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Essays in Banking and Trade

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Essays in Banking and Trade

DISSERTATION

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for the degree of

DOCTOR OF PHILOSOPHY

in Economics

by

Marco Antonio Martinez del Angel

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Professor Gary Richardson, Co-Chair
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2019

DEDICATION

To

my beloved parents Isidro and Juana Maria without whose love and support I would not have been able to achieve my goals. To my son Gaelito and my wife Maribel that are my inspiration. Additionally, I dedicate this work to my dear Professors , specially Gary Richardson, Dan Bogart, Eric Swanson, and Antonio Rodriguez, that supported and guided me through this endeavor.

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ABSTRACT OF THE DISSERTATION

Essays in Banking and Trade

by

Marco Antonio Martinez del Angel

Doctor of Philosophy in Economics

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Professor Gary Richardson, Co-Chair
Professor Eric Swanson, Co-Chair

This dissertation includes three essays. The first essay studies the question of whether multinationals that use inputs that are child labor intensive tend to outsource their production rather than producing them in-house. In the media, a commonly cited determinant of a multinational's decision to engage in outsourcing vs. FDI is child labor. If multinationals are in an industry, and sourcing from a country, where child labor is common, there is an incentive to purchase at arms-length rather than producing in-house. This is because the negative publicity that comes with sourcing child labor is much greater when the child labor is found to be in-house rather than from an arm's length firm. I test for this hypothesis and find a negative relationship between the share of imports that are intra-firm and the child labor intensity of the industry. I also show that the relationship is stronger when the goods are from poorer countries, countries that use more child labor, and in years when public opinion and the media is more focused on the problem of child labor.

The second essay studies the effect of uncertainty on firm level investment using time series data on shipping and stock prices from the English East India Company. The English East India Company was one of the world's first multinational corporations and it faced substantial political and economic risks for much of its history. Its business required large investments to send trading voyages to Asia and sustain an organizational structure in Asia. Using a discrete time duration model I find that higher levels of uncertainty, measured by stock return volatility, decrease the probability of sending trading voyages. In addition, I examine potential heterogeneous effects and I find that uncertainty has larger effects during the sailing season

The third essay, coauthored with Gary Richardson and Michael Gou, studies the relationship between bank failures and business failures between 1900 and 1933. During the Federal Reserve's formative years, banks failed frequently, and corporate bankruptcies followed. We employ new identification strategies that demonstrate a causal link between bank failures and business activity and illuminate the mechanism underlying that link. Our analysis indicates that bank failures triggered bankruptcies of firms that depended upon banks for ongoing access to commercial credit.

Chapter 1. Outsourcing Child Labor

1. Introduction

In recent years significant progress has been made to understand the determinants of the boundaries of the multinational firm. In particular, theories have been developed which extend Grossman-Hart-Moore property rights theory of the firm to the international context, while empirical evidence provides support for the basic predictions of these models.

In the media, a commonly cited determinant of a multinational's decision to engage in outsourcing vs. FDI is child labor. Simply stated, if multinationals are in an industry, and sourcing from a country, where child labor is common, there is an incentive to purchase at arms-length rather than producing in-house. This is because the negative publicity that comes with sourcing child labor is much greater when the child labor is found to be in-house rather than from an arm's length firm. If the goods are in another firm's factory, the purchaser cannot reasonably be responsible for what happens behind closed doors. Recent example of this is H&M's head of sustainability Helena Helmersson, who when asked about whether they could guarantee the quality of labor conditions in the factories that produce their goods. She answered "We do the very best we can… Remember that H&M does not own any factories itself. We are to some extent dependent on the suppliers – it is impossible to be in full control." (Siegle, 2012).This response is typical and shows that it is easier to distance one's self from the practice of child labor when goods are purchased at arm's length rather than in-house.

The goal of this paper is to provide a better understanding of how country's factor endowments, institutions and product characteristics impact the form that trade takes and what goods a country produces (i.e. whether multinationals decide to vertically integrate or outsource to its supplier) in child labor intensive sectors. The importance of these factors has been established in the recent literature on the boundaries of the multinational firm that highlights the role of contracting institutions in firms' production and integration decisions. Guided by these models I examine an untested country and product determinant of intra-firm trade: child labor. In particular, I construct new measures of child labor intensity based on the idea that children have a comparative advantage in some production processes as they are able to operate machinery or perform repetitive tasks due to their small bodies and nimble fingers or because they can be forced to work long hours or in an unhealthy environment. Thus, multinationals that produce child labor intensive inputs would outsource part of their production to foreign suppliers that employ children as in these establishments it is more difficult to monitor child labor laws.

I examine this hypothesis by testing whether child labor intensive industries tend to outsource more of their production. To quantify industry's child labor intensity I construct two variables that measure the "child labor content" of tasks and the extent to which there is evidence of child labor in economic sectors. For the first measure I use the Occupational Information Network (O*NET) Database that contains information on job tasks, skills, and work activities for hundreds of occupations. To measure industry's child labor intensity, I first develop an index that characterizes the "child labor content" of tasks by identifying abilities, skills and other occupation characteristics associated with child labor. Then, I combine this data with industry-level employment from the Bureau of Labor Statistics Occupational Employment Statistics and construct a variable that measures industry's child labor intensity. The second measure of child labor intensity is based on data from the 7th edition of the report *Department of Labor's List of Goods Produced by Child Labor or Forced Labor* that identifies the economic sectors of a country where child or forced labor is concentrated. I construct this variable by combining this data with industry level employment, so this index measures child labor intensity at the country-industry level.

The analysis produces several results. First, I find suggestive evidence consistent with the hypothesis that child labor is a determinant of intra-firm trade. According to my most conservative estimates, a one standard deviation increase in industry's child labor intensity leads to a 0.021 standard deviation decrease in the share of intra-firm trade. Second, I examine potential heterogeneous effects across country characteristics, and I find that there is evidence of differential effects on countries with higher incidence and media exposure of child labor. I also find larger effects of child labor intensity when restricting the sample to poor and middle income exporting countries.

The main empirical challenge in studying the relationship between child labor and trade at the industry level is the lack of cross country-industry level measures of child labor. An important contribution of my study is the construction of new measures of child labor intensity at the industry and country-industry level that overcome this problem. In addition, to the best of my knowledge, this is the first study that shows empirically the role of child labor as a determinant of intra-firm trade. The paper contributes to two bodies of research. First, the findings contribute to the literature that seeks to better understand the determinants of the sourcing decisions of multinational firms. They add to existing empirical studies – such as Antràs (2003), Yeaple (2006), Nunn and Trefler (2008, 2013), Bernard, Jensen, Redding and Schott (2010), Carluccia and Fally (2013), and Corcos, Irac, Mion and Verdier (2013) – that seek to better understand the decision to outsource or engage in FDI in a world of incomplete contracts. Second, the results contribute to the literature on child labor and international activity: for trade Edmonds and Pavnick (2006); Edmonds and Pavnick (2005); Cigno, Rosati and Guarcello (2002); Cigno, Giovannetti and Sabani (2015), and for FDI: Davies and Voy (2009) ; Neumayer and de Soysa (2005). Also, this article is closely related to studies of adaptation theories of multinational firms such as Costinot, Oldenski and Rauch (2011) that examine how routine tasks are supplied by multinational firms.

The paper is organized as follows. Section II provides a discussion of the conceptual background and empirical framework. Section III describes the data used in the analysis. Section IV reports the empirical results. Section V concludes.

2. Background and Empirical Framework

During the 1990's, many multinational companies were target of anti-sweatshop campaigns for using suppliers accused of employing children and having poor working conditions. Activists demanded improvements in working conditions and prohibition of child employment by spreading consumer boycott. A famous example of this anti-sweatshop movement, is the international campaign against Nike sweatshops in Indonesia in the early 1990's. The campaign created large media attention by criticizing poor working conditions and low minimum wage compliance in Nike's plants. As a result of this campaign, Nike established a code of conduct to comply with labor standards. Since then, interest in child labor and anti-sweatshop campaigns has decreased, but has been increasing again in recent years due to the growing evidence that child labor incidence is still high in many regions where a large number of suppliers of multinational companies are located.[3]

Over the last three decades global multinational activity and fragmentation of production grew substantially, and a significant fraction of the recent fragmentation of production has been intra-firm trade. For instance, Bernard et al. (2010) documented that about "Forty-six percent of U.S. imports occur between related parties". As a result of this, an extensive literature has emerged that studies the determinants of intra-firm trade. Antràs (2003) finds that the share of U.S. intra-firm imports is increasing in the capital

[3] See Amnesty International (2016) "This Is What We Die For: Human Rights Abuses in the Democratic Republic of the Congo Power the Global Trade in Cobalt" Amnesty International Ltd Peter Benenson House 1 Easton Street, London WC1X 0DW, United Kingdom

intensity of intermediate inputs provided by the headquarters firm. Yeaple (2006) shows that intra-firm trade is more prevalent in capital and R&D intensive industries and in industries with greater productivity dispersion across firms. Nunn and Trefler (2008, 2013) find strong support for Antràs and Yeaple results and provide evidence on the positive effect of improving supplier's contractibility on intra-firm imports. Carluccia and Fally (2013) find higher shares of intra-firm trade in complex products from countries with a low level of financial development. Using firm-level data Corcos et al. (2013) find that intra-firm imports are more likely in capital and skill intensive firms, in highly productive firms, and from countries with good judicial institutions. Lastly, Bernard et al. (2010) constructs a measure of product contractibility and finds that intra-firm trade is higher for products with low levels of contractibility. Even though this literature has developed in significant ways to study the determinants of the internalization decision of multinational firms, there are still many gaps in the literature due to the challenge of how to proxy for various unobserved determinants of intra-firm trade such as child labor. Thus, the goal of this paper is to fill the gap in the literature by constructing a new measure of industry level child labor intensity and empirically estimating its effect on intra-firm trade.

The effect of trade and FDI on child labor has been a major issue in the globalization debate. Recent studies have attempted to empirically examine the relationship between international activity and the incidence of child labor, however this literature has failed to produce conclusive evidence. For instance, Edmonds and Pavnick (2005) study the relationship between changes in the relative price of rice and child labor using household level data from Vietnam. They find that higher prices are associated with lower levels of child labor mainly due to the large income effects of price changes. Edmonds and Pavnick (2006) examine the effect of trade openness on child labor in a cross-country framework using instrumental variables to address the endogeneity of openness. Their findings indicate a negative relationship between openness and child labor, however this relationship is weaker when controlling for cross-country income differences. Similarly, Cigno et al. (2002) analyze the relationship between openness and child labor, finding no evidence that trade has a positive effect on child labor. Cigno et al. (2015) develop a two-period, two-country model that incorporates family decisions and trade of intermediate goods to study the effect of trade on child labor. They find that child labor is negatively associated with trade when country's skill endowment is large and when production activities relocated to that country are more skill intensive than those already carried out there. The main contribution of this study is to incorporate the effect of offshoring on child labor which has not been analyzed in previous studies. Lastly, a few studies have examined the effect of FDI on child labor. Neumayer and de Soysa (2005) is one of the first studies that examine the effect of FDI on child labor. They present evidence that FDI and trade openness have a negative effect on child labor, however they don't attempt to address the identification problem of endogeneity of FDI. Davies and Voy (2009) examine the relationship between FDI and child labor, finding that FDI has no effect on child labor after accounting for the endogeneity of FDI, trade and income. The review of the literature suggests that the overall effect of globalization on child labor depends on the different mechanisms (e.g. income effects) by which trade or FDI affect child labor. Thus, the findings of this paper add to this literature by providing evidence of an unexplored mechanism by which globalization interacts with child labor: outsourcing.

The aim of my analysis is to examine the hypothesis whether child labor is an important determinant of the boundary of multinational firms. My empirical specification is guided by the article by Nunn and Trefler (2008). Unlike previous empirical studies of intra-firm trade that have mostly used cross-section data, I test my hypothesis by estimating the following panel regression that accounts for unobserved country and time heterogeneity:

$$I_{ict} = \alpha_c + \alpha_t + \beta\, C_I + \gamma_S \frac{S_{it}}{L_{it}} + \gamma_K \frac{K_{it}}{L_{it}} + \gamma_I Y_{ct} + \varepsilon_{ict} \tag{1}$$

where $I_{ict} = M^V_{ict} / (M^V_{ict} + M^O_{ict})$ is the share of U.S. imports from country c in industry i and year t that are intra-firm; C_I is either C_{ci} , a measure of child-labor intensity in industry i in country c, or C_i a measure of child-labor intensity in industry i ; $\frac{S_{it}}{L_{it}}$ and $\frac{K_{it}}{L_{it}}$ denote skill and capital intensity measures in industry i in year t ; Y_{ct} is income per capita for country c in year t ; α_c and α_t denote country and year fixed effects; ε_{ict} is an error term clustered at industry level. In addition, I also consider variations of equation (1) that include interactions between the independent variables and country characteristics. The choice of country and industry-level controls is based on the recent literature on the boundaries of multinational firms and international trade and child labor [Antràs (2003); Yeaple (2006); Nunn and Trefler (2008, 2013); Edmonds and Pavnick (2006)].

The coefficient of interest in equation (1) is β, which is the estimated impact of child labor intensity on intra-firm trade. A negative coefficient indicates that more child labor intensive industries have a lower share of intra-firm imports. The empirical strategy has all the advantages and caveats of standard panel data estimators. Country fixed effects control for all time invariant factors that differ between countries while year fixed effects control for any secular patterns of intra-firm growth that affect all countries similarly.

Identification relies on the assumption that the child labor intensity measures are exogenous, time-invariant and that there is no serial correlation in the errors. The main threats to identification are the endogeneity of the child labor intensity measures and the existence of time-varying industry factors that make the time invariance assumption of the industry-level child labor intensity measures implausible. If there is reverse causality between intra-firm trade and child labor or if the child labor intensity measures vary over time , then the Fixed Effects estimates of β will be biased, and I may falsely conclude that there is a negative relationship between the share of imports that are intra-firm and the child labor intensity of the industry. However, ex-ante, the direction of the bias is not predictable. Because of the lack of long panel data to measure child labor over time across countries and industries, I am unable to address the main concerns about my identification assumptions.[4] Thus, the estimates of equation (1) should be interpreted with caution, as one cannot interpret these results as causal evidence of the effect of an industry's child labor intensity on intra-firm trade.

To test for heterogeneous effects and control for other determinants of intra-firm trade that, if omitted, may bias the estimates, I interact a number of country characteristics with the child labor intensity measure. I include interactions of the child labor intensity measure with income per capita, an indicator variable for whether a country signed the ILO child labor convention 138 on the minimum age of employment, the share of children age 7-14 years in employment, the percentage of primary-school-age children who are not enrolled in primary or secondary school and country's media exposure against child labor. Also, I test the sensitivity of my results to alternative samples that include only exports from poor and middle income countries and cross sectional regressions for year 2014 where country-year child labor data has less missing values and is most recent.

Before turning to the estimation results, I first describe the construction of the measures of child labor intensity and the data that I use.

3. Data

A. *Constructing measures of industry-level child labor intensity*

Ideally I would like to construct industry measures of child labor intensity for all countries, however, due to limited availability of data I follow the empirical literature on intra-firm trade that proxies industry controls using data related to the selling industry -i.e. U.S. headquarters importing goods from suppliers. Also due

[4]A possible extension of this analysis would be to use the 2009-2014 time period for which ILAB data is available. However this will result in loss of important time series variation.

to lack of long panel data my analysis uses the most recent available data. The empirical analysis relies on two measures of an industry's intensity in child labor. To construct these variables, I use data from the Occupational Information Network (O*NET) 21.2 database and the 7th edition of the report *Department of Labor's List of Goods Produced by Child Labor or Forced Labor*. The O*NET database contains information about the abilities, skills and occupational characteristics required in 963 occupations in the U.S. Since the seminal work of Autor, Levy and Murnane (2003) that studies the effect of computerization on job skill demand, this data has been widely used in the literature that investigates job polarization, technical change and offshoring. For each occupation, O*NET includes measures on the "importance" and "level" required of each characteristic. For instance, such characteristics include finger dexterity, general physical activities, and arm-hand steadiness. The report *Department of Labor's List of Goods Produced by Child Labor or Forced Labor* provides a list of goods and their source countries where there is significant evidence that are produced by child labor or forced labor in violation of international standards.

It has been argued that children are better suited for some types of work because they have specific attributes and abilities like small hands or a submissive character (e.g, the "nimble fingers" theory) that make them deftly to perform certain tasks such as hand sewing of carpets, soldering of tiny electric parts or producing illicit drugs . To construct the first industry-specific measure of child labor intensity, I select occupational characteristics from O*NET that characterize the "child labor content" of tasks and occupations. I use the task content framework developed by Autor et al. (2003) and Acemoglu and Autor (2011) to construct an index of how child labor intensive an occupation is. The variables included in the index identify work related attributes and skills required to perform "child labor tasks" identified in the report *Department of Labor's List of Goods Produced by Child Labor or Forced Labor*. Children's tasks include operating sewing machines, crushing rocks to extract minerals and manufacturing of garments, jewelry, and electronics. Like unskilled labor, children are employed in routine and automated jobs that involve repetitive hand and body movements, and monotonous tasks. Also, in some countries children are employed in occupations that expose them to poor working conditions and health hazards like artisanal mining or occupations involving the use of meat or paper cutting machines, etc. The occupation's child labor intensity index is a composite measure of the following O*NET Work Activities, Work Context, Work Values and Abilities importance measures:

Abilities

· **Arm-Hand Steadiness:** The ability to keep your hand and arm steady while moving your arm or while holding your arm and hand in one position.

· **Manual Dexterity:** The ability to quickly move your hand, your hand together with your arm, or your two hands to grasp, manipulate, or assemble objects.

· **Finger Dexterity:** The ability to make precisely coordinated movements of the fingers of one or both hands to grasp, manipulate, or assemble very small objects.

Work Activities

· **Performing General Physical Activities:** Performing physical activities that require considerable use of your arms and legs and moving your whole body, such as climbing, lifting, balancing, walking, stooping, and handling of materials.

· **Handling and Moving Objects:** Using hands and arms in handling, installing, positioning, and moving materials, and manipulating things.

· **Controlling Machines and Processes:** Using either control mechanisms or direct physical activity to operate machines or processes (not including computers or vehicles).

· **Making Decisions and Solving Problems (reverse):** Analyzing information and evaluating results to choose the best solution and solve problems.

Work Context

· **Spend Time Using Your Hands to Handle, Control, or Feel Objects, Tools, or Controls:** How much does a job require using your hands to handle, control, or feel objects, tools or controls.

· **Spend Time Bending or Twisting the Body:** How much does this job require bending or twisting your body?

· **Spend Time Making Repetitive Motions:** How much does a job require making repetitive motions.

· **Degree of Automation:** How automated is the job?

· **Importance of Repeating Same Tasks:** How important is repeating the same physical activities (e.g., key entry) or mental activities (e.g., checking entries in a ledger) over and over, without stopping, to performing this job.

Work Values

· **Working Conditions (reverse):** Occupations that satisfy this work value offer job security and good working conditions.

· **Achievement (reverse):** Occupations that satisfy this work value are results oriented and allow employees to use their strongest abilities, giving them a feeling of accomplishment.

· **Relationships (reverse):** Occupations that satisfy this work value allow employees to provide service to others and work with co-workers in a friendly non-competitive environment.

I follow Acemoglu and Autor (2011) methodology to construct my occupation's child labor intensity index. In a first step, I collapse O*NET occupational classification system into SOC occupations. Then, in a second step, I standardize each importance measure to have zero mean and standard deviation one using occupation employment weights from the 2015 Occupational Employment Statistics (OES) Survey. The occupation's child labor intensity index is equal to the summation of all the 15 standardized indicators. Lastly, I calculate the industry measure of child labor intensity as the weighted average of the occupation's child labor index in a 4-digit NAICS industry using occupation employment weights. The higher the child labor intensity index, the more child labor intensive an occupation or industry is. I label this variable O*NET industry child labor intensity index. Tables 1.1 and 1.2 present the ten most and ten least child labor intensive occupations and industries in the sample. Table 1.1 shows that the intensity of child labor content is highest in production and operative occupations that are specialized in routine and repetitive manual tasks, that do not involve frequent decision making and that have low levels of satisfying work environments. Table 1.2 shows that the most child labor intensive industries are also the most unskilled labor intensive manufacturing industries like textile mills, footwear manufacturing, etc. My ranking of industries in terms of child labor intensity is similar to Costinot et al. (2011) ranking in terms of a task routineness index. Even though both measures capture in a similar way the intensity of routine tasks content in occupations, both indexes are substantially different as the child labor intensity index captures manual and social task components of child labor occupations that are not measured in the routineness index. The main caveat to the interpretation of my results is the concern that my child labor intensity index is an imperfect proxy for an industry's intensity in child labor. Child labor is an imperfect substitute for unskilled adult labor, so the child labor intensity index may be capturing the effect of unskilled labor intensity rather than the effect of child labor intensity. Therefore, the estimates should be interpreted with caution since other mechanisms could lead to a negative relationship between intra-firm trade and the child labor intensity index. A second important caveat of my analysis is the assumption that these measures are constant over time. If this were not the case then my estimates would be biased due to omitted time varying factors. However, a priori, the direction of the bias is not predictable.

