758 | 15428 | 10652 | 10652 | 9758 | 15428 |
| Within $R^2$ | 0.395 | 0.395 | 0.361 | 0.386 | 0.395 | 0.395 | 0.361 | 0.386 |

Dependent variable $\log(1 + EX_{ijt})$. Country pair and year fixed effects are included in all regressions.
L. indicates one-year lag. $P$ is GDP deflator. $N$ is population. $Y$ is per capita real GDP.
$ap_{ijt}$, $aind_{ijt}$, $al_{ijt}$ measure changes in aggregate bank proximity, direct, and indirect linkages, respectively.
$bs_{ijt}$, $bs_{jit}$, $bf_{ijt}$, $bf_{jit}$ are measures of stocks and flows of bank claims from BIS.
Robust standard errors in parentheses. Within $R^2$ reported for pair fixed effects regressions.
812 country pairs. 29 countries. *(P< 0.10), **(P< 0.05), ***(P< 0.01)

Table 2: Gravity regressions with aggregate proximity measures — crisis and trend effects.

| | Full sample (1) | Full sample (2) | Full sample (3) | Full sample (4) | Full sample (5) | Full sample (6) |
|---|---|---|---|---|---|---|
| L.$ap_{ijt}$ (1) | 0.0203*** | 0.00686 | 0.0159 | | | |
| | (0.00560) | (0.0109) | (0.0110) | | | |
| L.$ap_{ijt} * Crisis$ (2) | 0.0713*** | | 0.0714*** | | | |
| | (0.0177) | | (0.0165) | | | |
| L.$ap_{ijt} * t$ (3) | | 0.00174 | 0.0000829 | | | |
| L.$al_{ijt}$ (4) | | | | 0.0200*** | 0.0110 | 0.0204* |
| | | | | (0.00521) | (0.0105) | (0.0107) |
| L.$al_{ijt} * Crisis$ (5) | | | | 0.0670*** | | 0.0703*** |
| | | | | (0.0170) | | (0.0159) |
| L.$al_{ijt} * t$ (6) | | | | | 0.00132 | -0.000346 |
| L.$aind_{jit}$ (7) | | | | 0.00188 | -0.0157** | -0.0169* |
| | | | | (0.00502) | (0.00797) | (0.00900) |
| L.$aind_{jit} * Crisis$ (8) | | | | 0.0303** | | 0.0185 |
| | | | | (0.0131) | | (0.0167) |
| L.$aind_{jit} * t$ (9) | | | | | 0.00192*** | 0.00171* |
| $bs_{ijt}$ | 0.0240** | 0.0520*** | 0.0455*** | 0.0242** | 0.0517*** | 0.0454*** |
| $bs_{jit}$ | 0.00869 | 0.0296* | 0.0368** | 0.00876 | 0.0297* | 0.0371** |
| $bf_{ijt}$ | -0.00390** | -0.00734** | -0.00708* | -0.00394** | -0.00726** | -0.00702* |
| $bf_{jit}$ | -0.0113*** | -0.0227*** | -0.0248*** | -0.0113*** | -0.0229*** | -0.0250*** |
| $bs_{ijt} * Crisis$ | -0.0385*** | | -0.0314*** | -0.0378*** | | -0.0309*** |
| $bs_{jit} * Crisis$ | -0.000308 | | 0.0290** | -0.000231 | | 0.0290** |
| $bf_{ijt} * Crisis$ | 0.00487 | | -0.000337 | 0.00484 | | -0.000408 |
| $bf_{jit} * Crisis$ | 0.00442 | | -0.0124 | 0.00478 | | -0.0121 |
| $bs_{ijt} * t$ | | -0.00252*** | -0.00136 | | -0.00248*** | -0.00133 |
| $bs_{jit} * t$ | | -0.00200 | -0.00319** | | -0.00200 | -0.00319** |
| $bf_{ijt} * t$ | | 0.000534** | 0.000418 | | 0.000527** | 0.000416 |
| $bf_{jit} * t$ | | 0.00130* | 0.00168** | | 0.00131** | 0.00169** |
| Within $R^2$ | 0.388 | 0.388 | 0.389 | 0.388 | 0.388 | 0.389 |
| Prob ((1)+(2)=0) | 0.000*** | | 0.000*** | | | |
| Prob ((4)+(5)=0) | | | | 0.000*** | | 0.000*** |
| Prob ((7)+(8)=0) | | | | 0.009*** | | 0.942 |
| Threshold year 1[a] | | 1994 | 1992 | | 1993 | 1990 |
| Threshold year 2[b] | | | | | 2003 | N.A. |

