Subnational Patterns of Exports, Banking, and Trade Costs

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Subnational Patterns of Exports, Banking, and Trade Costs

by Joseph Edward Archibald Vavrus

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(Professor James Markusen, Chair)

(Professor Jeronimo Carballo)

Date:__________________________

The final copy of this thesis has been examined by the signatories, and we find that both the content and the form meet acceptable presentation standards of scholarly work in the above mentioned discipline.
Vavrus, Joseph Edward Archibald (Ph.D., Economics)
Subnational Patterns of Exports, Banking, and Trade Costs
Thesis directed by Professor James Markusen

In my first chapter, I investigate how local access to credit affects large-scale firm outcomes like exporting. I answer this question by modeling the relationship between finance-constrained exporters and bank entry decisions. This generates bilateral trade equations where local access to banking increases the intensive and extensive margin of exporting. I estimate this model with a panel of Brazilian municipal-level trade and banking data and show that commercial bank presence per person increases bilateral exports.

In my second chapter, I analyze the geography of bank company branching decisions and their effect on access to finance. I focus on three essential aspects of this unit of analysis: financial products are largely homogeneous, yet banks still enjoy significant market power, many companies build multiple branches in a single market, and those markets are often geographically distant from the bank company’s headquarters. I capture these effects by building a model of heterogeneously productive banks that compete for the share of monopolistic profits by building bank branches. This paper shows that the effects of within-country geography on bank company behavior can help explain endogenous financial development.

For my final chapter, I look at economies of scale in shipping and patterns of subnational trade. I show that intranational trade between regions in goods destined for consumption in the U.S. is increasing in shipments destined for foreign markets. Ignoring this relationship means means that traditional trade flow estimates will overstate the effect of distance on trade.
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Chapter 1

Local Credit and International Trade

1.1 Introduction

Imperfect credit markets are known to restrict growth and hamper development. Studies show that cross-country differences in financial access have significant effects on trade and production\(^1\) but less is known about variation in credit constraints within countries. Theoretical and empirical work has shown that bank-to-firm distance remains an important driver of credit constraints\(^2\), meaning that local financial development is an important determinant of firm-level outcomes, especially in developing countries\(^3\). This effect varies by firm size, particularly at the margins: smaller firms are more sensitive to distance-driven credit constraints\(^4\). However, just as firm behavior is driven by access to finance, banks expand into areas that are more likely to export and experience economic growth (Aviat and Coeurdacier 2007).

This paper investigates the impact of local access to credit on the intensive and extensive margin of aggregate and industry-level bilateral exports and works to untangle the endogenous relationship between finance and trade. To do this, I augment a heterogeneous firms trade

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2. For a survey of this literature see Degryse and Ongena [2004].
4. Using U.S. data, Petersen and Rajan [2002], Agarwal and Hauswald [2010], and Berger et al. [2005] show that local lending relationships are most important for smaller businesses.
model to include a credit constraint determined by bank access. Less productive, smaller firms are excluded from the credit market, and therefore exporting, due to the costs of financing. To reflect the importance of local lending, I allow those costs to differ by region as a function of bank branching behavior. From this model, I show that bilateral trade, via the extensive margin, is decreasing in region-specific financing costs. I estimate the model with a panel of Brazilian municipality-level data, showing that access to banking services at the subnational level is a significant driver of export behavior.

This paper complements firm-level studies on finance and the extensive margin of exporting. In particular, start-up costs and increasing returns to scale make exporting firms reliant on access to credit. My modeling strategy reflects this: I include increasing returns and firm heterogeneity following Chaney [2008]'s approach. In my model, firms are liquidity constrained and reliant on external financing to expand their sales outside of their local region. This is similar to the setup by Manova [2013], whose model and cross-country empirical work shows that national indicators of financial development increase trade in finance-reliant sectors. The primary identification strategy in her paper relies on industry variation in financial dependence and asset tangibility.

In my model, I require that firms finance the fixed costs of exporting with funds from local banks. This allows me to avoid identification issues caused by cross-country variation in the laws and institutions that determine aggregate indicators of financial development. Instead, my identification strategy relies on the geographic distribution of bank branching behavior. Empirical work shows that bank headquarter location matters at the international level (Buch 2005) and the subnational level (Felici and Pagnini 2008) due to information costs that vary by distance (Dell'Ariccia and Marquez 2004). In particular, Agarwal and Hauswald [2010] present evidence that soft information on borrowers, particularly smaller firms, is primarily a local characteristic. Alessandrini et al. [2009] and Hauswald and Marquez [2006] argue that the distance from a bank’s headquarters to its branches makes the transmission of this information more diffi-

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3See Melitz [2003] and for models of this type.
icult, and thus makes lending in a region more costly. As such, I model the choice of banks to build branches in a region as a function of bank company characteristics and the location of their headquarters. Additionally, I include a simple externality to bank branching: when banks build branches, the average bank branch-to-firm distance decreases, so total monitoring costs are lower.

This setup generates several simple estimation equations that show that the intensive and extensive margins of bilateral trade are increasing in access to banking services, proxied with commercial bank branches per person. Empirically, I treat "local" as a Brazilian municipality and use data on commercial bank branches, HS4-level product exports, and city-level economic indicators to estimate the model.

To deal with the endogeneity of the banking/trade relationship at the industry level, I follow Manova [2013] and use industry-specific measures that relate to the financing constraint. Firms that have less collateralizable assets and are less able to fund operations internally are perceived to be higher default risk by bank companies and thus face higher financing costs. However, as banks build branches, lending costs to all sectors are lower. This effect is largest in credit constrained industries: bilateral exports in financially dependent sectors and those with less tangible assets respond more to lower lending rates than less risky industries.

To identify the effect of bank access at the city level, I use an instrumental variables method inspired by Frankel and Romer [1999] and build a predictor of bank branches per person in a region using information on bank company characteristics that are exogenous to a city’s export potential. My results show that a one standard deviation increase in bank branches per person raises city-level bilateral exports by at least 8.1%. This approach gives robust evidence that local financial development matters for the intensive and extensive margin of trade.

This paper is structured as follows. Section 1.2 presents a general equilibrium model of credit-constrained heterogeneous exporters and banking sector behavior. Section 1.3 includes model predictions and results that show how exports respond to increased access to banking services. In Section 1.4 I explain an empirical strategy to estimate the model with Brazilian data and present
results showing the magnitude of the banking and trade relationship. Section 1.5 concludes.

1.2 Credit-constrained production and trade

In this section, I set up a demand and production model to motivate firm-level responses to the trade and finance variables. The model augments Chaney [2008] by adding a credit constraint and a banking sector. I focus on foreign demand, assuming that firms do not require external credit for domestic production. Instead, fixed exporting costs must be financed through the lending market.

The model generates an endogenous productivity cutoff for exporting to a given destination. Firms with productivity draws below this threshold do not export to that country. The productivity cutoff ultimately depends on the endogenous, region-specific financing cost. Regions with high finance costs will have less exporters and exports.

1.2.1 Consumer demand

Consumers in a destination country, \( d \), derive utility from consuming agricultural goods, \( A \), and goods from \( k \in K \) manufacturing sectors, \( M \), in the following way:

\[
U = \prod_{k=1}^{K} M^{\mu_k} A^{1-\sum \mu_k} \quad M = \left[ \int_{Z_k} m(z) \frac{\sigma-1}{\sigma} dz \right]^{\frac{\sigma}{\sigma-1}} 
\]  

(1.1)

where \( \mu_k \) is the share of sector \( k \) goods in utility, \( z_k \in Z_k \) is the measure of available manufacturing varieties in sector \( k \), and \( \sigma > 1 \) is the elasticity of demand for a given variety, assumed to be the same across sectors.

The geography of trade is as follows. I assume there are \( D + 1 \) countries in the world with exogenous populations \( N_d \). One of those countries can be subdivided into \( o' \) sub-regions, which means there are \( D + o' \) exporter and importer regions in the world.

From equation (1.1), consumers in region \( d \) demand variety \( z_k \) goods produced in origin region \( o \in D + o' \) based on the following function
\[ m_{kod}(z) = \mu_k Y_d p_{od}(z)^{-\sigma} p_{kd}^{\sigma-1} \] (1.2)

where \( p_{od}(z) \) is the F.O.B. price, and \( Y_d \) and \( P_{kd}^{1-\sigma} = \int_{Z_k} p_{od}^{1-\sigma} dz \) are destination income and sector \( k \) ideal price index, respectively. Income in \( d \) comprises labor income \( w_d N_d \) and aggregate profits made by producers in that region \( \Pi_d \).

1.2.2 Production

I assume that the agricultural good is produced in a perfectly competitive market with a constant returns to scale technology in every region using \( \frac{1}{w_o} \) units of labor and can be traded costlessly. I set the price of this good to 1 and allow it to function as the numéraire. Wages in region \( o \) equalize across sectors and are therefore pinned down by the agricultural wage \( w_o \).

To export to a destination country \( d \), a manufacturing firm in region \( o \) must pay a fixed cost \( f_{od}^x \) of the numéraire and a variable iceberg trade cost \( \tau_{od}^x \geq 1 \), where \( \tau_{od}^x \) is the amount that must be shipped for one good to arrive in \( d \). Without loss of generality, I assume \( \tau_{oo}^x = 1 \) and \( f_{oo}^x < f_{od}^x \) for all \( d \neq o \).

Following Melitz [2003], the manufacturing sector comprises firms that differ in a stochastic productivity parameter \( \phi \) drawn from cumulative distribution function given by \( G(\phi) \) that is identical across regions and sectors. This is modeled as marginal-cost reducing productivity parameter that appears in the following per-unit cost function for a firm of productivity \( \phi \) in region \( o \) exporting to destination \( d \). This cost function is the same across sectors, but differs by origin and destination pair:

\[ c_{od}(\phi) = w_o \frac{\tau_{od}^x}{\phi} \] (1.3)

Firms are monopolistically competitive in that I assume that \( Y_d \) and \( P_{kd} \) are exogenous to the firm. In this sense, the volume of trade from a single, atomistic firm does not affect aggregate variables. Due to increasing returns to scale and no economies of scope, a firm of type \( \phi \) in sector
produces only one variety, so $\phi$ and $k$ are sufficient to index a good.

Given demand in equation (1.2) and the structure of competition, firms charge a constant markup over marginal cost, incorporating variable trade costs:

$$p_{od}(\phi) = \frac{\sigma}{\sigma - 1} \frac{\tau_{od}^x w_o}{\phi}$$

(1.4)

The price charged by firms is increasing in wages and trade costs and decreasing in the efficiency parameter.

### 1.2.3 Credit constraints and the productivity cutoff

Firms are credit constrained in that they cannot finance all costs internally. As in Manova [2013], I assume that firms must finance fixed export costs with external capital at the endogenous price $R_{ko} = 1 + r_{ko}$. Without loss of generality, I assume that all fixed costs must be financed externally. This means that a firm of type $\phi$ receives the following profits from exporting:

$$\pi_{kod}(\phi) = \mu_k \sigma^{-\sigma} Y_d \left( \frac{w_o \tau_{od}}{(\sigma - 1) \phi P_{kd}} \right)^{1-\sigma} - R_{o} f_{od}^x$$

(1.5)

The presence of the fixed cost means that firms will not sell goods to $d$ if they cannot make positive profits. Thus, I define the lowest level of productivity a firm can have to make non-negative profits as $\tilde{\phi}_{kod}$, which must satisfy $\pi_{kod}(\tilde{\phi}_{kod}) = 0$. Using the definition of profits given in equation (1.5), I can solve for the productivity cutoff for exporting:

$$\tilde{\phi}_{kod} = \left[ \left( \frac{\sigma}{\mu} \right)^{\frac{1}{\sigma - 1}} \frac{\sigma}{\sigma - 1} \right] \left[ \frac{w_o}{P_d Y_d^{\frac{1}{\sigma - 1}}} \right] \left[ \tau_{od}^x (f_{od}^x)^{\frac{1}{\sigma - 1}} \right] \left[ R_{ko} \right]^{\frac{1}{\sigma - 1}}$$

(1.6)

Firms from region $o$ in sector $k$ must have a productivity draw of $\phi_{kod} \geq \tilde{\phi}_{kod}$ export to $d$. An

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7 Alternatively, I could model firms that finance some fraction of labor costs. However, as wages are pinned down in the agricultural sector, equilibrium aggregate loan demand would simply depend on exogenous region size and would be uninteresting.

8 As long as firms must finance some positive fraction of their costs the qualitative results that follow are unchanged.
equation of this type is typical in the heterogeneous firms literature, but an important new result is that the sector threshold is increasing in regionally varying financing costs. This means the credit constraint is reducing the extensive and intensive margins of trade in a way that differs across regions.

Following Chaney [2008] and Arkolakis [2010], I do not impose free entry. Instead, I assume the potential number of entrants in each manufacturing sector is proportional to country size and equal to $w_o N_o$. This means that there will be profits earned by each firm with productivity higher than $\tilde{\phi}_{kod}$. I assume all consumers in region $o$ own an equal fraction of domestic firms and thus receive an equal fraction as income.

The amount of finance required by firms is equal to the total amount of fixed entry costs they must pay. In particular, aggregate loan demand from sector $k$ firms in region $o$ is given by the total fixed costs paid by exporters in that sector. It therefore depends on how many markets each firm is productive enough to enter:

$$L_{ko} = w_o N_o \sum_d f_{od}^x \left(1 - G(\tilde{\phi}_{kod})\right)$$ (1.7)

In the above equation financing costs only appear in the productivity cutoff. This means that the price-demand relationship for loans is exclusively channeled through the extensive margin of trade. The cutoff for exporting increases with financing costs, thus reducing the probability of exporting and therefore the number of exporters: $V_o^x = w_o N_o (1 - G(\tilde{\phi}_{kod}))$.

Conditional on the productivity distribution of firms, the size of each country, bilateral trade costs, and the endogenous supply and cost of financing, the above setup generates a full model of production, income, and trade. Regions with higher financing costs will have less exporting firms and therefore less exports.
1.2.4 Banking and loans

The source of loans in this model is a monopolistically competitive banking sector. Banks take funds from the central banks at the exogenous lending rate $r^d$ and supply them to firms. In order to match with firms in region $o$, banks must build bank branches in the region. Financing costs are affected by two things. First, there is a sector-specific probability of default $1 - \delta_k$. Additionally, I assume there is a simple information asymmetry: firms are able to shirk on paying back their loans unless banks pay a per loan monitoring cost, $C_o$. This is a simple adaptation of the costly state verification model in Townsend [1979].

Banks are homogeneous and split the lending market equally among $J^b_o$ (endogenous) active bank companies. Prices are set sector by sector to maximize the following variable profit function:

$$\pi_{ko}^b = \frac{L_{ko}}{J^b_o} (\delta_k R_{ko} - C_o (1 + r^d))$$  \hspace{1cm} (1.8)

For a given default rate $\delta_k$ and the (endogenous) elasticity of demand $\eta = -\frac{dL}{dR} \frac{R}{L}$, banks choose the optimal loan price as a markup over the cost of funds and monitoring:

$$R_{ko} = \frac{1}{\delta_k} \frac{\eta}{\eta - 1} C_o (1 + r^d)$$  \hspace{1cm} (1.9)

To generate an expression for loan demand, I assume that manufacturing firm-level productivity $\phi$ follows the Pareto distribution as is typical in the heterogeneous firm trade literature. Specifically, $G(\phi) = 1 - \phi^{-\gamma}$ where $\gamma > \sigma - 1 > 0$ is an inverse measure of the heterogeneity of firms in the manufacturing sector. This assumption is an approximation of the empirical size distribution of firms and allows for a closed form solution to the loan demand equation and its elasticity.

---

9 Both variable and fixed costs are paid in units of the numéraire.
10 Following Bremus et al. [2013] and De Blas and Russ [2013] we can also think of $\frac{\eta}{\eta - 1}$ as an upper bound on the markup that banks would charge. For example, if there were a search cost or documentation cost to applying for loans, we would likely see interest rates lower than those implied by the monopoly markup, but higher than the perfect competition case. Pure price competition would lead banks to price at marginal cost.
11 See Arkolakis and Muendler [2010] and Arkolakis [2013] for recent dynamic microfoundations for this assumption that are consistent with U.S. and Brazilian data on exporter firm size.
This assumption means that the probability of exporting is $1 - G(\tilde{\phi}_{kod}) = \tilde{\phi}_{kod}^{-\gamma}$ and the loan demand and elasticity are given by

$$L_{ko} = \left[ \frac{\sigma - 1}{\mu} \frac{\sigma}{\sigma - 1} \right]^{-\gamma} w_{o}^{1-\gamma} N_{o} [R_{ko}]^{-\gamma} \sum_{d} \tau_{od}^{x-\gamma} f_{od}^{x1-\frac{1}{\sigma-1}} \left[ P_{d} Y_{d}^{\frac{1}{\sigma-1}} \right]^{-\gamma}$$

(1.10)

$$\eta = \frac{\gamma}{\sigma - 1}$$

(1.11)

$$R_{ko} = \frac{1}{\delta k} \frac{\gamma}{\gamma - \sigma + 1} C_{o}(1 + r^{d})$$

(1.12)

This elasticity of loan demand is purely driven by the extensive margin of exporting. Intuitively, the markup is decreasing in $\gamma$ because a more homogeneous manufacturing sector has average lower productivity, therefore more firms are sensitive to increases in the financing of fixed costs. The markup is increasing in $\sigma$, the elasticity of demand for manufactured goods, because a high level of $\sigma$ indicates that the manufacturing sector is more competitive. Higher competition means only the most productive firms export, and, as they are further down their average cost curves, they are less sensitive to financing costs.

### 1.2.5 Endogenous access to finance

In this section, I augment the above financial sector to include multi-branch banking in a given region. First, I assume there is a convex cost to branch banking that varies based on a region-specific constant $\beta_{o}$. Second, I assume that banks can increase their share of the market by building bank branches in a simple way: market share is $b_{o}/J_{alt}$ where $b_{o}$ is branches per bank in region $d$.\(^{12}\) Empirical work on bank branching decisions in the U.S. give evidence that increasing

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\(^{12}\)See Appendix A.1.1 for this derivation.

\(^{13}\)Recall that I am analyzing a symmetric equilibrium so $b_{o}$ will be the same across bank companies.
branch network size is a tool used by companies to increase market share\textsuperscript{[14]}

Taking the above loan demand and pricing as given, I can express the banks aggregate profits as a function of branching as follows:

\[
\Pi^b_o = b_o \pi^b_o - \beta_o b_o^2 = b_o \frac{L_o C_o (1 + r^d)}{\sum_k \delta_k} (\frac{\sigma - 1}{\gamma - \sigma - 1}) - \beta_o b_o^2 \quad (1.13)
\]

where \( L_o \) is total loan demand in region \( o \).

Conditional on loan demand, banks choose the number of branches where the marginal benefit of branching is equal to the cost of branching: \( \pi^b_o = \beta b_o \), generating the following expression for bank branching behavior:

\[
b_o = \frac{j^b_o}{2\beta_o L_o (1 + r^d)C_o} \left( \frac{\gamma}{\sigma - 1} - 1 \right) \quad (1.14)
\]

This says that branches are increasing proportionally with firm entry, but decreasing with firm level variable profits. This is due to the convexity of costs and the symmetry of the banking equilibrium: bank competitors cannibalize each others profits when they build branches.