Table 1.1 : Ranking of Fifteen Most and Fifteen Least Child Labor Intensive Occupations. ONET Child Labor Intensity Index

	Top Fifteen Occupations	Occupation's Child Labor Intensity Index
1	Tire Builders	26.3
2	Textile Knitting and Weaving Machine Setters, Operators, and Tenders	20.3
3	Cutting and Slicing Machine Setters, Operators, and Tenders	19.9
4	Foundry Mold and Coremakers	19.7
5	Cutters and Trimmers, Hand	19.4
6	Tool Grinders, Filers, and Sharpeners	19.3
7	Coil Winders, Tapers, and Finishers	19.3
8	Painting, Coating, and Decorating Workers	19.3
9	Grinding and Polishing Workers, Hand	19.2
10	Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and	19.2
11	Shoe Machine Operators and Tenders	19.0
12	Helpers–Production Workers	18.7
13	Pourers and Casters, Metal	18.7
14	Roof Bolters, Mining	18.6
15	Adhesive Bonding Machine Operators and Tenders	18.6
	Bottom Fifteen Occupations	
1	English Language and Literature Teachers, Postsecondary	-25.2
2	Management Analysts	-24.9
3	Arbitrators, Mediators, and Conciliators	-24.8
4	Labor Relations Specialists	-24.5
5	Psychiatrists	-24.0
6	Clinical, Counseling, and School Psychologists	-23.4
7	Political Science Teachers, Postsecondary	-23.3
8	Directors, Religious Activities and Education	-23.0
9	Healthcare Social Workers	-22.8
10	Law Teachers, Postsecondary	-22.8
11	Genetic Counselors	-22.4
12	Industrial-Organizational Psychologists	-22.4
13	Marriage and Family Therapists	-22.4
14	Fundraisers	-22.4
15	Psychology Teachers, Postsecondary	-22.1

Table 1.2 : Ranking of Fifteen Most and Fifteen Least Child Labor Intensive Industries. ONET Child Labor Intensity Index

	Top Fifteen Industries	Industry's Child Labor Intensity Index
1	Fiber, Yarn, and Thread Mills	14.10
2	Apparel Knitting Mills	12.09
3	Animal Slaughtering and Processing	12.05
4	Fabric Mills	11.36
5	Postal Service (federal government)	11.31
6	Rubber Product Manufacturing	11.01
7	Support Activities for Crop Production	10.86
8	Motor Vehicle Manufacturing	10.78
9	Textile Furnishings Mills	10.61
10	Sawmills and Wood Preservation	10.57
11	Foundries	10.49
12	Logging	10.41
13	Footwear Manufacturing	10.30
14	Veneer, Plywood, and Engineered Wood Product Manufacturing	10.08
15	Seafood Product Preparation and Packaging	10.06
	Bottom Fifteen Industries	
1	Securities and Commodity Exchanges	-12.64
2	Securities and Commodity Contracts Intermediation and Brokerage	-11.10
3	Other Financial Investment Activities	-10.79
4	Elementary and Secondary Schools	-10.61
5	Grantmaking and Giving Services	-10.52
6	Junior Colleges	-10.16
7	Other Investment Pools and Funds	-9.97
8	Educational Support Services	-9.90
9	Management, Scientific, and Technical Consulting Services	-9.85
10	Monetary Authorities-Central Bank	-9.78
11	Colleges, Universities, and Professional Schools	-9.16
12	Business, Professional, Labor, Political, and Similar Organizations	-9.13
13	Software Publishers	-9.09
14	Business Schools and Computer and Management Training	-9.09
15	Agents and Managers for Artists, Athletes, Entertainers, and Other Public F	-9.06

To exploit cross-country variation in the goods produced by child labor, I construct a second measure of child labor intensity using data from ILAB's report. Goods are included in the report if there is credible evidence that child or forced labor was used in their production. If child labor or forced labor was used in both the production of raw materials or component articles and manufacture of final goods, both raw materials and final goods are included in the list. To construct this measure, I match for each country, their goods listed in ILAB's report to a 6-digit NAICS product code that identifies the manufacture of the good. For example, the good "soccer ball" is matched to 339920 6-digit NAICS product code "Balls, baseball, basketball, football, golf, tennis, pool, and bowling, manufacturing". Goods produced by child or forced labor are identified by an indicator variable equal to one if the good is listed in the report. Then, I calculate the country-industry measure of child labor intensity as the weighted average of the indicator variable in a 4-digit NAICS industry using occupation employment weights. The index ranges from 0 to 1, with a higher value indicating higher levels of child labor intensity. I label this variable ILAB child labor intensity index.

Table 1.3 shows the ranking of industries by child labor intensity. Similar to the ONET ranking the most child labor intensive industries are manufacturing industries like textile mills, footwear manufacturing, etc.

Table 1.3 : Ranking of Fifteen Most and Fifteen Least Child Labor Intensive Industries. ILAB Child Labor Intensity Index

	Top Fifteen Industries	Industry's Child Labor Intensity Index
1	Household and Institutional Furniture and Kitchen Cabinet Manufacturing	1
2	Cut and Sew Apparel Manufacturing	1
3	Apparel Accessories and Other Apparel Manufacturing	1
4	Coal Mining	1
5	Textile and Fabric Finishing and Fabric Coating Mills	1
6	Footwear Manufacturing	1
7	Hardware Manufacturing	1
8	Office Furniture (including Fixtures) Manufacturing	1
9	Leather and Hide Tanning and Finishing	1
10	Other Leather and Allied Product Manufacturing	1
11	Support Activities for Animal Production	1
12	Glass and Glass Product Manufacturing	1
13	Apparel Knitting Mills	1
14	Fabric Mills	0.66
15	Animal Slaughtering and Processing	0.5
	Bottom Fifteen Industries	
1	Clay Product and Refractory Manufacturing	0.25
2	Computer and Peripheral Equipment Manufacturing	0.25
3	Other Textile Product Mills	0.2
4	Cement and Concrete Product Manufacturing	0.2
5	Other Chemical Product and Preparation Manufacturing	0.2
6	Other Miscellaneous Manufacturing	0.16
7	Support Activities for Crop Production	0.16
8	Commercial and Service Industry Machinery Manufacturing	0.16
9	Metal Ore Mining	0.14
10	Other Wood Product Manufacturing	0.14
11	Nonferrous Metal (except Aluminum) Production and Processing	0.14
12	Other Food Manufacturing	0.12
13	Grain and Oilseed Milling	0.12
14	Foundation, Structure, and Building Exterior Contractors	0.12
15	Basic Chemical Manufacturing	0.09

B. *Constructing a country-year measure of child labor in the media*

I measure country's media exposure against child labor as the number of articles on "child labor" that are from the country and appeared in major news, web, and social media between 1999 and 2014. I replace missing values by zero. The data were obtained from Factiva website using the *Factiva Free Text Search Tool* to download document counts.

The search included the following filters: Free Text: "child labor"; Search for free-text terms in: Title and Lead Paragraph; Source: All Sources; Date: 19990101 to 20141231; Company: All Companies; Subject: All Subjects; Industry: All Industries; Region: All Regions; Language: English;

C. *Other data and their sources*

Prevalence of child labor in the exporting country

To measure the prevalence of child labor in the exporting country over time, I use the natural log of country's *Percentage of children ages 7-14 in employment in all economic sectors and in major industrial sectors*, *Percentage of primary-school-age children who are not enrolled in primary or secondary school* and *Percentage of primary-school-age children out of school* calculated as 1 minus the enrollment rate from the World Bank Development Indicators (World Bank, 2017). For countries classified as High Income by the World Bank, I replaced missing values with zero.

Intra-firm and total trade

Data on intra-firm and total trade are from the U.S. Census Bureau Related Party Database. The trade data are at the 6-digit NAICS level for years 1999 to 2014. Each shipment imported into the United States is accompanied by a form which asks about the value of the shipment, the 10-digit Harmonized System code and whether or not the transaction is with a related party i.e., whether or not the transaction is intra-firm or at arm's length. Imports are classified as intra-firm if one of the parties owns at least 6% of the other. These data is reported at the two through six-digit HS and NAICS codes. My key dependent variable is intra-firm imports as a share of total U.S. imports.

Capital intensity and skill intensity

Capital and skill intensities are constructed using data from the U.S. Census Bureau's *Annual Survey of Manufactures* for the years 1999 to 2014. As previously discussed, I use U.S. factor intensities, assuming that they are correlated with factor intensities of production in exporting countries. For each 6-digit NAICS industry I collect information on annual capital expenditures, wages of production workers and non-production workers. Capital intensity $\frac{K_i}{L_i}$ is measured as the natural log of capital expenditures divided by all worker wages. Skill intensity $\frac{S_i}{L_i}$ is the log ratio of non-production worker wages to total worker wages.

Income per capita

Income per capita is measured as the natural logarithm of gross domestic product in current U.S. dollars per person. Data were taken from the World Bank World Development Indicators (World Bank, 2017).

Signataries of ILO 138 Convention

Using data from ILO's Ratification of C138- Minimum Age Convention, 1973 (No.138) database, I construct an indicator variable equal to one if a country signed the 138 convention or if it is classified as High Income by the World Bank, and zero otherwise.

Table 1.4 shows the correlations for all of the variables described previously.

Table 1.4 : Relationship between Industry Characteristics

	ln (ILAB Child Labor Intensity)	ONET Child Labor Intensity	ln (GDP per capita)	ln (K/L)	ln (S/L)
ln (ILAB Child Labor Intensity)	1				
ONET Child Labor Intensity	0.0676*	1			
ln (GDP per capita)	-0.0854*	-0.0048	1		
ln (K/L)	-0.0888*	-0.0619*	0.0261*	1	
ln (S/L)	-0.0397*	-0.8512*	-0.0026	-0.0898*	1

Correlation coefficients are reported. * indicates significance at the 1 percent level.

4. Estimation Results

Estimates of equation (1) using the ONET industry-level child labor intensity measure are reported in Table 1.5 as well as its standard error clustered at the 4-digit NAICS industry level. The first column reports estimates of (1) with year and country fixed effects only. The estimated coefficient for the child labor intensity index is negative and statistically significant, a result that supports the hypothesis that more child labor intensive industries have a lower share of intra-firm trade. Because I report standardized beta coefficients, one can compare the relative magnitudes of the child labor intensity index with the capital and skill variables. According to the estimates, a one standard deviation increase in child labor intensity results in a 0.168 standard deviation decrease in the share of intra-firm trade. The results on the effect of capital intensity are positive, statistically significant and consistent with the findings of Antràs (2003) and Nunn and Trefler (2008, 2013). On the other hand, the estimated coefficient of skill intensity is negative and statistically insignificant. The lack of significance of the skill intensity coefficient may be explained by the fact that the child labor intensity index is highly negatively correlated with industries' skill intensity. Lastly, GDP per capita is statistically significant and positively correlated with the share of intra-firm trade.

As previously discussed, I test for heterogeneous effects and control for other determinants of intra-firm trade that, if omitted, may bias my estimates. I control for the importance of economic development by including an interaction of the log of each exporting country's GDP per capita with each industry's child labor intensity. This interaction controls for the possibility that low income countries specialize in child labor intensive products. I also control for the importance of country's skill abundance by including an interaction of the child labor intensity index with the exporting country's share of children age 7-14 years in employment and percentage of primary-school-age children who are not enrolled in primary or secondary school. These interactions capture the notion that child labor incidence is lower in countries with greater skill abundance. One ought to be cautious in interpreting the results as the main problem with this data is the lack of long panel data and gaps in the time series. Motivated by recent news that multinationals use child labor, I include an interaction between the child labor intensity index and the contemporaneous and one year lag of the log of the number of articles about child labor that are from the exporting country. These interactions measure the effect of country's media exposure against child labor on intra-firm trade. Lastly, I include an interaction between the child labor intensity index and an indicator variable for whether the exporting country signed the ILO child labor convention 138 on the minimum age of employment. This control variable captures the effect of country's compliance with child labor laws.

Table 1.5 : The determinants of intra-firm trade. ONET Child Labor Intensity

Dependent Variable :	Share of U.S. intra-firm imports								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ONET Child Labor Intensity	-0.168***	-0.152*	-0.173**	-0.167**	-0.186***	-0.146**	-0.178***	-0.178***	-0.168***
	(0.00416)	(0.00655)	(0.00510)	(0.00509)	(0.00407)	(0.00424)	(0.00454)	(0.00458)	(0.00366)
Capital Intensity	0.0382*	0.0383*	0.0527**	0.0554**	0.0380*	0.0457**	0.0369	0.0372	0.0244
	(0.0109)	(0.0109)	(0.0118)	(0.0120)	(0.0109)	(0.0107)	(0.0110)	(0.0110)	(0.0121)
Skill Intensity	-0.0136	-0.0137	-0.0122	-0.0106	-0.0136	-0.0183	-0.0164	-0.0157	-0.00888
	(0.0578)	(0.0579)	(0.0704)	(0.0713)	(0.0578)	(0.0600)	(0.0608)	(0.0608)	(0.0517)
GDP per capita	0.179***	0.182***	0.189***	0.136***	0.179***	0.162***	0.152***	0.148***	0.160***
	(0.0107)	(0.0116)	(0.0163)	(0.0170)	(0.0107)	(0.0113)	(0.0131)	(0.0130)	(0.0119)
GDP per capita * ONET Child Labor Intensity		-0.0164							
		(0.000679)							
Log Children in employment, total * ONET Child Labor Intensity			0.0225						
			(0.00879)						
Log Children in employment, total			-0.00932						
			(0.0834)						
Log Child employment in manufacturing * ONET Child Labor Intensity				-0.000430					
				(0.0170)					
Log Child employment in manufacturing				0.00564					
				(0.173)					
ILO Indicator * ONET Child Labor Intensity					0.0246**				
					(0.000795)				
ILO Indicator					-0.00667				
					(0.00708)				
Log No. Articles in t * ONET Child Labor Intensity						-0.0447***			
						(0.000293)			
Log No. Articles in t-1 * ONET Child Labor Intensity						-0.0405***			
						(0.000283)			
Log No. Articles in t						0.0402***			
						(0.00211)			
Log No. Articles in t-1						0.0345***			
						(0.00234)			
Log not enrolled in school * ONET Child Labor Intensity							0.0155		
							(0.000416)		
Log not enrolled in school							-0.0167		
							(0.000422)		
Log out of school * ONET Child Labor Intensity								0.0249	
								(0.000493)	
Log out of school								-0.0329*	
								(0.00384)	
Observations	153,438	153,438	74,318	70,530	153,438	133,374	105,669	105,329	86,713
R-squared	0.181	0.181	0.209	0.211	0.181	0.201	0.199	0.197	0.109
P-value of F-test for joint significance of interaction terms	0.00355	5.74e-05	0.249	0.906	0.0193	3.01e-08	0.286	0.140	0.00143
# Clusters	85	85	85	85	85	85	85	85	85

The dependent variable is the share of intra firm imports. An observation is a NAICS4-country pair. Standardized 'beta' coefficients are reported.
Standard errors clustered at the 4-digit NAICS industry level appear in parenthesis. All regressions include Country and Year Fixed Effects.
*** p<0.01, ** p<0.05, * p<0.1

The results with the set of interactions are reported in columns 2 to 8. In all the specifications, the child labor intensity estimate remains statistically significant and negative. The estimates for capital intensity are positive and marginally significant in the majority of cases, while the estimates for skill intensity are not statistically different from zero. Nevertheless, only the interaction terms with the ILO indicator variable and the lags of number of articles about child labor have a statistically significant effect on intra-firm trade. An F-test for the joint significance of the interaction is able to reject the null hypothesis that the terms are jointly equal to zero.[5] The positive coefficient of the ILO interaction indicates that the negative effect of child labor intensity on intra-firm trade is stronger for countries that have not signed on to the ILO 138 convention.[6] Furthermore, all the media exposure interactions appear with the expected sign and are statistically significant. These findings are consistent with accounts that multinationals outsource more of their child labor intensive production when media exposure against child labor is higher. Puzzingly, the main effects of the media exposure controls are positive and significant, suggesting that the overall effect of media exposure on intra-firm trade is positive. In column 9, I check the robustness of my estimates to the use of an alternative sample that excludes high income exporters. The child labor intensity index is negative, significant and of similar magnitude to previous estimates, however the coefficients for capital and skill intensity are statistically insignificant. Lastly, I explore the robustness of the results to alternative specifications that include interactions of the child labor intensity index with the capital and skill intensity variables. The results using these alternative specifications, which I report in Appendix Table A1 for brevity, are qualitatively identical to the estimates from my baseline equation. Overall, the results provide suggestive evidence of the importance of child labor intensity on intra-firm trade.

As discussed earlier, a major concern is that the ONET child labor intensity index is picking up the effects of unskilled labor intensity. If this is the case, then the previous evidence is in line with the findings of Costinot et al. (2011) showing that more routine industries have a lower share of intra-firm trade, as unskilled labor specializes in routine tasks. To address this concern, I construct an alternative measure of child labor intensity based on ILAB's report that directly identifies the countries and industries where there is evidence of child labor. The main caveat about the use of this variable is the concern that industry's child labor intensity is not constant over time. In this case, the Fixed Effects estimates would be biased due to omitted factors that vary simultaneously by country, industry and time, although, it is not clear how this could

[5] Note that the estimates in columns 3, 4, and 7 are imprecisely estimated due to the lack of inter-temporal variation and limited availability of child labor data for all countries. Also these estimates may be biased due to measurement error if these controls are imperfect proxies of skill endowment.

[6] Although not reported here the results are similar if I consider a one year delayed effect after a country signed the ILO convention.

bias the results. With this caveat in mind, I estimate equation (1) using the log of ILAB country-industry child labor intensity index. The results are reported in Table 1.6. The first column estimates (1) with only the year and country fixed effects included. The coefficient on the child labor intensity index is negative and statistically significant, which means that a one standard deviation increase in child labor intensity results in a 0.021 standard deviation decrease in the share of intra-firm trade. Note that the magnitude of the coefficient is significantly smaller than the one obtained with the ONET child labor intensity index. The estimated coefficients for capital and skill intensity are positive and significant, so these results are consistent with the findings of Nunn and Trefler (2008, 2013). Columns 2 to 8 report the results with the set of control interactions. The estimated relationship between child labor intensity and intra-firm trade is generally negative and small in magnitude, however only the coefficients for columns 5-8 are statistically significant. In all the specifications but column 2 and 6, the F-test of joint significance of the interaction terms does not reject the null hypothesis that the interaction controls are jointly equal to zero. These results indicate that the set of country's skill endowment interactions do not properly identify heterogeneous impacts which may underlie the child labor intensity average effect on intra-firm trade. Similar to the previous estimates, the results of column 6 show that the estimated effect of child labor intensity is stronger when media attention is high. Finally, in column 9 I obtain larger effects of child labor intensity if I restrict my sample to only exclude high income countries. As I show in Appendix Table A2 the findings are qualitative identical to my baseline results if I include the interactions of the child labor intensity index with capital and skill intensity controls. In contrast to the results based on the ONET child labor intensity measure, these estimates provide more robust evidence on the negative relationship between child labor intensity and intra-firm trade.