[a]Threshold year 1 is the first year in which Prob ((1)+(3)=0),or ((4)+(6)=0) is less than 0.1.
[b]Threshold year 2 is the first year in which Prob ((7)+(9)=0) is less than 0.1.
Dependent variable $\log(1 + EX_{ijt})$. Country pair and year fixed effects are included in all regressions.
L. indicates one-year lag.
$ap_{ijt}$, $aind_{ijt}$, $al_{ijt}$ measure changes in aggregate bank proximity, direct, and indirect linkages, respectively.
$bs_{ijt}$, $bs_{jit}$, $bf_{ijt}$, $bf_{jit}$ are measures of stocks and flows of bank claims from BIS.
$crisis_t = 1$ in 2008 and 2009, $t \in [1; 19]$ is linear trend, Y is year.
Controls for population and GDP per capita are included in all regressions but not reported in the interest of space.
Robust standard errors in parentheses. Not reported for trend interactions and BIS variables in the interest of space.
15428 observations. 812 country pairs. 29 countries. *(P< 0.10), **(P< 0.05), ***(P< 0.01)

Table 3: Gravity regressions with aggregate proximity measures — by Rauch (1999) categories of exports.

| | Differentiated (1) | Exchange (2) | Reference price (3) | Differentiated (4) | Exchange (5) | Reference price (6) |
|---|---|---|---|---|---|---|
| L.$ap_{ijt}$ | 0.0511*** | 0.0295** | 0.0296*** | | | |
| | (0.00721) | (0.0133) | (0.00723) | | | |
| L.$al_{ijt}$ | | | | 0.0478*** | 0.0267** | 0.0293*** |
| | | | | (0.00660) | (0.0126) | (0.00663) |
| L.$aind_{ijt}$ | | | | 0.00554 | -0.0135 | 0.00453 |
| | | | | (0.00742) | (0.0139) | (0.00765) |
| $bs_{ijt}$ | -0.00458 | 0.000850 | 0.0168 | -0.00473 | 0.000211 | 0.0168 |
| | (0.0129) | (0.0224) | (0.0145) | (0.0129) | (0.0224) | (0.0145) |
| $bs_{jit}$ | 0.00949 | 0.0121 | -0.00842 | 0.00925 | 0.0116 | -0.00851 |
| | (0.00934) | (0.0192) | (0.0122) | (0.00933) | (0.0192) | (0.0122) |
| $bf_{ijt}$ | 0.000146 | -0.00327 | -0.000527 | 0.000136 | -0.00328 | -0.000533 |
| | (0.00185) | (0.00345) | (0.00192) | (0.00185) | (0.00344) | (0.00192) |
| $bf_{jit}$ | -0.00965* | -0.000880 | -0.00166 | -0.00953* | -0.000684 | -0.00162 |
| | (0.00494) | (0.00982) | (0.00669) | (0.00494) | (0.00981) | (0.00668) |
| $N_i$ | 1.463*** | -1.110** | 2.160*** | 1.465*** | -1.097* | 2.160*** |
| | (0.414) | (0.559) | (0.350) | (0.414) | (0.561) | (0.350) |
| $N_j$ | 2.264*** | -0.0559 | 1.714*** | 2.258*** | -0.0640 | 1.711*** |
| | (0.390) | (0.537) | (0.374) | (0.390) | (0.537) | (0.374) |
| $Y_i$ | 0.838*** | 0.221 | 0.957*** | 0.840*** | 0.225 | 0.958*** |
| | (0.138) | (0.252) | (0.163) | (0.138) | (0.252) | (0.163) |
| $Y_j$ | 0.916*** | 1.319*** | 0.617*** | 0.916*** | 1.318*** | 0.617*** |
| | (0.145) | (0.254) | (0.146) | (0.145) | (0.254) | (0.146) |
| Observations | 14364 | 14364 | 14364 | 14364 | 14364 | 14364 |
| Within $R^2$ | 0.404 | 0.105 | 0.291 | 0.404 | 0.105 | 0.291 |