To endogenize access to finance, I assume a simple externality in the banking sector: as bank branches relative to the population increase, monitoring costs go down:

\[
C_o = C \left( \frac{B_o}{N_o} \right) \quad (1.15)
\]

where \( B_o \) is the total number of bank branches in the region: \( j^b_o b_o \). This function means financing costs are decreasing in bank branches, \( C' < 0 \), which is a simplification of results from the theoretical and empirical literature on the relationship between banks and credit access. In effect, I am parameterizing \( C_o \) as a decreasing function of “operational distance” to banking services.

Assuming free entry in the banking sector, the total number of banks that enter is given by

\textsuperscript{14}Dick [2007] and Cohen and Mazzeo [2010] show that bank branching can function as a means of quality-induced product differentiation and advertising, both towards the goal of increasing market share.
\[ J^b_o = \frac{L_o C_o (1 + r^d)}{\sum_k \delta_k} \left( \frac{\sigma - 1}{\gamma - \sigma - 1} \right) \quad (1.16) \]

First, note that in equilibrium total bank branches depend only on the branching cost parameter \( \beta_o \), \( b_o = \frac{1}{2b_o} \). This is due to the aforementioned cannibalization and symmetry. However, aggregate branching is affected by bank entry: \( B_o = J^b_o \frac{1}{2b_o} \). The endogeneity of financial sector entry is revealed here: bank companies enter regions with more loan demand. As they enter they build bank branches and increase access to finance for firms.

To guarantee an equilibrium in the presence of this externality, I make the additional assumption that \( \frac{\partial C(\cdot)}{\partial J^b_o} \frac{1}{J^b_o} < 1 \). In essence, this means bank profits continue to decrease in bank entry even as marginal lending costs decrease.\[15\]

For the moment, I hold this endogeneity fixed and analyze the goods market equilibrium conditional on a given level of monitoring costs \( C_o \).

### 1.2.6 Goods market equilibrium

Given the expression for loan costs and the explicit distribution of productivity, I can solve for the equilibrium level of trade in this economy. The sectoral price index is determined by firm-level pricing and the measure of active firms and can be expressed as follows:

\[ P_{kd} = Y^d_1 \gamma - \frac{1}{\sigma - 1} \Theta_d \sigma_p \delta_k \frac{\gamma(\sigma - 1 - \gamma)}{\sigma - 1} \quad (1.17) \]

\[ \Theta_d^{-\gamma} = \sum_o w_o^{1-\gamma} N_o \left( \frac{\sigma}{\sigma - 1} \right) (f_{rod})^{1-\frac{\gamma}{\sigma - 1}} \quad (1.18) \]

Aggregate prices are increasing in the probability of default \( 1 - \delta_k \), decreasing in income, and

---

\[15\] This will hold true for most empirically relevant applications, because population size is large relative to bank companies. At the limit, (imagine enough banks enter such that profits are now convex in costs), I assume an exogenous number of potential national bank companies to have a solution at this corner.

\[16\] \( \sigma_p^{-\gamma} = \left[ \left( \frac{\sigma}{\sigma - 1} \right) \frac{\sigma - 1}{\sigma - 1 - \gamma} \right]^{\sigma - 1 - \gamma} \left( \frac{\gamma}{\gamma + 1 - \sigma} (1 + r_d) \right)^{1-\frac{\gamma}{\sigma - 1}} \)
increasing in the so-called "multilateral resistance" term: $\Theta_d$. This variable is a measure of prices faced by county $d$ weighted by their relative trade costs (Anderson and Van Wincoop [2003]). This term has the same form as in Chaney [2008], but now also reflects average financial costs. All else equal, region $d$ faces higher prices if it is closer to regions with less bank presence.

Exports and income in this model depend on the volume of producing firms and their average revenues. Exports are given by $w_d N_o \tilde{\pi}^\gamma k \bar{\sigma} \bar{\pi}_{kd}$. Integrating over the productivity distribution gives me average exports per firm:

$$\bar{x}_{kd} = \bar{\pi}_{kd} = \sigma \frac{C_o(1 + r_d)}{\delta_k} f_{od}$$  \hspace{1cm} (1.19)

Per firm profits are increasing in financing costs and default risk. Intuitively, this is because as the credit constraint becomes more binding, less firms enter and thus the median producer is more productive and makes higher profits.

Using the price index, the productivity cutoff, and the aggregate export equation I can solve for equilibrium income. In Appendix A.1.2 I show that the profit share of aggregate regional income depends on a weighted average of expenditure shares, which I define as $\bar{\lambda}_d = \frac{X_{dl}}{Y_l}$  \hspace{1cm} (1.20)

Equilibrium income is then given by

$$Y_d = w_d L_d \frac{\sigma}{\sigma - \bar{\lambda}_d}$$  \hspace{1cm} (1.21)
1.3 Model predictions

This model is simple, but it generates important results for how finance effects city-level exports. In this section, I go over predictions from the model that show how the intensive and extensive margins of trade respond to local access to finance.

1.3.1 Bilateral exports

Combining the banking and goods sectors generates a gravity-style trade equation that captures typical bilateral trade features as well as financial sector variables:

\[
X_{kod} = \sigma - \frac{\lambda_o}{\sigma} Y_o Y_d \sigma_x \left( \frac{w_o}{\Theta_d} \right)^{-\gamma} \left( \frac{1}{\delta_k} C \left( B_o \frac{N_o}{N_0} \right) \right)^{1 - \frac{\gamma}{\sigma - 1}} \tau_{od}^{x - \gamma} f_{od}^{1 - \frac{\gamma}{\sigma - 1}} \sum_k \delta_k^{\frac{y + 1 - \sigma}{\sigma - 1}} \mu_k^{\frac{y}{\sigma - 1}} \tag{1.22}
\]

\[
X_{od} = \sigma - \frac{\lambda_o}{\sigma} Y_o Y_d \sigma_x \left( \frac{w_o}{\Theta_d} \right)^{-\gamma} \left( C \left( B_o \frac{N_o}{N_0} \right) \right)^{1 - \frac{\gamma}{\sigma - 1}} \tau_{od}^{x - \gamma} f_{od}^{1 - \frac{\gamma}{\sigma - 1}} \sum_k \delta_k^{\frac{y + 1 - \sigma}{\sigma - 1}} \mu_k^{\frac{y}{\sigma - 1}} \tag{1.23}
\]

\[\sigma_X = \left[ \left( \frac{\sigma}{\mu} \right)^{\frac{1}{\sigma - 1}} - \frac{\sigma}{\sigma - 1} \right]^{1 - \frac{\gamma}{\sigma - 1}} \frac{\gamma}{\gamma - \sigma + 1} \left( 1 + r_d \right)^{1 - \frac{\gamma}{\sigma - 1}} \sigma_p^{-\gamma}
\]

The amount of bilateral exports can be decomposed into five parts. The results are the same for both sectoral and aggregate bilateral exports, as they are proportional conditional on the aggregate default risk.

1. It is increasing in the typical country size measures \(Y_o\) and \(Y_d\). This result is typical in the literature and had been assumed in early applied trade research. In particular, it says that the elasticity of bilateral trade to importer or exporter size is one.

2. Exports are decreasing in both variable and fixed bilateral costs to exporting. This result is identical to [Chaney [2008]], where the elasticity of trade to variable trade costs only depends on the productivity distribution of firms via \(\gamma\), a supply-side parameter.

3. Bilateral trade depends on the destination country’s relative remoteness to the rest of the world. Recall that \(\Theta_d\) is measure of how high prices are in region weighted by its distance to
the countries with whom it trades. The elasticity of remoteness to trade is $\gamma > 0$ indicating that higher relative prices in $d$ makes it easier for firms in $o$ to compete in that market. As $\gamma$ increases, productivity levels are more homogeneous and thus the aggregate market is more competitive and firms are more sensitive to aggregate price index changes.

(4) The level of wages and the share of profits in income also affect bilateral trade. First, note that $\frac{\sigma - \lambda_o}{\sigma} Y_o w_o^{-\gamma} < Y_o$ which means that aggregate income over counts the effect of exporter size. I can write the term $\frac{\sigma - \lambda_o}{\sigma} Y_o w_o^{-\gamma}$ as $w_o N_o w_o^{-\gamma}$, meaning the term captures origin region non-financial characteristics that increase the number of exporters. In effect, $\frac{\sigma - \lambda_o}{\sigma} w_o^{-\gamma}$ is a downward adjustment to the effect of $Y_o$, reflecting that the term comprises characteristics of firm-level productivity and profits more than just labor income.

(5) Bilateral trade is decreasing in costs of financing. This component leads my first relevant empirical prediction:

**Prediction 1: Regions with higher access to banking, $\frac{B_o}{N_o}$, will have higher bilateral exports.** There are two channels at work here. First, higher financing costs mean less firms are productive enough to enter a given export market. The elasticity of exporting firms to bank costs is $-\frac{Y}{\sigma - 1} < 0$. However, higher financing costs mean that the average productivity of exporting firms is higher and therefore their profits are higher. The elasticity of average-firm level revenues to financing costs is 1. In total, for a given trade pair, the elasticity of trade to exporter monitoring costs is $1 - \frac{Y}{\sigma - 1} < 0$ given the assumption that $\gamma > \sigma - 1$.

(6) Industry-level bilateral trade is decreasing in default-risk, $1 - \delta_k$. Looking at the combined expression $\frac{1}{\delta_k} C \left( \frac{B_o}{N_o} \right)$ gives me my second prediction:

**Prediction 2: The relative effect of bank access on bilateral trade is higher in financially risky industries, $\frac{\partial X_{kod}}{\partial \delta_k \partial \frac{B_o}{N_o}} < 0$.** This says that for a financially risky sector ($1 - \delta_k$ high), the decrease in monitoring costs via $\frac{B_o}{N_o}$ will have a larger effect than on a sector with low

\[ \frac{\partial X_{kod}}{\partial \delta_k \partial \frac{B_o}{N_o}} = \left( \frac{Y}{\sigma - 1} - 1 \right) \frac{X_{kod} C'}{C} \frac{C'}{C} < 0 \]
default risk. In later sections, I will use indexes for asset tangibility and financial dependence to determine financial riskiness.

### 1.3.2 Extensive margin of trade

Combining the trade and goods sectors generates the following expression for number of bilateral exporters in a given sector:

\[
V_{x_{od}} = \sigma_j \frac{\sigma - \bar{\lambda}_o}{\sigma} Y_o Y_d \left( \frac{w_o \tau_{x_{od}}}{\Theta_d^{-\gamma} \sigma_p^{-\gamma}} \right)^{-\gamma} \frac{1}{\delta_k} C_o \left( \frac{\sigma}{\sigma - 1} \right)^{\frac{-\gamma}{\sigma - 1}} f_{x_{od}}^{\frac{-\gamma}{\sigma - 1}} \sum_k (\mu_k \delta_k)^{\frac{-\gamma}{\sigma - 1}} \tag{1.24}
\]

\[
V_{x_{od}} = \sigma_j \frac{\sigma - \bar{\lambda}_o}{\sigma} Y_o Y_d \left( \frac{w_o \tau_{x_{od}}}{\Theta_d^{-\gamma} \sigma_p^{-\gamma}} \right)^{-\gamma} \left( C_o \right)^{\frac{-\gamma}{\sigma - 1}} f_{x_{od}}^{\frac{-\gamma}{\sigma - 1}} \sum_k (\mu_k \delta_k)^{\frac{-\gamma}{\sigma - 1}} \tag{1.25}
\]

\[21\]

The interpretation of this equation is nearly identical to that intensive margin equation above. The number of bilateral exporters is a function of country sizes, exporter firm characteristics, bilateral trade costs, and the costs of export financing.

**Prediction 3: Number of exporting firms is increasing in access to banking.** The elasticity of exporters to finance costs is \( \frac{-\gamma}{\sigma - 1} < 0 \). The effect here is larger than the aggregate effect, as per firm exports are increasing in bank costs. However, empirically firm-level export counts are often unobserved. So I consider the following prediction related to number of products as a function of the financial sector

**Prediction 4: The number of bilateral varieties shipped is increasing in access to banking.** This follows directly from above, as varieties are equivalent to firms in this model.

---

\[21\sigma_j \equiv \left( \left( \frac{\sigma}{\sigma - 1} \right) \frac{-\gamma}{\sigma - 1} \right)^{-\gamma} \left[ \frac{r}{r - \sigma + 1} \right] \frac{-\gamma}{\sigma - 1} \]
1.4 Empirical specification and results

In this section, I outline an approach to estimate the model predictions and show the effects of local bank access on city-level export behavior. While this model has a global equilibrium, I will be focusing on the $o'$ subregions of one country exporting to $D$ destinations.

1.4.1 Brazilian data

I test these predictions looking at a panel of Brazilian banking and trade data from 2007-2012. Empirically, I treat "local", or the $o'$ subregions, as Brazilian municipalities, the most geographically disaggregated administrative level in the country. This allows for a relatively precise measure of nearby banking services.

I use data on bilateral exports of HS4-level commodities aggregated to either the ISIC 3 digit industry level or the aggregate city level. Table 1.1 summarizes the data. The median Brazilian exporting city exports $8.2 million in goods to 12 foreign export partners. I use two different distance measures. The first is the greatest circle distance from the city to the capital of the destination country. However, Brazilian municipal trade data is based on the location of the Brazilian company that exports, not necessary the location where the good was produced. To account for this, I run specifications with a measure of export port to destination distance. I first calculate the port’s share in a city’s exports to a destination country $\tilde{p}_{odp} = \frac{X_{odp}}{X_{od}}$. Then, I use this as a weight on the distance from those port cities to the destination capital: $\sum_{p} \tilde{p}_{odp}(1+d_{pd})^{22}$.

The banking data that I use is primarily count data on Agências registered by the Central Bank of Brazil. Agências are full-service bank branches with legally set hours of operation, the most likely category of bank institution to engage in direct firm lending. State-owned banks still play a large role in credit access in Brazil. However, their branching behavior and contribution

\[\text{This measure is similar to Chen}\ [2004]\text{'s weighting scheme for calculating internal distance.}\]
to firm-level exports at the local level is difficult to identify given the potential endogeneity of their location choices. For example, a portion of employee payroll taxes are automatically deposited at the federal government owned Caixa Econômica Federal. Brazil’s largest state bank, Banco do Brasil, has a special role in distributing subsidized rural and housing credit. It is highly plausible that these institutions may move into areas with high levels of economic activity that are correlated with export behavior.

To abstract from the role of state banks, I focus on a smaller indicator of bank access: the quantity of commercial bank branches in a municipality. I define this as branches that are part of bank companies where the government does not hold majority ownership. The median Brazilian export city has approximately one commercial branch per 20,000 people.

1.4.2 Endogeneity and commercial bank branching

In this section, I formally define the bank-branch externality and discuss how to deal with potential endogeneity.

First, I give an explicit functional form to the marginal cost function: \( C\left( \frac{B_o}{N_o} \right) = \exp\left( -\frac{B_o}{N_o} \right) \). This says that the marginal cost reducing externality is highly convex on its own. However, note that

\[
\frac{\partial C(\cdot)}{\partial B_o} \frac{1}{J_o} = \left( \frac{1}{2J_o} \right) \left( \frac{1}{\sigma - 1} - 1 \right) \exp\left( \frac{B_o}{N_o} \left( \frac{1}{2J_o} \right) \left( \frac{1}{\sigma - 1} - 1 \right) \right) \frac{1}{J_o} \frac{B_o}{N_o}.
\]

As the number of bank companies in a region is generally much smaller than the population, this expression will be less than one, avoiding a corner solution.

Once this functional form has been established, there are still potential endogeneity issues in any attempt to estimate the effect of bank access on export behavior. \( \frac{B_o}{N_o} \) can be correlated with the error term due to reverse causality: exporters drive loan demand and loan demand drives bank entry. To control for this, I need a predictor for \( \frac{B_o}{N_o} \) that is uncorrelated with the error term.

To do this, I use a three stage estimation approach. Stage zero is a reduced-form extension of the structural banking model. First, note the symmetric, simultaneous equilibrium in the banking sector says the number of bank branches per person reduces to
Table 1.1: Summary statistics

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Median</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>General</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GDP (1000 US Dollars)</td>
<td>1044252.60</td>
<td>187634.86</td>
<td>6916732.63</td>
</tr>
<tr>
<td>GDP/pop (US Dollars)</td>
<td>9821.14</td>
<td>7685.94</td>
<td>9612.03</td>
</tr>
<tr>
<td>Population</td>
<td>86091.14</td>
<td>25800.50</td>
<td>370665.43</td>
</tr>
<tr>
<td>Population Density</td>
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</tr>
<tr>
<td>Establishments</td>
<td>2506.75</td>
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<td><strong>Banking</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Commercial Bank Branches</td>
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<td>2.00</td>
<td>55.30</td>
</tr>
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<td>Commercial Branches per 10k people</td>
<td>0.63</td>
<td>0.55</td>
<td>0.58</td>
</tr>
<tr>
<td>Branch remoteness (KM)</td>
<td>872.55</td>
<td>644.33</td>
<td>691.36</td>
</tr>
<tr>
<td>Bank Branches in 1995</td>
<td>8.08</td>
<td>3.00</td>
<td>48.74</td>
</tr>
<tr>
<td><strong>Exports</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aggregate Exports (1000 US Dollars)</td>
<td>124370.25</td>
<td>8247.56</td>
<td>545606.54</td>
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<td>Export Destinations</td>
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<td>12.00</td>
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<td>Exported Products (HS4Digit)</td>
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<td>Distance: City to Destination(KM)</td>
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<td>7660.13</td>
<td>3217.95</td>
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<td>Distance: Port to Destination (KM)</td>
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<tr>
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</tbody>
</table>

Notes: Observations: Brazilian cities with positive trade from 2007 - 2012. Sources: IBGE, Central Bank of Brazil, Ministry of Development, Industry and Foreign Trade. Data notes: Port to Destination distance is a weighted average of distance from most used ports. Branch remoteness is a weighted average of distance to bank company headquarter cities.
\[
\frac{B_o}{N_o} = h \left( \sum_k \delta_k \left( 1 + r^d \right) \frac{1}{2} \beta_o \frac{1}{N_o} \sum_d f_{od} x_{od} \frac{1}{\sum_k \delta_k \left( 1 + r^d \right) \frac{1}{2} \beta_o^{-1}} \right)^{23}. \]

The primary exogenous, region-varying parameter here is the \( \beta_o \) branching cost parameter.

To estimate this equation, I start from the bank company level and assume \( \beta_{ob} \) varies by banking company, \( b \). In particular, I treat this variable as in information-based entry cost. Building branches is effectively expanding market reach and thus involves gathering new clients. These costs can thought of as the adverse selection issues encountered on expanding into a market as available clients may be the worst (Dell’Ariccia et al. 1999, Dell’Ariccia 2001). In the context of relationship lending this parameter could measure the "time, effort, and resources that it takes to build lending relationships and for the losses that a bank might incur" upon entry (Hauswald and Marquez 2006).