As a final check, I test the robustness of my baseline results in a cross section regression for year 2014. The benefit of this strategy is that I am able to overcome data limitations such as the sparsity of control variables and limited availability of data that could bias my estimates. Additionally, by using the most recent cross-country data my identification strategy does not rely on the assumption that industry's child labor intensity measures are constant across time. An important caveat is that these estimates could be biased and inconsistent as a result of omitting unobservable country specific variables. The results are reported in Tables 1.7 and 1.8. Although the sign of the ONET child labor intensity coefficient is negative, its estimated effect is not different from zero in the majority of cases. This indicates that in the cross section the negative relationship between the ONET child labor intensity and intra-firm trade is weakened substantially. On the other hand, when I use the ILAB child labor intensity index, the results are stronger and show similar patterns to my baseline results. Two patterns in particular stand out. First, when country's skill endowment

Table 1.6 : The determinants of intra-firm trade. ILAB Child Labor Intensity

Dependent Variable :	Share of U.S. intra-firm imports								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ILAB Child Labor Intensity	-0.0210***	0.0555	-0.0137	-0.000929	-0.0208***	-0.0182*	-0.0215**	-0.0229**	-0.0318***
	(0.0332)	(0.158)	(0.0622)	(0.0611)	(0.0334)	(0.0458)	(0.0506)	(0.0444)	(0.0338)
Capital Intensity	0.0598**	0.0597**	0.0760***	0.0787***	0.0598**	0.0675***	0.0590**	0.0591**	0.0437
	(0.0118)	(0.0118)	(0.0124)	(0.0125)	(0.0118)	(0.0116)	(0.0117)	(0.0117)	(0.0132)
Skill Intensity	0.132***	0.132***	0.135***	0.135***	0.132***	0.133***	0.132***	0.132***	0.137***
	(0.0295)	(0.0295)	(0.0345)	(0.0353)	(0.0295)	(0.0309)	(0.0300)	(0.0299)	(0.0277)
GDP per capita	0.181***	0.184***	0.189***	0.136***	0.181***	0.167***	0.152***	0.152***	0.163***
	(0.0106)	(0.0106)	(0.0164)	(0.0171)	(0.0106)	(0.0112)	(0.0131)	(0.0130)	(0.0118)
GDP per capita * ILAB Child Labor Intensity		-0.0766**							
		(0.0200)							
Log Children in employment, total * ILAB Child Labor Intensity			0.00173						
			(0.247)						
Log Children in employment, total			0.00918						
			(0.0524)						
Log Child employment in manufacturing * ILAB Child Labor Intensity				-0.0104*					
				(0.397)					
Log Child employment in manufacturing				0.00917					
				(0.126)					
ILO Indicator * ILAB Child Labor Intensity					-0.000284				
					(0.0401)				
ILO Indicator					0.00707				
					(0.00399)				
Log No. Articles in t * ILAB Child Labor Intensity						0.00394			
						(0.0108)			
Log No. Articles in t-1 * ILAB Child Labor Intensity						-0.00865*			
						(0.0113)			
Log No. Articles in t						0.00350			
						(0.00107)			
Log No. Articles in t-1						0.00222			
						(0.00105)			
Log not enrolled in school * ILAB Child Labor Intensity							-0.000534		
							(0.0162)		
Log not enrolled in school							-0.00927		
							(0.00160)		
Log out of school * ILAB Child Labor Intensity								0.00133	
								(0.0106)	
Log out of school								-0.0124*	
								(0.00145)	
Observations	153,438	153,438	74,318	70,530	153,438	133,374	105,669	105,329	86,713
R-squared	0.174	0.174	0.202	0.204	0.174	0.192	0.192	0.190	0.104
P-value of F-test for joint significance of interaction terms	0.00379	7.08e-06	0.663	0.169	0.360	0.00241	0.446	0.232	0.00124
# Clusters	85	85	85	85	85	85	85	85	85

The dependent variable is the share of intra firm imports. An observation is a NAICS4-country pair. Standardized 'beta' coefficients are reported.
Standard errors clustered at the 4-digit NAICS industry level appear in parenthesis. All regressions include Country and Year Fixed Effects.
*** p<0.01, ** p<0.05, * p<0.1

interactions are included, the effect of child labor intensity is ambiguous, indicating that the relationship between child labor intensity and intra-firm trade is influenced by the level of skill endowment. In columns 8 and 9 the main effect of child labor intensity is negative and significant, and the F-test of joint significance of the interaction terms shows that the set of control interactions is significant. Also, the estimated coefficient of the level of skill endowment is negative and significant. Moreover, in columns 4 and 5 the estimated coefficient of child labor intensity is significant, and positive. These results should be interpreted cautiously as the estimates could be biased due to omission of unobservable country characteristics. Second, the estimates of the child labor intensity index remain stable and significant when controlling for country fixed effects, the level of GDP per capita, and when excluding high income countries. Similarly, the main effect of child labor intensity is negative and significant when controlling for whether countries signed the ILO convention. Taken together, the evidence suggests that child labor intensity is associated with a lower level of intra-firm trade. [7]

[7] Even though I do not report them here, I find that the estimated coefficients for alternative specifications that include interactions of the child labor intensity index with the capital and skill intensity variables are generally similar to my baseline estimates. The estimates are available upon request.

Table 1.7 : The determinants of intra-firm trade. ONET Child Labor Intensity, Restricted Sample 2014

Dependent Variable :	Share of U.S. intra-firm imports									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ONET Child Labor Intensity	-0.0882	-0.100	-0.267**	-0.0788	-0.0689	-0.131*	-0.0481	-0.116	-0.109	-0.0932
	(0.00519)	(0.00542)	(0.0103)	(0.00617)	(0.00626)	(0.00540)	(0.00558)	(0.00658)	(0.00630)	(0.00479)
Capital Intensity	0.0580**	0.0574*	0.0573*	0.115***	0.120***	0.0579**	0.0685**	0.0617**	0.0606**	0.0202
	(0.0130)	(0.0133)	(0.0133)	(0.0116)	(0.0116)	(0.0133)	(0.0133)	(0.0140)	(0.0140)	(0.0141)
Skill Intensity	0.0564	0.0299	0.0317	0.0455	0.0498	0.0303	0.0371	0.0400	0.0417	0.0530
	(0.0869)	(0.0894)	(0.0890)	(0.0999)	(0.101)	(0.0894)	(0.0942)	(0.0973)	(0.0973)	(0.0803)
GDP per capita		0.172***	0.142***	0.0523**	0.109***	0.176***	0.188***	0.113***	0.0843***	
		(0.00391)	(0.00782)	(0.0122)	(0.0107)	(0.00398)	(0.00439)	(0.00482)	(0.00492)	
GDP per capita * ONET Child Labor Intensity			0.173							
			(0.000939)							
Log Children in employment, total * ONET Child Labor Intensity				0.103***						
				(0.0180)						
Log Children in employment, total				-0.231***						
				(0.162)						
Log Child employment in manufacturing * ONET Child Labor Intensity					0.0585*					
					(0.0473)					
Log Child employment in manufacturing					-0.0819**					
					(0.403)					
ILO Indicator * ONET Child Labor Intensity						0.0347				
						(0.00237)				
ILO Indicator						-0.0397***				
						(0.0199)				
Log No. Articles in t * ONET Child Labor Intensity							-0.0552**			
							(0.000820)			
Log No. Articles in t-1 * ONET Child Labor Intensity							-0.0980***			
							(0.000737)			
Log No. Articles in t							0.0731***			
							(0.00658)			
Log No. Articles in t-1							0.115***			
							(0.00621)			
Log not enrolled in school * ONET Child Labor Intensity								0.0379		
								(0.000869)		
Log not enrolled in school								-0.187***		
								(0.00683)		
Log out of school * ONET Child Labor Intensity									0.0374	
									(0.000723)	
Log out of school									-0.222***	
									(0.00575)	
Observations	9,779	9,265	9,265	4,179	4,085	9,243	8,013	6,269	6,269	5,676
R-squared	0.191	0.046	0.047	0.056	0.038	0.047	0.062	0.074	0.080	0.157
P-value F test Interaction terms	0.187	0.153	0	0	0.0489	0.00570	2.07e-10	0	0	
# Clusters	85	85	85	85	85	85	85	85	85	85

The dependent variable is the share of intra firm imports. An observation is a NAICS4-country pair for year 2014. Standardized 'beta' coefficients are reported.
Standard errors clustered at the 4-digit NAICS industry level appear in parenthesis. Only regression 1 includes Country Fixed Effects.
*** p<0.01, ** p<0.05, * p<0.1

Table 1.8 : The determinants of intra-firm trade. ILAB Child Labor Intensity, Restricted Sample 2014

Dependent Variable :	Share of U.S. intra-firm imports									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ILAB Child Labor Intensity	-0.0218**	-0.0149*	-0.0341	0.0164**	0.0161**	-0.0292*	-0.0148	-0.0407**	-0.0366***	-0.0358***
	(0.0517)	(0.0405)	(0.473)	(0.115)	(0.122)	(0.0716)	(0.0928)	(0.115)	(0.0759)	(0.0508)
Capital Intensity	0.0714***	0.0736***	0.0736***	0.126***	0.131***	0.0737***	0.0830***	0.0767***	0.0754***	0.0321
	(0.0120)	(0.0124)	(0.0124)	(0.0112)	(0.0109)	(0.0124)	(0.0125)	(0.0127)	(0.0127)	(0.0129)
Skill Intensity	0.138***	0.123***	0.123***	0.103***	0.106***	0.123***	0.131***	0.129***	0.130***	0.137***
	(0.0306)	(0.0321)	(0.0321)	(0.0385)	(0.0391)	(0.0322)	(0.0346)	(0.0351)	(0.0351)	(0.0282)
GDP per capita		0.172***	0.172***	0.0535**	0.109***	0.176***	0.189***	0.113***	0.0837***	
		(0.00408)	(0.00409)	(0.0123)	(0.0107)	(0.00415)	(0.00458)	(0.00485)	(0.00494)	
GDP per capita * ILAB Child Labor Intensity			0.0193							
			(0.0531)							
Log Children in employment, total * ILAB Child Labor Intensity				-0.0134**						
				(1.462)						
Log Children in employment, total				-0.143***						
				(0.130)						
Log Child employment in manufacturing * ILAB Child Labor Intensity					0.00273					
					(7.654)					
Log Child employment in manufacturing					-0.0321					
					(0.246)					
ILO Indicator * ILAB Child Labor Intensity						0.0128				
						(0.0944)				
ILO Indicator						-0.0312***				
						(0.0123)				
Log No. Articles in t * ILAB Child Labor Intensity							0.0262*			
							(0.0223)			
Log No. Articles in t-1 * ILAB Child Labor Intensity							-0.0400			
							(0.0498)			
Log No. Articles in t							0.0304**			
							(0.00355)			
Log No. Articles in t-1							0.0401***			
							(0.00411)			
Log not enrolled in school * ILAB Child Labor Intensity								0.0240		
								(0.0522)		
Log not enrolled in school								-0.160***		
								(0.00341)		
Log out of school * ILAB Child Labor Intensity									0.0195*	
									(0.0364)	
Log out of school									-0.193***	
									(0.00303)	
Observations	9,779	9,265	9,265	4,179	4,085	9,243	8,013	6,269	6,269	5,676
R-squared	0.190	0.045	0.045	0.053	0.037	0.046	0.057	0.073	0.079	0.157
P-value F test Interaction terms	0.0344	0.0770	0	8.18e-11	0.279	0.00327	2.54e-05	0	0	0
# Clusters	85	85	85	85	85	85	85	85	85	85

The dependent variable is the share of intra firm imports. An observation is a NAICS4-country pair for year 2014. Standardized 'beta' coefficients are reported.
Standard errors clustered at the 4-digit NAICS industry level appear in parenthesis. Only regression 1 includes Country Fixed Effects.
*** p<0.01, ** p<0.05, * p<0.1

5. Conclusions

I have examined the relationship between industry's child labor intensity and intra-firm trade, and despite the data limitations, I find suggestive evidence consistent with the hypothesis that child labor is a determinant of intra-firm trade. According to my estimates, less child labor intensive industries have a lower share of intra-firm trade. This results is generally robust to the inclusion of other determinants of intra-firm trade. In addition, I examine potential heterogeneous effects of industry's child labor intensity, and I find that there is suggestive evidence of differential effects on countries with higher incidence and media exposure of child labor. I also find larger effects of child labor intensity when restricting the sample to exclude high income countries.

My results contribute to the literature on the determinants of intra-firm trade by showing the role of child labor in determining intra-firm trade. Likewise, my findings complement the studies that examine the relationship between trade and child labor. The results presented here suggest directions for future research. The first, is to collect time series of industry-level child labor data that is necessary for constructing better measures of industry's child labor intensity measures. The main empirical challenge is how to measure child labor at the industry or country level due to the limited availability of data. Thus, the main contribution of this study is to overcome this problem by constructing new measures of child labor intensity. The second, is to address the potential endogeneity of the child labor intensity measure that could bias the estimates. Lastly, it is necessary to employ new identification strategies to examine the causal mechanisms underlying the relationship between child labor and intra-firm trade.

Chapter 2. Uncertainty and Investment: Evidence from the East India Company Shipping

1. Introduction

There is a considerable body of research that shows the negative effect of uncertainty on investment. However, there is little historical evidence that supports the predictions of theoretical models that firms are more likely to delay investments when uncertainty increases. Government changes, political instability and economic shocks are some of the risks that firms face when they make investment decisions. For instance, elections can create uncertainty about future policies which can affect firm's expected returns to investing. This paper examines the effect of uncertainty on the English East India Company's voyage investment over a 138-year period in which the Company faced substantial political and economic risks.

The English East India Company (or EIC) was founded in 1601 and operated until 1858. The Company was granted a monopoly over all trade between England and Asia in return for the payment of customs duties or taxes. For instance, several English monarchs forced the EIC to lend and pay additional taxes in return of the Company's charter renewal. Its business required large investments to send trading voyages to Asia and sustain an organizational structure in England, China and India. The EIC later became what Stern (2011) calls a "Company-State", jointly controlling territory in India and servicing trade. It had a lasting impact by establishing British rule in India and by transforming markets and consumption in England.

The paper uses new series of EIC ship-level and stock price data from 1692 to 1833 to examine whether uncertainty, measured by the volatility of stock returns, had an effect on EIC's decision to send trading voyages to Asia. Financing of voyages required irreversible investments to get ships ready to depart, such as purchases of precious metals to settle accounts or funds to buy commodities. Thus, trading voyages provide a useful measure of EIC's investment. Departure of ships was potentially affected by multiple uncertainty shocks, however historic evidence suggests that news from Asia, operational disruptions, and political and economic shocks were the major sources of uncertainty faced by EIC's decision makers (Chaudhuri (1978)).

We restrict the analysis to the first stage of trade cycles, voyages from England to Asia, as we are interested in analyzing the role of European political and economic uncertainty shocks on the decision to sail.

The baseline empirical model is a panel data hazard model of survival time that regresses an indicator variable for ships that departed to Asia on stock return volatility, a survival time step function, and control variables that measure voyage performance. Our results show that higher levels of stock volatility decrease the probability of sending trading voyages to Asia. The baseline estimates suggest that average uncertainty decreases the probability of sailing by 4.76% . When we study extreme volatility events, mostly caused by political events, such as the imposition of additional duties on EIC's imports during the 1690s, we find that uncertainty decreases the probability of sailing in the range from 4% to 70%. We also find that arrival of ships and captain experience have a significant effect on the decision to sail. Lastly, we examine potential heterogeneous effects, and find that uncertainty has larger negative effects during the optimal sailing season of the Indian Ocean. We undertake sensitivity checks regarding the existence of confounding omitted factors and our results remain robust to the inclusion of additional controls and fixed effects. Overall, the estimates are consistent with the hypothesis that uncertainty delayed EIC's voyage investment.

This paper contributes to a number of literatures. First, by studying EIC's voyage investment, we provide evidence of the effect of uncertainty shocks on investment over a long time- span, so our study fills a gap in the literature on uncertainty and investment, as much of the pre-existing evidence analyzes short-run outcomes. [1] Our findings also add to studies on political stability, policy risk and investment by analyzing extreme volatility events, which were mostly caused by political instability. In studying trade cycles and the effect of measures of voyage performance on the decision to sail, our paper complements the literature on EIC's shipping.[2]

The paper is organized as follows. Section 2 provides background on the EIC's history and shipping . Sections 3 and 4 provide the data and empirical framework. Section 5 shows the estimation results and section 6 concludes.

[1] See Brandon and Yook (2012) and Baker, Bloom and Davis (2016) for a sample of works on policy uncertainty and investment.In addition, our study provides new empirical evidence supporting the theoretical predictions of the real options literature.

[2] See Chaudhuri (1978), Bogart (2016), and Solar (2013).

2. Background

A. *The Origins of the English East India Company*

The English East India Company was founded in 1600 through a charter granted by Queen Elizabeth and operated until 1858. Management was in the hands of a governor and a board of directors which were elected by shareholders. The Company was given a monopoly over all trade and traffic from the Cape of Good Hope to the Straits of Magellan. It was to last 15 years, except if the Company violated the provisions of the charter. In that case, the charter could be voided by the monarch with two years notice (Scott (1912)). The main business of the EIC in its early years was to import highly valued spices and textiles from the East Indies. The EIC sold some manufactured goods, but most of its export revenues came from New World silver, which was highly valued in the East. The EIC's charter was renegotiated several times in the seventeenth century. Notable renegotiation occurred in 1609, 1657, 1661, 1669, 1674, 1677, 1683, 1686, 1693, and 1694 (Scott (1912)). Some of these charters expanded the EIC's powers. For instance, the new charter of 1657 helped to reformulate the EIC as a joint stock company. Also, many of these renegotiations were accompanied by side payments or loans to the Monarch.

The English monarchy also leveraged threats by private traders known as interlopers. Interlopers petitioned to enter the EIC's market and thereby capture some of their profits. Interlopers offered loans or political support as bribes. In the end, the monarch usually sided with the EIC against the interlopers, but the process was often protracted and costly. The most famous interloper challenge came in the late 1690s. An interloper syndicate offered 2 million at 8% interest with the expectation that they would get the EIC's monopoly. As a result of this challenge, the Parliament authorized an act in 1698 that gave monopoly rights over the trade to this "New" East India Company as of September 1701. The Old Company began a lobbying campaign to reestablish its trading rights. In 1702, the monarch approved a merger between the New and Old Companies.

As illustrated by the episode with the "New" Company, Parliament was not always friendly to the interests of the EIC. The House of Commons made a famous declaration in 1694 that "all subjects of England have equal right to trade in the East Indies, unless prohibited by act of parliament" (see Tripta (1984)). As a consequence, Parliament was subsequently involved in all future renegotiation involving the EIC. Together the Monarchy and Parliament renegotiated the terms of the EIC's charter again in 1712, 1730, and 1740. In two cases (1730 and 1740), parliament helped to secured additional loans or payments from the EIC to the government.

During the 1770s there were more aggressive attacks on the EIC in Parliament. It followed from the EIC's acquisition of territorial revenues in Bengal during the 1760s, which led to new sources of revenue and abuse by Company officials. The first major Act of Parliament to regulate the EIC's management came in 1773. It created a Governing Council in India with 3 of the 5 members being appointed by Parliament, and the rest by the Company. The Regulating Act of 1773 did not alter the trading monopoly, but it required the EIC to pay £400,000 annually to the government. Also, there were further attacks on the EIC in Parliament during the 1780s, as a series of governments tried to extract financial concessions and gain control over the EIC. The monopoly over trade with India and China finally ended through an act of Parliament in 1813 and 1833, respectively . It was undone by several factors, most notably a free trade campaign led by industrialists in Liverpool and Manchester. There was also a change of government in 1812 which undermined the EIC's support in the House of Commons (Philips (1961), Bogart (2016)).

The EIC also had conficted relations with governments in India, one of its largest markets. The EIC operated under a different charter in India, first granted by the Mughal Emperor Jahangir in 1618. It required the EIC to make annual payments in lieu of custom duties and refrain from piracy in Indian coastal waters. In return the Emperor gave the EIC official recognition. Subsequent charters gave the EIC rights to build forts and forbade unauthorized extraction from Mughal officials throughout India. As it turned out, the Mughal emperor was unable to prevent local extraction. The EIC was regularly forced to pay extra duties when entering ports or traveling up rivers. Disputes with Indian governments continued to be a problem in the eighteenth century. The EIC tried to protect itself by expanding its naval power and building fortifications in Bombay, Madras, and Calcutta. In Madras, the EIC was successful in deterring further extraction (Chaudhuri (1978)). In Calcutta, military provocation aggravated relations with local rulers. By the 1750s the EIC was in open conflict with the Nawabs of Bengal, which famously led to their acquisition of territory. A similar set of events occurred near Bombay, where the EIC challenged the Marathas and other local powers and were ultimately successful in gaining political control (Watson (1980)).

Lastly, hostile relations with other European companies also posed a significant problem for the EIC in India. The Dutch and English companies had several naval battles in the Indian ocean during the 17th century. Later in the 1740s and 1750s the English and French companies fought a series of land and naval battles. While the English were ultimately victorious, conflicts were costly in terms of lost ships, resources, and trade.

B. ***The English East India Company Shipping***

The English East India Company shipping history can be divided into three periods. In the first period, from the creation of the Company to late seventeenth century, the EIC steadily expanded its shipping capacity in terms of number and tonnage of ships, reaching an all-time high in 1680. However, in the last decades of the seventeenth century, shipping and trade growth stagnated due to wars and political instability in Europe and Asia, such as the occurrence of the Mughal War and the Glorious Revolution. The second period, from early eighteenth century to 1750-1760, was a period of stability and growth for the EIC. The post-war boom in inter-continental trade and the experience gained in the management of shipping during wartime, helped the Company to establish its dominance in the Asian seas by mid-century. Improvements in the efficiency of turn-round periods, stability of shipping supply and peacetime allowed the Company to decrease unused tonnage capacity from wartime, so profitability of voyages increased due to reductions in freight and demurrage rates (Bruijn and Gaastra (1993)). Finally, in the last period from 1760 to 1833, new technical improvements in navigation and the construction of ships, such as copper sheathing increased the longevity and capacity of ships decreasing shipping costs (Solar (2013)). Even though cost reductions increased shipping profitability in the early nineteenth century , the Company experienced the loss of trade and shipping capacity due to the end of the India and China monopolies and the emergence of wars. Thus, the end of EIC's hegemony in Asia was at an end.