Dependent variable $\log(1 + EX_{ijt})$. Country pair and year fixed effects are included in all regressions.
L. indicates one-year lag. $N$ is population. $Y$ is per capita real GDP.
$ap_{ijt}$, $aind_{ijt}$, $al_{ijt}$ measure changes in aggregate bank proximity, direct, and indirect linkages, respectively.
$bs_{ijt}$, $bs_{jit}$, $bf_{ijt}$, $bf_{jit}$ are measures of stocks and flows of bank claims from BIS.
Full sample Comtrade results not different from DOTS. All results are robust to excluding Crisis years (2008, 2009).
Robust standard errors in parentheses. Within $R^2$ reported for pair fixed effects regressions.
756 country pairs. 28 countries (Panama is not in the sample). *(P< 0.10), **(P< 0.05), ***(P< 0.01)

Table 4: Gravity regressions with aggregate proximity measures — effects of insurance premium.

| | Full sample (1) | Full sample (2) | Full sample (3) | Full sample (4) |
|---|---|---|---|---|
| L.$ap_{ijt}$ | 0.0263*** | 0.0235*** | | |
| | (0.00592) | (0.00590) | | |
| L.$ap_{ijt} * (\rho_j - \rho_i)$ | | 0.100*** | | |
| | | (0.0284) | | |
| L.$al_{ijt}$ | | | 0.0259*** | 0.0225*** |
| | | | (0.00553) | (0.00546) |
| L.$al_{ijt} * (\rho_j - \rho_i)$ | | | | 0.0943*** |
| | | | | (0.0277) |
| L.$aind_{ijt}$ | | | 0.00298 | 0.00469 |
| | | | (0.00526) | (0.00514) |
| L.$aind_{ijt} * (\rho_j - \rho_i)$ | | | | -0.0152 |
| | | | | (0.0358) |
| $\rho_j - \rho_i$ | -0.188** | -0.224*** | -0.189** | -0.224*** |
| | (0.0748) | (0.0767) | (0.0746) | (0.0764) |
| $bs_{ijt}$ | 0.00921 | 0.00762 | 0.00909 | 0.00766 |
| $bs_{jit}$ | 0.0114 | 0.0109 | 0.0113 | 0.0110 |
| $bf_{ijt}$ | 0.000959 | 0.00117 | 0.000951 | 0.00113 |
| $bf_{jit}$ | -0.0105** | -0.0100** | -0.0105** | -0.0100** |
| Population$_i$ | 1.339*** | 1.353*** | 1.340*** | 1.353*** |
| Population$_j$ | 1.468*** | 1.455*** | 1.466*** | 1.450*** |
| Per capita real GDP$_i$ | 0.734*** | 0.730*** | 0.735*** | 0.731*** |
| Per capita real GDP$_j$ | 1.141*** | 1.148*** | 1.140*** | 1.148*** |
| | (0.132) | (0.132) | (0.132) | (0.132) |
| Observations | 15148 | 15092 | 15148 | 15092 |
| Within $R^2$ | 0.384 | 0.384 | 0.384 | 0.384 |

Dependent variable $\log(1 + EX_{ijt})$. Country pair and year fixed effects are included in all regressions.
L. indicates one-year lag.
$ap_{ijt}$, $aind_{ijt}$, $al_{ijt}$ measure changes in aggregate bank proximity, direct, and indirect linkages, respectively.
$bs_{ijt}$, $bs_{jit}$, $bf_{ijt}$, $bf_{jit}$ are measures of stocks and flows of bank claims from BIS.
$\rho$ is the export insurance premium. Missing for the U.S. for years 1990-1995.
All results are robust to excluding Crisis years (2008, 2009).
Robust standard errors in parentheses. Not reported for BIS and macro variables in the interest of space.
812 country pairs. 29 countries. *(P< 0.10), **(P< 0.05), ***(P< 0.01)

Table 5: Gravity regressions with aggregate proximity measures — effects of access to export insurance.