To have a plausibly exogenous measure of branching costs, I deal with bank-company-specific geography. In particular, I focus on city to bank headquarter distance, as empirical work has shown that bank branching is decreasing in regions that are remote to the company\( ^{24} \). In addition to the geographic characteristics of the bank branching decision, aggregate company-specific characteristics are exogenous to a given city’s level of exports. For example, the size of a bank in terms of assets or credit operations is a national bank-company variable that determines whether a bank branches into difference regions.

As such, I express company-specific branching costs as a a function of headquarter distance, company effects, and city-level variables. Using the company-level branch equation, \( b_{ob} = \frac{1}{2\rho_{ob}} \), I can then transform this into a regression of company-level branches per person on bilateral (headquarter city to export city) distance and company and export city fixed effects.

\[
\frac{b_{ob}}{N_o} = \psi_o + \psi_b + \zeta_B \ln(1 + d_{ob}) + \epsilon_{ob} \tag{1.26}
\]

where \( \psi_o \) is a city-level fixed effect capturing city characteristics, \( \psi_b \) captures bank company

---

\(^{23}\)h(·) is the product log function

\(^{24}\)See Felici and Pagnini [2008], Buch [2005], Degryse and Ongena [2004, 2005] for this work. If we think of bank branching as bank-holding company investment, Goetz et al. [2013, 2016] show that distance is negatively correlated with bank expansion. A classic example of this process is the retail sector is the expansion of Wal-Mart in the United States (Holmes 2011).
size, and $d_{ob}$ is the distance to the bank headquarter region. After this estimation, I can instrument $\frac{B_o}{N_o}$ with

$$\left( \frac{\hat{B}_o}{N_o} \right) = \sum_b \left( \frac{\hat{b}_{ob}}{N_o} \right)$$

(1.27)

This procedure is reminiscent of the Frankel and Romer [1999] work that uses predicted trade shares as an instrument for observed trade shares using the exogeneity of bilateral distance to identify effects.\(^{25}\)

Table 1.2 shows the results of the bank company-level regression of estimation equation (1.26). Columns (1) and (2) exclusively contain the dyadic headquarter distance term and the bank company specific fixed effect and credit operations variable. The company-specific terms are significant determinants of company-level branching behavior with the expected signs: larger and closer banks are more likely to enter a given region.

Columns 3-5 add various city-level characteristics including the presence of government branches, per capita income, and a city-level fixed effect. However, as noted by Ortega and Peri [2014], the city-level characteristics include variables that affect trade and are therefore part of the endogeneity that I am trying to purge from my model. What those results do show, however, is that the coefficient on company-size and headquarter distance are significant and similar across models. This indicates that estimates of the bank-company specific variables are not biased by the exclusion of city-level fixed effects and controls. Though it appears that commercial banks are less likely to branch into regions with government banks, their presence doesn’t substantially change the results from columns 1 and 2.

As an additional robustness check, instead of building from the bank-level up, I can think of a weighted-average of headquarter distance as an indicator of potential branching behavior. I define a financial remoteness term that measures how far the largest bank companies are from a given city:

\(^{25}\)See Goetz et al. [2013] and Goetz et al. [2016] for examples of using this strategy in the banking literature. See Neumark et al. [2008] for using Wal-Mart expansion in this way.
Table 1.2: Company-level determinants of commercial bank branch presence

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
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<tbody>
<tr>
<td>Dep. Var.</td>
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<td>Dist</td>
<td>FE</td>
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<td>City 2</td>
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<td>Ln HQ Distance</td>
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<td>-0.00392***</td>
<td>-0.00408***</td>
<td>-0.00358***</td>
<td>-0.00408***</td>
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<tr>
<td></td>
<td>(0.000121)</td>
<td>(0.000121)</td>
<td>(0.000180)</td>
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<td>Ln Bank Credit</td>
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<td>0.000148***</td>
<td>0.000148***</td>
<td>0.000148***</td>
<td>0.000148***</td>
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<tr>
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<td>(0.0000107)</td>
<td>(0.0000107)</td>
<td>(0.0000107)</td>
<td>(0.0000107)</td>
<td>(0.0000107)</td>
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<tr>
<td>Ln GDP per capita</td>
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<td></td>
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<td></td>
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<td>0.00110***</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>(0.000169)</td>
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<td>(0.00000541)</td>
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<tr>
<td>$R^2$</td>
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<td>0.115</td>
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<td>2588608</td>
<td>2588608</td>
<td>2588608</td>
<td>2588608</td>
</tr>
</tbody>
</table>

* p < 0.1, ** p < 0.05, *** p < 0.01.

Notes: Standard errors clustered at the city-bank headquarter level. HQ distance is the greatest circle distance from the branching city to the bank headquarter city. Bank credit is the total bank credit operations over all branches. Government owned branches are those where the government owns a majority of the company’s shares.
\[
REMOTE_o = \sum_{b_h} \left( \frac{SIZE_b}{\sum_b SIZE_b} d_{obh} \right)
\] (1.28)

where size can stand in for various bank company characteristics such as assets, credit operations, or branch network\textsuperscript{26}

I consider \((\hat{B}_o/\hat{N}_o)\) as constructed from estimates in column 2 of Table 1.2 and \(REMOTE_o\) using credit operations as the size measure separately and use each in the first stage regression. The second stage of this estimation procedure will be any of the below tests of the effects of bank access on city-level export outcomes\textsuperscript{27}

1.4.3 City-level trade

1.4.3.1 Intensive margin

I use the functional form of the externality assumption and the instruments from above to test Prediction 1 (bank access increases bilateral trade). I take logs of the bilateral gravity equation (1.23), plug in \(C(\frac{B_o}{N_o}) = \exp(-\frac{B_o}{N_o})\), and estimate the following :

\[
\ln X_{od} = \zeta_{x1} \ln \tilde{J}_o + \zeta_{x2} \ln Y_o + \zeta_{x3} \ln Y_d + \zeta_{x4} \tau_{od} + \zeta_{x5} \frac{B_o}{N_o} + \psi_d + \zeta_{x5} \ln \tilde{\delta}_o + \epsilon_{od}
\] (1.29)

where \(\ln \tau_{od} = -\gamma \ln \tau_{od}^x - (1 - \frac{\gamma}{\sigma-1}) \ln f_{od}^x\), \(\psi_d = \Theta_d^{-\gamma}\), and \(\epsilon_{od}\) as the error term. The indicator for bank access appears in level form and it’s coefficient is \(\zeta_{x4} = \frac{\gamma}{\sigma-1} - 1 > 0\), as increased access to banking lowers effective fixed export costs and thus increases bilateral trade. \(\psi_d\) is a importer fixed effect that is a function of multilateral resistance.

\textsuperscript{26}Rose and Spiegel [2009] also use financial remoteness as a plausibly exogenous way to measure financial market effects. Their indicator is the distance of a country from the one of three major global financial centers. This term is also comparable to “functional distance” in Alessandrini et al. [2009]. Their measure, however, is explicitly related to the headquarter location of active branches in a region and is therefore not appropriate to use for estimating potential bank branch presence.

\textsuperscript{27}The results below are qualitatively robust to instruments constructed from each model in Table 1.2. Additionally, the results are robust to calculating \(REMOTE_o\) with bank branches or bank assets.
There are two other terms in this equation I need to deal with more carefully. The first is
\[ \ln \tilde{\delta}_o = \sum_k \tilde{\delta}_k \frac{\gamma^{1-\sigma}}{\sigma^{1-\gamma}} \mu_k, \]
which is generated by aggregating up from the sector level. Effectively, this term is an indicator of city-level default risk that varies based on the sectoral composition of a given city. To control for this, I calculate industry shares of trade for each city and generate a new variable that is a linear combination of financial riskiness indicators that I call \( xdelta_o \). The second term is
\[ \ln \tilde{J}_o = \ln \frac{\sigma - \lambda_o}{\sigma} - \gamma \ln w_o. \]
Traditionally in the gravity literature, you can absorb \( \ln \tilde{J}_o \) into an exporter fixed effect. The issue is that the coefficient of interest \( B_o N_o \) generally varies at the city level over. To control for this, I follow a strategy laid out in [Head and Mayer, 2015] to generate a monadic variable that functions as an exporter fixed effect. I define \( \bar{D}_o \) as the average characteristics of each exporter and calculate it as
\[ \bar{D}_o = \frac{\sum \tilde{\tau}_{od} D}{\tilde{D}}. \]

Table 1.3 presents the results from this regression. All regressions include time fixed effects to control for aggregate time trends and time-varying destination fixed effects to control for changes in destination multilateral resistance and market size. For exporters, I include population density, firm count data, \( \bar{D}_o \), and \( xdelta_o \) as controls, and city-level GDP as the traditional measure of exporter size.

The first two columns are different OLS specifications of equation (1.29) with alternate measures for distance. The first is the traditional measure of greatest circle distance used in the trade literature. In the second, I use the weighted distance from the port city to destination country, which I carry through for the rest of my regressions. In all cases, the distance coefficients have the expected signs. The level of exports are decreasing in bilateral distance.

The most relevant coefficient in my analysis is the effect of Bank Access, measured by commercial bank branches per 10,000 people. Across the distance specifications, the result is the same: bank branch access increases the level of bilateral exports in a statistically significant way.

Columns 4-5 are alternative ways of dealing with the endogeneity of bank presence and exports, with each presenting the second stage results with different instruments for bank presence as defined in Section 1.4.2. Column 4 uses predicted bank presence from the stage 0 regression.
Table 1.3: The effect of bank access on bilateral exports

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<tr>
<th>Dep. Var.: LnXod</th>
<th>OLS</th>
<th>2SLS</th>
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<tbody>
<tr>
<td></td>
<td>Predicted Branch share</td>
<td>Credit Remoteness</td>
</tr>
<tr>
<td>Bank Access</td>
<td>0.141*** (0.0285)</td>
<td>0.159*** (0.0300)</td>
</tr>
<tr>
<td>LnDist</td>
<td>-0.606*** (0.0553)</td>
<td>-1.034*** (0.0215)</td>
</tr>
<tr>
<td>LnExporter GDP</td>
<td>0.552*** (0.0159)</td>
<td>0.385*** (0.0159)</td>
</tr>
<tr>
<td>LnPop Density</td>
<td>-0.222*** (0.0122)</td>
<td>-0.250*** (0.0120)</td>
</tr>
<tr>
<td>Exporter Delta</td>
<td>0.0273*** (0.00184)</td>
<td>0.0332*** (0.00196)</td>
</tr>
<tr>
<td>Exporter Control</td>
<td>1.632*** (0.0559)</td>
<td>1.298*** (0.0545)</td>
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</table>

<table>
<thead>
<tr>
<th>Distance Measure</th>
<th>City</th>
<th>Port</th>
<th>Port</th>
<th>Port</th>
<th>Port</th>
<th>Port</th>
</tr>
</thead>
<tbody>
<tr>
<td>CountryYearFE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>YearFE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>HQ regions</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
</tr>
</tbody>
</table>

| First Stage F | 205.4 | 240.0 | 220.0 |
| $R^2$          | 0.237 | 0.287 | 0.277 |
| Observations   | 188301 | 188301 | 179390 |

* p < 0.1, ** p < 0.05, *** p < 0.01.

Notes: Standard errors clustered at the exporter-year level. Bank access is commercial bank branches per 10,000 people. City distance is the greatest circle distance from the city to the destination country capital. Port distance is the weighted greatest circle distance from a city’s most used ports to the destination country capital. Columns 3-6 are second stage regressions with the column title as the instrument used. Predicted branch share is estimated in column 2 of Table 2. Credit remoteness is the distance from a city to headquarter regions weighted by the credit operations of banks in that region.
and column 5 uses a bank-size-weighted measure of headquarter distance. Both instruments pass the weak instrument test and the coefficients on bank access remain positive and significant. For additional robustness of my results, in columns 3 and 6, I exclude regions with major bank headquarters.

Conditional on distance, foreign demand, and exporter controls, a one standard increase in bank access increases bilateral exports from 8.1% up to 20.0%.

1.4.3.2 Extensive margin

In place of firm-level data, I can analyze the bilateral number of varieties exported which corresponds to the number of exporters in my model. Taking logs of (1.25) and including the financial access externality I have a firm-level flavored bilateral gravity equation:

$$\ln V_{od} = \zeta_{v1} \ln \hat{J}_o + \zeta_{v2} \ln Y_o + \zeta_{v3} \ln Y_d + \zeta_{v4} \ln \tau_{od} + \zeta_{v4} \frac{B_o}{N_o} + \psi_{d} + \zeta_{v5} \ln \delta_o + \epsilon_{od}$$

(1.30)

This is almost identical to the aggregate bilateral equation, however \(\ln \tau_{od}\) is now given as

$$\ln \tau_{od} = -\gamma \ln \tau_{x} - \frac{\sigma}{\sigma-1} \ln \hat{f}_{x}$$

and \(\zeta_{v4} = -\frac{\gamma}{\sigma-1}\).

The estimation procedure here replicates the discussion of the intensive margin above. The estimates here are presented in Table 1.4 and the coefficient on bank access remains positive and significant. The estimated increase in exported varieties due to a one standard deviation increase in bank access ranges from 11.7% to 43.8%.

1.4.4 Industry-level trade

In this section, I use industry-level trade data to allow for additional controls and to emphasize the credit mechanism at work. First, I replicate the exercise above to show the aggregate industry-level bank access effect. Second, I use measures of sector-specific default rates to show that bank access has a relatively larger effect in financially vulnerable industries.
Table 1.4: The effect of bank access on number of exported bilateral varieties

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>Predicted Branch share</th>
<th>Credit Remoteness</th>
<th>Predicted Branch share</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dep. Var.: LnVod</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bank Access</td>
<td>0.202***</td>
<td>0.213***</td>
<td>0.208***</td>
<td>0.728***</td>
</tr>
<tr>
<td></td>
<td>(0.0175)</td>
<td>(0.0160)</td>
<td>(0.0163)</td>
<td>(0.0448)</td>
</tr>
<tr>
<td>LnDist</td>
<td>-0.376***</td>
<td>-0.649***</td>
<td>-0.630***</td>
<td>-0.659***</td>
</tr>
<tr>
<td></td>
<td>(0.0250)</td>
<td>(0.00969)</td>
<td>(0.00971)</td>
<td>(0.00977)</td>
</tr>
<tr>
<td>LnExporter GDP</td>
<td>0.248***</td>
<td>0.144***</td>
<td>0.132***</td>
<td>0.121***</td>
</tr>
<tr>
<td></td>
<td>(0.00877)</td>
<td>(0.00658)</td>
<td>(0.00653)</td>
<td>(0.00702)</td>
</tr>
<tr>
<td>LnPop Density</td>
<td>0.0853***</td>
<td>0.0677***</td>
<td>0.0649***</td>
<td>0.0606***</td>
</tr>
<tr>
<td></td>
<td>(0.00570)</td>
<td>(0.00496)</td>
<td>(0.00528)</td>
<td>(0.00572)</td>
</tr>
<tr>
<td>Exporter Delta</td>
<td>-0.0101***</td>
<td>-0.00631***</td>
<td>-0.00643***</td>
<td>-0.00930***</td>
</tr>
<tr>
<td></td>
<td>(0.000797)</td>
<td>(0.000650)</td>
<td>(0.000645)</td>
<td>(0.000755)</td>
</tr>
<tr>
<td>Exporter Control</td>
<td>0.630***</td>
<td>0.419***</td>
<td>0.391***</td>
<td>0.386***</td>
</tr>
<tr>
<td></td>
<td>(0.0272)</td>
<td>(0.0217)</td>
<td>(0.0217)</td>
<td>(0.0262)</td>
</tr>
</tbody>
</table>

| Distance Measure     | City               | Port                   | Port               | Port                   | Port                   | Port                   |
|                      | Yes                | Yes                    | Yes                | Yes                    | Yes                    | Yes                    |
| CountryYearFE        | Yes                | Yes                    | Yes                | Yes                    | Yes                    | Yes                    |
| YearFE               | Yes                | Yes                    | Yes                | Yes                    | Yes                    | Yes                    |
| HQ regions           | Yes                | Yes                    | No                 | Yes                    | Yes                    | No                     |

First Stage F                       205.4       240.0       220.0
$R^2$                                0.380       0.484       0.459
Observations                      188634      188634      179720

Notes: Dependent variable is the log of total number of HS4 level varieties exported from a given city to a destination country in a given year. Standard errors clustered at the exporter-year level. Bank access is commercial bank branches per 10,000 people. City distance is the greatest circle distance from the city to the destination country capital. Port distance is the weighted greatest circle distance from a city’s most used ports to the destination country capital. Columns 3-6 are second stage regressions with the column title as the instrument used. Predicted branch share is estimated in column 2 of Table 2. Credit remoteness is the distance from a city to headquarter regions weighted by the credit operations of banks in that region. 1995branches is total number of bank branches in the city in 1995. First Stage F stat is the Kleibergen-Paap rk Wald F statistic from the first stage regressions.

* p < 0.1, ** p < 0.05, *** p < 0.01.
1.4.4.1 Sector-level regressions

For this specification I take logs of (1.22) and (1.24) generate estimation equations for sectoral exports and varieties:

\[
\ln X_{kod} = \psi_k + \psi_d + \psi_{ok} + \xi_1 \frac{B_o}{N_o} + \xi_2 \ln Y_o + \xi_3 \ln d_{od} + \bar{D}_o + \epsilon_{od} \tag{1.31}
\]

\[
\ln V_{kod} = \psi_k + \psi_d + \psi_{ok} + \xi_1 \frac{B_o}{N_o} + \xi_2 \ln Y_o + \xi_3 \ln d_{od} + \bar{D}_o + \epsilon_{od} \tag{1.32}
\]

where \(\psi_k\) is a sector-level fixed effect that controls for variation in default risk; \(\psi_d\) is an importer fixed effect that controls for foreign income and price indexes, and \(\psi_{ok}\) is an exporter-sector fixed effect that captures sector-specific outward multilateral resistance. As in the previous specification, I include exporter income, population density, and \(\bar{D}_o\) as exporter controls, and I use the weighted port distance measure to control for bilateral trade costs.

The results in Tables 1.5 and 1.6 demonstrate that this result is robust to the further controls provided by using industry-level data. Under this setup, increasing bank access increases industry-level bilateral trade with an effect ranging from 10.0% to 58.7% and industry-level bilateral varieties from 5.0% to 20.8%.

1.4.4.2 Identifying the credit channel

To demonstrate that it is the credit channel at work in these results, my empirical strategy relies on the relationship between sector-specific default rates and bank access. Following Manova [2013], I define two industry-specific measures: asset tangibility and financial dependence using indexes calculated by Braun [2005]. I apply these to Brazilian city-level data at the ISIC 3-digit level.