The East India Company's shipping and trading activities were organized with reference to voyage cycles between England and Asia. EIC's operations were divided into two main systems based in London and one based in Asia (Chaudhuri (1978), p.34). Of the two systems in London one dealt with the financial activities of the Company like issuing of stocks and raising new share capital , while the other system was in charge of shipping activities, imports and exports of goods, and sales of imported commodities. The system in Asia managed shipping operations, inter-factory traffic, and the administration of Asian settlements that included local trading, hiring of personnel, and defense activities. Each trade cycle involved a sequence of activities which required coordination between the three systems in order to ensure the correct functioning of the multinational trade network. A trade cycle was composed of the following main operational activities: raising of funds for voyage, purchasing and loading of commodities, acquisition and stocking of money for trading activities, shipping of commodities, trading of goods in Asia, purchasing and shipping of Asian commodities, and trading of goods in Europe (Chaudhuri (1978)).

The commercial success of the East India Company relied on the joint solution of two operational problems : 1) choose the optimal number of ships to charter, and 2) minimize ships' turn-round time. By solving these problems, the Company was able to maximize profits by ensuring a stable source of revenue and reducing its two main variable shipping costs: freight rates and demurrage. Freight rates were mostly determined by competition and shipping supply, so by choosing the optimal level of ships, the EIC was able to reduce the effect of supply shocks on freight rates. On the other hand, demurrage costs were largely determined by the operation of Asian factories, as disruptions in operations delayed the return of ships which incurred in charges of demurrage fees. The simultaneous solution to both problems was affected by another operational component, private trade, as captains and other crew members were allowed to engage in this practice in order to incentivize profit sharing and the expansion of EIC's operations.

Operational problems in any of the aforementioned systems affected the departure of voyages, however other external factors, such as weather (e.g. droughts, storms at sea), wars, changes in market conditions, and political instability in England and Asia also had a considerable effect on the decision to sail. Weather was an important determinant of departures , as seasonal weather conditions such as winds and rain restricted the sailing season to the months of January through May and June of each year. Solar (2013) shows that before 1820, most of EIC voyages were concentrated in the first six months of the year, but after 1820 departures were also occurring during the summer. Wars and changes in governments and policies, such as elections, charter renewals, etc., had a major effect in EIC's shipping decisions as most of these changes were exogenous to EIC's trade environment (Bogart (2016)). For instance, some monarchs would demand a loan or impose new taxes with the implicit threat they would renegotiate the EIC's charter if it did not go along (Bogart (2017)). To reduce uncertainty, the Company established an information network based in London aimed to provide a regular stream of information between Europe and Asia. The communication network provided to the Company's directors and managers information on the state of affairs in Asia that was key to monitor and correct any operational problems. In sum, departure of ships was potentially affected by multiple uncertainty shocks, however anecdotal and historical evidence suggest that weather, operational disruptions, and political and economic shocks were the major sources of uncertainty faced by EIC's decision makers (Chaudhuri (1978); Bogart (2017)).

EIC shipping activities required large physical and financial irreversible investments, such as capital to expand shipping capacity or fund voyages. Long-term physical capital was necessary to expand, protect and sustain operations, while financial investment was mainly used to finance short-term investments and voyages. Financing of voyages required investments to get vessels ready to depart to Asia, like funds to repair ships, purchase commodities, pay wages and freight rates, etc. Irreversibility of individual voyage investment arise because of two factors: 1) the investment was industry specific as it couldn't be used productively in another industry within the Company, and 2) uncertainty could make impossible for managers to send voyages (and reallocate capital), so the investment would be a sunk cost.[3] For a number of reasons we focus our attention on the first stage of trade cycles, the Company's decision to send individual voyages from England to Asia. The first reason is that voyages departing from England responded stronger to European uncertainty shocks than voyages departing from Asia as the Company's information network and decision making process was centralized in London. The second reason is to keep our model as simple as possible, as we restrict the analysis to the first half of the trade cycle that is unaffected by contemporaneous shocks in Asia. Our goal is to isolate the effects of contemporaneous shocks from Europe on the decision to sail.

3. Data

Our time period of interest spans the late seventeenth century to mid nineteenth century. Before proceeding with the empirical framework, we describe the data used in the analysis and present summary statistics and descriptive data of the evolution of EIC's shipping and the measure of uncertainty.

A. *Shipping Data*

Ship-level data are from Farrington (1999), which provides information for 1,474 ships and includes the voyages of each ship, ports of call, captain, dates of ship departure and arrival, crew size and tonnage when available. We construct a monthly recurrent event panel data for each ship starting in the second date of departure and ending in the date of the last voyage.[4] We exclude from the analysis the launch of ships as we don't have consistent data on the date when ships were built, so we are unable to determine the time of entry to the sample period. Thus, our sample is restricted to ships that have at least 2 voyages. In our panel, a ship is ready to depart when it arrived back in England, so the unit of observation is at the month-ship level. Our final sample is a panel of 2742 voyages and 781 ships between years 1692 to 1830. [5]

We present summary statistics on characteristics of EIC voyages to Asia such as number of operating ships, duration of voyages, number of captains per voyage, seasonality of departures, etc., as many of these factors are determinants of the decision to ship. Figures 2.1 and 2.2 present data on EIC's shipping capacity and number of ships. Both tonnage and number of ships exhibit an increasing trend with considerable

[3]The real options model of investment states that firms have the choice to invest or delay under uncertainty. The decision to delay allows investors to wait for new information about market conditions before committing resources, so increased uncertainty discourages investment. For more details see Pindyck (1991).

[4]We aggregated the shipping data to the monthly level in order to exploit the granularity of our stock price data.

[5]We dropped ships with missing dates of departure and arrival, and with inconsistent information that we were unable to correct.

fluctuations in some years. These trends continued until the end of the India monopoly in 1813 when shipping capacity started to decline. Figure 2.3 confirms the seasonality of voyages, as the majority of departures occurred from January to May, during the sailing season. Lastly, figure 2.4 plots the empirical survival function which shows that about 50 % of the voyages occurred before 14 months after arrival. This fact indicates that after arrival, ships were stationed in England for long periods of time before departing again. We exploit this variation in the timing of vessel departures to estimate the effect of uncertainty on the decision to sail.

Figure 2.1: East India Company Number of Ships

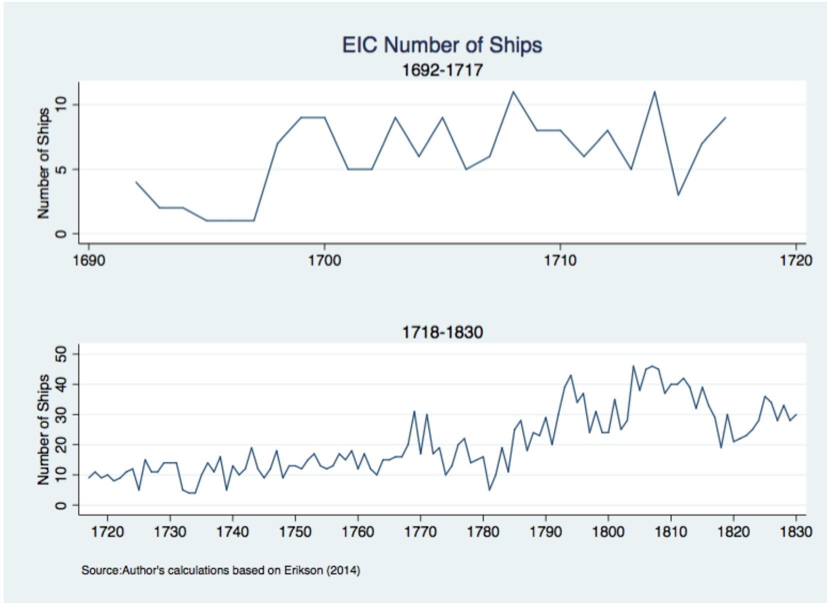


Figure 2.2: East India Company Log Tonnage

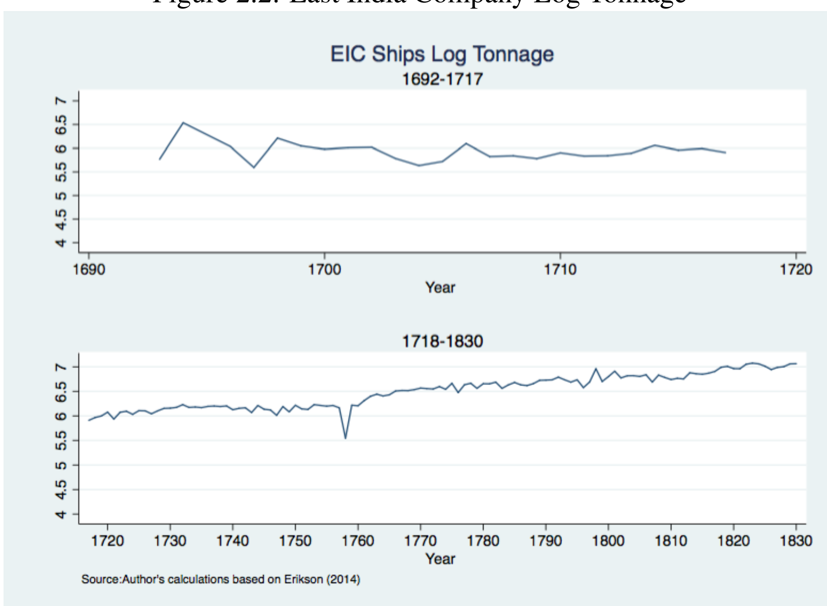


Figure 2.3: East India Company Seasonality of Voyages

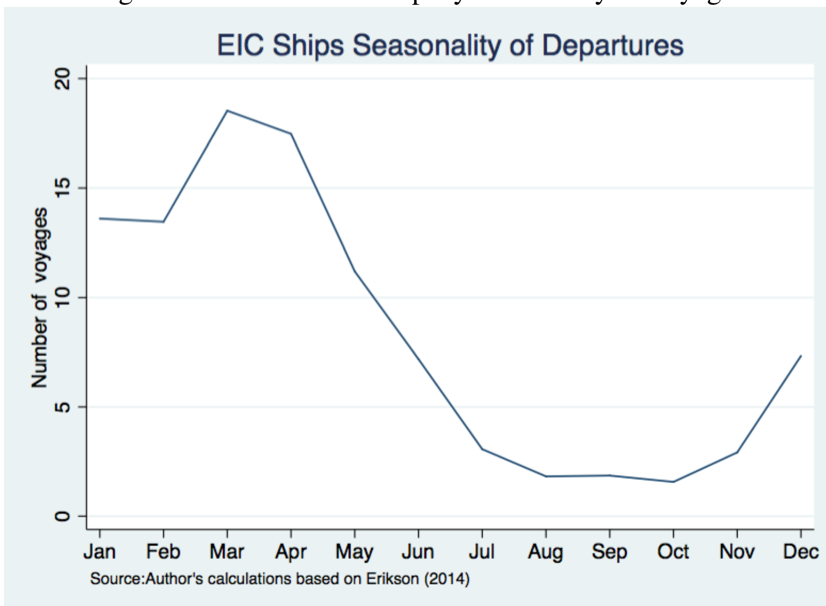


Figure 2.4: East India Company Survivor Function of Voyages

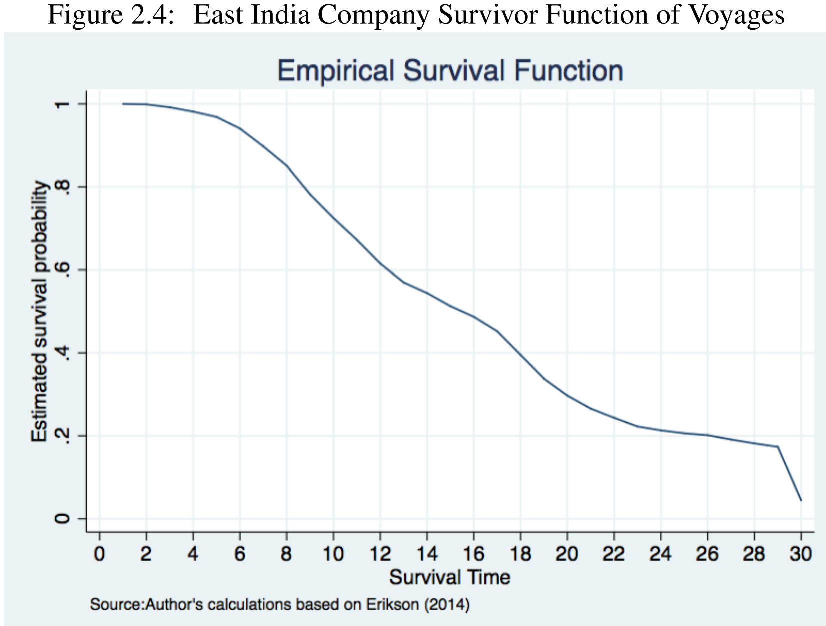


Table 2.1 shows summary statistics of the key variables of our analysis which measure voyage performance. The table reports that the probability of departing in our monthly panel is around 5%, a low occurrence event. The table also shows that 98% of the voyages had only one captain, in around 50% of the voyages the captain was replaced from previous voyage and the average number of captain's previous voyages is 1.35. These variables are important factors that influenced the decision to sail as captain's sailing experience and turnover capture captain's risk preferences and skills (e.g. propensity to navigate

risky weather conditions, engage in adventurous private trade, etc.) that could have affected the success of voyages. Another important determinant of voyage performance was ship's working life, as vessels suffered considerable damage after long voyages so they required costly repairs. Solar (2013) argues that the Company had a four voyage cap, as it was too risky to ship high value goods in heavily used vessels. On average, ships had 1.63 previous voyages, ship's previous voyage duration was 1.5 years, and voyages had 1.73 intended destinations. Also, as a proxy of information exchange that could have affected ship's travel plans we include in the analysis an indicator variable equal to one if any ship arrived from Asia during the month of ship's departure. Erickson (2014) argues that when ships arrived in London, an intense exchange of information occurred between captains, market participants and EIC's personnel, as captains possessed valuable information on market conditions and prices in Asia. In about 50% of voyages a ship arrived from Asia during the same month of departure.

Table 2.1 : Determinants of Voyage Performance

Variable	Mean	Std. Dev.
Departure Indicator	0.05	0.23
Voyages with one captain	0.98	0.12
Captain was changed from previous voyage	0.48	0.49
Number of captain's previous voyages	1.35	1.65
Number of ship's previous voyages	1.63	1.87
Length of ship's previous voyage in months	18.43	7.7
Number of intended destinations	1.73	0.64
Ships arrived in month of departure	0.54	0.49

Source: Author's calculations based on Farrington (1999)

B. ***Measure of Uncertainty***

East India Company stock prices are from Global Financial Data, and are available from 1692 to 1868 on a daily basis. We measure uncertainty using monthly stock return volatility, defined as the standard deviation of stock returns divided by the square root of the number of days spanned between the first and last available trading dates in a month. Due to data gaps in the time series, we calculated stock returns as the log difference between closing price in time t and earliest closing price available in time t-1. We also constructed an alternative measure of volatility by dividing the standard deviation of stock returns by the number of trading days available in a month, as in periods of uncertainty the number of days the stock market was open or the stock was traded could have been affected by economic or political events.

To check the robustness of our results, we constructed a similar measure of volatility using Bank of England stock data that is available from 1694 to 1868. Figure 2.5 plots EIC monthly average stock prices over our sample period. The graph shows that there is substantial variation in stock prices and that the series exhibit an increasing trend towards the end of the 18th century.

Figure 2.5: East India Company Stock Prices

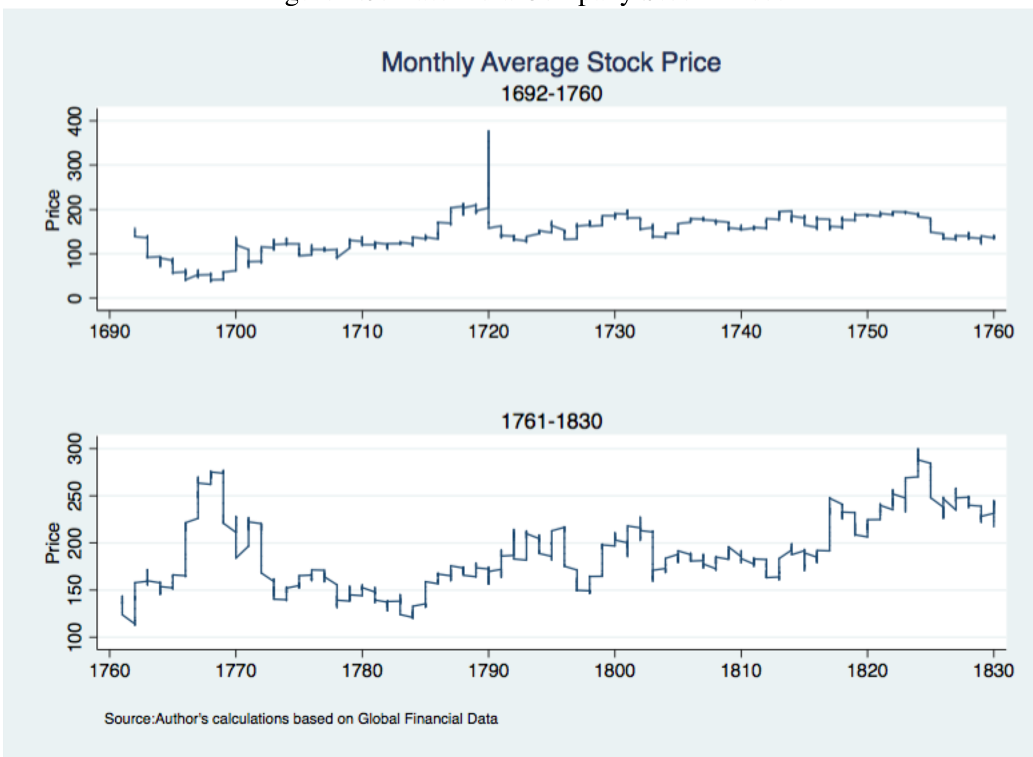


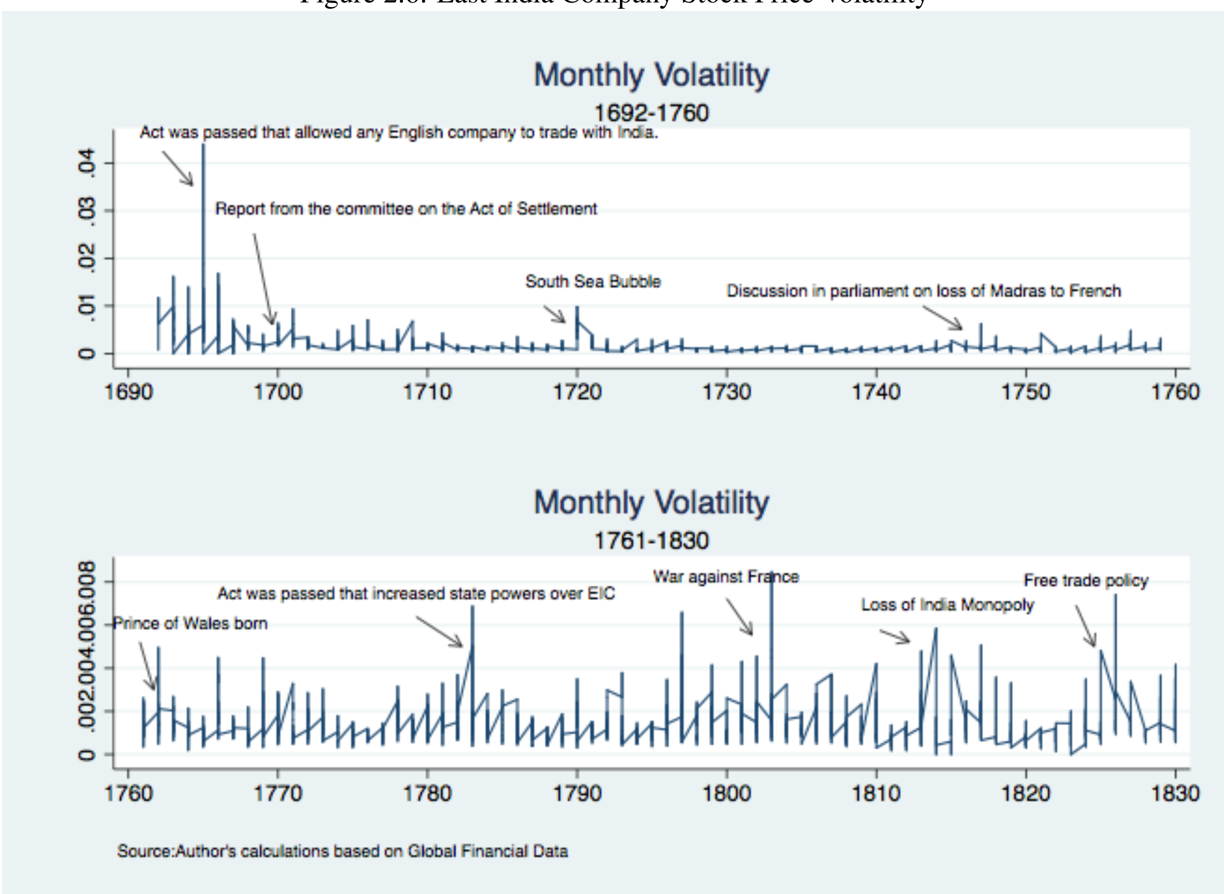
Figure 2.6 plots our volatility measure. The figure shows that EIC stock returns were relatively stable, however there are periods when volatility rose dramatically. These periods of unusual high volatility are associated with the occurrence of policy changes against the EIC, war, or major political and economic events, such as the South Sea Bubble or the passage of the 1698 Act of Parliament that gave a charter to the "New" East India Company. The patterns observed in the data indicate that the level of uncertainty may have mattered to delay or accelerate voyages. We further explore this by asking whether extreme volatility events had a larger effect on investment. Lastly, Table 2.2 shows that average EIC stock volatility is 0.0013, almost 1.6 bigger than average Bank of England volatility. The coefficient of correlation between both variables is 0.39.