| | Full sample (1) | Full sample (2) | Full sample (3) | Full sample (4) |
|---|---|---|---|---|
| L.$ap_{ijt}$ | 0.0470*** | 0.0469*** | | |
| | (0.0120) | (0.0120) | | |
| L.$ap_{ijt} * (S_i + S_j)$ | -0.00058** | | | |
| | (0.00025) | | | |
| L.$ap_{ijt} * S_i$ | | -0.00014 | | |
| | | (0.00031) | | |
| L.$ap_{ijt} * S_j$ | | -0.0011*** | | |
| | | (0.00034) | | |
| L.$al_{ijt}$ | | | 0.0451*** | 0.0450*** |
| | | | (0.0113) | (0.0112) |
| L.$al_{ijt} * (S_i + S_j)$ | | | -0.00055** | |
| | | | (0.00023) | |
| L.$al_{ijt} * S_i$ | | | | -0.00021 |
| | | | | (0.00030) |
| L.$al_{ijt} * S_j$ | | | | -0.00094*** |
| | | | | (0.00031) |
| L.$aind_{ijt}$ | | | 0.0152 | 0.0162 |
| | | | (0.0123) | (0.0124) |
| L.$aind_{ijt} * (S_i + S_j)$ | | | -0.00025 | |
| | | | (0.00029) | |
| L.$aind_{ijt} * S_i$ | | | | 0.00019 |
| | | | | (0.00039) |
| L.$aind_{ijt} * S_j$ | | | | -0.00077** |
| | | | | (0.00037) |
| $bs_{ijt}$ | 0.0103 | 0.0100 | 0.0104 | 0.0101 |
| $bs_{jit}$ | 0.0105 | 0.0110 | 0.0105 | 0.0109 |
| $bf_{ijt}$ | 0.000563 | 0.000681 | 0.000536 | 0.000612 |
| $bf_{jit}$ | -0.00938** | -0.00965** | -0.00934** | -0.00964** |
| Population$_i$ | 1.289*** | 1.288*** | 1.288*** | 1.286*** |
| Population$_j$ | 1.460*** | 1.465*** | 1.458*** | 1.464*** |
| Per capita real GDP$_i$ | 0.755*** | 0.757*** | 0.756*** | 0.757*** |
| Per capita real GDP$_j$ | 1.130*** | 1.132*** | 1.130*** | 1.132*** |
| | (0.130) | (0.130) | (0.130) | (0.130) |
| Observations | 15428 | 15428 | 15428 | 15428 |
| Within $R^2$ | 0.386 | 0.386 | 0.386 | 0.386 |

Dependent variable $\log(1 + EX_{ijt})$. Country pair and year fixed effects are included in all regressions.
L. indicates one-year lag.
$ap_{ijt}$, $aind_{ijt}$, $al_{ijt}$ measure changes in aggregate bank proximity, direct, and indirect linkages, respectively.
$bs_{ijt}$, $bs_{jit}$, $bf_{ijt}$, $bf_{jit}$ are measures of stocks and flows of bank claims from BIS.
$S$ is total insured export claims computed as described in the text.
All results are robust to excluding Crisis years (2008, 2009).
Robust standard errors in parentheses. Not reported for BIS and macro variables in the interest of space.
812 country pairs. 29 countries. *(P< 0.10), **(P< 0.05), ***(P< 0.01)

Table 6: Gravity regressions with aggregate proximity measures by OECD membership.

| | OECD importer (1) | non-OECD importer (2) | OECD importer (3) | non-OECD importer (4) |
|---|---|---|---|---|
| L.$ap_{ijt}$ | 0.0195*** | 0.0443*** | | |
| | (0.00606) | (0.0123) | | |
| L.$al_{ijt}$ | | | 0.0299*** | 0.0590*** |
| | | | (0.00676) | (0.0138) |
| L.$aind_{ijt}$ | | | 0.00726 | 0.0181* |
| | | | (0.00563) | (0.0103) |
| $bs_{ijt}$ | 0.00389 | 0.0369 | 0.00370 | 0.0397 |
| | (0.0122) | (0.0303) | (0.0124) | (0.0337) |
| $bs_{jit}$ | 0.00681 | 0.00261 | 0.00628 | 0.0287 |
| | (0.00839) | (0.0278) | (0.00856) | (0.0292) |
| $bf_{ijt}$ | -0.00000203 | -0.00176 | 0.00121 | -0.00197 |
| | (0.00149) | (0.00479) | (0.00159) | (0.00526) |
| $bf_{jit}$ | -0.00825** | 0.00133 | -0.00743* | -0.0148 |
| | (0.00418) | (0.0151) | (0.00426) | (0.0161) |
| $N_i$ | 1.086*** | 1.694** | 0.901** | 1.580** |
| | (0.396) | (0.700) | (0.404) | (0.746) |
| $N_j$ | 1.320*** | 0.541 | 1.268** | 0.500 |
| | (0.496) | (0.641) | (0.496) | (0.649) |
| $Y_i$ | 0.657*** | 0.980*** | 0.619*** | 0.970*** |
| | (0.125) | (0.262) | (0.129) | (0.278) |
| $Y_j$ | 1.255*** | 0.649** | 1.207*** | 0.797*** |
| | (0.182) | (0.254) | (0.192) | (0.276) |
| Observations | 10640 | 4788 | 9828 | 4183 |
| Within $R^2$ | 0.380 | 0.406 | 0.376 | 0.375 |