Financial dependence is a measure of how reliant firms are on external funds. This measure is based on the percentage of capital expenditures financed internally. In particular, it is capital expenditures less cash flows from operations divided by total capital expenditure. This value is
Table 1.5: The effect of bank access on industry-level bilateral exports

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>2SLS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dep. Var.: LnXkod</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Bank Access</strong></td>
<td>0.195***</td>
<td>0.925***</td>
</tr>
<tr>
<td>(0.0480)</td>
<td>(0.183)</td>
<td>(0.454)</td>
</tr>
<tr>
<td><strong>LnDist</strong></td>
<td>-0.829***</td>
<td>-0.821***</td>
</tr>
<tr>
<td>(0.0176)</td>
<td>(0.0176)</td>
<td>(0.0175)</td>
</tr>
<tr>
<td><strong>LnExporter GDP</strong></td>
<td>0.224***</td>
<td>0.117***</td>
</tr>
<tr>
<td>(0.0182)</td>
<td>(0.0368)</td>
<td>(0.0722)</td>
</tr>
<tr>
<td><strong>LnPop Density</strong></td>
<td>-0.169***</td>
<td>-0.147***</td>
</tr>
<tr>
<td>(0.0225)</td>
<td>(0.0266)</td>
<td>(0.0296)</td>
</tr>
<tr>
<td><strong>Exporter Control</strong></td>
<td>0.346***</td>
<td>0.394***</td>
</tr>
<tr>
<td>(0.0591)</td>
<td>(0.0649)</td>
<td>(0.0716)</td>
</tr>
</tbody>
</table>

|                      |              |              |
| **Importer+YearFE**  | Yes          | Yes          |
| **YearFE**           | Yes          | Yes          |
| **SectorFE**         | Yes          | Yes          |
| **ExporterRegion+SectorFE** | Yes  | Yes  |
| **Sector+CountryFE** | No           | Yes          |
| **HQ regions**       | Yes          | Yes          |

| First Stage F        | 69.94        | 57.81        |
|                      | 75.57        |
| *R^2*                | 0.498        | 0.537        |
| Observations         | 498012       | 497607       |
|                      | 443043       |

Notes: Standard errors clustered at the exporter-year level. Bank access is commercial bank branches per 10,000 people. Columns 3-6 are second stage regressions. Columns 4 and 6 used the bank prediction measure. Column 5 uses bank remoteness. Columns 3 and 6 exclude headquarter regions from the estimation.
Table 1.6: The effect of bank access on number of industry-level exported bilateral varieties

<table>
<thead>
<tr>
<th>Dep. Var.: LnVkod</th>
<th>OLS</th>
<th>2SLS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bank Access</td>
<td>0.0921*** (0.0108)</td>
<td>0.0967*** (0.0114)</td>
</tr>
<tr>
<td></td>
<td>0.354*** (0.0354)</td>
<td>0.360*** (0.0366)</td>
</tr>
<tr>
<td>LnDist</td>
<td>-0.203*** (0.00629)</td>
<td>-0.199*** (0.00642)</td>
</tr>
<tr>
<td></td>
<td>-0.206*** (0.00641)</td>
<td>-0.202*** (0.00658)</td>
</tr>
<tr>
<td>LnExporter GDP</td>
<td>0.0772*** (0.00459)</td>
<td>0.0847*** (0.00504)</td>
</tr>
<tr>
<td></td>
<td>0.0506*** (0.00523)</td>
<td>0.0583*** (0.00545)</td>
</tr>
<tr>
<td>LnPop Density</td>
<td>-0.0133*** (0.00390)</td>
<td>-0.0108*** (0.00412)</td>
</tr>
<tr>
<td></td>
<td>-0.0104*** (0.00450)</td>
<td>-0.00802* (0.00472)</td>
</tr>
<tr>
<td>Exporter Control</td>
<td>0.135*** (0.0203)</td>
<td>0.130*** (0.0210)</td>
</tr>
<tr>
<td></td>
<td>0.115*** (0.0213)</td>
<td>0.111*** (0.0218)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Yes</th>
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<th>Yes</th>
<th>Yes</th>
<th>Yes</th>
<th>Yes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Importer+YearFE</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>YearFE</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>SectorFE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Sector+CountryFE</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>HQ regions</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
</tr>
</tbody>
</table>

First Stage F | 171.6 | 105.7 | 107 |
First Stage R² | 0.763 | 0.774 | 0.782 |
Observations   | 498856 | 498451 | 443888 |

Notes: Standard errors clustered at the exporter-year level. Bank access is commercial bank branches per 10,000 people. Columns 3-6 are second stage regressions. Columns 4 and 6 used the bank prediction measure. Column 5 uses bank remoteness. Columns 3 and 6 exclude headquarter regions from the estimation.
negative if cash flows are higher than capital expenditure, i.e. there are enough internal funds to finance operations. This has been used in many studies of financial development to tease out causal effects: Rajan and Zingales [1998] show that better financial markets increase growth in sectors dependent on external finance. Here, I argue that perceived default risk, $1 - \delta_k$ is increasing in financial dependence. While my model requires that firms finance the entirety of their foreign fixed costs, banks realize that firms will be better able to pay back if they have cash on hand. In this index, for example, professional and scientific equipment is highly dependent on finance, while the tobacco sector relies on internal funds.

Asset tangibility is a way to capture whether or not firms have collateral for banks to take in the event of default. It is defined as the ratio of physical asset value to total value of a firm. Physical assets include property, buildings, and equipment, things that a bank could seize in the case of bankruptcy. A sector with a larger proportion of physical assets has high asset tangibility and is a lower default risk for banks, as they are able to recoup a portion of the firms assets in the case of default. An example of a highly tangible sector is the iron and steel industry, while footwear producers have less physical assets as a proportion of their total value.

I express the interaction of $C_o$ with $\delta_k$ as a function of bank access, bank access interacted with asset tangibility and financial dependence, and various fixed effects to estimate prediction 2: the relative effect of bank access on bilateral trade is higher in financially risky industries. The estimation equations for city-level industry exports and city level industry varieties are:

$$\ln X_{od}^k = \psi_k + \psi_d + \xi_1 \frac{B_o}{N_o} + \xi_2 \frac{B_o}{N_o} \cdot FinDep_k + \xi_3 \frac{B_o}{N_o} \cdot AssetTan_k + \xi_3 \ln Y_o + \xi_4 \ln d_{od} + \xi_5 \bar{D}_o + \epsilon_{od}$$ (1.33)

$$\ln V_{od}^k = \psi_k + \psi_d + \xi_1 \frac{B_o}{N_o} + \xi_2 \frac{B_o}{N_o} \cdot FinDep_k + \xi_3 \frac{B_o}{N_o} \cdot AssetTan_k + \xi_3 \ln Y_o + \xi_4 \ln d_{od} + \xi_5 \bar{D}_o + \epsilon_{od}$$ (1.34)

I expect the total effect of bank access to be positive, $\zeta_1 > 0$, but for that effect to be larger
in sectors with high financial dependence $\xi_2 > 0$ and low asset tangibility $\xi_3 < 0$.

Table 1.7 presents the results from this estimation. Columns 1-3 replicate equation 1.33 above and the results are significant with the coefficients matching my predicted signs. The extensive margin results in columns 4-6 have the correct signs but are not consistently significant. It appears that the extensive margin of industry-level exports is driven primarily by the capital structure of firms via the financial dependence measure.

Across all specifications the estimates match the predicted relationship between bank access and financial vulnerability. More tangible sectors respond less to increased bank branches and financially dependent sectors respond more. For example, we would expect to see large effects in the professional and scientific industry with asset tangibility in the 10th percentile and external financial dependence in the 99th. A one standard deviation increase in bank access raises bilateral exports in this sector by 46.0% and bilateral varieties exported by 10.5%. Whereas in the industrial chemical sector with asset tangibility in the 80th percentile and financial dependence in the 15th percentile, we would only see exports increase by 3.0% and varieties decrease by .7%

\[\text{Results here are based on coefficients from the models with the full set of controls in columns 3 and 6.}\]
Table 1.7: Industry-level exports, bank access, and financial vulnerability

|                        | Log Industry Exports | | Log Industry Varieties | | |
|------------------------|----------------------|--|--|------------------|--|--|
|                        | (1) | (2) | (3) | (4) | (5) | (6) |
| Branches per 10k people| 0.303** | 0.279** | 0.464*** | 0.0109 | 0.0378 | 0.0270 |
|                        | (0.0991) | (0.0989) | (0.112) | (0.0225) | (0.0202) | (0.0220) |
| Branches x FinDep      | 0.263** | 0.378*** | 0.539*** | 0.286*** | 0.284*** | 0.295*** |
|                        | (0.0865) | (0.0871) | (0.102) | (0.0317) | (0.0264) | (0.0314) |
| Branches x AssetTan    | -0.625* | -0.744** | -1.251*** | -0.0419 | -0.0905* | -0.0823 |
|                        | (0.281) | (0.276) | (0.322) | (0.0488) | (0.0424) | (0.0481) |
| LnDist                 | -0.830*** | -0.771*** | -0.761*** | -0.196*** | -0.200*** | -0.193*** |
|                        | (0.0176) | (0.0171) | (0.0174) | (0.00621) | (0.00647) | (0.00654) |
| LnExporter GDP         | 0.220*** | 0.295*** | 0.224*** | 0.0617*** | 0.0828*** | 0.0675*** |
|                        | (0.0184) | (0.0187) | (0.0205) | (0.00391) | (0.00504) | (0.00419) |
| Exporter Control       | 0.351*** | 0.220*** | 0.232*** | 0.124*** | 0.129*** | 0.119*** |
|                        | (0.0592) | (0.0581) | (0.0590) | (0.0193) | (0.0210) | (0.0199) |
| LnPop Density          | -0.169*** | -0.178*** | -0.126*** | -0.0148*** | -0.00994* | -0.0120** |
|                        | (0.0226) | (0.0226) | (0.0278) | (0.00416) | (0.00412) | (0.00443) |
| SectorFE               | Yes | Yes | Yes | Yes | Yes | Yes |
| Importer+YearFE        | Yes | Yes | Yes | Yes | Yes | Yes |
| YearFE                 | Yes | Yes | Yes | Yes | Yes | Yes |
| ExporterRegion+SectorFE| Yes | Yes | Yes | No | No | No |
| Sector+CountryFE       | No | Yes | Yes | No | Yes | Yes |
| HQ region              | Yes | Yes | No | Yes | Yes | No |

$R^2$ 0.499 0.537 0.545 0.772 0.774 0.783
Observations 498012 497607 443043 444294 498451 443888

Notes: Standard errors clustered at the city-year level. Log distance is the (weighted) distance in KM from the origin port to the destination country capital. Branches x FinDep is Branches per 10k people interacted with the industry-level financial dependence level. Branches x AssetTang is Branches per 10k people interacted with the industry-level asset tangibility level.
1.5 Conclusion

In this paper, I approach the "black box" of financial development at the national level and show that it is theoretically and empirically relevant at the city-level in Brazil. In particular, I augment a heterogeneous firms model with a banking sector and a geographically varying financial constraint. The model is tractable and allows me to estimate bilateral gravity equations at the city and industry level. The inclusion of the banking sector is a micro-foundational approach to the geographic spread of financial development: banks expand outward from their headquarters a rate that is decreasing in distance, increasing in bank size, and increasing in the level of development of the markets they enter. I focus on the distance and bank size characteristics to deal with this underlying endogeneity. This allows me to identify a causal relationship between city-level financial development, proxied by bank branches per person, and a large scale firm outcome: exports.

At the industry-level, I show the mechanisms by which bank access effects trade: financially vulnerable sectors export more in the presence of bank branches. My results here show that the effects captured by Manova [2013] at the country level are not equally distributed.

My use of Brazilian data is evidence that my results are part of an economic development story. Brazil is a middle income country that has experienced relatively high levels of financial development. This has important implications for regional development policy: poorer regions might lag behind the rest of the country if they do not have access to the same levels of financing. Any welfare gains may be concentrated in wealthy cities close to bank headquarters. Future research can work to untangle the role of bank regulation policy and the role of state banks in either exacerbating or ameliorating these trends toward unequal within-country financial development.
Chapter 2

Distance, Geography, and Branch Banking

2.1 Introduction

2.1.1 Strategic bank branching and the geography of financial access

Banks serve an important role in the economy as financial intermediaries who are often the primary interface between the financial sector and individuals. At the same time, banks also act like strategic agents in the economy competing for customers via loan prices (De Blas and Russ 2013), service quality and expertise (Almazan 2002), and proximity to customers (Calem and Nakamura 1998, Ho and Ishii 2011, Dick 2007). Banks routinely attempt to soften competition by capturing firms via relationship lending (Berger et al. 2005, Elsas 2005) where they differentiate themselves from other banks by acquiring proprietary soft information on borrowers (Hauswald and Marquez 2006). There is a strong geographic component to this strategic behavior as the ability to acquire information on creditworthiness and form lending relationships with borrowers requires geographic proximity (Degryse and Ongena 2005, Agarwal and Hauswald 2010).

As banks enter a region, they have the ability to increase access to finance. In particular, within-country, local financial development is often entirely filtered through bank branches in a
city, especially for individuals and small firms (Jayaratne and Strahan 1996, Dick 2006).

In this paper, I investigate the relationship between these strategic choices by banks and local financial development. In particular, I focus on how the strategic expansion of bank branching relates to measures of financial depth, the most common indicator of financial development. To do this, I focus on three essential aspects of bank branch strategic behavior: financial products are largely homogeneous, yet banks still enjoy significant market power; many companies build multiple branches in a single market; and banks generally build branches geographically proximate to their headquarter region.

I capture these effects by building a model of heterogeneously productive banks that compete for the share of monopolistic profits by building bank branches. I embed this in a general equilibrium economic geography model of production. Producers have a simple cash-in-advance constraint: all variable labor costs must be financed with external capital. The model shows that bank branching behavior and market share are driven by company size and geographic characteristics of the bank’s headquarter region. I test the predictions using Brazilian bank branch balance sheet data and show that the bilateral relationship between a company’s headquarter city and the markets they branch into are significant determinants of company behavior. This company-level effect aggregates into explaining city-level financial outcomes: bank access is decreasing in remoteness from headquarter regions. I show that this result means that financial depth is also decreasing in remoteness due to lower bank access.

My work is directly related to the literature on distance-related aspects of bank lending behavior that generate geographic variation in access to credit. Degryse and Ongena [2005], Alessandrini et al. [2009], and Agarwal and Hauswald [2010] show that proximity between firms and banks increases access to finance as banks with better information are more willing to lend. In his study of foreign lending in Pakistan, Mian [2006] shows that cultural distance can further drive geographic variation in credit access. He demonstrates that loans originating from foreign and domestic banks distant from a region are less profitable due to information costs that arise from differences in corporate culture and the way local areas treat legal and regulatory norms.
My modeling and empirical strategy take these distance constraints seriously, and I present additional evidence towards the importance of bank-to-firm and bank branch-to-headquarter distance as drivers of credit access.

This article also builds off of the literature on the geography of strategic bank branching. Previous studies have shown that larger banks are more likely to expand away from their headquarter region (Felici and Pagnini 2008, Cohen and Mazzeo 2010), a feature that I replicate with my analytical and empirical work. To do this I embed banks with heterogeneous lending efficiency in a large-scale production model like De Blas and Russ (2013) and Bremus et al. (2013). Unlike those papers, however, I focus on bank branching as a form of non-price strategic behavior as in Kim and Vale (2001) and Cerasi et al. (2002). A new result is that this non-strategic bank behavior can generate an externality in terms of increased bank access if there are barriers to matching banks with firms.

2.2 Model

2.2.1 Demand and production

2.2.1.1 Consumption

I use a simple demand structure to model the geographic distribution of consumption, production, and demand for loanable funds. In particular, I am augmenting the structure of a canonical economic geography model of economic activity.\footnote{See Fujita et al. (1999)}

In region $j$, $N_j$ identical consumers gain utility from goods that are uniquely differentiated by sector $\omega$ over a total of $S$ endogenous varieties.

$$U_j = \left[ \int_0^S q_j(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right]^\frac{\sigma}{\sigma-1}$$

(2.1)

where $\sigma > 1$ is the elasticity of substitution between goods. Consumers choose $q_j(\omega)$ subject
to their income \( y_j \), which is generated from supplying one unit of labor for wage \( w_j \) and owning bank stocks.

\[
y_j \geq \int_0^S q_j(\omega)p_j(\omega)d\omega \tag{2.2}
\]

Goods are produced without economies of scope, meaning that each variety will be produced by only one firm in each of the \( I \) regions. There are standard “iceberg” trade costs: for one good shipped from \( i \) to \( j \), only \( \tau_{ij}^d \) goods arrive. Considering this, maximizing (2.1) subject to (2.2) and aggregating across consumers generates the following bilateral level of demand for variety \( \omega \) produced in region \( i \)

\[
q_{ij}(\omega) = \frac{Y_j}{P_j^{1-\sigma}} \left( p_i(\omega)\tau_{ij}^d \right)^{-\sigma} \tag{2.3}
\]

with

\[
P_j \equiv \left[ \sum_{i=1}^I \int_\Omega \left( p_i(\omega)\tau_{ij}^d \right)^{1-\sigma}d\omega \right]^{\frac{1}{1-\sigma}} \tag{2.4}
\]

as region \( j \)’s ideal price index, \( Y_j \) defined as its total income, and \( p_i(\omega) \) the mill price charged by the firm.