Table 2.2 : Measures of Volatility

Variable	Mean	Std. Dev.
EIC stock return volatility	0.0013	0.0011
Bank of England stock return volatility	0.0008	.0009

Source: Author's calculations based on Global Financial Data

Figure 2.6: East India Company Stock Price Volatility



4. Empirical Framework

We are interested in examining the relationship between firm level investment and uncertainty. Specifically, we test the hypothesis that uncertainty, measured by the volatility of stock returns, has a negative effect on EIC's irreversible decision to send trading voyages from England to Asia. As previously discussed, we restrict the analysis to the first half of trade cycles, so we postpone for future work the discussion of a model where uncertainty affects the departure and return of ships. To test our hypothesis, we use a discrete time recurrent event duration model to estimate the effect of volatility on ships' probability to sail. This model is used to capture the idea that the probability of sailing should decline over time as the sailing season ends. Also, this framework takes into account the fact that some ships may not depart by the end of the sailing season. We follow this approach as this model has been used to empirically test the effect of uncertainty on models of irreversible investment and firm's market entry and exit decisions.

The event of interest is the departure of ship i, and the "hazard rate", $Pr(m_i = m | m_i \geq m)$, is the probability that a ship departs in month m given it has "survived" until that time. We assume that a ship is ready to depart in the same month it arrived back from Asia, so departures can occur at months $m_i = \{1,2,3..\}$ (i.e., "survival time"). For each ship we observe three events over its lifetime: launch or first departure, all voyages but first and last voyage, and last sailing or exit. In our analysis, we consider all voyages but the launch of ships as we don't have complete data on the date when ships were built. In sum, our sample includes all ships that are "at risk" to depart, as ships can have multiple voyages or "recurrent events". We employ an additive hazard model composed of a linear function of covariates and a baseline hazard modeled specified as a flexible step function of survival time.

Our baseline estimating equation is based on a panel data linear probability model of survival time that accounts for unobserved ship and time heterogeneity:

$$S_{ivty} = \beta V_{ty} + \gamma X_{ivty} + \delta Z_{ty} + \alpha_i + \alpha_t + \alpha_y + \alpha_a + \varepsilon_{ivty} \tag{1}$$

where S_{ivty} is an indicator variable equal to one if ship $i's$ voyage v , departed in month t and year y; V_{ty} is EIC stock return volatility in month t in year y; X_{ivty} is a vector of ship i voyage's v time varying characteristics that capture determinants of voyage performance which include number of ship's previous voyages, duration of ship's previous voyage, number of captain's previous voyages, an indicator variable that equals one when captain is different from previous voyage, an indicator variable equal to one if any ship arrived from Asia in month of departure t , and a survival time step function with monthly indicator variables for durations up to 30 months with a single indicator for durations higher than 30; Z_{ty} is EIC's monthly average stock return in month t in year y ; α_i, α_t, α_y, and α_a denote ship, month and year of departure and month of arrival fixed effects; ε_{ivty} is an error term clustered at ship level.

Number of ship's previous voyages and duration of ship's previous voyage proxy for ship's operational lifetime, so positive estimates indicate that ship durability increase the probability of departing. The indicator variables for whether captain is different from previous voyage and for whether ships arrived in the month of departure are intended to proxy for other sources of uncertainty that could have affected the decision to sail. Erickson (2014) argues that captain's experience and information networks were important determinants of a ship's travel plans, as managers usually hired the same captain for several voyages if the previous voyages was successful. Thus, captain turnover could increase uncertainty about ship's performance and decrease the probability of shipping. Koudijs (2016) provides evidence that English stock prices traded in Amsterdam strongly reacted after the arrival of boats carrying news from England. In a similar way, Chaudhuri (1978) documents that EIC's ships coming back from Asia carried important information on market conditions in the form of private correspondence, so arrival of ships is presumably correlated with higher volatility and delays in shipping.

Average stock return captures the effect of first moment shocks on shipping. Ship fixed effects control for all time invariant factors that differ between ships such as sheathing and size. Year fixed effects, and month of departure and arrival fixed effects control for any time specific shocks and seasonal factors that affect all ships similarly. Of particular interest is the effect of month of departure fixed effects as they capture the importance of departing during the sailing season from January to May, as ships that missed the season had to wait until the next when winds and weather were optimal for sailing. To test the sensitivity of our estimates we consider alternative specifications that include captain and intended destination fixed effects as these variables may capture potentially omitted factors that affect voyage performance such as the importance of captain's skills and the effect of formal destination orders. Also, to control for omitted differential effects of departure time, we include interaction terms of volatility with month of departure. Lastly, we test whether our baseline findings are robust to the inclusion of an alternative measure of aggregate volatility, Bank of England (BOE) stock returns volatility.

The coefficient of interest in Equation (1) is β, which is the estimated impact of EIC stock return volatility on the probability of sailing. A negative coefficient indicates that higher levels of uncertainty decrease the probability of departing. In other words, uncertainty is delaying investment. In addition, we examine the impact of volatility on hazard rates. A concern of our estimates is the potential endogeneity of volatility. In particular, if voyages increase uncertainty, lets say because the ship is commanded by an unexperienced captain or because it is traveling to a destination with political conflict, then volatility suffers from reverse causality, so our OLS estimate of β would be biased. To minimize concerns about potential omitted variables we control for additional controls and fixed effects. The empirical strategy has all the caveats of discrete time linear probability hazard models, however we prefer this specification to discrete choice hazard models used for recurrent events (i.e., Conditional Logit, Random Effects models) due to its computational advantages when estimating high dimensional fixed effects.

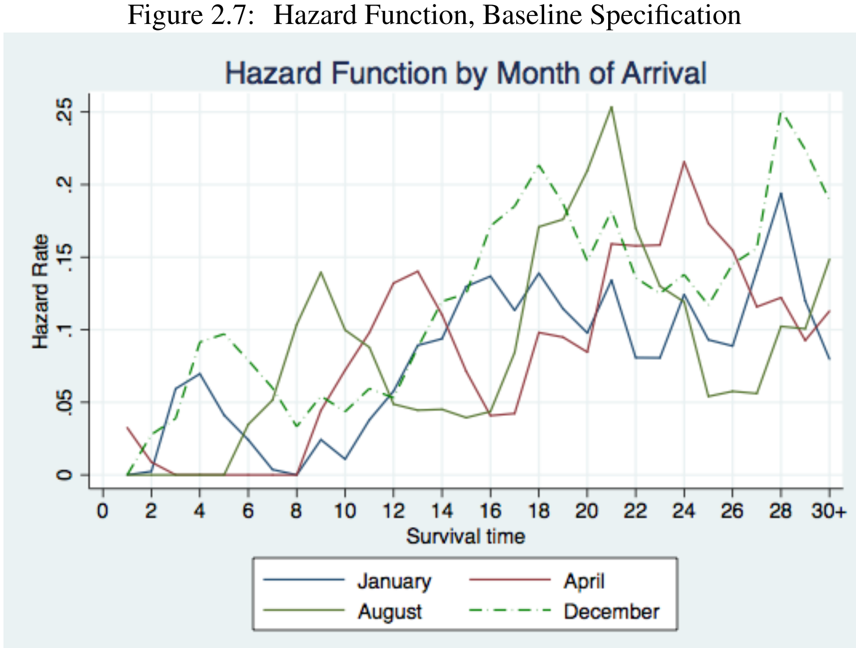
5. Estimation Results

Estimates of equation (1) are reported in Table 2.3. The first column reports estimates of (1) with ship, year, and month of departure and arrival fixed effects only. In columns (2) -(4) we include sets of control variables one at a time and all together. In all the regressions, the volatility estimate is statistically significant at 10-percent level and negative, a result that supports the hypothesis that uncertainty lowers investment by decreasing the probability of departing. The estimates for number of ship's previous voyages and duration of ship's previous voyage are significant and positive as expected. The coefficients for the indicator variables for whether captain is different from previous voyage and for whether ships arrived in the month of departure are negative and significant but small in magnitude. This is consistent with the initial hypothesis that these events are an additional source of uncertainty that delays departures. Number of captain's previous voyages is positive and marginally statistically significant, while the estimated coefficient for average stock return is not statistically different from zero in any of the specifications. In columns (5)- (7) we control for captain and destination fixed effects and Bank of England volatility. The volatility coefficient remains negative and statistically significant, but smaller in magnitude.

Interestingly, the trends in the coefficients on the month of departure fixed effects indicate the seasonality of departures. The coefficients are positive or not statistically different from zero in the first five months of the year and then they become negative and larger in magnitude up to October when they start to raise again (measured relative to the base month of January). Solar (2013) argues that the seasonality of voyages changed over time due to several factors like shorter duration of voyages. It is reassuring that our estimates are consistent with this seasonality pattern even after controlling for year fixed effects.

To illustrate the seasonality of departures, we plot in Figure 2.7 the estimated hazard functions using the results of column (1), specification that only includes ship, year, and month of departure and arrival fixed effects. To summarize the individual hazard probabilities, we averaged predictions over months of arrival. For simplicity, we limit our analysis to January, April, August and December months of arrival.[6] As it is clear from the figure, hazard functions display seasonality, hazards are upward-sloping from January to May, and then become downward-sloping. Also, the hazard functions are increasing, as the probability of departing in any month increases over time. To illustrate better the seasonality pattern of departures, consider the example of December, just before the beginning of the sailing season. During the first year, the hazard function slopes upward until May, where it exhibits a local peak and it descends until August from where it fluctuates up and down until next December. After the second year, the hazard displays a similar pattern, an upward trend during the first 5 months of the year, and then becomes downward sloping.

Figure 2.7: Hazard Function, Baseline Specification



To assess the magnitude of the volatility effects, we calculate a back of the envelope estimate. The empirical probability of departing in our sample is 5.75 % , the average volatility is 0.0013 with a standard deviation of 0.0011. Considering the estimate of column (4) -2.082, the estimated effect of average volatility is a reduction of 0.2742 percentage points in the probability of sailing or a reduction of about 4.76% , a small effect in economic terms. It is important to note that ship's departure after arrival from Asia was a

[6]Note that ship departures can occur one or more years after arrival, so months of arrival only capture the month and not the month and year of arrival. Since the predicted individual hazard rates of the Linear Probability Model can be negative, we replaced negative probabilities with zero.

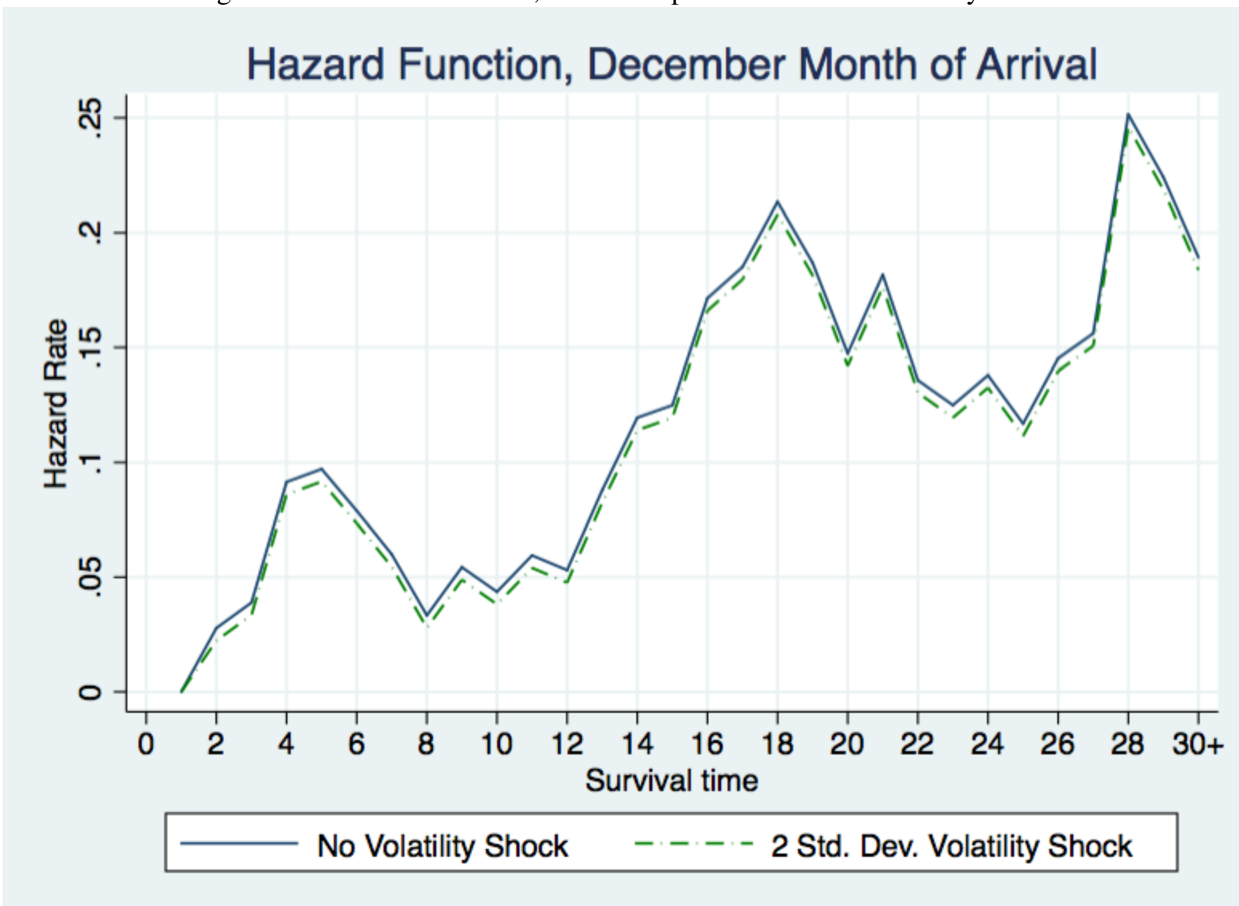
low probability event as ship preparation plans required considerable amount of time for different tasks like repairment of ships, loading and unloading of goods, etc. In addition, funding plans of voyages, weather, and internal conflicts inside the Company could have affected the intended plans to sail.[7] Thus, in this context, it is not implausible that average volatility had a modest effect on the probability of departing throughout the year.

We also focus our attention on the effects of major events that caused unusual high volatility, such as the time period in which the renewal of monopoly rights was under discussion, as during these events uncertainty significantly lowered investment (Bogart (2016)). Extreme volatility events are defined as events with volatility levels two standard deviations higher than the mean. As an alternative method to analyze the effect of extreme volatility events, we plot predicted hazard rates at a baseline level with contemporaneous values of volatility, and at a volatility level two standard deviations higher than the original value. We perform a similar procedure to that described above for the estimation of hazard functions in Figure 2.7. For simplicity, we also focus on December month of arrival and the estimates of column (1). As Figure 2.8 shows, the volatility shock shifts down the hazard function by about one third of a percentage point ($-2.314 \times 2 \times V_{my}$). Even though the uncertainty shock is large, the effect on the hazard function is still small. This happens because of the linearity of the functional form that rules out potential differential effects of uncertainty across time. Thus, this result indicates that the linearity assumption is less informative about the relationship between volatility and the decision to sail. Overall, these results suggest that uncertainty had a negative but small effect on EIC's investment.

To test the robustness of our results and explore potential heterogeneous effects, we allow the volatility effects to differ across month of departure, as volatility might have a differential effect during the sailing season. The results of this flexible version of equation (1) that includes interaction effects are reported in Table 2.4. All volatility estimates, which correspond to the base month of January, are highly significant, negative and substantially larger than the baseline estimates of table 2.3 that measure the average effect of volatility over all months of departure. The interaction terms between volatility and month of departure are in general significant, positive, and become smaller in magnitude over time, indicating that the effect of volatility is concentrated during the sailing season. For example, the estimated interaction effects of column (1) indicate that volatility has a negative and significant effect on the probability of departing during February, April, and December, and zero during the rest of the year (excluding June which has a significant

[7] Due to limited availability of data we are unable to control for these unobserved determinants of departure. However, the inclusion of different fixed effects would mitigate the bias from omission of unobservables.

Figure 2.8: Hazard Function, Baseline Specification with Volatility Shock



positive estimate). This evidence is consistent with the idea that departures were restricted to seasonal weather conditions, as volatility has an effect during the months when it was possible to sail.[8] Lastly, we also calculate the effect of extreme volatility events using the estimates of column (1). Figure 2.9 shows the estimated hazard function with and without volatility shock for December arrivals. As it is clear from the graph, the volatility shock has the largest effects during the first year of survival time, as it shifts down the hazard function by approximately 4 percentage points, around 70 % of the empirical probability of departing. This effect is economically meaningful and its much larger than the baseline estimate. Also, the volatility shock slightly changed the shape of the hazard function, specially during the first sailing season.

In sum, the findings support our initial hypotheses that individual voyage investment is more sensitive to extreme volatility events and that uncertainty has larger effects during the sailing season. Also, our main result that uncertainty delays voyages remains robust to the inclusion of additional control variables and fixed effects. We interpret these findings as suggestive evidence that uncertainty distorted trade cycles and

[8]The estimated sums of the main effect of volatility and the interaction coefficients that are statistically significant at 10% level are: February =-9.83, April=-13.63, June=7.64 and December=-13.74 .

the operation of the East India Company, as delays in departures delayed shipping operations and return voyages from Asia. Therefore, our estimates may be capturing a partial effect of uncertainty on departures. In line with historical evidence, we find that major political and economic events with volatility levels two standard deviations higher than the mean, are the main sources of uncertainty that affected the probability of sailing.