Dependent variable $\log(1 + EX_{ijt})$. Country pair and year fixed effects are included in all regressions.
L. indicates one-year lag. $N$ is population. $Y$ is per capita real GDP.
$ap_{ijt}$, $aind_{ijt}$, $al_{ijt}$ measure changes in aggregate bank proximity, direct, and indirect linkages, respectively.
$bs_{ijt}$, $bs_{jit}$, $bf_{ijt}$, $bf_{jit}$ are measures of stocks and flows of bank claims from BIS.
All results are robust to excluding Crisis years (2008, 2009). *(P< 0.10), **(P< 0.05), ***(P< 0.01)
Robust standard errors in parentheses. Within $R^2$ reported for pair fixed effects regressions.

Table 7: Arellano-Bond regressions.

| | Full sample (1) | Full sample (2) | yr< 2008 (3) | yr< 2008 (4) |
|---|---|---|---|---|
| L.log$(1 + EX_{ijt})$ | 0.496*** | 0.492*** | 0.498*** | 0.494*** |
| | (0.0104) | (0.0104) | (0.0111) | (0.0112) |
| $ap_{ijt}$ | 0.0402*** | 0.0495*** | 0.0406*** | 0.0490*** |
| | (0.00624) | (0.00686) | (0.00657) | (0.00746) |
| L.$ap_{ijt}$ | | 0.0232*** | | 0.0172* |
| | | (0.00843) | | (0.00909) |
| $bs_{ijt}$ | -0.0135* | -0.0130* | 0.00574 | 0.00556 |
| | (0.00776) | (0.00775) | (0.00861) | (0.00860) |
| $bs_{jit}$ | 0.00567 | 0.00694 | 0.00144 | 0.00230 |
| | (0.00687) | (0.00687) | (0.00740) | (0.00740) |
| $bf_{ijt}$ | 0.00249 | 0.00235 | 0.000996 | 0.00121 |
| | (0.00203) | (0.00202) | (0.00238) | (0.00238) |
| $bf_{jit}$ | -0.00627* | -0.00700* | -0.00497 | -0.00527 |
| | (0.00380) | (0.00380) | (0.00418) | (0.00418) |
| $N_i$ | 0.605*** | 0.594*** | 0.558*** | 0.549*** |
| | (0.110) | (0.110) | (0.126) | (0.126) |
| $N_j$ | 0.340*** | 0.344*** | 0.430*** | 0.431*** |
| | (0.110) | (0.110) | (0.126) | (0.126) |
| $Y_i$ | 0.564*** | 0.555*** | 0.392*** | 0.387*** |
| | (0.0552) | (0.0553) | (0.0636) | (0.0637) |
| $Y_j$ | 0.807*** | 0.802*** | 0.689*** | 0.680*** |
| | (0.0570) | (0.0571) | (0.0656) | (0.0658) |
| Observations | 14616 | 14616 | 12992 | 12992 |

Dependent variable $\log(1 + EX_{ijt})$. Country pair and year fixed effects are included in all regressions.
L. indicates one-year lag. $N$ is population. $Y$ is per capita real GDP.
$ap_{ijt}$ measures changes in aggregate bank proximity.
$bs_{ijt}$, $bs_{jit}$, $bf_{ijt}$, $bf_{jit}$ are measures of stocks and flows of bank claims from BIS.
Standard errors in parentheses. *(P< 0.10), **(P< 0.05), ***(P< 0.01)