**2.2.1.2 Production and pricing**

Goods are produced by monopolistically competitive firms that are ex-ante identical within a given region. There is a fixed and variable labor cost to production. The credit constraint faced by these firms is that they must obtain external financing at price \( 1 + r_{mi}(\omega) = R_{mi}(\omega) \) to finance a portion of their wage bill, where \( m \) indexes the bank the firm works with. Without loss of generality, I assume all variable labor costs must be financed with external capital. The labor requirement for production of \( q_i \) goods then becomes:

\[
n_i(\omega) = f^d + R_{mi}q_i(\omega) \tag{2.5}
\]
where \( f^d \) is the region-invariant fixed cost to production. Given the production function (2.5) and bilateral demand (2.3), monopolistically competitive firms charge a constant markup over their variable labor costs, which include regional wages \( w_i \) and the cost of financing those wages \( R_{mi} \):

\[
p_i(\omega) = \frac{\sigma}{\sigma - 1} w_i R_{mi}(\omega)
\]  

(2.6)

This mill price is ex-ante identical across firms within a given region. Summing up bilateral demand given by (2.3) accounting for trade costs and inserting the pricing equation (2.6) gives a full expression for sectoral demand in region \( i \):

\[
q_i(\omega) = \left( \frac{\sigma}{\sigma - 1} w_i R_{mi}(\omega) \right)^{-\sigma} \sum_{j=1}^{l} \frac{Y_j}{p_j^{(\sigma - 1)}} (\tau_{ij})^{1-\sigma}
\]  

(2.7)

Banks do not price discriminate by sector, so I will drop the \( \omega \) notation. Loan demand faced by a bank in a given region is the total variable wage bill: \( s_i w_i q_i \), where \( s_i \) is the number of varieties, and therefore firms, in region \( i \):

\[
L_{mi} = \left( \frac{\sigma}{\sigma - 1} \right)^{-\sigma} s_i w_i^{1-\sigma} R_{mi}^{-\sigma} \sum_{j=1}^{l} \frac{Y_j}{p_j^{(\sigma - 1)}} (\tau_{ij})^{1-\sigma}
\]

(2.8)

### 2.2.2 Banking and finance

This section solves for bank pricing behavior, branching behavior, and entry into a given region conditional on its own characteristics, active competitors, and the structure of regional loan demand. The economy has an exogenous level of \( \bar{M} < I \) active banking companies that differ in headquarter location and lending efficiency. This setup allows for a geographic bank-level competent to the entry decision, as well as a bank size effect on pricing and market structure. The strategy to solve these variables is as follows: (1) Solve for equilibrium loan pricing structure independent of entry and market share; (2) Solve for optimal bank branching behavior on entry given the pricing rule; (3) Solve for entry conditional on expected profits.
2.2.2.1 Loan pricing and variable bank profits

The price of loans is set by banks active in a given region. There is a region-specific probability that firms will default on their loans: $1 - \theta_i$. Additionally, I assume there is a simple information asymmetry: firms are able to shirk on paying back their loans unless banks pay a monitoring cost. This is an adaptation of the costly state verification model in Townsend [1979]. Banks pay a common, region-invariant monitoring cost $\zeta$, and have idiosyncratic monitoring efficiency $\phi$ drawn from a common distribution $G(\phi)$. I assume that banks have access to funds from the central bank at the rate $r^d$, generating this region-invariant marginal lending cost function:

$$C_{mi}(\phi) = \zeta \frac{1 + r^d}{\phi}$$

(2.9)

A bank $m$ that faces no competition has the following variable profit function when lending in region $i$ and sector $\omega$:

$$\pi_{mi}(\omega) = L_i(\omega) \left[ \theta_i R_{mi}(\omega) - \zeta \frac{1 + r^d}{\phi} \right]$$

(2.10)

From equation (2.8), the price elasticity of loan demand is a constant, $\sigma$. Given this result, price-setting banks will charge a constant markup over their expected lending costs:

$$R_{mi}(\phi) = \frac{\sigma}{\sigma - 1} \frac{1}{\theta_i} \left( \zeta \frac{1 + r^d}{\phi} \right)$$

(2.11)

As the elasticity of loan demand doesn’t vary by sector, neither does the price of financing. Instead, the price is determined by the region-specific default rate, $1 - \theta_i$ and the firm-specific level of productivity $\phi$. Combining the pricing rule, loan demand function, and bank profit function and aggregating across sectors generates the following regional profits for the bank:

$$\pi_{mi}(\phi) = \left( \frac{\sigma}{\sigma - 1} \right)^{1-2\sigma} s_i \left( \frac{w_i}{\theta_i} \right)^{1-\sigma} \left( \zeta \frac{1 + r^d}{\phi} \right)^{1-\sigma} \sum_{j=1}^{l} \frac{Y_j}{p_j^{1-\sigma}} (\tau_{ij})^{1-\sigma}$$

(2.12)
2.2.2.2 Ex-ante product and lending market equilibrium

Holding banking behavior fixed, I can solve for lending and product market equilibrium. In
principal, this is pinned down by free entry in the goods market. First, I define the average
interest rate faced by firms in region \( i \) as \( \bar{R}_i \). This term is endogenous and will ultimately be
determined by the pricing rule in equation (2.11), the productivity distribution of bank companies
that enter, and their market share.

Income in region \( j \) comprises the following: wages paid in the goods market and profits
earned by bank companies. Assuming banks pay no market access costs, regional income is
given by

\[
Y_j = N_j w_j (1 - \frac{\sigma - 1}{\sigma^2})
\]

(2.13)

with the price index solving

\[
P_{1-\sigma}^j = \left[ \frac{(\sigma - 1)^{\sigma - 1}}{\sigma f^d} \sum_{i=1}^{I} N_i \left( w_i \bar{R}_i \tau_{ij}^d \right)^{1-\sigma} \right].
\]

(2.14)

Given the average loan price, \( s_i^* \) firms break even even by supplying \( q_i^* \) goods:

\[
s_i^* = \frac{N_i}{f^d \sigma}
\]

(2.15)

\[
q_i^* = \frac{f^d (\sigma - 1)}{\bar{R}_i}
\]

(2.16)

Plugging firm-pricing behavior from equation (2.6) and income from equation (2.13) into the
demand equation (2.7) and setting it equal to (2.16) allows me to solve for the equilibrium wage
in region \( i \):

\[
w_i = \sigma_1 \left( \frac{1}{\bar{R}_i} \right)^{\frac{\sigma - 1}{\sigma}} \left( \frac{1}{f^d} \sum_{j=1}^{I} N_j w_j \tau_{ij}^d \bar{R}_i^{1-\sigma} \prod_{j=1}^{I} \left( \frac{P_{1-\sigma}^j}{\bar{R}_i} \right)^{1-\sigma} \right)^{\frac{1}{\sigma}}
\]

(2.17)
This is the typical market potential equation as in Fujita et al. [1999] and Redding and Venables [2004] that has wages (income) increasing in access to wealthy markets, but now has wages decreasing in financing costs. Conditional on $\bar{R}_i$, I can follow Duranton et al. [2014] and say that given an equilibrium wage in all cities but $i$, I can solve for an equilibrium in $i$. In essence, if the ex post productivity and market entry decisions of banks were exogenous, this would be sufficient for general equilibrium.

### 2.2.2.3 Bank market share

In order to lend in a given market, a bank $m \in M$ with its headquarters located in region $h$ needs to build branches to establish market share in that region. They need to pay a company-specific entry cost $f_{ihm}$ that is a function of their headquarter location in order to build their first branch. I will denote $b_{ih}(\phi)$ as the number of branches built by a company with productivity $\phi$ and headquarter location $h$, as this fully identifies company $m$.

For a market with $s_i$ firms searching for loans, banks match with them based on a market share function $\mu(b_{ih}(\phi), B_i) \in [0, 1]$. This function is decreasing in the total number of active branches in the region $B_i = \sum_{m=1}^{M_i} b_{mi}$ and is quasi-concave in $b_{ih}$. This function captures that bank market share is increasing in the expansion of the branching network at a decreasing rate due to self-stealing, as each branch is drawing from the same pool of potential clients.

Another characteristic is that market share is decreasing in the presence of competing bank companies. In the most general version, I allow the constant marginal cost of branching to vary by headquarter region: $\beta_{ih} < 1$. This leads to the following expression for bank profits in a given region:

$$\Pi_{ih}^b(\phi) = \mu(b_{ih}, B_i)\pi_i(\phi) - \beta_{ih}b_{ih} - f_{ih}$$ (2.18)

This setup is closest to the stylized model in Cerasi [1996] and its empirical reduced form

$$\tilde{\sigma}_1 = \frac{(\sigma-1)\sigma^2}{\sigma}(1 - \sigma^{-1})$$
in Cerasi et al. [2002]. In both papers, bank heterogeneity comes specifically from branching behavior. The primary difference between banks in my model comes from the lending efficiency parameter $\phi$ as it appears in equation (2.9). Conditional on market share, more efficient banks are able to make larger profits from lending.

The second difference between banks is their branching and entry costs, $\beta_{ih}$ and $f_{ih}$, respectively. These terms are assumed to be independent of firm productivity. Instead they are driven by bank-specific infrastructure costs and informational barriers that make entry and the expansion of market share more costly. These costs are increasing in distance from the market to the location of the bank headquarters (Dell’Ariccia 2001, Dell’Ariccia et al. 1999). For banks from the same headquarter region, these costs are identical.

For analytical simplicity, equation (2.18) relies on the assumption that bank market share is ex-ante independent of price. In essence, bank companies expand their branch networks to gain a fraction of potential monopolistic profits conditional on their price choice.

The competitive relationship can be thought of as follows: firms build a bank branch in a market to reach a portion of customers and charge them the monopolistic price. I make the following assumption about the marginal amount of profits captured by building a new bank branch:

$$\pi_i(\phi)\mu'(b_{ih}) = 1 - \frac{\eta}{\pi_i(\phi)}(B_i + b_{ih})$$  \hspace{1cm} (2.19)

Equation (2.19) captures two important features, the strength of which are measured by the parameter $\eta > 0$. First, the amount of new firms reached by building a bank branch is increasing in the size of the market, $\pi_i(\phi)$, due to economies of density. Second, the amount of new firms reached by building a bank branch is decreasing in the number of competitor banks (competition effect) and the number of own bank branches (self stealing). I choose $\eta$ such that $\mu'(b_{mi}) \geq 0$ to

---

3Cerasi [1996] assumes that banking products are differentiated by branch, while Cerasi et al. [2002] allow for branching costs to differ across companies.

4I use a similar strategy as Arkolakis [2010] to derive a reasonable market share function.
ensure market share is never decreasing in bank branches.\footnote{Effectively, this means I restrict the ratio \( \frac{b_{mi} + b_{mi}}{\pi_{mi}} < \frac{1}{\eta} \). Intuitively, this means that banks don’t build too many branches relative to the market size. In equilibrium, under profit maximization this will always be true due to the concavity of the bank profit function.}

Given the above marginal market share function and the condition that \( \mu(0) = 0 \), means that market share can be expressed as follows:

\[
\mu(b_{mi}, B_i) = \frac{b_{mi}}{\pi_{mi}} \left( 1 - \frac{\eta B_i}{\pi_{mi}} \right)
\] (2.20)

### 2.2.2.4 Bank entry and branching behavior

To simplify the analysis and characterize the equilibrium, I assume analytically that there is a single headquarter region \( h \) where all banks companies are located. Bank companies expand from region \( h \) into region \( i \) by paying the fixed cost \( f_{ih} \) assuming the profits from branching are high enough. Once firms enter, they simultaneously choose \( b_{ih} \), setting the marginal benefit of building an additional branch equal to its cost: \( \pi_i(\phi) \mu'(b_{ih}, B_i) = \beta_{ih} \).

I assume \( f_{ih} \) and \( \beta_{ih} \) are increasing functions of the distance from region \( i \) to region \( h \). The use of this geographic branching cost is based on existing theoretical and empirical work on branch banking and entry. First, banks that are further away from a region are likely to be late entrants into the market. This means that for distant banks there may be adverse selection issues as available clients may be the worst \cite{DellAriccia2001, DellAricciaetal1999, HauswaldMarquez2006}. This increases the cost of matching with appropriate clients upon initial entry, thus increases \( f_{ih} \). Next, bank headquarter-to-firm distance can be important for the approval process. Much local firm-level information is soft and is not easily passed along from branch-based loan officers to distant superiors within a bank \cite{Alessandrinietal2009}. \( \beta_{ih} \) is effectively the marginal cost of market expansion. If it is difficult to have loans approved or new bank branches approved, this marginal cost is higher.

The presence of the fixed cost and the structure of market share and variable profits means that there will be a cutoff productivity level in each region \( \phi_{ih}^* \) such that \( \Pi_i^B(\phi_{ih}^*) = 0 \).
only enter if their productivity is higher than $\phi^*_{ih}$. 

Following [Melitz, 2003], I define the variable $\bar{\phi}_i$ as the average productivity of banks that enter market $i$. I also define $\bar{\pi}_i$ as the potential loan revenue of a firm with average productivity given by equation (2.12):

$$\bar{\phi}_i = \int_{\phi^*_{ih}}^{\infty} \frac{g(\phi)}{1 - G(\phi^*_{i})} \phi^{1-\sigma} d\phi, \quad \bar{\pi}_i = \Gamma_i \bar{\phi}_i$$

with $\Gamma_i$ as a regional demand shifter that is exogenous to the bank company.

Given average profits and the endogenous level of active banking firms in a region, $M_i$, profit maximization in bank branching yields the optimal bank branch reaction function for a given firm with productivity $\phi$, as well as the aggregate number branches in a region:

$$\begin{aligned}
    b_{ih}(\phi) &= \begin{cases} 
    1 - \frac{\beta_{ih}}{\eta} \Gamma_i \left( \phi^{\sigma-1} - \bar{\phi}_i \left( \frac{M_i}{1 + M_i} \right) \right) & \phi \geq \phi^*_{ih} \\
    0 & \phi < \phi^*_{ih}
    \end{cases} \\
    B_i &= \frac{1 - \beta_{ih}}{\eta} \left( \frac{M_i}{1 + M_i} \right) \bar{\pi}_i
\end{aligned}$$

Equation (2.22) says that banks with higher productivity relative to the rest of the market are more likely to build branches in a given region. The amount of total bank branches in the economy is increasing in the number of active bank companies in the region and net expected profits conditional on entry. As more bank companies enter and build branches, individual banks reduce their branching behavior as they are less willing to build branches to compete for a smaller share of the market.

Equation (2.23) shows how city-level bank branching behavior appears in equilibrium. There are more bank branches in regions with more bank companies and higher average potential profits.

$^{6} \Gamma_i \equiv \left( \frac{\sigma}{\sigma - 1} \right)^{1-2\sigma} \left( \frac{\omega_1}{\sigma} \right)^{1-\sigma} \left( \zeta(1 + r^d) \right)^{1-\sigma} \left( \sum_{j=1}^{I} \frac{Y_j^*}{r_{ij}^*} (1 - \sigma)^{1-\sigma} \right)$

$^{7}$The below results rely on assuming that the weak law of large numbers holds for the best guess of entering firms based on their knowledge of $g(\phi)$ and $\phi^*_{i}$. 

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2.2.2.5 Regional lending cutoff

To generate clearer predictions, for the rest of the paper, I assume that productivity is power law distributed as follows $G(\phi) = 1 - \phi^{-\gamma}$, where $\gamma$ is an inverse measure of the heterogeneity of bank efficiency.

Firms decide to enter a region if their optimum branching and lending behavior given their productivity draw generates enough profits to overcome the fixed entry cost $f_{ih}$. Equilibrium bank profits conditional on entry and optimal branching can be expressed as follows:

$$\Pi_{ih}^{b}(\phi) = \frac{1}{\eta \pi_{i}(\phi)} \left[ (1 - \beta) \Gamma_{i} \left( \phi^{\sigma-1} - \phi_{i}(\frac{M_{i}}{1 + M_{i}}) \right) \right]^{2} - f_{ih} \quad (2.24)$$

To solve for the productivity cutoff, I assume bank companies enter a region sequentially. In particular, firms enter from most productive to least productive. $M_{i}$ is determined by the exogenous number of banks, $\bar{M}$, and the productivity distribution: $M_{i} = \bar{M}(\phi_{ih}^{*})^{-\gamma}$. The total that enter is decreasing in the productivity cutoff, because as $\phi_{ih}^{*}$ increases, less productive banks are excluded from the region. I then define a function $M(\phi_{ih}^{*}) = 1 - \frac{M_{i}}{1 + M_{i}} \frac{\gamma}{\sigma - 1}$ that is an inverse measure of competitiveness in the banking sector of a given region.

With this, I can write an implicit solution for the regional productivity cutoff:

$$\phi_{ih}^{*} = \left[ \frac{\eta f_{ih}}{\Gamma_{i} \left( (1 - \beta_{ih}) M_{i}^{2} \phi_{ih}^{*} \right)} \right]^{\frac{1}{\sigma - 1}} \quad (2.25)$$

This equation says that all else equal, a bank company needs to be more productive to enter if costs are high, demand is low, or banking competition is fierce. The following proposition is that this implicit function generates a unique solution for the productivity cutoff in region $i$.

**Proposition.** Given the productivity distribution $G(\phi) = 1 - \phi^{-\gamma}$, for one headquarter region $h$, and the assumption that $\frac{\eta f_{ih}}{(1 - \beta_{ih}) (1 + M_{i})^{\gamma}(\sigma - 1)} > \Gamma_{i}$, there is a unique productivity cutoff $\phi_{ih}^{*}$.

**Proof.** See Appendix [B.1]
Intuitively, this result is about the relationship between competition and the productivity cut-off. When the most productive firm enters, $M_i$ will increase so $M(\phi^{*}_{ih})$ will decrease, representing a more competitive banking environment. As firms enter by productivity ranking, competition will increase ($M(\phi^{*}_{ih})$ will decrease) until the marginal bank with productivity $\phi^{*}_{ih}$ enters, and it is not profitable for lower efficiency banks to enter. The assumption $\frac{\eta_{ih}}{(1 - \beta) \left(1 - \frac{M}{1 + M} \frac{\rho_{ih}}{1 - \sigma - 1}\right)} > \Gamma_i$ effectively says that at the lowest possible productivity cutoff where all banks are productive enough to enter, $\phi^{*}_{ih} = 1$, $M(\phi^{*}_{ih})$ is very close to 0. In other words, competition is very high if all bank companies build branches in a region. Given this assumption, there is a unique solution to equation (2.25).

Given the existence of this cutoff, solutions then exist for the specific bank companies that enter, their level of productivity, and their strategic bank branching behavior. Given this, in the next section I take the above equations for bank company behavior and estimate them with Brazilian city-level data.

### 2.3 Empirical strategy and estimation

I take the above theoretical setup and apply it to Brazilian banking data. I use city-level bank company branch balance sheet data to analyze the strategic choices of bank companies. I supplement this with city-level loan demand controls.

First, I show the effect of bilateral headquarter distance on bank company presence in a region, capturing the extensive margin of branch banking. Next, I look at the intensive market of branch banking by investigating the relationship between distance and company-level branching and market share. I show that headquarter distance is a significant driver of bank company behavior.

Next, at the aggregate city-level, the effect of distance is felt in terms of access to finance. I show that financial remoteness, as measured by weighted distance from headquarter regions, is a strong driver of aggregate bank branch presence. Additionally, I investigate the relationship
between bank presence and financial depth. I show that increased bank presence drives increased credit to GDP ratios at the local level.

### 2.3.1 Bank company entry

To analyze the geography of bank company entry into a region, I will focus on the relationship between the bilateral fixed cost and company presence in a city. From the model, headquarter distance reduces entry. Higher fixed cost means a firm needs to be more productive or the market size must be larger to enter. Whether or not a bank enters a region is governed by the relationship between their productivity and the entry cutoff. A firm with productivity \( \phi \) enters only if

\[
\frac{\phi}{\eta} \Gamma_i \left( (1-\beta) M^2(\phi^*) \right)^{\frac{1}{\sigma-1}} > 1^{8}
\]

If I define an indicator variable \( Z_{im} = 1 \) if a bank is active in a region and \( Z_{im} = 0 \) otherwise, we can say that

\[
Z_{im} = 1 \iff \phi \left[ \frac{\frac{f_{ih}}{(1-\beta)} M^2(\phi^*)}{\eta} \right]^{\frac{1}{\sigma-1}} > 1^{8}
\]

By assumption, \( f_{ih} \) and \( \beta_{ih} \) are increasing in the distance to a bank company’s headquarters. I express this as

\[
\frac{f_{ih}}{(1-\beta)} = (d_{ih})^{\delta_1} \exp(\delta_2 \text{Shared state}) \text{ where } d_{ih} \text{ is a function of headquarter to region distance.}
\]

Taking logs I can write this equation as a function of firm-level characteristics, company-level productivity, and the bilateral fixed cost:

\[
z_{im} = \delta + \delta_i + \delta_m + \delta_1 \ln d_{ih} + \delta_2 \text{SharedState} + \epsilon_{im} \tag{2.26}
\]

with \( \delta \) absorbing all the constants, \( \delta_i = \frac{1}{\sigma-1} \ln \Gamma_i + \frac{2}{3} \ln M(\phi^*) \) as a city-level fixed effect, \( \delta_m = \ln \phi \) as a company-level fixed effect, and \( \epsilon_{im} \) as the error term.

I estimate equation (2.26) as a linear probability model under several specifications for the bilateral entry and branching costs. First, I treat \( d_{ih} \) as purely a linear function of distance to company headquarters. I compare this to a specification with a headquarter distance step function. I estimate the model with all bank companies, then I separate them by public versus private.