Figure 2.9: Hazard Function, Flexible Specification with Volatility Shock

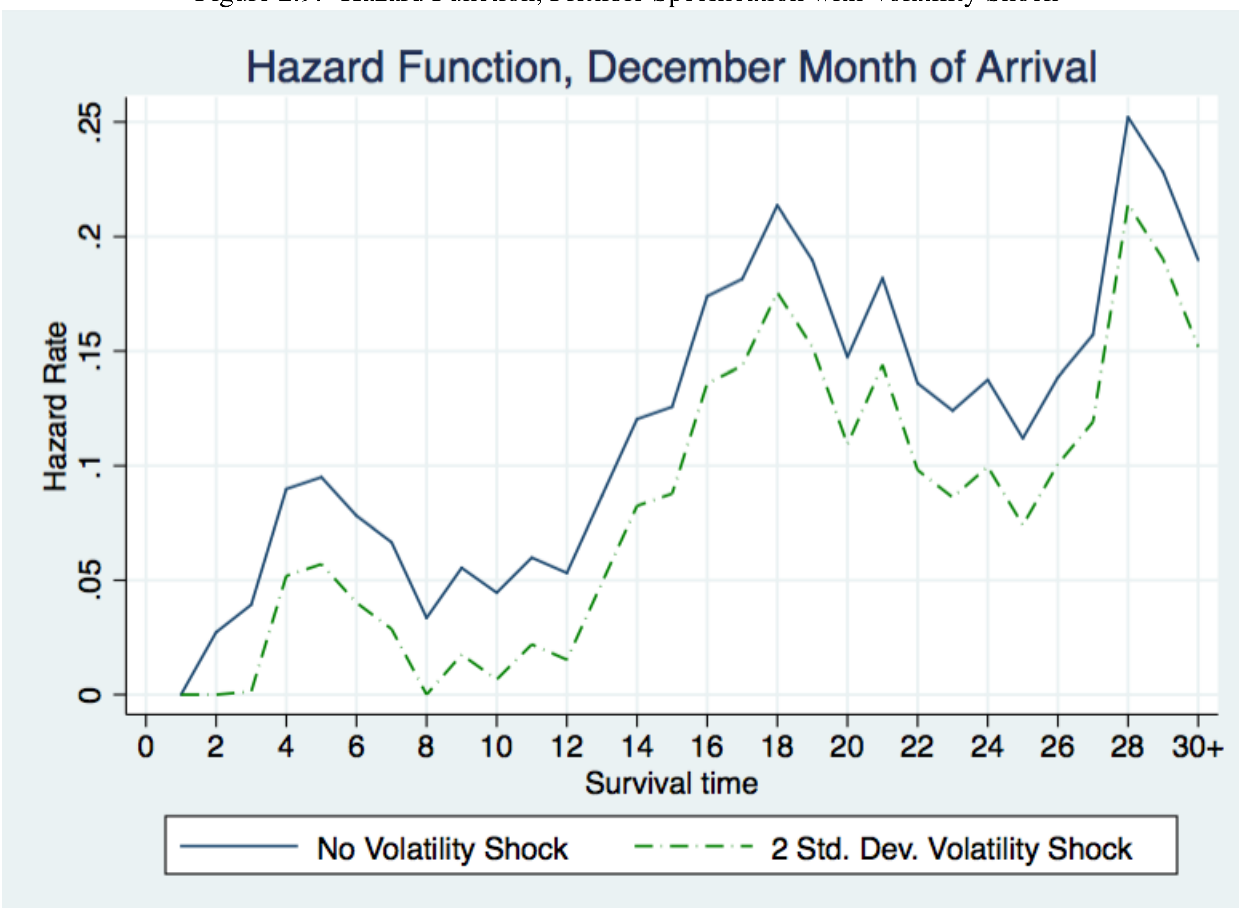


Table 2.3 : The Effect of Volatility on Sailing:Baseline Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable:				Departure Indicator			
EIC Stock Volatility	-2.314**	-2.376**	-2.028*	-2.082*	-1.110**	-1.249**	-1.252**
	(1.156)	(1.159)	(1.096)	(1.097)	(0.510)	(0.491)	(0.496)
Captain changed from previous voyage		-0.00690**		-0.0202***	-0.0783***	-0.0789***	-0.0779***
		(0.00315)		(0.00579)	(0.0140)	(0.0144)	(0.0142)
Number of Captain's previous voyages		0.00203*		0.000594	-0.739***	-0.764***	-0.767***
		(0.00119)		(0.00241)	(0.0457)	(0.0417)	(0.0414)
Indicator variable for when ships arrived in month of departure		-0.0109***		-0.00790***	-0.00212**	-0.00180*	-0.00164*
		(0.00267)		(0.00239)	(0.00108)	(0.000969)	(0.000961)
Number of Ship's previous voyages			0.166***	0.167***	0.771***	0.795***	0.798***
			(0.0356)	(0.0356)	(0.0319)	(0.0277)	(0.0274)
Length of Ship's previous voyage			0.00362***	0.00382***	0.00257**	0.00281***	0.00274***
			(0.000838)	(0.000852)	(0.00101)	(0.000907)	(0.000895)
Average EIC Stock daily return			-0.163	-0.159	-0.118	-0.122	-0.125
			(0.280)	(0.279)	(0.131)	(0.126)	(0.135)
BOE Stock Volatility							-0.104
							(0.414)
Feb	-0.000321	0.000794	-0.00453	-0.00369	-0.00130	-0.00121	-0.00128
	(0.00636)	(0.00638)	(0.00539)	(0.00540)	(0.00164)	(0.00150)	(0.00149)
Mar	0.0453***	0.0468***	0.0286***	0.0298***	0.00638**	0.00524**	0.00528**
	(0.00784)	(0.00786)	(0.00749)	(0.00753)	(0.00263)	(0.00243)	(0.00240)
Apr	0.0499***	0.0534***	0.0279***	0.0305***	0.00775**	0.00702**	0.00679**
	(0.00806)	(0.00817)	(0.00800)	(0.00816)	(0.00307)	(0.00286)	(0.00284)
May	0.0196**	0.0237***	-0.00141	0.00169	-0.000635	-0.000865	-0.00103
	(0.00818)	(0.00835)	(0.00841)	(0.00863)	(0.00333)	(0.00309)	(0.00307)
Jun	-0.0110	-0.00660	-0.0304***	-0.0270***	-0.00992**	-0.00929**	-0.00917**
	(0.00756)	(0.00778)	(0.00827)	(0.00853)	(0.00389)	(0.00362)	(0.00361)
Jul	-0.0388***	-0.0344***	-0.0600***	-0.0567***	-0.0188***	-0.0175***	-0.0175***
	(0.00626)	(0.00650)	(0.00789)	(0.00819)	(0.00487)	(0.00449)	(0.00450)
Aug	-0.0496***	-0.0445***	-0.0726***	-0.0689***	-0.0234***	-0.0217***	-0.0216***
	(0.00594)	(0.00623)	(0.00814)	(0.00847)	(0.00569)	(0.00525)	(0.00525)
Sept	-0.0520***	-0.0477***	-0.0791***	-0.0760***	-0.0269***	-0.0250***	-0.0241***
	(0.00582)	(0.00603)	(0.00887)	(0.00913)	(0.00638)	(0.00595)	(0.00588)
Oct	-0.0603***	-0.0589***	-0.0900***	-0.0890***	-0.0311***	-0.0289***	-0.0288***
	(0.00555)	(0.00560)	(0.00963)	(0.00968)	(0.00732)	(0.00683)	(0.00681)
Nov	-0.0587***	-0.0576***	-0.0929***	-0.0921***	-0.0323***	-0.0302***	-0.0301***
	(0.00565)	(0.00569)	(0.0106)	(0.0107)	(0.00801)	(0.00751)	(0.00751)
Dec	-0.0296***	-0.0305***	-0.0723***	-0.0730***	-0.0263***	-0.0247***	-0.0246***
	(0.00619)	(0.00618)	(0.0125)	(0.0125)	(0.00830)	(0.00786)	(0.00787)
Constant	0.101***	0.104***	-3.325***	-3.326***	-2.261***	-1.777***	-1.789***
	(0.0347)	(0.0354)	(0.834)	(0.835)	(0.528)	(0.532)	(0.535)
Observations	42,855	42,855	42,855	42,855	42,855	42,855	42,283
R-squared	0.100	0.101	0.237	0.238	0.796	0.819	0.822
Number of ships	781	781	781	781	781	781	777
Fixed Effects:							
Ship	Y	Y	Y	Y	Y	Y	Y
Year of Departure	Y	Y	Y	Y	Y	Y	Y
Month of Arrival	Y	Y	Y	Y	Y	Y	Y
Captain	N	N	N	N	Y	Y	Y
Intended Destination	N	N	N	N	N	Y	Y
# Clusters	781	781	781	781	781	781	777

The dependent variable is an indicator variable equal to one if a ship departed. Standard errors clustered at the ship level appear in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1

Table 2.4 : The Effect of Volatility on Sailing: Alternative Specification with Heterogeneous Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable:				Departure Indicator			
EIC Stock Volatility	-16.11***	-16.80***	-11.58***	-12.11***	-5.396***	-5.209***	-5.106***
	(4.215)	(4.222)	(3.804)	(3.815)	(1.933)	(1.916)	(1.921)
Captain changed from previous voyage		-0.00690**		-0.0202***	-0.0784***	-0.0789***	-0.0780***
		(0.00315)		(0.00579)	(0.0140)	(0.0144)	(0.0142)
Number of Captain's previous voyages		0.00206*		0.000626	-0.739***	-0.764***	-0.767***
		(0.00119)		(0.00241)	(0.0457)	(0.0417)	(0.0414)
Indicator variable for when ships arrived in month of departure		-0.0113***		-0.00810***	-0.00227**	-0.00192*	-0.00174*
		(0.00266)		(0.00238)	(0.00109)	(0.000983)	(0.000972)
Number of Ship's previous voyages			0.166***	0.167***	0.771***	0.794***	0.797***
			(0.0356)	(0.0356)	(0.0319)	(0.0277)	(0.0274)
Length of Ship's previous voyage			0.00362***	0.00382***	0.00257**	0.00281***	0.00274***
			(0.000837)	(0.000851)	(0.00101)	(0.000906)	(0.000894)
Average EIC Stock daily return			-0.159	-0.155	-0.0741	-0.0748	-0.0690
			(0.283)	(0.283)	(0.140)	(0.136)	(0.145)
BOE Stock Volatility							0.0645
							(0.477)
Feb	-0.0151	-0.0142	-0.0144	-0.0138	-0.00484	-0.00475	-0.00504
	(0.0111)	(0.0111)	(0.00980)	(0.00981)	(0.00370)	(0.00350)	(0.00357)
Mar	0.0114	0.0109	0.00412	0.00363	-0.00394	-0.00398	-0.00483
	(0.0131)	(0.0130)	(0.0114)	(0.0114)	(0.00402)	(0.00396)	(0.00400)
Apr	0.0384***	0.0408***	0.0238**	0.0256**	0.00530	0.00405	0.00584
	(0.0139)	(0.0139)	(0.0120)	(0.0121)	(0.00456)	(0.00443)	(0.00449)
May	-0.0112	-0.00803	-0.0230**	-0.0207*	-0.00799*	-0.00727*	-0.00686*
	(0.0120)	(0.0120)	(0.0107)	(0.0108)	(0.00420)	(0.00409)	(0.00412)
Jun	-0.0480***	-0.0435***	-0.0585***	-0.0552***	-0.0208***	-0.0195***	-0.0193***
	(0.0114)	(0.0115)	(0.0104)	(0.0105)	(0.00506)	(0.00472)	(0.00471)
Jul	-0.0648***	-0.0605***	-0.0773***	-0.0741***	-0.0287***	-0.0268***	-0.0270***
	(0.0107)	(0.0108)	(0.0102)	(0.0104)	(0.00587)	(0.00552)	(0.00553)
Aug	-0.0805***	-0.0766***	-0.0956***	-0.0927***	-0.0325***	-0.0300***	-0.0296***
	(0.00971)	(0.00978)	(0.00974)	(0.00987)	(0.00641)	(0.00592)	(0.00589)
Sept	-0.0794***	-0.0761***	-0.0979***	-0.0955***	-0.0359***	-0.0334***	-0.0324***
	(0.00982)	(0.00991)	(0.0104)	(0.0105)	(0.00707)	(0.00661)	(0.00648)
Oct	-0.0859***	-0.0857***	-0.108***	-0.108***	-0.0403***	-0.0377***	-0.0373***
	(0.00949)	(0.00948)	(0.0109)	(0.0109)	(0.00808)	(0.00753)	(0.00746)
Nov	-0.0823***	-0.0828***	-0.110***	-0.110***	-0.0397***	-0.0363***	-0.0355***
	(0.00981)	(0.00979)	(0.0117)	(0.0117)	(0.00864)	(0.00813)	(0.00809)
Dec	-0.0386***	-0.0411***	-0.0740***	-0.0760***	-0.0311***	-0.0301***	-0.0297***
	(0.0114)	(0.0114)	(0.0137)	(0.0136)	(0.00807)	(0.00772)	(0.00767)
Feb*EIC Stock Volatility	6.275	6.245	4.027	4.022	1.058	1.193	1.400
	(5.897)	(5.893)	(5.253)	(5.246)	(2.127)	(2.021)	(2.111)
Mar*EIC Stock Volatility	21.71***	23.12***	15.79***	16.94***	6.552***	5.809**	6.564***
	(6.936)	(6.927)	(6.028)	(6.020)	(2.426)	(2.325)	(2.392)
Apr*EIC Stock Volatility	2.950	3.647	-1.373	-0.828	-0.0669	0.547	-1.322
	(8.090)	(8.076)	(6.938)	(6.930)	(2.638)	(2.506)	(2.449)
May*EIC Stock Volatility	19.27***	19.92***	13.59***	14.08***	4.285*	3.640*	3.201
	(5.699)	(5.702)	(4.951)	(4.953)	(2.188)	(2.151)	(2.203)
Jun*EIC Stock Volatility	23.75***	23.67***	18.31***	18.28***	6.960***	6.526***	6.509***
	(5.339)	(5.323)	(4.724)	(4.710)	(2.280)	(2.178)	(2.194)
Jul*EIC Stock Volatility	15.14***	15.26***	10.09**	10.17**	5.829***	5.524**	5.621**
	(4.842)	(4.835)	(4.343)	(4.339)	(2.153)	(2.166)	(2.183)
Ago*EIC Stock Volatility	19.62***	20.46***	14.87***	15.50***	5.678**	5.168**	4.897**
	(4.977)	(4.996)	(4.557)	(4.568)	(2.232)	(2.177)	(2.203)
Sept*EIC Stock Volatility	16.72***	17.33***	11.44***	11.89***	5.590***	5.150**	5.098**
	(4.718)	(4.725)	(4.262)	(4.275)	(2.082)	(2.050)	(2.063)
Oct*EIC Stock Volatility	15.41***	16.18***	11.14***	11.71***	5.830***	5.535***	5.377***
	(4.251)	(4.256)	(3.889)	(3.903)	(2.050)	(2.022)	(2.032)
Nov*EIC Stock Volatility	13.76***	14.80***	9.899**	10.69***	4.252**	3.358	2.886
	(4.625)	(4.626)	(4.057)	(4.067)	(2.159)	(2.131)	(2.195)
Dec*EIC Stock Volatility	2.371	3.434	-1.905	-1.057	2.251	2.790	2.686
	(5.656)	(5.669)	(5.103)	(5.124)	(2.142)	(2.079)	(2.093)
Constant	0.121***	0.124***	-3.309***	-3.309***	-2.255***	-1.771***	-1.783***
	(0.0355)	(0.0360)	(0.835)	(0.836)	(0.528)	(0.533)	(0.535)
Observations	42,855	42,855	42,855	42,855	42,855	42,855	42,283
R-squared	0.101	0.102	0.238	0.239	0.796	0.819	0.822
Number of shipid	781	781	781	781	781	781	777
Fixed Effects:							
Ship	Y	Y	Y	Y	Y	Y	Y
Year of Departure	Y	Y	Y	Y	Y	Y	Y
Month of Arrival	Y	Y	Y	Y	Y	Y	Y
Captain	N	N	N	N	Y	Y	Y
Intended Destination	N	N	N	N	N	Y	Y
# Clusters	781	781	781	781	781	781	777

The dependent variable is an indicator variable equal to one if a ship departed. Standard errors clustered at the ship level appear in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1

6. Conclusions

This paper has documented historical evidence of the negative effect of uncertainty on investment. Focusing on EIC's trading voyages to Asia, we show that average uncertainty decreases the probability of sailing by 4.76%, a sizable magnitude. Also, we examine potential heterogeneous effects and the impact of extreme volatility events, and find that uncertainty has larger negative effects during the optimal sailing season of the Indian Ocean. These findings are consistent with the historical narrative that political and economic uncertainty influenced EIC's trade environment. The results presented here suggest directions for future research. First, our findings show that an important topic for future research is the study of full trade cycles, as this analysis will shed light on the effect of uncertainty on departure and return voyages that influenced EIC's optimal decision to reduce turn-round times. Finally, a second avenue for future studies is to analyze in detail the effect of political events and the arrival of ships from Asia on the decision to sail, as there is ample evidence that these factors were major sources of uncertainty.

Chapter 3. Banking Panics and Business Failures: Evidence from the Federal Reserve's Formative Years

1. Introduction

Banks' and banking panics' influence on the economy has long been and remains the subject of debate.[1] According to some scholars, banks play an important role as financial intermediaries, aggregating the savings of depositors, transforming liquid low-yield deposits into longer-term higher-yielding assets, screening and monitoring the recipients of this credit, and financing economic activities that would not occur in the absence of this intermediation. According to other scholars, bank operations have little impact on the economy. In the absence of banks, other financial intermediaries would readily provide financing, and economic activity would remain much the same. Theoretical models support both lines of research, demonstrating that economies could function with or without banks.[2] In macroeconomic models popular in the 1990s and 2000s, banks typically had little (or no) role in the economy. [34]

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[1] Please note that in this early draft, the citations are not complete. On this point, we know that Adam Smith discussed banking and bank regulation in the Wealth of Nations. At about the same time, the Founding Fathers of the United States debated similar issues. Walter Bagehot's On Lombard Street in 1873 is another classic in this ongoing debate.
[2] Our examination of these time-series statistics builds upon previous studies of cross-sectional and panel data drawn from business censuses. Richardson and Troost (2010) show that wholesale activity – measured by lending, borrowing, sales, employees, and number of firms – contracted after banks failed during the banking panic in the fall of 1930, at least for the region that they study, which straddled the borders of the 6th and 8th Federal Reserve Districts in Mississippi. Richardson and Komai (in progress) generalize that result to wholesale activity in all counties in the United States during the early 1930s. Those studies demonstrate the correlation between bank failures (identified as plausibly exogenous) and wholesale activity. This study builds upon that literature by expanding the chronological span of the analysis (from years to decades) and comparing the impact of bank failures on the survival of bank-dependent and bank-independent businesses.
[3] Microeconomics of Banking, 2009
[4] An example are Arrow-Debreu general-equilibrium models.

Since theories support both lines of argument, resolving the debate requires empirical analysis, in which we determine which classes of models best represent the real world. This empirical analysis needs to answer questions such as: in our economy, do (or did) banks have important functions? Did the existence of banks facilitate manufacturing and trade? Did the failure of banks force businesses into bankruptcy? Why did bank failures matter?

Answers to these questions remain elusive for three principal reasons. The first is changes in economic institutions. Over time, innovation and competition change relationships between firms, banks, and other financial intermediaries. So do regulatory changes, such as restrictions on the activities of intermediaries (e.g. the Glass-Steagall Act of 1933) or the creation of deposit insurance (e.g. Banking Act of 1935). The United States, for example, reformed the structure of financial regulation in the 1930s to preclude the possibility of financial panics and minimize links between financial failures and aggregate economic activity. The second is deficiencies in data. Scholars lack data about the activities of financial intermediaries, such as the quantity of credit issued or the number of firms seeking but unable to find loans for profitable projects. For many periods in the past, scholars even lack data about the number of financial intermediaries and reasons that firms entered or ceased operations, such as failures and mergers. The third reason is endogeneity. Banks' decisions influence firms. Firms' decisions influence banks. Events that effect one institution also influence the other. Leaders of banks and firms understand the reciprocal relationship, forecast future decisions and events, and act accordingly. These interrelationships mean that causality could run in many directions: from banks to firms, or firms to banks, or past to future, or (anticipation of) future to present.

Endogeneity bedevils empirical analysis to such an extent that we should discuss it in terms of the issue at the heart of this essay: the relationship between the failure of banks and the bankruptcy of firms. In theory, causality could run in both directions. A bank could fail because it loaned funds to a firm which invested in a risky project, received a low return, went out of business, and failed to repay the loan. A firm could fail because it needed to borrow to finance ongoing operations, had in the past borrowed from a single bank, and after that bank failed, could not find a lender willing to provide it with sufficient credit at a reasonable rate. Of course, both banks and firms could fail for reasons unrelated to loan repayment or access to credit. Banks, for example, could fail if depositors panicked. Firms could fail if the costs of conducting business increased or returns to investments fell (e.g. weather, regulations, fuel prices). In reality, banks and firms fail for all of these reasons. Empirically, it is difficult to disentangle these different channels.

This essay relaxes all three constraints on scholarly studies of the bank-business relationship. To address the first issue, we focus on the United States between 1900 and 1932. During this era, banks played prominent roles financing operations of firms. Financial panics occurred periodically. The federal government seldom intervened in financial markets, and did not, until the banking holiday in the winter of 1933, intervene to save banks deemed too big to fail. When compared to the present day, banks operated with far fewer legal constraints. Regulation and central-bank intervention had less influence on the operation of the financial system.