# A Appendix

Figure A.1: Distribution of exports in our sample

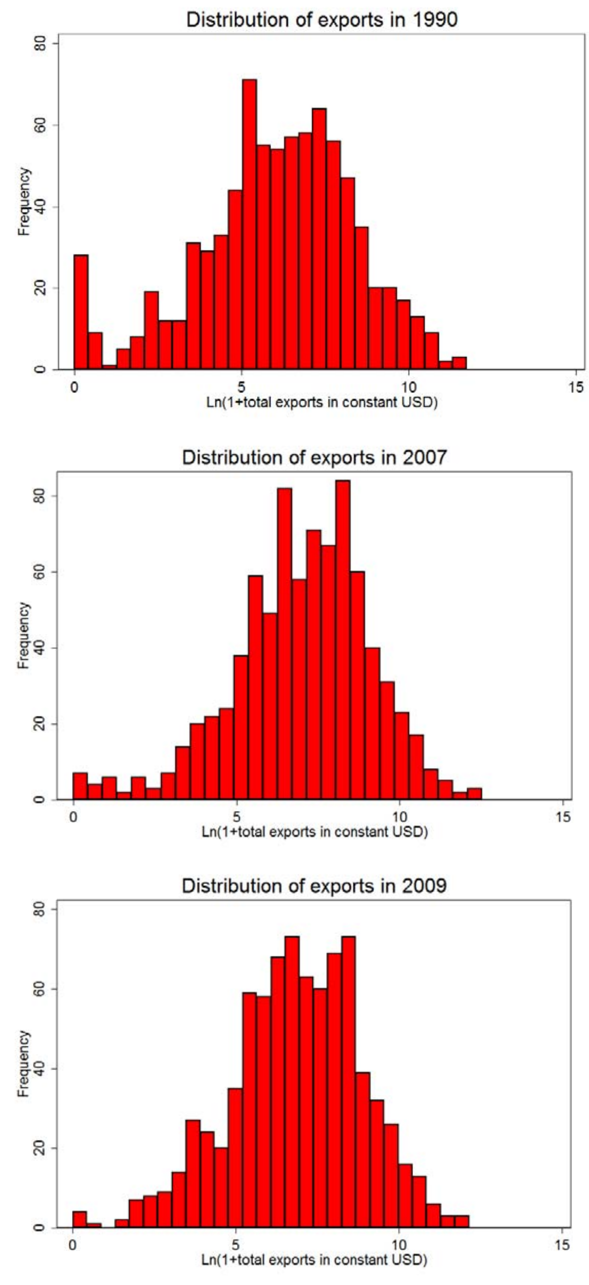

Figure A.2: Financial integration and financial flows

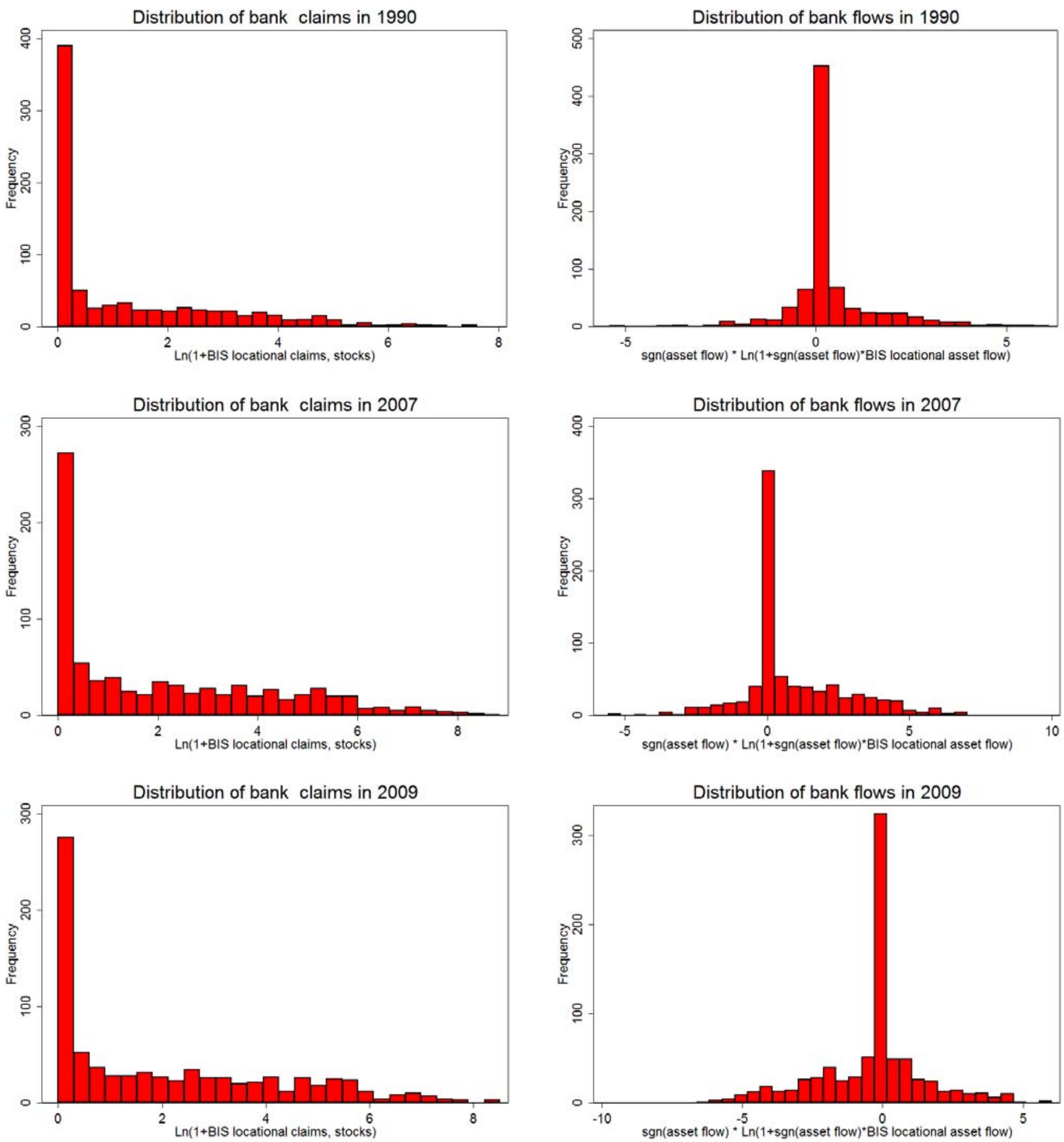

Table A.1: Gravity regressions.
Dependent variable $\log(1 + EX_{ijt})$

| | Full sample | Full sample | year< 2008 | Full sample | Full sample | year< 2008 |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| popsource | 1.478*** | 1.095*** | 0.905*** | 1.478*** | 1.512*** | 1.320*** |
| | (0.241) | (0.304) | (0.325) | (0.357) | (0.436) | (0.480) |
| poptarget | 1.579*** | 1.414*** | 1.267*** | 1.579*** | 1.914*** | 1.873*** |
| | (0.235) | (0.290) | (0.317) | (0.328) | (0.371) | (0.388) |
| gdppcsource | 0.777*** | 0.883*** | 0.808*** | 0.777*** | 0.788*** | 0.728*** |
| | (0.101) | (0.127) | (0.135) | (0.120) | (0.143) | (0.148) |
| gdppctarget | 1.113*** | 1.298*** | 1.211*** | 1.113*** | 1.130*** | 1.057*** |
| | (0.111) | (0.133) | (0.137) | (0.128) | (0.150) | (0.160) |
| priceratio | | 0.0195** | 0.0212** | | 0.0241*** | 0.0217*** |