Table (2.1) shows that headquarter distance has a significant effect on entry behavior for all

---

8I am using the same strategy to turn latent cutoff values into 0, 1 bilateral entry equations as [Helpman et al. 2008](#) and [Manova 2013](#).
Table 2.1: The effect of distance on bank entry

<table>
<thead>
<tr>
<th>Entry</th>
<th>(1) All Banks</th>
<th>(2) All Banks</th>
<th>(3) Private</th>
<th>(4) Private</th>
<th>(5) State</th>
<th>(6) State</th>
</tr>
</thead>
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<tr>
<td>LogDistance</td>
<td>-0.0150***</td>
<td>-0.00800***</td>
<td>-0.0240***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.000680)</td>
<td>(0.000555)</td>
<td>(0.00256)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Same State</td>
<td>0.0175***</td>
<td>0.0254***</td>
<td>0.0682***</td>
<td>0.0111***</td>
<td>0.569***</td>
<td>0.571***</td>
</tr>
<tr>
<td></td>
<td>(0.00107)</td>
<td>(0.00109)</td>
<td>(0.000871)</td>
<td>(0.000831)</td>
<td>(0.0161)</td>
<td>(0.0169)</td>
</tr>
<tr>
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<td>-0.0120***</td>
<td>-0.0847***</td>
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<td></td>
<td></td>
</tr>
<tr>
<td></td>
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<td>(0.00207)</td>
<td>(0.0241)</td>
<td></td>
<td></td>
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</tr>
<tr>
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<td>-0.0164***</td>
<td>-0.101***</td>
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<tr>
<td></td>
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<td>(0.00211)</td>
<td>(0.0242)</td>
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<td>-0.0168***</td>
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<td></td>
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<td>(0.00209)</td>
<td>(0.0241)</td>
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<td>2000 &lt; km</td>
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<td>-0.0200***</td>
<td>-0.137***</td>
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<td>(0.00209)</td>
<td>(0.0243)</td>
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<td>2588608</td>
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<td>198558</td>
<td>198558</td>
</tr>
</tbody>
</table>

Standard errors clustered by Headquarter-City pair. Dependent variable is a bank entry dummy variable. All regressions include bank, city, and year FE.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

bank companies. As shown in column 5, the effect is largest for state bank companies, likely driven by banks run by state governments who have a limited geographic purview. The step function in column 6 indicates that the probability that state banking company entering a given city drops by .4 if it is more than 100km away from the headquarters.

The effects of distance on commercial banks in columns 3 and 4 are driving the overall results in columns 1 and 2. While the result is smaller than with state banks, there is a clear negative effect of distance on the probability of bank entry. A one standard deviation increase in headquarter distance approximately decreases the probability of entry of a given bank company by .01. This effect is relatively large, however, as the unconditional probability of entry is only .012.

2.3.2 Bank company branching

To analyze the geography of bank branching decisions, I will focus on relative bank entry into a market. Using the bank company branching equation (2.22) and the aggregate branching
equation (2.23), it is convenient to define the following measure of bank branch market share:

\[
\frac{b_{mi}}{B_i} + 1 = \frac{(1 - \beta_{ih})}{(1 - \bar{\beta}_i)} \frac{\phi^{\sigma - 1}}{(M_i + M_i) \bar{\phi}_i}
\]  

(2.27)

The left hand side of this equation is a measure of a bank company’s relative market presence in a region. The larger the share, the more of the lending market served by the bank company. This is determined by the relationship between the bank company’s cost structure and those of competing firms. All else equal, banks with high productivity \( \phi \) and headquarters located close to a city, low \( \beta_{ih} \), will serve more of a market. These terms are evaluated in comparison to market averages.

With multiple headquarter regions, \( \bar{\beta}_i = \frac{1}{M_i} \sum_{m=1}^{M_i} \beta_{ih} \), a weighted average of headquarter distance of active bank branches in a city. A high \( \bar{\beta}_i \) indicates that a lending market is geographically distant from the headquarter regions of active banks. As branching remoteness increases, a given bank company will find it easier to capture market share. \( \frac{M_i}{1+M_i} \) captures the competition effect generated by the productivity cutoff. A higher cutoff means less banks enter to build branches. Lastly, \( \bar{\phi}_i \), represents the productivity level of active bank branches. Productive banks build more branches, thus reducing the market share of any other given bank.

To absorb these complicating measures of market remoteness, productivity, and competitiveness, I estimate a market share equation similar to the bank entry procedure above. Taking logs of (2.27) generates the following estimation equation:

\[
\ln\left(\frac{b_{mi}}{B_i} + 1\right) = \delta + \delta_i + \delta_m + \ln d_{ij} + \epsilon_{im}
\]  

(2.28)

with the city fixed effect \( \delta_i = -\left(\ln(1 - \bar{\beta}_i) + \ln\left(\frac{M_i}{1+M_i}\right) + \ln \bar{\phi}_i\right) \), the company level fixed effect \( \delta_m = (\sigma - 1) \ln \phi \), and the bilateral term a function of distance: \( d_{ij} = \ln(1 - \beta_{ih}) \). Once again, I use multiple functional forms for distance, and estimate the model separately by bank ownership.

As shown in Table (2.2), the results largely mirror those for bank entry: closer banks of all
Table 2.2: The effect of distance on branch market share

<table>
<thead>
<tr>
<th>Log Branch Share + 1</th>
<th>(1) All Banks</th>
<th>(2) All Banks</th>
<th>(3) Private</th>
<th>(4) Private</th>
<th>(5) State</th>
<th>(6) State</th>
</tr>
</thead>
<tbody>
<tr>
<td>LogDistance</td>
<td>-0.00376***</td>
<td>-0.000653***</td>
<td>-0.00433***</td>
<td>0.000203</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0000950)</td>
<td>(0.0000950)</td>
<td>(0.00119)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Same State</td>
<td>0.00816***</td>
<td>0.00929***</td>
<td>0.00419***</td>
<td>0.00419***</td>
<td>0.264***</td>
<td>0.261***</td>
</tr>
<tr>
<td></td>
<td>(0.000353)</td>
<td>(0.000376)</td>
<td>(0.000273)</td>
<td>(0.000274)</td>
<td>(0.00860)</td>
<td>(0.00900)</td>
</tr>
<tr>
<td>99 &lt; km &lt; 500</td>
<td>-0.00338***</td>
<td>0.000421</td>
<td>-0.0262*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.000921)</td>
<td>(0.000539)</td>
<td>(0.0132)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>500 ≤ km &lt;1000</td>
<td>-0.00706***</td>
<td>-0.000989</td>
<td>-0.0322*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.000979)</td>
<td>(0.000565)</td>
<td>(0.0130)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1000 ≤ km &lt; 2000</td>
<td>-0.00831***</td>
<td>-0.000689</td>
<td>-0.0325*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00102)</td>
<td>(0.000557)</td>
<td>(0.0130)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2000 ≤ km</td>
<td>-0.0118***</td>
<td>-0.00167**</td>
<td>-0.0358**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00102)</td>
<td>(0.000558)</td>
<td>(0.0131)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>2787166</td>
<td>2787166</td>
<td>2588608</td>
<td>2588608</td>
<td>198558</td>
<td>198558</td>
</tr>
</tbody>
</table>

Standard errors clustered by Headquarter-City pair. All regressions include, bank, city, and year FE. Dependent variable is a (log) company share of branches in a given market.

* p < 0.05, ** p < 0.01, *** p < 0.001

types capture higher market share. Again, there is a strong state-specific effect for publicly owned banks.

### 2.3.3 Aggregate bank branching

The model predicts aggregate bank branching is driven by city-specific loan demand characteristics as follows:

\[ B_i = \left( \frac{M_i}{1 + M_i} \right) (1 - \beta_i) \Gamma_i \varphi_i \]  

(2.29)

Branches in a city are increasing in the number of companies that enter, \( M_i \), with this effect bounded between \( \frac{1}{2} \) and 1. With multiple HQ locations, I am going to define the distance weighted productivity of the banking system as an inverse proxy for:
Table 2.3: The effect of financial remoteness on bank branch behavior

<table>
<thead>
<tr>
<th>Log Branches</th>
<th>(1) All Banks</th>
<th>(2) All Banks</th>
<th>(3) Private</th>
<th>(4) Private</th>
<th>(5) State</th>
<th>(6) State</th>
</tr>
</thead>
<tbody>
<tr>
<td>Companies</td>
<td>1.133***</td>
<td>1.490***</td>
<td>1.401***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0672)</td>
<td>(0.0927)</td>
<td>(0.101)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Remoteness</td>
<td>-0.181***</td>
<td>-0.270***</td>
<td>-0.149***</td>
<td>-0.248***</td>
<td>0.0745*</td>
<td>0.221***</td>
</tr>
<tr>
<td></td>
<td>(0.0187)</td>
<td>(0.0186)</td>
<td>(0.0236)</td>
<td>(0.0209)</td>
<td>(0.0329)</td>
<td>(0.0346)</td>
</tr>
<tr>
<td>LnPop</td>
<td>0.473***</td>
<td>0.635***</td>
<td>0.456***</td>
<td>0.653***</td>
<td>0.359***</td>
<td>0.415***</td>
</tr>
<tr>
<td></td>
<td>(0.0242)</td>
<td>(0.0138)</td>
<td>(0.0312)</td>
<td>(0.0205)</td>
<td>(0.0188)</td>
<td>(0.0217)</td>
</tr>
<tr>
<td>LnGdp/pop</td>
<td>0.235***</td>
<td>0.311***</td>
<td>0.179***</td>
<td>0.269***</td>
<td>0.214***</td>
<td>0.200***</td>
</tr>
<tr>
<td></td>
<td>(0.0168)</td>
<td>(0.0173)</td>
<td>(0.0233)</td>
<td>(0.0284)</td>
<td>(0.0173)</td>
<td>(0.0189)</td>
</tr>
<tr>
<td>N</td>
<td>12067</td>
<td>12067</td>
<td>6191</td>
<td>6191</td>
<td>7816</td>
<td>7816</td>
</tr>
</tbody>
</table>

Standard errors clustered by city. All regressions include year FE
* p < 0.05, ** p < 0.01, *** p < 0.001

\[ REMOTE_i = \sum_{b \neq i} \left( \frac{SIZE_b}{\sum_b SIZE_b} d_{ib} \right) \] (2.30)

where SIZE is an indicator of relevant bank productivity such as assets, credit operations, or branch network. \( \Gamma_i \) is the loan demand shifter from the goods market that I control for with population and income per capita, estimating the following equation:

\[ \ln(B_i) = \zeta_0 + \zeta_1 \ln \frac{M_i}{1 + M_i} + \zeta_2 \ln REMOTE_i + \chi_i + \ln d_{ij} + \epsilon_i \] (2.31)

The results for this regression are presented in Table 2.3. First, unsurprisingly, as more companies enter a region, more bank branches are built by all types of banks. Part of this is a somewhat mechanical relationship between bank branches and bank companies, as a company must build a branch to enter a region. However, the non-linearity in the bank company variable makes the estimated relationship slightly different. Doing a quick back of the envelope calculation, shows that a jump from a banking monopoly to perfect competition \( (M \rightarrow \infty) \) would cause the number of branches in the city to do little more than double.
Second, notice that the elasticity of bank branching to remoteness is negative and significant for the average bank and for private banks. On the one hand, this is due to marginal bank branching costs increasing with distance from headquarter regions. On the other, closer less productive banks may have a higher incentive to enter as their branching costs are relatively low. This can drive down average productivity and therefore average profitability of a region. If the bank company term is not included, the remoteness term captures part of the extensive margin effect.

In the last two columns, the remoteness measure is actually positive. This is evidence that the model may not capture the incentives of government-run banks. For example, small state banks with a limited geographic purview may build many branches in a city that is far from larger bank headquarters. Unlike small private banks, there may not be as clear a relationship between scale, efficiency, and the incentive to build branches and capture market share. For larger, nationwide state banks, they may intentionally move towards under-served remote regions as a social prerogative, even if it is more costly than closer cities.

2.3.4 Financial depth

Lastly, I investigate how bank branching behavior relates to financial development via various measures of financial depth.

To analyze how bank entry affects the goods market, imagine a scenario in which a city is small and/or far from the headquarter region. This city may only have one bank company that builds only one branch. Then the portion of the market served is \( \frac{1}{\pi_1(\phi)} \left( 1 - \frac{\eta}{\pi_1(\phi)} \right) < 1 \). This means some firms in the market were not able to obtain financing and therefore pay their variable wage bill and produce. In essence, the firms in the goods market must not only contend with financing costs, but they have to deal with potentially being excluded from the market. Effectively this means that the ratio of finance to GDP is determined by bank behavior.

I test this relationship with the following reduced-form estimation equation:
Table 2.4: Bank branches and financial depth

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Log Private Branches</td>
<td>0.559***</td>
<td>0.193**</td>
<td>0.522***</td>
<td>0.341***</td>
<td>0.582***</td>
<td>0.737***</td>
<td>0.403***</td>
<td>0.187***</td>
</tr>
<tr>
<td></td>
<td>(0.0266)</td>
<td>(0.0633)</td>
<td>(0.0232)</td>
<td>(0.0509)</td>
<td>(0.0221)</td>
<td>(0.0476)</td>
<td>(0.0284)</td>
<td>(0.0678)</td>
</tr>
<tr>
<td>Log State Branches</td>
<td>0.682***</td>
<td>0.717***</td>
<td>0.669***</td>
<td>0.665***</td>
<td>0.630***</td>
<td>0.597***</td>
<td>0.724***</td>
<td>0.770***</td>
</tr>
<tr>
<td></td>
<td>(0.0283)</td>
<td>(0.0310)</td>
<td>(0.0312)</td>
<td>(0.0317)</td>
<td>(0.0313)</td>
<td>(0.0320)</td>
<td>(0.0345)</td>
<td>(0.0384)</td>
</tr>
<tr>
<td>Companies</td>
<td>1.335***</td>
<td>1.508***</td>
<td>0.579***</td>
<td>0.558***</td>
<td>0.380***</td>
<td>0.218*</td>
<td>1.078***</td>
<td>1.304***</td>
</tr>
<tr>
<td></td>
<td>(0.102)</td>
<td>(0.117)</td>
<td>(0.0947)</td>
<td>(0.105)</td>
<td>(0.0911)</td>
<td>(0.0983)</td>
<td>(0.115)</td>
<td>(0.140)</td>
</tr>
<tr>
<td>LnPop</td>
<td>0.179***</td>
<td>0.251***</td>
<td>0.254***</td>
<td>0.246***</td>
<td>0.285***</td>
<td>0.218***</td>
<td>0.203***</td>
<td>0.297***</td>
</tr>
<tr>
<td></td>
<td>(0.0257)</td>
<td>(0.0370)</td>
<td>(0.0200)</td>
<td>(0.0274)</td>
<td>(0.0198)</td>
<td>(0.0261)</td>
<td>(0.0249)</td>
<td>(0.0367)</td>
</tr>
<tr>
<td>LnGdp/pop</td>
<td>-0.674***</td>
<td>-0.610***</td>
<td>-0.677***</td>
<td>-0.685***</td>
<td>-0.673***</td>
<td>-0.733***</td>
<td>-0.692***</td>
<td>-0.609***</td>
</tr>
<tr>
<td></td>
<td>(0.0335)</td>
<td>(0.0436)</td>
<td>(0.0243)</td>
<td>(0.0299)</td>
<td>(0.0220)</td>
<td>(0.0264)</td>
<td>(0.0324)</td>
<td>(0.0431)</td>
</tr>
<tr>
<td>N</td>
<td>10205</td>
<td>10205</td>
<td>10205</td>
<td>10205</td>
<td>10205</td>
<td>10205</td>
<td>10205</td>
<td>10205</td>
</tr>
</tbody>
</table>

Standard errors clustered by City. All estimations include year fixed effects.

* $ p < 0.05$, ** $ p < 0.01$, *** $ p < 0.001$

\[
\ln(Depth_i) = \delta_0 + \delta_1 \ln B_o + \delta_2 \ln \left( \frac{M_i}{1 + M_i} \right) + \bar{X}_i + \epsilon_i
\]  

(2.32)

in which $B_o$ includes both private and state banks and $\bar{X}_i$ collects city-level controls. $Depth_i$ is the ratio of finance to GDP that I construct using several indicators of financial assets in a city. These are defined in Appendix B.2.

I am primarily interested in how bank branching behavior affects the level of financial development in a given city. However, there is the possibility that instead of bank branches increasing the use of finance, they are instead arriving in response to the demand for credit. To control for this I go back to the aggregate bank branch estimation equation. The excluded variable here is $REMOTE_i$, which should only affect the use of finance in a city via the banking system. I use this in a two-stage least squares procedure to control for this potential reverse causality, instrumenting private branches with the remoteness measure.

As shown in Table 2.4, bank branching behavior is a significant determinant of financial depth in a city. The elasticity of financial development to both publicly and privately owned branches is positive and significant across all specifications.
2.4 Conclusion

I presented a model of branch banking that includes firm heterogeneity and strategic interaction between bank companies that I estimated with Brazilian bank branch and city-level data. Together these results paint a very direct picture for how financial development endogenously spreads across a country. After establishing headquarters, banks slowly expand their networks into markets that are either large enough or close enough to be profitable. Throughout this process smaller, more distant cities are excluded from the financial market and may not be served.

However, there is qualitative evidence that state banks have the ability to fill this gap. Banks with limited geographic purview expand into local, financially remote regions within their states, and large national banks expand into other remote areas with the specific goal of expanding access to financial services.

Finally, it should be noted that the model structure did not appear to fit state bank behavior. Further researcher is needed to confirm whether or not state banks are actually able to ameliorate trends towards geographic inequality in credit access.
Chapter 3

Port Regions, Exports, and Subnational Trade

3.1 Introduction

Even as tariff barriers and transportation costs have fallen, trade costs remain a fundamental determinant of the spatial distribution of economic activity (Hummels 2007). In particular, distance from suppliers and markets is a large driver of per capita income inequality across countries (Redding and Venables 2004). Endogenous trade costs exacerbate these processes if relative transport costs are declining for areas with high economic activity. For example, existing work has shown that developed countries have more efficient ports with better quality physical infrastructure. This gives them a comparative advantage in export sectors and makes infrastructure-poor countries more remote (Clark et al. 2004, Blonigen and Wilson 2008). Those channels are also at work within countries, as subnational transportation costs have the potential to be as restrictive as international borders (Coughlin and Novy 2012).

In this paper, I investigate what I call "port regions," the final domestic location a good travels to before it is exported. In particular, I analyze whether those regions experience the benefits of declining intranational transportation costs due to economies of scale in shipping. To do
this, I focus on two trade flows: the transport of goods shipped to port regions for export and the transport of goods to port regions for domestic consumption. I augment a simple reduced form bilateral trade equation with domestic transportation costs that decline in volume of goods shipped though that same trade route. In the model, the elasticity of trade to demand shocks is larger than one due to these economies of density. I estimate the model with U.S. subnational trade data and show that increases in export shipments along a given trade route lead to higher volumes of intranational trade meant for domestic consumption.