To address the second issue, we gather the most detailed data possible on failures of banks and firms. Our data on bank failures comes from an array of contemporary sources and from the archives of the Federal Reserve System. Our data on firm failures comes from publications of R.G. Dun and Company (an ancestor of today's Dun and Bradstreet Corporation) and the Statistical Abstract of the United States. We process these sources to create accurate, consistent, and high-frequency data on failures of firms and banks from 1895 through 1933. We compare these series to determine the relationship between bank failures and firm bankruptcies.

We address the third issue – causality – in three ways. Our initial examination of the evidence illuminates chronological correlation between failures of banks and firms. In this phase of the research, the notion of causality stems from the logical proposition *post hoc ergo propter hoc*, a Latin phrase meaning after this therefore because of this, or in other words, if one event immediately follows another event, then assume the initial event caused the later event. We operationalize this logic using methods typical of time-series macroeconomics. These methods are Granger causality tests and impulse-response graphs derived from vector-auto regressions. Weaknesses in this method of causal identification motivate additional methods.

Our next method builds upon the first, operationalizing the idea of treatment and control. In this method, we use the structure of the economy to identify firms that rely upon commercial banks to finance ongoing operations. These bank-dependent firms financed ongoing operations via bank loans. Access to loans involved repeated financial relationships between bank as lender and firm as borrower. These bank-dependent firms tended to be smaller firms engaged in wholesale trade. Larger manufacturing firms typically financed fixed costs in other ways, such as issuing bonds or selling stock. Larger firms also tended to be creditors of banks, holding deposits in excess of outstanding debts. Knowledge of the structure of the economy enables us to determine which firms depended upon repeated relationships with banks to finance ongoing operations and which firms did not. The structure of the economy also enables us to identify firms which tended to be debtors of banks and firms that tended to be creditors of banks (and other financial intermediaries). This information enables us to compare the ways in which firms responded to the failure of banks. The difference in responses indicates the extent to which failures of banks triggered failures of firms.

The last method builds upon the initial examinations of the data, operationalizing the idea of exogenous shocks. We do this by identifying financial crises whose origins appear to lie within the dynamics of the financial system. We base identification of these crises on recent research by Andrew Jalil (2011) and Gary Richardson (2006, 2007). The ultimate source of this information comes from observations of contemporary financial professionals as reported in the business press and routine reports of bank regulators, particularly the Division of Bank Operations of the Federal Reserve Board.

The remainder of this essay lays out our argument. Section 2 describes the structure of the commercial credit system and identifies the types of firms that relied on banks for credit. Section 3 discusses the nature of business bankruptcies and bank failures, the stability of the data-generating process, and the ways in which we identify banking panics. Section 4 describes our statistical methods and results. Section 5 discusses the implications of our estimates. Failure of banks and failures of firms were clearly correlated during the first three decades of the twentieth century. All of the correlation above that which could be attributed to random chance appears to be due to the failure of bank-dependent firms in the six months following banking panics. Our research design – including the comparison of exogenous and endogenous shocks and the comparison of effects on treatment and control groups – enables us to identify causal relationships. These patterns indicate that failures of banks triggered failures of firms that depended on banks for credit. The pattern stems almost entirely from pronounced increase in failure of bank-dependent firms following events identified as financial panics. These statistical findings appear consistent with widespread claims by contemporary observers that banking panics influenced economic activity through what we now describe as a bank-lending channel.

2. Commercial Credit and Bank Dependent Firms

During the Federal Reserve's formative years, a system of production, distribution, and financing spanned the United States. This system facilitated the flow of goods from manufacturers, to wholesalers, to retailers, and eventually to consumers. The system also facilitated the return flow of payments from final users to initial manufacturers. This section describes that system, and presents data about sources and uses of credit, and discusses evidence that contemporaries collected concerning the impact of the disruption of the commercial credit cycle. A key issue is to identify firms that depended upon commercial banks for working capital, and firms that supplied credit to commercial banks.

2.1 Creditors and Debtors of Commercial Banks

In the early twentieth century, which firms deposited money in and which firms borrowed money from commercial banks? In the 1920s, large manufacturing corporations were, as a group, creditors to banks. This conclusion was shared by all scholars who studied this issue. Koch finds that for large manufacturing and trading corporations, bank loans "were unimportant as a source of funds … bank loans of corporations are small relative to their bank deposits … [the aggregate of] large manufacturing and trade concerns as a group was the net creditor rather than the net debtor of the banking community (Koch 1943, p. 3-5)." Lutz (1945, p. 52) concludes that "during the 1920s, bank credit was of little importance for large manufacturing corporations …large manufacturing corporations were largely independent of bank credit (Lutz 1945 p. 52)." In 1929, sixty percent of large manufacturers had no bank loans on their balance sheets. For large manufacturers with loans outstanding, bank loans totaled less than 2.6 percent of their combined assets, which was less than their holdings of bank liabilities (deposits plus notes) (Lutz 1945 p.

52). [5]A wide range of scholars concluded that small manufacturing firms and most wholesalers and retailers depended upon commercial banks for working capital. [6]

Figure B.1 presents data from the balance sheets of manufacturing firms for the 1920s. The vertical axis indicates the ratio of manufacturing firms' bank deposits to bank loans. Firms with more deposits than loans (indicated by the horizontal dotted line) would be net creditors to the banking system. The 84 large manufacturers whose balance sheets were compiled by the NBER's business finance studies group became net creditors to banks by 1921 and their credit balance expanded throughout the 1920s (solid line).[7] The net position of smaller manufacturers becomes apparent only after the Internal Revenue Service (IRS) began publishing that information. In 1924, the IRS indicated that the 81,748 manufacturers which submitted balance sheets held on aggregate $0.57 of bank notes and deposits for each dollar that they borrowed from banks (IRS data denoted by triangles). That figure rose to $0.73 for the 86,268 manufacturers that submitted balance sheets in 1925 and to $0.88 for the 84,251 manufacturers that submitted balance sheets in 1926. In that year, the IRS provided information on 103 large manufacturers (each of which earned profits over $5,000,000 in that year). These firms held $2.49 in bank notes and deposits for each $1 that they borrowed from banks. They were net creditors of banks. The 26,042 manufacturers which earned

[5] Currie (1945) reaches a similar conclusion. In 1928, bank loans amounted to 3.8% of firms' total assets and 8.4% of firms inventories. Firms borrowed from banks, Currie concluded, due to "a small company or for a large one whose earnings are receding it is virtually impossible to raise funds either through a bond or stock issue, and banks are the only practicable source of supply (Currie 1945 p. 707)."

[6] Koch (1943) and Lutz (1945) study the balance sheets of 84 large manufacturing and 27 large trading firms compiled by the NBER's business finance program. Currie (1945) analyzes a sample of 729 firm balance sheets which he compiled for the years 1922 through 1929. Data for large corporations in this time period comes primarily from firms, like Moody's and Poor's, which compiled corporate balance sheets and from the Internal Revenue Service, which collected data on balance sheets of firms large enough to pay incomes taxes.

[7] The rise of corporate cash balances during the 1920s remains unexplained. Little literature exists on the issue. A plausible explanation is the Revenue Act of 1921, which introduced a tax rate on capital gains of 12.5% as opposed to tax rates on ordinary income of up to 58% (Blakely 1922).

profits less than \$5,000, in contrast, held \$0.34 in bank notes and deposits for each \$1 that they borrowed from banks. They were net borrowers from banks.[8]

Figure B.1 also presents data from the balance sheets of trading firms for the 1920s. As with manufacturers, the net position of typical trading firms becomes apparent only after the IRS began publishing that information. In 1924, the IRS indicated that the 19,175 wholesalers which submitted balance sheets held on aggregate \$0.35 of bank notes and deposits for each dollar that they borrowed from banks (plotted as hollow triangle); 40,259 retailers held on average \$0.36 in bank notes and deposits for each dollar that they borrowed (plots for retailers indistinguishable from plots for wholesalers). In 1925, the figure for 20,844 wholesalers fell to \$0.20 and for 42,593 retailers to \$0.21. In 1926, the IRS ceased distinguishing wholesalers and retailers. Instead, the IRS lumped wholesalers and retailers together with department stores, mail order houses, and an array of other trading firms, and reported balance sheets for all of those institutions in tiers by size of profits. The 42,881 trading firms which earned profits less than \$5,000, in contrast, held \$0.34 in bank notes and deposits for each \$1 that they borrowed from banks.[9]

The Census Bureau did not enumerate the number of retailers and wholesalers until it conducted the censuses of distribution in 1929, which found 1,543,158 retailers and 169,702 wholesalers in operation. These enumerations indicated that the IRS data missed over one and a half million trading firms which were small both in terms of size and profitability. Censuses of

[8] Small manufacturers comprised a substantial fraction of business enterprises in the U.S. at the time, employed a large percentage of the work force, and, in many areas of the country, were the economic bedrock of local communities. In short, economic recovery and social stability was linked to the fate of these firms. The IRS required manufacturers to file balance sheets and tax returns if they exceeded either a size (i.e. minimum capital) or profitability threshold. The 1925 Census of Manufacturers enumerates 187,399 manufacturing firms. This indicates that approximately 100,000 small manufacturing firms did not appear in the IRS data. Data on their relationships with commercial banks is unavailable until the year 1929, when a survey (which we will describe in detail in Section 2.3) determined that 86% of small manufacturing firms depended upon banks for working capital (Department of Commerce 1935 p. 65-6).

[9] The 27 large trading corporations whose balance sheets were compiled by the NBER's business finance studies group became net creditors to banks by 1922. These were very large firms with nationwide operations. The sample includes nationwide chain stores and mail order houses such as J.C. Penny, Woolworth, Montgomery Ward, and Sears Roebuck. Their credit balance peaked in the middle of the 1920s. The top tier consisted of 12 large trading firms (each of which earned profits over \$5,000,000 in that year). These firms held \$21.63 in bank notes and deposits for each \$1 that they borrowed from banks. They were clearly creditors to banks. The NBER names all of these firms.

distribution conducted in 1929, 1933, and 1935 as well as a series of special studies provided information about the amount of credit extended by these firms and the amount which these firms received from commercial banks. For example, the Wholesale Census for 1929 found that wholesale establishments reported that sales on credit constituted 56.3 percent of net sales (Census 1933 v.1 p.8). The Wholesale Census for 1933 found that wholesalers reported that sales on credit constituted 56.8 percent of net sales (Census 1935 Table 4 p. A-27). [10]

Retailers also bought and sold goods on credit. About one third of retail sales were conducted on credit (Plummer 1930). Retailers themselves extended the preponderance of this credit. Little came from commercial banks or other financial institutions. In 1929, the census of retail distribution found that "credit sales exceed one-third of the total sales of all stores in the United States…. Installment sales are approximately 13 per cent of total sales and that open-account sales are approximately 21 per cent of total sales. This is on the basis of credit reported as having been extended by retailers (Retail Distribution, 1929, p.26-27)." In addition, sales finance companies financed installment purchases amounting to about 2.6 per cent of total sales.

The majority of retailers borrowed from banks to finance acquisitions of inventory and sales to consumers. In the Department of Commerce's *Consumer Debt Stud*y (1935), the majority of retail firms (51.3%) reported commercial banks as the source of the credit that financed their business and 22.0% reported wholesalers as their primary source of working capital (La Crosse 1935 p. 22).

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[10] This figure for 1929 may be a lower bound for credit sales as a fraction of wholesale transactions. For wholesalers only, the amount of credit sales amounted to 62.19 of total sales. Automotive wholesales (including sales arms of manufacturers) reported an extremely low percentage of credit sales. This may have been due to the phrasing of the question and the method for financing automotive distribution. The Census of Distribution for 1933 found that only 67.9 percent of wholesale establishments reported their credit business. For establishments reporting their credit business, sales on credit constituted 82.4 percent of net sales. Manufacturers' sales branches reported that 92.0 of their sales were on credit (Census, 1935, p. 62).

The IRS reports for 1926 provide the clearest picture of the net-credit position of large and small manufacturing and trading firms and the best source for comparing net-credit across size and line of business. Table B.1 presents the key information. The ratio of deposits to loans indicates the net credit position of firms in each group. For both manufacturers and traders, the smallest firms owed banks about 5 times what banks owed to them. Manufacturers with profits in the range of $100,000 to $250,000 per year owed banks just about what banks owed to them. The break-even group for trading firms earned in the $1 million to $5 million range. The groups of manufacturers which were clearly net-creditors to banks (i.e. D/L ratio above 1.1) consisted of 2,150 manufacturing firms which possessed 71.8% of the assets of all manufacturing firms which reported their balance sheets to the IRS. The groups of traders which were clearly net-creditors to banks (i.e. D/L ratio above 1.1) consisted of 12 firms which possessed nearly 6.5% of the assets of all trading firms which reported their balance sheets to the IRS.[11]

2.2 Contemporary Descriptions of the Commercial Credit Cycle

Contemporaries described the commercial credit cycle that prevailed in the early twentieth century in a wide array of articles and books written for popular, business, and academic audiences. This section summarizes that literature. These sources indicate that commercial banks and large manufacturing firms played key roles as creditors. Banks received equity investments from stock holders and raised additional funds via deposits. Large manufacturers sold equity shares via investment banks and stock exchanges and used these funds to finance fixed capital, such as buildings and machinery. Large manufacturers financed working capital, including funds which

[11] The amount of bank credit utilized varied by lines of business. The IRS and several surveys from the early to mid 1930s present evidence. Using this information is difficult, because our principal data sources (Duns Review, IRS, the Census Bureau, and various surveys) define lines of business differently. Some classify lines of manufacturing by principal inputs used. Others classify lines of industry by the type of output produced. Given these differences, we explore this information with skepticism, outlining how where the data appear consistent with our hypothesis, but emphasizing the tentative nature of the conclusions that we draw.

they loaned to downstream wholesalers, by issuing bonds and retaining earnings. Large manufacturers typically kept substantial sums on deposit and even owned commercial banks. Smaller manufacturers typically raised equity from partners in the firm, family members, and local networks. To finance working capital, such as payments for inputs to production, and medium terms needs, such as purchasing new machinery, smaller manufacturers relied on loans from commercial banks (Koch, 1940; Jacoby and Saulnier, 1942).

Wholesalers played a different role in this system. Wholesalers financed their activity by borrowing from manufacturers and commercial banks. Wholesalers' decisions set the system in motion. Wholesalers predicted what consumers wanted in upcoming seasons. Wholesalers contacted manufacturers and ordered merchandise. Wholesalers encapsulated orders in contracts that specified goods that would be delivered now and at future dates, such as in 90 days or just prior to Christmas.

Manufacturers offered merchants two ways to pay for these products. One, merchants could pay in the future, after they sold the merchandise. In this case, the merchant would sign a draft, known as an acceptance, that promised payment at a specific future date. The manufacturer deposited the acceptance in his bank, which would collect the proceeds at the appropriate time and place, and then credit the funds to the manufacturer's account. If the manufacturer needed funds immediately, perhaps to pay workers' wages or suppliers' invoices, the bank would purchase the acceptance at a discount off its face value. The discount provided the interest on the loan that the bank implicitly extended to the manufacturer, when it purchased the trade acceptance (Silver, 1920).

Two, merchants could pay in cash on the date of purchase. Manufacturers preferred immediate cash payment, because in the United States in the late 19th and early 20th centuries, cash shortages occurred seasonally and cyclically. Manufacturers preferred to keep substantial sums of cash on hand, so that they could continue operations during seasonal spikes in interest rates and periodic banking panics. To encourage immediate payment, manufacturers offered a lower, discounted price to wholesalers who paid on the spot[12].

Wholesalers brought these contracts to a local bank (Figure B.2, Step 1), with which they had a long-run relationship, and requested financing for the transaction. The banks agreed to loan money to the wholesaler and provided the wholesaler with documents guaranteeing to finance the transaction (step 2). The wholesaler then sent this letter of credit to the manufacturer (3).

The letter of credit promised a payment of X dollars at date Y in the future. The wholesalers' bank (Bank 1) guaranteed to make this payment. It provided this guarantee because the wholesaler promised to pay the bank the amount X plus interest and service charges soon after that date. Bank 1 trusted the wholesaler because of their long-run relationship and because in case of default the contract enabled the bank to sue the wholesaler and seize the merchandise. In turn, the wholesaler trusted the manufacturer because of (i) their repeated interactions, (ii) the manufacturers' reputation for satisfying other customers, and (iii) legal recourse should the manufacturer fail to fulfill its part of the bargain. The value of the letter of credit, in turn, was built upon this tower of trust and recourse.

The manufacturer took this valuable letter of credit to their local bank (step 4), which accepted it at a discount on its face value and deposited that discounted sum in the manufacturer's account (5). The manufacturer used those funds to purchase supplies and hire laborers. With those inputs, the manufacturer produced the merchandise which it shipped to the wholesaler who initiated the transaction (6). Upon delivery of the goods, the wholesaler received receipts which

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[12] There are few jobbers in business who can afford to fail to take advantage of the discount offered on goods purchased. The margin of profit which competition permits in the jobbing business is not large and in many lines the discount saving is one of the chief items of profit. Therefore the jobber in turn must find funds to pay cash for his purchases, and he very naturally turns to the banks (Eldridge 1915, p 5).

indicated that the manufacturer had fulfilled his obligations and released to him any final payments. This receipt completed a cycle of prediction, purchase, production, and delivery that began with the wholesalers' decision to acquire merchandise to sell in the next season.

Another cycle that needed to be completed was the cycle of commercial credit, which began with loan documents leaving the wholesalers bank and ended when the loan documents returned. Today, businessmen typically refer to these arrangements as letters of credit or short-term commercial paper. At the turn of the twentieth century, businessmen typically referred to these instruments as bankers' acceptances, a term whose origins we will now explain. Figure B.2 showed the initiation of this credit cycle, when the wholesalers' bank accepted responsibility to pay X dollars on date Y to the bearer of a letter of credit and the manufacturer sold that note at a discount off its face value to its bank.

Figures B.3 and B.4 illustrate the completion of this cycle. The manufacturers' bank (Bank 2) could return the note to the originating bank through one of two routes. The first was simple and direct. Bank 2 brought the note to Bank 1 (or perhaps sent it via intermediaries) and on the maturation date received face value. By the middle of the nineteenth century in Europe and by the turn of the twentieth century in the United States, a second route predominated. This route required the manufacturers' bank to add its name to the guarantors of the note. Accepting this liability turned the letter of credit into a bankers' acceptance, a short term credit instrument deemed an almost sure thing, since its repayment was guaranteed by two financial institutions, a wholesaler, a manufacturer, and ultimately, the merchandise itself. The manufacturers' bank could sell this note in the acceptance market (1). Acceptance markets operated nationally and internationally. The purchaser of the note paid a discount on the face value (2), held the note to maturity, redeemed it at the originating bank (3), and received the full payment (4). These actions completed commercial credit cycle.

In the nineteenth and early twentieth centuries, financing commercial transactions of this type was considered by many economists, bankers, businessmen, and policy makers to be the principal purpose of commercial banks (hence the name). According to this consensus, commercial banks needed to invest the bulk of their resources in short-term, safe commercial transactions, because commercial banks' principal source of funds was demand deposits, which depositors could withdraw at any time. This ideal underlay the Federal Reserve Act of 1913, which permitted Federal Reserve Banks to discount, rediscount, and loan funds only upon the security of 'eligible paper' that financed 'self-liquidating commercial transactions' of the type described in the previous paragraph (Sprague, 1914; Moulton, 1918; Silver, 1920; Currie, 1931). This rule remained in force until 1932, when Congress expanded forms of collateral that the Federal Reserve could accept in response to the prolonged contraction and the creation of the Reconstruction Finance Corporation.

To complete our description of the commercial credit cycle, we need to describe the movement of merchandise. The manufacturer sent the merchandise to the wholesaler, who sold the goods to numerous retailers, who in turn sold the goods to consumers. Cash payments flowed from consumers to retailers to the wholesaler. The latter used proceeds from these transactions to repay his debt to the bank, completing the interlocking cycles of credit and commerce that the wholesaler initiated many months in the past.[13]

Our description of the commercial credit cycle enables us to characterize relationships between the banks and businesses involved in the process. One way to characterize these relationships is to identify creditors and debtors. Commercial banks served as creditors of

[13] Note that in the 19th century, consumers and retailers often paid for merchandise with cash, but that these transactions could also be facilitated by credit, often listed as receivable in the accounts of wholesalers and retailers. Commercial banks served as the ultimate source of this credit. The most common mechanism involved allowing wholesalers to repay their loans at a point in time (say 60 to 120 says) after receiving the merchandise from the manufacturer and/or selling it to the retailer. Retail and consumer credit expanded rapidly in the United States during the 1920s.

wholesalers, who borrowed funds from banks and loaned funds to manufacturers and retailers. Wholesalers were debtors of banks and creditors of manufacturers and retailers. Manufacturers borrowed funds from wholesalers, which they repaid in kind (i.e. with merchandise), and deposited funds in commercial banks, making the manufacturer a debtor of the wholesaler and creditor of the bank. This commercial credit cycle closed when the wholesaler's bank redeemed bankers' acceptance at maturity. In that link, the wholesaler's bank was the debtor, and the manufacturer's bank was the creditor. The retail epicycle branched from the principal commercial credit cycle. In this epicycle, the manufacturer was the creditor and the retailer was the debtor. If the retailer in turn extended credit to consumers, the retailer served as the creditor in that transaction; the consumer was the debtor.