| | | (0.00880) | (0.00937) | | (0.00630) | (0.00632) |
| areasource | -0.486*** | -0.328** | -0.244* | | | |
| | (0.107) | (0.136) | (0.145) | | | |
| areatarget | -0.497*** | -0.450*** | -0.381*** | | | |
| | (0.103) | (0.128) | (0.140) | | | |
| contig | 1.141*** | 1.064*** | 1.055*** | | | |
| | (0.0303) | (0.0338) | (0.0350) | | | |
| comlang off | 0.545*** | 0.586*** | 0.577*** | | | |
| | (0.0256) | (0.0303) | (0.0313) | | | |
| colony | -0.0347 | -0.0419 | -0.0334 | | | |
| | (0.0284) | (0.0332) | (0.0345) | | | |
| comcol | 0.167*** | 0.0838 | 0.0390 | | | |
| | (0.0644) | (0.0912) | (0.0942) | | | |
| distcap | -0.000146*** | -0.000148*** | -0.000149*** | | | |
| | (0.00000215) | (0.00000268) | (0.00000277) | | | |
| N | 16240 | 11436 | 10542 | 16240 | 11436 | 10542 |
| $R^2$ | 0.871 | 0.879 | 0.881 | 0.390 | 0.399 | 0.363 |
| Year FE | Y | Y | Y | Y | Y | Y |
| Source FE | Y | Y | Y | N | N | N |
| Target FE | Y | Y | Y | N | N | N |
| Pair FE | N | N | N | Y | Y | Y |

Robust standard errors in parentheses. Within $R^2$ reported for pair fixed effects regressions.