My work builds off of existing research into the causes and consequences of trade cost endogeneity, particularly economies of scale. Much of the recent endogenous transportation cost literature has focused on the effect of trade imbalances and "back and forth trade." For example, recent papers by Behrens and Picard [2011], Jonkeren et al. [2011], and Wong [2017] analyze how trade imbalances, especially in large container ships, increase trade costs for importers and exporters. This is largely due to the opportunity cost of empty carrier vessels traveling back to their origin port. However, this effect is less relevant for intranational trade flows, especially within the continental United States. For example, the majority of trade by value and weight in the United States is either by truck or by parcel, modes that are less reliant on filling large vessels and returning to their origin port.

Other endogenous transportation cost research has emphasized the nature of competition in providing transport services. Francois and Wooton [2001] and Hummels et al. [2009] show that less served trade routes are less competitive and have higher transportation costs as a result of shippers’ market power. This is a self-reinforcing problem, as high trade volume in developed countries induces transport firms to enter those markets and lower prices via competition.

The branch of the literature that is closest to my approach deals explicitly with economies of transportation density, defined as trade costs that are decreasing in the volume of trade. Mori and Nishikimi [2002] and Skiba [2017] model threshold points of volume after which the effect of distance is mitigated by increased public and private transportation infrastructure. Their analysis is most applicable to large scale "hub" ports in international shipping, however I will use parts of
their modeling structure to motivate my empirical analysis of subnational trade.

3.2 Reduced-form model

In this section, I augment a standard bilateral trade model to capture the relationship between port regions and transport costs. First, I decompose the equation to allow exporters to travel in two stages: first from their region to port, and then from the port to the foreign market. Second, I parameterize region-to-port trade costs as a decreasing function of trade shipments along that same route. The result is a trade equation in which the endogenous trade cost serves to magnify demand shocks.

3.2.1 Structure of domestic and foreign trade

I start with a simple, reduced-form gravity equation\(^2\) that relates bilateral trade at the sectoral level to monadic and dyadic variables of interest:

\[
X_{ij}^k = A^k Y_i Y_j \left( \tau_{ij}^k \right)^{-\eta} \Pi_i^k \theta_j^k
\]  

(3.1)

Here exports from origin region \(i\) to final destination region \(j\) in sector \(k\) are given by the standard trade model variables: both region’s income levels, \(Y_i\) and \(Y_j\), and a bilateral, sector-specific iceberg trade cost \(\tau_{ij}^k\) with an elasticity of \(-\eta\). The equation also includes measures of exporter and importer "multilateral resistance," \(\Theta_i^k\) and \(p_j^k\), respectively. These terms capture each

---

1 Subnational trade costs themselves have been studied extensively. For some recent examples, see Duranton et al. [2014] and Carballo et al. [2017] on the relationship between internal road networks and trade costs; Atkin and Donaldson [2015] on how spatial pricing leads to underestimation of trade costs in developing countries; and Tombe and Winter [2016] on how differential government spending and tax policies influence internal trade costs in Canada.

2 This strategy is the spirit of Berthelon and Freund [2008]’s reduced form analysis of changing distance elasticities over time.

3 This equation generally requires CES preferences, but can be generated by a variety of models. Two examples are (1) heterogeneous firms models with Pareto distributed productivity (Chaney 2008) and (2) goods differentiated by place of production (Anderson and Van Wincoop 2003).
region’s trade costs and price indexes relative to the rest of the global market. Effectively, they are price indexes weighted by the distance from each country to all potential trading partners. Lastly, $A^k$, captures sector-specific consumption shares relative to total country income.

I make the following assumptions about the process for shipping a good abroad. First, if the good is being exported, it must first be transported to a domestic port region $p$. The value of that shipment is given by $S^k_{ip}$, which is mutually exclusive with domestic trade on that same route, $X^k_{ip}$, for the purposes of this analysis.

Second, firms choose to ship their goods to this port because it has the cheapest total transportation costs including both domestic and international. I denote the subset of countries for which this is true $J_{ip}$. This means that the value of total domestic shipments from country $i$ to domestic port region $p$ in sector $k$ destined for foreign markets can be expressed as the following sum:

$$S^k_{ip} = \sum_{j \in J_{ip}} X^k_{ij} \tag{3.2}$$

This expression implies that the choice of export port are independent of a port region’s individual demand characteristics. Additionally, the value of shipments potentially includes goods destined for multiple countries, whereas domestic goods in the sample are defined as those meant for a single region.

This leads into my third assumption: firms make their export production and trade route choices independently of domestic markets and trade costs. This assumption is based on the fact that total iceberg trade costs are strictly greater for shipments going abroad than those that remain in the U.S. This is simply due to the fact that transporting a good from the port region to a foreign country is not costless. Total iceberg trade costs for exporters can be expressed as

$$\tau^k_{ij} = \tau^k_{ip} \tau^k_{pj} \geq \tau^k_{ip} \tag{3.3}$$

where $\tau^k_{pj}$ is considered strictly exogenous for the purpose of this analysis.
Lastly, while domestic transportation costs are endogenous, they are affected by aggregate outcomes that are external to final good producers. This prevents firms from entering a foreign market with the express goal of lowering their own trade costs.

### 3.2.2 Endogenous trade costs

To generate trade costs that respond to the volume of export shipments over a given trade route, I make a simple adjustment to the typical iceberg cost equation. International trade costs are given by \( \tau_{pj}^k = D_{pj} \), a collection of exogenous bilateral parameters such as distance, borders, and language. Domestic costs are assumed to be decreasing in large-scale export shipments. I express this as

\[
\tau_{ip}^k = D_{ip}(s_{ip}^k)^{-\gamma}
\]

where \( 0 < \gamma < 1 \) is the elasticity of iceberg trade costs to increased export shipments. The elasticity of domestic trade along a route to export shipments along those routes is then equal to \( \eta \gamma \).

To guarantee a solution, I assume that neither \( \gamma \) nor the elasticity of trade to trade costs are jointly too high. Specifically: \( \eta \gamma < 1 \). This avoids a situation in which a trade shock leads to infinitely low trade costs and infinitely high exports.

To see how this works in practice, consider equation (3.1) above. For simplicity, I am going to absorb the country-specific terms into origin and destination variables that vary by sector, \( \Gamma_i^k \) and \( \Gamma_j^k \), respectively:

\[
X_{ij}^k = A_k \Gamma_i^k \Gamma_j^k \left( \tau_{ij}^k \right)^{1-\gamma}
\]

**Proposition 1.** The elasticity of bilateral exports in sector \( k \) to a demand shock is larger than one and finite in the range \( (1, \frac{1}{1-\eta \gamma}] \)

**Proof.** See Appendix C.1
To see this in practice, imagine a positive demand shock from a foreign importer that results in an increase in $\Gamma^k$. Holding $\Gamma_i$ fixed, the mechanism is as follows: higher demand increases exports from $i$ to $j$ in sector $k$. This increases shipments along the domestic route via $S_{ij}$. This in turn decreases domestic shipping costs, generating an elasticity greater than one. Bounding $\eta \gamma$ below one, keeps the elasticity finite. That this elasticity is greater than one represents the economies of density.

3.3 Empirical analysis of U.S. trade flows

3.3.1 Data

My primary data source is the 2012 U.S. Commodity Flow Survey Public Use Microdata on shipments within the United States. The CFS has been conducted every 4-5 years since 1993, but 2012 is the first year to have shipment-level data available to the public. Origin and port regions, $i$ and $p$, respectively, are Commodity Flow Survey Areas (CFSA). These are metropolitan statistical areas (MSA) indexed by state when possible. Shipments are classified by 44 different North American Industry Classification System (NAICS) sectors, listed in Appendix C.2.

To analyze trade costs, I use data on routed distance for each shipment as well as a state border variable calculated by hand. The primary outcome variable is the value of shipments destined for domestic consumption, and the primary explanatory variable is the value of shipments destined for export. These are calculated by trade route at the aggregate, NAICS, and mode levels.

3.3.2 Empirical strategy

In this section, I use U.S. intranational trade data to analyze the effect of economies of scale in shipping for export on domestic transportation costs and subnational trade. My main specification is as follows. First, I include trade cost terms in the expression for $\tau_{ij}^k$ from equation
(3.4):

\[ \tau_{ip}^k = (S_{ip}^k)^{-\gamma} d_{ip} \exp(Border_{ip}) \]  

(3.6)

with \( d_{ip} \) representing the average miles traveled per shipment from region \( i \) to the port region. \( Border_{ip} \) is a dummy variable equal to one if the origin state borders the port region’s state.

Next plugging (3.6) into (3.5) and taking logs generates the following estimation equation:

\[ \ln \ X_{ip}^k = \delta^k + \delta_i^k + \delta_j^k + \beta_1 \ln d_{ij} + \beta_2 Border_{ip} + \beta_3 \ln S_{ip}^k \]  

(3.7)

The dependent variable is the log value of goods shipped to port regions for domestic consumption. The general specification includes fixed effects to control for sector-specific consumption shares, \( \delta^k \), and origin and destination income and sectoral price indexes, \( \delta_i^k \) and \( \delta_j^k \), respectively. The coefficients of interest are the betas, which show the bilateral trade cost characteristics. I also estimate a version of the above with a dummy variable for positive exports. This allows me to see if there is specifically a threshold effect as well as a density effect.

There are multiple ways for the economies of density to work at different levels of (dis)aggregation. For example, the scale effect could vary by mode. To deal with this complication, I also estimate the same construction disaggregated by transportation mode to allow for differential costs by means of transportation.

### 3.3.3 Results

Table 3.1 reports the results of estimating the export shipment volume effects at the aggregate industry level and the mode level. Table 3.2 reports the results for the threshold effect. Tables 3.3 and 3.4 report the results of this same exercise disaggregated by the two most common modes of transport, truck and parcel.

The results across these specifications match the expected predictions. The elasticity of domestic trade to distance is always negative and statistically significant. However, adding the variables analyzing shipments for export does not change the distance elasticity in a significant
Table 3.1: The effect of distance and shipment volume on subnational trade

<table>
<thead>
<tr>
<th></th>
<th>Log Exports by NAICS</th>
<th>Log Exports By Mode and NAICS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) (2) (3) (4)</td>
<td>(5) (6) (7) (8)</td>
</tr>
<tr>
<td>LnRoutedDistance</td>
<td>-1.150*** (0.0145)</td>
<td>-1.135*** (0.0148)</td>
</tr>
<tr>
<td></td>
<td>-0.337*** (0.0355)</td>
<td>-0.326*** (0.0357)</td>
</tr>
<tr>
<td></td>
<td>-0.796*** (0.0106)</td>
<td>-0.764*** (0.0110)</td>
</tr>
<tr>
<td></td>
<td>-0.428*** (0.0346)</td>
<td>-0.431*** (0.0344)</td>
</tr>
<tr>
<td>Border</td>
<td>-0.0447 (0.0312)</td>
<td>-0.0449 (0.0313)</td>
</tr>
<tr>
<td></td>
<td>-0.990*** (0.0232)</td>
<td>-0.926*** (0.0235)</td>
</tr>
<tr>
<td>LnExShipments</td>
<td>0.0100*** (0.00121)</td>
<td>0.0118*** (0.00128)</td>
</tr>
<tr>
<td></td>
<td>0.0350*** (0.00132)</td>
<td>0.0363*** (0.00134)</td>
</tr>
<tr>
<td>Mode FE</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Importer-Exporter FE</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td></td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>R²</td>
<td>0.605</td>
<td>0.606</td>
</tr>
<tr>
<td>Observations</td>
<td>108507</td>
<td>108507</td>
</tr>
</tbody>
</table>

* p < 0.1, ** p < 0.05, *** p < 0.01.

Notes: Standard errors clustered at the exporter-importer level. All regressions include importer-sector, exporter-sector, and sector level fixed effects. The dependent variable in columns 1-4 is log within country shipments out at the sector level. In columns 5-8 the data is disaggregated to trade by sector and mode.

Table 3.2: The effect of distance and having exported on subnational trade

<table>
<thead>
<tr>
<th></th>
<th>Log Exports by NAICS</th>
<th>Log Exports By Mode and NAICS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) (2) (3) (4)</td>
<td>(5) (6) (7) (8)</td>
</tr>
<tr>
<td>LnRoutedDistance</td>
<td>-1.150*** (0.0145)</td>
<td>-1.147*** (0.0146)</td>
</tr>
<tr>
<td></td>
<td>-0.337*** (0.0355)</td>
<td>-0.334*** (0.0356)</td>
</tr>
<tr>
<td></td>
<td>-0.796*** (0.0106)</td>
<td>-0.769*** (0.0108)</td>
</tr>
<tr>
<td></td>
<td>-0.428*** (0.0346)</td>
<td>-0.430*** (0.0344)</td>
</tr>
<tr>
<td>Border</td>
<td>-0.0447 (0.0312)</td>
<td>-0.0445 (0.0312)</td>
</tr>
<tr>
<td></td>
<td>-0.990*** (0.0232)</td>
<td>-0.934*** (0.0234)</td>
</tr>
<tr>
<td>ExportDummy</td>
<td>0.0547*** (0.0196)</td>
<td>0.0771*** (0.0209)</td>
</tr>
<tr>
<td></td>
<td>0.460*** (0.0188)</td>
<td>0.475*** (0.0190)</td>
</tr>
<tr>
<td>Mode FE</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Importer-Exporter FE</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td></td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>R²</td>
<td>0.605</td>
<td>0.606</td>
</tr>
<tr>
<td>Observations</td>
<td>108507</td>
<td>108507</td>
</tr>
</tbody>
</table>

* p < 0.1, ** p < 0.05, *** p < 0.01.

Notes: Standard errors clustered at the exporter-importer level. All regressions include importer-sector, exporter-sector, and sector level fixed effects. The dependent variable in columns 1-4 is whether or not there were export shipments at the sector level. In columns 5-8 the data is disaggregated to trade by sector and mode.
Table 3.3: The effect of distance and shipment volume on subnational trade by mode

<table>
<thead>
<tr>
<th></th>
<th>Truck</th>
<th>Parcel, USPS, or courier</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) (2) (3) (4)</td>
<td>(5) (6) (7) (8)</td>
</tr>
<tr>
<td>LnRoutedDistance</td>
<td>-1.088***</td>
<td>-0.654***</td>
</tr>
<tr>
<td></td>
<td>(0.0133)</td>
<td>(0.0121)</td>
</tr>
<tr>
<td>Border</td>
<td>-0.114***</td>
<td>-0.0646*</td>
</tr>
<tr>
<td></td>
<td>(0.0291)</td>
<td>(0.0267)</td>
</tr>
<tr>
<td>LnExShipments</td>
<td>0.00522***</td>
<td>0.0107***</td>
</tr>
<tr>
<td></td>
<td>(0.00162)</td>
<td>(0.00168)</td>
</tr>
<tr>
<td>Mode FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Importer-Exporter FE</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>R²</td>
<td>0.571</td>
<td>0.623</td>
</tr>
<tr>
<td>Observations</td>
<td>73937</td>
<td>78618</td>
</tr>
</tbody>
</table>

*p < 0.1, ** p < 0.05, *** p < 0.01.

Notes: Standard errors clustered at the exporter-importer level. The dependent variable is log within country shipments out at the sector level. Columns 1-4 restrict the transportation mode to be by truck. Columns 5-8 restrict the mode to be by parcel. All regressions include importer-sector, exporter-sector, and sector level fixed effects.

Table 3.4: The effect of distance and having exported on subnational trade by mode

<table>
<thead>
<tr>
<th></th>
<th>Truck</th>
<th>Parcel, USPS, or courier</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) (2) (3) (4)</td>
<td>(5) (6) (7) (8)</td>
</tr>
<tr>
<td>LnRoutedDistance</td>
<td>-1.088***</td>
<td>-0.654***</td>
</tr>
<tr>
<td></td>
<td>(0.0133)</td>
<td>(0.0121)</td>
</tr>
<tr>
<td>Border</td>
<td>-0.114***</td>
<td>-0.0646*</td>
</tr>
<tr>
<td></td>
<td>(0.0291)</td>
<td>(0.0267)</td>
</tr>
<tr>
<td>ExportDummy</td>
<td>0.0613**</td>
<td>0.125***</td>
</tr>
<tr>
<td></td>
<td>(0.0246)</td>
<td>(0.0220)</td>
</tr>
<tr>
<td>Importer-Exporter FE</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>R²</td>
<td>0.571</td>
<td>0.623</td>
</tr>
<tr>
<td>Observations</td>
<td>73937</td>
<td>78618</td>
</tr>
</tbody>
</table>

*p < 0.1, ** p < 0.05, *** p < 0.01.

Notes: Standard errors clustered at the exporter-importer level. The dependent variable is whether or not there were export shipments at the sector level. Columns 1-4 restrict the transportation mode to be by truck. Columns 5-8 restrict the mode to be by parcel. All regressions include importer-sector, exporter-sector, and sector level fixed effects.
Table 3.5: Marginal effects of export shipments

<table>
<thead>
<tr>
<th>Level of aggregation of data</th>
<th>Controls</th>
<th>Log Shipments</th>
</tr>
</thead>
<tbody>
<tr>
<td>NAICS</td>
<td>Border</td>
<td>4.75%</td>
</tr>
<tr>
<td>NAICS</td>
<td>Pair</td>
<td>5.6%</td>
</tr>
<tr>
<td>Mode, NAICS</td>
<td>Mode, Border</td>
<td>10.1%</td>
</tr>
<tr>
<td>Mode, NAICS</td>
<td>Mode, Pair</td>
<td>10.4%</td>
</tr>
<tr>
<td>Truck, NAICS</td>
<td>Border</td>
<td>1.4%</td>
</tr>
<tr>
<td>Truck, NAICS</td>
<td>Pair</td>
<td>1.9%</td>
</tr>
<tr>
<td>Parcel, NAICS</td>
<td>Border</td>
<td>7.5%</td>
</tr>
<tr>
<td>Parcel, NAICS</td>
<td>Pair</td>
<td>3.2%</td>
</tr>
</tbody>
</table>

This implies that the effect of economies of density on trade costs may not be distance dependent. In fact, the effect of trade flows may be a network effect instead of a transport effect. This would be in line with research by Besedeš and Prusa [2011] and Morales et al. [2015] on firms entering foreign markets. They show that entering and remaining in a given market increases firm networks and familiarity, ultimately lowering the costs of trading with new partners.

The variables reflecting economies of density created by export shipments are all positive and significant. These results are robust to a variety of controls including fixed effects at the importer-sector level, exporter-sector level, and bilateral trade route pair. The bilateral pair controls for unobservable trade route characteristics that are not captured by distance, borders, or the export shipment effect.

The magnitudes show that there is a significant effect at the top end of the distribution of shipments for export. Table 3.5 reports the marginal effects of increasing exports from the 50th to 75th percentile of positive export flows. Along these lines, the economies of density from such a jump in exports increase domestic trade volume by as much as 10.4% at the mode level and 5.6% at the sector level. Comparing different modes, the export effect is larger for parcel shipments than route shipments.

See Appendix C.2 for a summary of these changes.
3.4 Conclusion

In this paper, I modeled and estimated potential economies of density along domestic trade routes. The reduced form model generated a framework in which port regions experience lower domestic trade costs due to exports being shipped along those same routes. Empirical results confirm that this channel is active: controlling for sector, transport mode, and region characteristics, I showed that subnational trade between regions in goods destined for consumption in the U.S. is increasing in shipments destined for foreign markets.

As the elasticity of distance was not affected by the addition of the export variable, it may be that the scale effects are about networks and familiarity effects. Future work would involve disentangling these components of the density effect.