*(P< 0.10), **(P< 0.05), ***(P< 0.01)

Table A.2: Gravity regressions with financial integration and capital flows.
Dependent variable $\log(1 + EX_{ijt})$

| | Full sample | Full sample | Full sample | year< 2008 | year< 2008 | year< 2008 |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $bs_{ijt}$ | 0.0238** | | 0.0211* | 0.0339*** | | 0.0331*** |
| | (0.0110) | | (0.0116) | (0.0112) | | (0.0119) |
| $bs_{jit}$ | -0.000795 | | 0.0125 | -0.00591* | | 0.00994 |
| | (0.00313) | | (0.00891) | (0.00320) | | (0.00861) |
| $bf_{ijt}$ | | 0.00116 | -0.000789 | | -0.0000949 | -0.00383** |
| | | (0.00155) | (0.00167) | | (0.00164) | (0.00174) |
| $bf_{jit}$ | | -0.00254* | -0.00872* | | -0.00501*** | -0.0101** |
| | | (0.00142) | (0.00462) | | (0.00144) | (0.00448) |
| priceratio | 0.0243*** | 0.0241*** | 0.0244*** | 0.0217*** | 0.0216*** | 0.0219*** |
| | (0.00629) | (0.00630) | (0.00629) | (0.00632) | (0.00631) | (0.00632) |
| popsource | 1.579*** | 1.512*** | 1.581*** | 1.410*** | 1.311*** | 1.411*** |
| | (0.427) | (0.435) | (0.427) | (0.471) | (0.480) | (0.471) |
| poptarget | 1.972*** | 1.915*** | 1.961*** | 1.967*** | 1.866*** | 1.952*** |
| | (0.372) | (0.372) | (0.372) | (0.389) | (0.388) | (0.390) |
| gdppcsource | 0.766*** | 0.790*** | 0.773*** | 0.686*** | 0.732*** | 0.689*** |
| | (0.143) | (0.144) | (0.144) | (0.147) | (0.148) | (0.147) |
| gdppctarget | 1.116*** | 1.130*** | 1.115*** | 1.037*** | 1.058*** | 1.034*** |
| | (0.150) | (0.150) | (0.150) | (0.160) | (0.160) | (0.160) |
| N | 11436 | 11436 | 11436 | 10542 | 10542 | 10542 |
| $R^2$ | 0.399 | 0.399 | 0.399 | 0.364 | 0.364 | 0.365 |
| Year FE | Y | Y | Y | Y | Y | Y |
| Pair FE | Y | Y | Y | Y | Y | Y |

Robust standard errors in parentheses. Within $R^2$ reported for pair fixed effects regressions.
*(P< 0.10), **(P< 0.05), ***(P< 0.01)

Table A.3: Summary statistics for proximity measures

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Country-pair-year level | | | | | |
| Average proximity $p$ | 16240 | .581 | .455 | 0 | 1 |
| Share of directly linked bank pairs | 16240 | .564 | .454 | 0 | 1 |
| Number of bank pairs | 16240 | 30.5 | 87.05 | 0 | 1082 |
| Aggregate proximity (Sum $p$) $AP$ | 16240 | 27.95 | 82.05 | 0 | 1082 |
| Number of banks directly linked $AL$ | 16240 | 27.05 | 80.35 | 0 | 1082 |
| Sum of indirect proximities | 16240 | .871 | 3.60 | 0 | 73.3 |
| Log change in aggregate proximity $ap$ | 16240 | .369 | .788 | 0 | 6.46 |
| Log change in number of direct links $al$ | 16240 | .366 | .799 | 0 | 6.43 |
| Log change in indirect proximity $aind$ | 14817 | .001 | .443 | -13.9 | 4.06 |
| Insurance premium differential $\rho$ | 15904 | 0 | .145 | -.972 | .972 |
| Average elasticity $\sigma$ | 14360 | 9.67 | 1.59 | 3.23 | 22.9 |
| Country-year level | | | | | |
| Export insurance premium | 658 | .551 | .118 | .344 | 1.45 |
| Country level | | | | | |
| Insured export credit (bil. 2000 USD) | 29 | 13.44 | 11.1 | .943 | 48.5 |
| SITC4 level | | | | | |
| Armington elasticity | 281 | 8.96 | 8.22 | 2.6 | 29 |