Regardless, these results imply that transportation costs may be reinforcing patterns of inequality: not only do regions with better access to foreign markets benefit by increased export sales, those regions also experience cheaper access to domestically produced final and intermediate goods.
Bibliography


Appendix A

Appendix to Chapter 1

A.1 Model derivations

A.1.1 Expression for loan demand elasticity and markup

Loan demand is given by:

\[ L_{ko} = \left[ \left( \frac{\sigma}{\mu} \right)^{\frac{1}{\sigma-1}} \frac{\sigma}{\sigma-1} \right]^{-\gamma} w_o^{1-\gamma} N_o [R_{ko}]^{\frac{-\gamma}{\sigma-1}} \sum_d \tau_d^{x-\gamma} f_{od}^{x^{1-\frac{1}{\sigma-1}}} \left[ P_d Y_d^{\frac{1}{\sigma-1}} \right]^{-\gamma}. \]

Bank companies take aggregate prices indexes as given, so I absorb all variables not varying directly with the price of loans into the term \[ \Gamma_1 \] allowing me to write \[ L_{ko} = \Gamma_1 [R_{ko}]^{\frac{-\gamma}{\sigma-1}} \]

Differentiating with respect to \( R_o \) finally gives us this result: \[ \eta = -\frac{dL}{dR} / L = \frac{\gamma}{\sigma-1}. \] Plugging this into \[ R_o = \frac{\eta}{\eta^{\frac{1}{\gamma}} - \frac{\Gamma_1}{\Gamma_1} \lambda_o} \] gives us \[ R_o = \frac{\gamma}{\gamma + 1 - \sigma} \]

A.1.2 Equilibrium income

In this section, I show that the profit share of aggregate regional income depends on a weighted average of foreign import (home export) trade shares, that I define as \[ \tilde{\lambda}_o = \sum_d \frac{X_{od}}{Y_d} \]
resulting in an equilibrium income of \[ Y_o = w_o N_o \frac{\sigma}{\sigma - \lambda_o}. \]

First, recall that \[ Y_d = w_d N_d + \Pi_d. \] Define \[ \pi_d = \frac{\Pi_d}{w_d N_d}, \] then \[ Y_d = w_d N_d (1 + \pi_d). \] Next, note that I can write \[ \frac{X_{od}}{Y_d} \] as a function of exporting firms and per firm export trade shares. \[ \frac{X_{od}}{Y_d} = w_o N_o \lambda_{od} \]

\[ \Gamma_1 \equiv \left[ \left( \frac{\sigma}{\mu} \right)^{\frac{1}{\sigma-1}} \frac{\sigma}{\sigma-1} \right]^{-\gamma} w_o^{1-\gamma} N_o \sum_d \tau_d^{x-\gamma} f_{od}^{x^{1-\frac{1}{\sigma-1}}} \left[ P_d Y_d^{\frac{1}{\sigma-1}} \right]^{-\gamma} \]
where $\lambda_{od} = \left[ \left( \frac{\sigma'}{\mu} \right) \frac{1}{\sigma-1} \right]^{-\gamma} \frac{\sigma-1}{\gamma-\sigma-1} \left( \frac{w_{od}^{\sigma'}}{\Theta_d \sigma_p} \right)^{-\gamma} \left( \frac{\gamma}{\gamma-\sigma+1} C_o (1 + r_d^d)^{f_{od}} \right)^{1-\frac{\gamma}{\sigma-1}} \sum k \delta_k^{\frac{\gamma}{\sigma-1}-1}$, a function of parameters and trade costs.

\[
\bar{\lambda}_d = \sum_o X_{do} \frac{Y_d}{Y_o} = w_d N_d \sum_o \left[ \left( \frac{\sigma'}{\mu} \right) \frac{1}{\sigma-1} \right]^{-\gamma} \frac{\sigma-1}{\gamma-\sigma-1} \left( \frac{w_{od}^{\sigma'}}{\Theta_o \sigma_p} \right)^{-\gamma} \left( \frac{\gamma}{\gamma-\sigma+1} C_d (1 + r_d^d)^{f_{od}} \right)^{1-\frac{\gamma}{\sigma-1}} \sum k \delta_k^{\frac{\gamma}{\sigma-1}-1}
\]

(1) Balanced Trade

Balanced trade says that aggregate exports equal aggregate imports. For country $o$: $\sum_d X_{od} = \sum_d X_{do}$.

\[
\sum_d w_o N_o \lambda_{od} Y_d = \sum_d w_d N_d \lambda_{do} Y_o \iff w_o N_o \sum_d \lambda_{od} Y_d = Y_o \sum_d w_d N_d \lambda_{do} \iff w_o N_o \sum_d \lambda_{od} Y_d = Y_o \sum_d w_d N_d \lambda_{do} \iff \frac{Y_o}{w_o N_o} = \frac{\sum_d \lambda_{od} Y_d}{\sum_d w_d N_d \lambda_{do}} \iff 1 + \pi_o = \frac{\sum_d \lambda_{od} Y_d}{\sum_d w_d N_d \lambda_{do}}
\]

(2) Aggregate profits

\[
\Pi_o = \sum_d \frac{1}{\sigma} X_{od} = \sum_d \frac{1}{\sigma} n_o L_o \lambda_{od} Y_d, \text{ so } \pi_o = \sum_d \frac{1}{\sigma} \lambda_{od} Y_d
\]

Combining the results from (1) and (2):

\[
\frac{1+\pi_o}{\pi_o} = \frac{\sum_d \lambda_{od} Y_d}{\sum_d w_d N_d \lambda_{do} \sum \lambda_{od} Y_d}.
\]

\[
1 + \pi_o = \frac{\sigma}{\sigma - \sum_d w_d N_d \lambda_{do}}, \text{ where } w_d N_d \lambda_{do} = X_{do} \frac{Y_d}{Y_o}, \text{ or the share of } o \text{ income spent on } d.
\]

With $\sum_d w_d N_d \lambda_{do} = \bar{\lambda}_o$

Thus $1 + \pi_o = \frac{\sigma}{\sigma - \lambda_o}$ and $Y_o = w_o N_o \frac{\sigma}{\sigma - \lambda_o}$.
Appendix B

Appendix to Chapter 2

B.1 Uniquely determined cutoff

Proposition 1 Restated

Given the productivity distribution \( G(\phi) = 1 - \phi^{-\gamma} \), for one headquarter region \( h \), and the assumption that \( \frac{\eta f_{ih}}{(1-\beta_{ih})(1-M_{ih}^{\gamma}-\phi)} > \Gamma_i \), there is a unique productivity cutoff \( \phi_{ih}^\star \).

Proof. The productivity cutoff is determined by the equation

\[
\left( \phi_{ih}^\star \right)^{\sigma-1} = \frac{\eta f_{ih}}{\Gamma_i \left(1-\beta_{ih}M_{ih}(\phi_{ih}^\star)^2\right)} > \Gamma_i.
\]

Banks enter sequentially in order of most productive to least. If an equilibrium hold, I need for bank company entry to increase the productivity cutoff. Out of equilibrium, \( M_i \) is increasing as each bank company enters, pushing down \( M_i(\phi_{ih}^\star)^2 \), and thus pushing up \( \phi_{ih}^\star \). This continues until the firm with productivity equal to \( \phi_{ih}^\star \) enters the region.

To find \( \phi_{ih}^\star \), there needs to be a solution to

\[
z(\phi_{ih}^\star) = \phi_{ih}^\star - \left( \frac{\eta f_{ih}}{\Gamma_i (1-\beta_{ih})M_{ih}(\phi_{ih}^\star)^2} \right)^{\frac{1}{\sigma-1}} = 0.
\]

Given that \( \frac{\eta f_{ih}}{(1-\beta_{ih})(1-M_{ih}^{\gamma}-\phi)} > \Gamma_i \), \( z(1) = 1 - \frac{\eta f_{ih}}{\Gamma_i \left(1-M_{ih}^{\gamma}-\phi\right)} < 0 \). As \( \phi_{ih}^\star \) approaches \( \infty \), \( z(\phi_{ih}^\star) \) converges to \( \infty \). So given some arbitrarily large \( x \), \( z(x) > 0 \). Thus, by the intermediate value theorem, there is a \( \phi_{ih}^\star \in [1, \infty) \) that solves \( z(\phi_{ih}^\star) = 0 \).

I will next prove that this solution is unique. First, note that \( z \) is clearly increasing in \( M_i(\phi_{ih}^\star) \).

Also, recall that \( M_i(\phi_{ih}^\star) \equiv 1 - \frac{M_i}{1+M_i} \frac{\gamma}{\gamma-\sigma-1} \) and \( M_i = M_i(\phi_{ih}^\star)^{-\gamma} \). This means

\[
\frac{\partial M_i(\phi_{ih}^\star)^{-\gamma}}{\partial \phi_{ih}^\star} = \frac{\gamma^2}{\gamma-\sigma-1 (1+M_i)^2 \phi_{ih}^\star} > 0 \text{ given } \gamma > \sigma - 1 > 0, M_i > 0, \text{ and } \phi_{ih}^\star \in [1, \infty). \text{ Thus } z' > 0.
\]
If the solution is not unique, then there is an \( x \) and \( x' \): \( z(x) = z(x') = 0 \). By Rolle’s Theorem, there must be a number \( c \in (x, x') : z'(c) = 0 \). However, as shown above \( h'(c) > 0 \) for all \( c \in [1, \infty) \). Therefore, \( z(\phi_{ih}) \) cannot have more than one solution. \( \Box \)

**B.2 Measures of bank size**

To build the indicator \( REMOTE_i \), I used bank branch network as the measure of size. I also tested all of the following for robustness. These variables were used as alternative measures of financial depth for a given city.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Credit</td>
<td>Total credit operations in a given city</td>
</tr>
<tr>
<td>Assets A</td>
<td>Adjusted assets less intrabank branch finance</td>
</tr>
<tr>
<td>Assets B</td>
<td>Sum of: deposits, interbank lending, liquid assets, intrabank branch finance, credit operations, leases, physical assets</td>
</tr>
<tr>
<td>Assets C</td>
<td>Assets B less intrabank branch finance</td>
</tr>
</tbody>
</table>
Appendix C

Appendix to Chapter 3

C.1 Elasticity of exports to demand shocks

Proposition 1 Restated The elasticity of bilateral exports in sector $k$ to a demand shock is larger than one and finite in the range $(1, \frac{1}{1-\eta})$.

Proof. First, the expression for exports is given by $X_{ij}^k = A_k \Gamma_i^k \Gamma_j^k \tau_{ij}^k$ and the expression for trade costs is given by $t_{ij}^k = \tau_{pj}^k \tau_{ip}^k = D_{pj} D_{ip} (S_{ip}^k)^{-\gamma}$. A positive demand shock, is represented by an increase in $\Gamma_j^k$ that has no effect on $\Gamma_i^k$.

$$- \frac{dX_{ij}^k}{d\Gamma_j^k} = \frac{-\eta X_{ij}^k}{\tau_{ij}^k} \frac{d\tau_{ij}^k}{d\Gamma_j^k} + \frac{X_{ij}^k}{\Gamma_j^k}$$

$$- \frac{dT_{ip}^k}{dT_j^k} = \frac{-\gamma X_{ij}^k}{S_{ip}^k} \frac{dX_{ij}^k}{d\Gamma_j^k}$$

given that $S_{ip}^k = \sum_{j \in J_{ip}} X_{ij}^k$.

These imply that $\frac{dX_{ij}^k}{d\Gamma_j^k} = \frac{-\eta X_{ij}^k}{\tau_{ij}^k} \frac{d\tau_{ij}^k}{d\Gamma_j^k} + \frac{X_{ij}^k}{\Gamma_j^k} \implies 1 = \eta \frac{X_{ij}^k}{S_{ip}^k} \frac{dX_{ij}^k}{d\Gamma_j^k} + \frac{d\Gamma_j^k}{d\Gamma_j^k}$.

The elasticity of bilateral trade to a demand shock is given by:

$$\text{elas}_{X_{ij}^k \Gamma_j^k} = \frac{dX_{ij}^k}{d\Gamma_j^k} \frac{\Gamma_j^k}{X_{ij}^k} = \frac{1}{1-\eta} \frac{X_{ij}^k}{S_{ip}^k}$$

Note that $S_{ip}^k \geq X_{ij}^k$ by definition. If $S_{ip}^k = X_{ij}^k$, then $\text{elas}_{X_{ij}^k \Gamma_j^k} = \frac{1}{1-\eta}$.

As $S_{ip}^k \to \infty$, $\text{elas}_{X_{ij}^k \Gamma_j^k} \to 1$. For $0 < \eta \cdot \gamma < 1$, $\frac{1}{1-\eta} > 1$. Given that this function is monotonic
for all possible values of the variables and parameters in question, $\text{elas}_{X_{ij}^{k}\Gamma_{j}} \in (1, \frac{1}{1-\eta}]$
## C.2 Data notes

### Table C.1: NAICS industries in sample

<table>
<thead>
<tr>
<th>NAICS</th>
<th>Description</th>
<th>NAICS</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>212</td>
<td>Mining (except oil and gas)</td>
<td>4231</td>
<td>Motor vehicle and parts merchant wholesalers</td>
</tr>
<tr>
<td>311</td>
<td>Food manufacturing</td>
<td>4232</td>
<td>Furniture and home furnishing merchant wholesalers</td>
</tr>
<tr>
<td>312</td>
<td>Beverage and tobacco product manufacturing</td>
<td>4233</td>
<td>Lumber and other construction materials merchant wholesalers</td>
</tr>
<tr>
<td>313</td>
<td>Textile mills</td>
<td>4234</td>
<td>Commercial equip. merchant wholesalers</td>
</tr>
<tr>
<td>314</td>
<td>Textile product mills</td>
<td>4235</td>
<td>Metal and mineral (except petroleum) merchant wholesalers</td>
</tr>
<tr>
<td>315</td>
<td>Apparel manufacturing</td>
<td>4236</td>
<td>Electrical and electronic goods merchant wholesalers</td>
</tr>
<tr>
<td>316</td>
<td>Leather and allied product manufacturing</td>
<td>4237</td>
<td>Hardware and plumbing merchant wholesalers</td>
</tr>
<tr>
<td>321</td>
<td>Wood product manufacturing</td>
<td>4238</td>
<td>Machinery, equipment, and supplies merchant wholesalers</td>
</tr>
<tr>
<td>322</td>
<td>Paper manufacturing</td>
<td>4239</td>
<td>Miscellaneous durable goods merchant wholesalers</td>
</tr>
<tr>
<td>323</td>
<td>Printing and related support activities</td>
<td>4241</td>
<td>Paper and paper product merchant wholesalers</td>
</tr>
<tr>
<td>324</td>
<td>Petroleum and coal products manufacturing</td>
<td>4242</td>
<td>Drugs and druggists’ sundries merchant wholesalers</td>
</tr>
<tr>
<td>325</td>
<td>Chemical manufacturing</td>
<td>4243</td>
<td>Apparel, piece goods, and notions merchant wholesalers</td>
</tr>
<tr>
<td>326</td>
<td>Plastics and rubber products manufacturing</td>
<td>4244</td>
<td>Grocery and related product merchant wholesalers</td>
</tr>
<tr>
<td>327</td>
<td>Nonmetallic mineral product manufacturing</td>
<td>4245</td>
<td>Farm product raw material merchant wholesalers</td>
</tr>
<tr>
<td>331</td>
<td>Primary metal manufacturing</td>
<td>4246</td>
<td>Chemical and allied products merchant wholesalers</td>
</tr>
<tr>
<td>332</td>
<td>Fabricated metal product manufacturing</td>
<td>4247</td>
<td>Petroleum and petroleum products merchant wholesalers</td>
</tr>
<tr>
<td>333</td>
<td>Machinery manufacturing</td>
<td>4248</td>
<td>Beer, wine, and alcoholic beverage merchant wholesalers</td>
</tr>
<tr>
<td>334</td>
<td>Computer and electronic product manufacturing</td>
<td>4249</td>
<td>Miscellaneous nondurable goods merchant wholesalers</td>
</tr>
<tr>
<td>335</td>
<td>Electrical equipment, appliance, and component manufacturing</td>
<td>4541</td>
<td>Electronic shopping and mail-order houses</td>
</tr>
<tr>
<td>336</td>
<td>Transportation equipment manufacturing</td>
<td>45431</td>
<td>Direct selling establishments</td>
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<tr>
<td>337</td>
<td>Furniture and related product manufacturing</td>
<td>4931</td>
<td>Warehousing and storage (includes 484)</td>
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<tr>
<td>339</td>
<td>Miscellaneous manufacturing</td>
<td>5111</td>
<td>Newspaper, periodical, book, and directory publishers</td>
</tr>
</tbody>
</table>
Table C.2: Effects of export shipment volume on the elasticity of trade to distance

<table>
<thead>
<tr>
<th>Dep. Var.</th>
<th>Level of aggregation of data</th>
<th>Controls</th>
<th>Change in distance elasticity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log Shipments</td>
<td>NAICS</td>
<td>Border</td>
<td>-1.3%</td>
</tr>
<tr>
<td>Log Shipments</td>
<td>NAICS</td>
<td>Pair</td>
<td>-3.3%</td>
</tr>
<tr>
<td>Export Dummy</td>
<td>NAICS</td>
<td>Border</td>
<td>~.3%</td>
</tr>
<tr>
<td>Export Dummy</td>
<td>NAICS</td>
<td>Pair</td>
<td>~.9%</td>
</tr>
<tr>
<td>Log Shipments</td>
<td>Mode, NAICS</td>
<td>Mode, Border</td>
<td>-4.0%</td>
</tr>
<tr>
<td>Log Shipments</td>
<td>Mode, NAICS</td>
<td>Mode, Pair</td>
<td>~.7%</td>
</tr>
<tr>
<td>Export Dummy</td>
<td>Mode, NAICS</td>
<td>Mode, Border</td>
<td>-3.4%</td>
</tr>
<tr>
<td>Export Dummy</td>
<td>Mode, NAICS</td>
<td>Mode, Pair</td>
<td>~.5%</td>
</tr>
<tr>
<td>Log Shipments</td>
<td>Truck, NAICS</td>
<td>Border</td>
<td>~.5%</td>
</tr>
<tr>
<td>Log Shipments</td>
<td>Truck, NAICS</td>
<td>Pair</td>
<td>~.3%</td>
</tr>
<tr>
<td>Export Dummy</td>
<td>Truck, NAICS</td>
<td>Border</td>
<td>~.4%</td>
</tr>
<tr>
<td>Export Dummy</td>
<td>Truck, NAICS</td>
<td>Pair</td>
<td>~.3%</td>
</tr>
<tr>
<td>Log Shipments</td>
<td>Parcel, NAICS</td>
<td>Border</td>
<td>~1.5%</td>
</tr>
<tr>
<td>Log Shipments</td>
<td>Parcel, NAICS</td>
<td>Pair</td>
<td>~.3%</td>
</tr>
<tr>
<td>Export Dummy</td>
<td>Parcel, NAICS</td>
<td>Border</td>
<td>~1.3%</td>
</tr>
<tr>
<td>Export Dummy</td>
<td>Parcel, NAICS</td>
<td>Pair</td>
<td>0%</td>
</tr>
</tbody>
</table>