Another way to characterize these relationships is to indicate which tended to be unique and repeated and which tended to be multiplicative and competitive. The latter description characterized relationships among wholesalers, retailers, and manufacturers. Wholesalers typically purchased products from many manufacturers, and manufacturers typically sold products to many wholesales. Wholesalers typically sold merchandise to multiple retailers, and retailers typically purchased merchandise from multiple wholesalers.[14] The latter description also characterized relationships involving the manufacturer's bank. In cities and sizeable towns, banks typically accepted deposits from numerous manufacturing firms (call this number N).[15] Each depositor would present letters of credit from numerous wholesalers (call this number M). The manufacturer's bank would then hold N times M acceptances drawn on different banks used by

[14] In some industries in the early 20th century, gigantic firms developed, which vertically integrated manufacturing, distribution, and financing. General Motors and Ford Motors are examples. These firms did not follow the traditional commercial credit cycle. Instead, they tended to finance fixed investment by issuing equity and ongoing operations by issuing bonds. These firms deposited the bulk of their cash in commercial banks; which in many cases, they also owned a controlling stock interest. Thus, these modern conglomerates served as creditors (i.e. depositors and stockholders) of commercial banks at the base of the commercial credit cycle.

[15] Note that this may not have been the case in small rural towns with limited numbers of firms and banks.

different wholesalers, which the manufacturer's bank would typically sell in the nation (or international) acceptance market. Competition typically set prices in the acceptance market and in all of the other multiplayer markets linking wholesalers, retailers, and manufacturers.

A key relationship typically took a different form. The relationship between the wholesaler and its bank tended to be unique, long-run, and repeated. A wholesaler typically relied upon a single (or at most a small number) of banks for access to circulating credit. The long-run repeated relationship enabled the parties involved to develop reputations, accumulate information, and monitor the performance of their counterparty. Commercial banks specialized in providing this service, which enabled them to extend commercial credit in larger quantities and at lower cost than they would have otherwise been able.

Another way of classifying firms in the commercial credit cycle is to ask who had access to which sources of funds and for what purposes. We will consider manufacturers, retailers, and wholesalers. Manufacturers typically relied on equity (stock sales) to finance fixed costs such as investments in plant and equipment. Manufacturers increasingly relied upon debt (bond sales) to finance shorter run projects. Manufacturers also tended to build deposit balances, enabling them to finance operations via retained earnings. To pay for inputs and labor to fulfill orders from wholesalers, manufacturers typically relied on commercial credit, which the wholesaler extended after acquiring a letter of credit from their bank. Retailers often worked on a cash and carry basis. Customers paid cash for products. Retailers paid cash to acquire stock. Retailers who increasingly relied upon credit received the bulk of credit from wholesalers. In this system, wholesalers stood in a unique position. Wholesalers typically relied on one (or a small number) of banks to finance their operations. Wholesalers lacked the ability to raise funds via stocks and bonds, and since their debts to banks typically exceeded their deposit balances, lacked the ability to fund operations with retained earnings.

In the United States, the legal and regulatory structure recognized the importance and uniqueness of the relationship between commercial banks and wholesale firms. This recognition culminated in the Federal Reserve Act of 1913. From 1913 through 1932, the only financial instrument which the Federal Reserve System could accept as collateral was 'eligible paper' consisting of commercial credit for self-liquidating transactions. This is the type of commercial credit described throughout this section.

2.3 Disruptions of the Commercial Credit Cycle

During the early twentieth century, academics, practitioners, and politicians widely discussed bank failures' impact on economic activity. The studies of the National Monetary Commission on this topic may be the best example. Data on the subject at the firm level, however, began to be collected only during the early 1930s. A series of studies highlighted credit difficulties faced by small firms.

A study conducted by the National Industrial Conference Board (NICB) in 1932 illustrates the correlation between credit problems and size of the firm. The NICB conducted the study at the invitation of the Federal Reserve Bank of New York and with the cooperation of all 12 Federal Reserve Banks. The NICB surveyed 3,438 firms, the majority of which were manufacturers, in the first half of 1932. The NICB asked whether the firms had been "compelled to curtail operations in consequence of refusal or restriction of credit accommodation by banks (NICB 1932 p. 5)" Of the firms which reported routinely using banks as the source of working capital before the onset of the contraction, 22% reported that refusals or restrictions of bank credit had impeded their operations (NICB 1932 p. 62).[16] The preponderance of the refused loan requests (96%) were for working capital (NICB 1932 p. 89-91).

[16] Of all firms surveyed by the NICB, 466 (13.6%) reported that refusals or restrictions of bank credit had impeded their operations; 1,650 (48.0%) reported that they had no difficulty with banks or in obtaining sufficient bank credit

Table B.2 reports key statistics from the NICB survey. The NICB found that small firms borrowed working capital from banks more frequently than larger firms. Difficulties acquiring credit were concentrated among smaller establishments, whether ranked by number of employees in 1929 or capital in 1932 (NICB 1932 pp. 69, 71). While the Mercantile Agency Reference Book of R.G. Dun & Company (Dun) ranked four out of ten firms denied credit as poor credit risks (rankings of limited and unrated), Dun's ranked five out of ten firms as good credit risks (high and good ratings). The survey concludes that credit refusals often occurred for firms that "would have readily commanded bank credit in normal times (NICB 1932 p. 99)." The preponderance of the refused loan requests (96%) were for working capital (NICB 1932 p. 89-91). Over a third (37.6%) of the firms denied credit had offered collateral for the loan, including bankers' acceptances, receivables, warehouse receipts, stocks, bonds, and real estate (NICB 1932 p. 94). In one third of the cases (33.0%), lines of bank credit which were promised to or regularly used by firms were withdrawn or seriously curtailed (NICB 1932 p. 96). Credit refusals often occurred due to changes in the condition or policy of the bank. In 23% of cases, the lenders' difficulties – typical withdrawals by depositors – compelled them to curtail credit or call loans (NICB 1932 p. 111)[17].

3. Data Sources and Issues

This section discusses features of the data that shape our analysis. Key issues include the definitions of firm bankruptcy and bank suspension, the reason our analysis spans the years 1900 to 1932, and the way in which we identify banking panics. An appendix provides additional details and citations to sources of data.

to meet their business requirements; 1,322 (38.5%) reported that they did not need or typically borrow working capital from banks.

[17] See Tables B.3 and B.4 for additional data on credit difficulties.

Data on bankruptcies of firms comes from publications of R.G. Dun and Company (a predecessor of today's Dun and Bradstreet Corporation).[18] Dun's defined a business failure as the involvement of a firm in a court proceeding or voluntary action which was likely to end in loss to creditors (and in most cases involved the liquidation of the organization). Personal bankruptcies of professional individuals such as doctors, dentists, and lawyers were excluded. Dun's reporting network collected information from court filings in every county in the United States.

Dun's defined branches of business according to classifications devised by the Census Bureau for the census of 1890, which appeared a few years before Dun's began publishing its bankruptcy data series. Dun's defined branches of business consistently through the early 1930s. The Census Bureau, however, revised their industrial classification scheme extensively between 1890 and 1920. The Internal Revenue Service employed a different industrial classification scheme in their publications. Differences in cross-sectional industrial classification schemes complicate efforts to examine and interpret differences in patterns at the level of individual industries or branches of business, except at the sectoral level of all manufacturing firms and all trading firms, which all sources appear to distinguish in a consistent manner.

Dun's classified firms by size using measures of revenue in the year prior to bankruptcy. Large firms had revenues above \$5,000 per year. Small firms had revenues below \$5,000. The Census Bureau and IRS defined the size of firms in several ways, including number of employees, total assets, net profits, and total revenues. All of these measures appear highly correlated in our

[18] The quality of Dun's data on bankruptcies was widely recognized. Dun's data appeared in the Survey of Current Business, The Statistical Abstract of the United States, and the monthly reviews and annual reports of the Federal Reserve banks and board. Dun's data formed the basis of articles published in newspapers such as the New York Times, Wall Street Journal, and Commercial and Financial Chronicle. Dun's Review noted the popularity of its data when the editors wrote that "not only trade and manufacturing organizations recognize the importance of the records regarding their especial lines, but annual books of reference, almanacs, and even the monthly report of the Bureau of Statistics publishes the figures under the direction of the Treasury Department at Washington (Dun's Review, 13 July 1901, p. 6.)." The fact that both businessmen and bureaucrats used Dun's data indicates that they found it valuable. Dun's data on business failures was certainly watched by everyone interested in economic trends from the 1890s through the 1930s.

data sources, all of which provide tables classifying firms by size in multiple ways. All of these measures also appear inversely correlated with bank borrowing. Larger firms, no matter the measure of size, borrowed less from banks. Smaller firms borrowed more from banks. The size measure in all of our sources, in other words, is a useful proxy for reliance on bank credit. The primary credit source for all firms classified as small by Dun's would have been their local commercial banks. Some firms classified as large by Dun's would have relied on the same source, but the larger firms in this category would have been creditors to banks.

The definition of a bank suspension differed from the definition of a firm bankruptcy. A bank suspension occurs when a bank ceases payments to depositors on a business day and fails to reopen by 9am on the next business day. Some suspended banks reopened for operations. Others entered liquidation during which a court (or in some states, the superintendent of banking) or the Comptroller of Currency appointed a receiver (typically a lawyer) to wind up the bank's affairs, paying off the depositors and collecting assessments from stockholders.

Our study focuses on the period from 1900 through 1932, because during that period, the procedures for firm bankruptcies and bank liquidations remained stable. The Banking Act of 1898 standardized bankruptcy procedures for firms throughout the United States. This bankruptcy regime continued in operation until 1933. In that year and the year that followed, a series of amendments to the bankruptcy act altered the nature of bankruptcy throughout the United States. These amendments altered the threshold for forcing firms into bankruptcy, allowed firms to enter bankruptcy voluntarily, and enabled firms to use bankruptcy to reorganize the debts and continue in operation. In those same years, a series of laws altered the nature of bank liquidation. The federal government shut down all banks in the United States, determined which banks would reopen for business, recapitalized thousands of banks both large and small, and forced thousands of other banks to merge or cease operations. These laws created the Federal Deposit Insurance Corporation, which in addition to insuring deposits at most banks in our nation, became the liquidator of all banks that participated in the insurance scheme.

We identify banking crises whose origins appear to lie within the dynamics of the financial system by building on the work of other scholars. Andrew Jalil (2010) identifies panics as clusters of bank suspensions reported in the financial press. Lee Davison and Carlos Ramirez (2015) identify panics as chronological and geographical clusters of banks failures from FDIC reports of all banks failing in the United States during the 1920s and 1930s. Richardson (2007a) identifies local and national banking panics from examiners' reports of runs on banks. Richardson and Mitchener (2016) identify panics in microdata using examiners' reports as well as geographic and temporal clustering and in aggregate data by detecting sudden spikes in suspension rates associated with large numbers of bank runs and large numbers of banks being closed by their own directors, rather than official regulators. These four sets of scholars come up with similar results for the years that they examine. We display this information in Table B.5. We base our estimates on the panics described by Jalil and Richardson and conduct a series of robustness checks to ensure that our results is robust to the panic detection method.

Table B.6 and B.7 summarizes the available time-series evidence. Table B.6 describes quarterly data. The key information which we use for our study, which distinguishes failures of firms that borrow from banks from failures of firms that do not, spans the years 1900 through 1933. A consistent series of information on bank suspensions ends at the end of 1932. Most of these series are stationary, with the exception of bank suspensions (which are rising over time and thus have a trend) and small business failures. All of the series are stationary when differenced by subtracting the value of the variable 4 quarters prior from the value of the variable today. Year-over-year differencing also removes seasonality form the data.

Table B.7 describes the data available on a monthly basis. This set includes all of the data available quarterly, plus three additional types of information. The first is data on aggregate quantities including industrial production, retail trade, and wholesale trade. The second is data on financial prices, including the risk premium (Baa minus AAA rates) and discount and acceptance rates in New York City. The third is data on the volume of dollar acceptances and commercial paper on the market in New York City. Many of these series are non-stationary in levels. All are stationary when differenced by subtracting the value of the variable 12 months prior from the value of the variable today. Year-over-year differencing also removes the sizeable seasonality form the data.

4. Methods and Results

In this section, we estimate a series of vector autoregressions (VARs). These VARs yield Granger causality tests, impulse-response functions, and variance decomposition statistics that reveal the relationship between failure rates for banks and firms. Our VARs take the form:

(1) $Y_t = A_0 + A_1 Y_{t-1} + \cdots + A_l Y_{t-l} + \epsilon_t$

Here, Y_t is a vector of variables which includes measures of bank failures, firm bankruptcies, and in some specifications, other variables. To ensure stationarity and control for seasonality, the variables are differenced by subtracting the value in the current period from the value in the same quarter or month in the previous year. The time period is t, which in quarterly specifications runs from the first quarter of 1900 through the fourth quarter of 1932 and in monthly specifications runs from January 1922 through December 1932. A_i represents matrices of the VAR's coefficients. The number of lags is *l*. In the tables which we present, *l* equals 2 for monthly data and 4 for quarterly data.[19]

[19]The lag order was selected based on the standard information criteria: sequential modified LR test statistics (LR),

Figure B.5 summarizes a fundamental pattern in the data. The figure plots impulse response functions generated from a VAR with two variables, bank failures and firm bankruptcies. The confidence intervals are at the 95% level. The lower-left panel reveals the substantial response of firm bankruptcies to an unpredicted one-standard deviation increase in bank failures, which from now on we will refer to as a bank-failure shock. The response was sizeable, prolonged, and statistically significant. The upper-right panel reveals the response of bank failures to an unpredicted one-standard deviation increase in firm bankruptcies. In this case, the response appears muted. The mean estimate is near zero and statistically insignificant.

Table B.8 presents Granger causality tests and forecast error variance decompositions (FEVD). The results for the VAR depicted in Figure B.5 appear in the first column's initial rows. The Granger causality tests indicates that the null-hypothesis that bank failures did not precede firm bankruptcies can be rejected at the 5% level (p-value=0.01) in both quarterly and monthly data. The variance decomposition exercise indicates bank-failure shocks explain 54.3% of the volatility of firm bankruptcies in quarterly data and 30.5% in monthly data. The remaining rows of the table indicate the robustness of this result to the choice of detrending method. Similar results arise from data that has been HP filtered and data that has been seasonally adjusted and then HP filtered. The table does not report the results for the inverse relationship, from firm bankruptcies to bank failures. In every case, the Granger causality test indicate that we cannot reject the null hypothesis that unexpected surges in business bankruptcies did not precede increases in bank failures. Variance decompositions indicate that only a small fraction of bank failures can be

The Final Prediction Error (FPE), the Akaike information criterion (AIC), the Schwarz information criterion (SIC), and the Hannan–Quinn information criterion (HQIC) (Ivanov and Killian, 2005). Both BSIC and HQIC typically recommend a lag order of 1 or 2, while FPE, AIC, and LR recommend a lag order of 1 to 4 for the monthly data. While, BSIC and HQIC generally recommend a lag order of 1 or 5, and FPE, AIC, and LR recommend a lag order of between 6 to 8 for the monthly data The SBIC and HQIC statistics give consistent estimates of the true lag order, while the AIC and the FPE tend to overestimate it (Luktepohl, 2005). We estimate quarterly models using 4 lags and monthly models using 2 lags. The results do not change significantly if the number of lags included decreases or increases although increasing the number of lags tends weaken the results and create larger error bands for our impulse response functions.

attributed to shocks to business failures. The channel from business bankruptcies to bank failures, in other words, appears to be substantively and statistically insignificant.

Our results indicate a chronological correlation: sudden increases in failures of banks preceded surges in bankruptcies of firm. This chronological correlation could, of course be consistent with many models of the economy. Equation 2 tries to narrow the set of plausible interpretations by examining the impact of bank failures on firms that depended on banks to finance ongoing operations and on firms that did not. Using our knowledge of the state of economy during the time period, we impose restrictions on the VAR. Equation 2 is order as bank failures, net-creditors, and then net-debtors[20]. By ordering the variables this way we are imposing the restriction that bank failures are the most exogenous variable and large manufacturing failures are the most endogenous variables (i.e. large manufacturing failures are the slowest moving variable and bank failures are the fastest moving variable). We explain why we ordered the variables this way.

We are assuming that an impulse from bank failures would impact business failures and not the other way around. Lending typically starts at banking institutions. Banks lend to trading businesses. Once trading businesses have credit, they give cash to manufacturing businesses to produce goods for them. The trading businesses then sell their goods to customers. The customers give the trading businesses cash in return for their goods. The trading businesses use the cash and repay their loans to the banks.

During a banking crisis this flow of credit is disrupted. When banks fail, trading businesses lose their primary access to credit. With no credit available, trading businesses also fail. When trading businesses fail, manufacturing businesses lose their main supply of cash and fail. Bank

[20] Our findings are robust to changing the ordering of the variables in the VARs. Bank failures precede firm bankruptcies, but firm bankruptcies do not precede bank failures

failures precede trading business failures. Trading business failures precede manufacturing business failures.

Figure B.6 reports impulse response functions generated from equation 2. Row 2 in Column 1 illustrates that debtors, trading and small manufacturing firms, of banks exhibit a positive and significant response to a one standard deviation increase in bank failures. In table B.8, granger-causality tests are rejected for the null-hypothesis that banks do not granger cause debtor bankruptcies at the 10% level (p-value=0.08). FEVD graphs report that bank failures explain roughly 47% of debtor bankruptcies. Row 3 in Column 1 illustrates that net-creditors of banks, large manufacturing firms, also respond to an increase in bank failures. The null hypothesis that banks do not granger cause net-creditor bankruptcies is rejected (p-value=0.06) and the FEVD graphs report that bank failures explain roughly 46% of creditor bankruptcies. The data suggest that all classifications of firm bankruptcies respond to bank failures. It's possible that large manufacturers only started to become net-creditors after 1920. In further results, we show that large manufacturers do not respond to bank failures using monthly data from 1922 to 1932.

We identify the effect of banking panics, by expanding equation 2 and sorting bank failures into banks failing during panic periods and banks failing during non-panic periods. Quarterly data from 1900 to 1932 is used to include bank panics prior to 1921 and the model is conducted with 4 lags. Figure B.7 reports impulse response functions generated from this expanded VAR. Row 3 and column 1 illustrates that debtors do not experience a large significant response to banks failing during non-panic quarters[21]. Row 3 and column 2 illustrates that bank panics have a substantial and significant effect on debtor bankruptcies. The null-hypothesis that bank panics do not granger cause net-debtor bankruptcies is rejected at the 5% level (p-value=0.007). FEVD graphs report

[21] Granger-causality test show non-panic bank failures do granger-cause debtor bankruptcies, but IRFs are not positive and the 95% confidence intervals capture zero. The FEVD report non-panic bank failures explaining only 5% of the variation in debtor bankruptcies

that bank failing during panic periods explain roughly 15% of debtor bankruptcies. However, row 3 and column 4 illustrate that debtors respond to a one standard deviation increase in net-creditors. The null-hypothesis that net-creditors do not granger cause net-debtors cannot be rejected (p-value=.008). Interestingly, after a one-standard deviation shock in panic bank failures, net-creditor bankruptcies do substantially increase reported in row 4 and column 2. The null-hypothesis that panic bank failures do not granger cause net-creditors cannot be rejected (p-value=.008) and FEVD report panic bank failures explain 22% of net-creditor bankruptcies. The results suggest that panic bank failures do have an impact on net-debtors at the quarterly frequency and that net-creditors may have a positive impact on net-debtors.

Results from equation 2 analyzing quarterly data from 1900 to 1932 suggest that all classifications of firms, including large manufacturing firms, respond to bank failures. However, large manufacturing firms only started to become net creditors in 1921 as shown in Figure B.1. In the year 1921, the ratio of manufacturing firms' bank deposits to bank loans is slightly above 1. We re-estimate equation 2 analyzing monthly data from 1922 to 1932 to determine if large manufacturing firms became bank-independent during this time period. Figure B.8 illustrates impulse response functions generated from this VAR. Row 2 in Column 1 illustrates that debtors, trading and small manufacturing firms, of banks exhibit a positive and significant response to a one standard deviation increase in bank failures. Table B.8 illustrates that granger-causality tests are rejected for the null-hypothesis that banks do not granger cause debtor bankruptcies at the 5% level (p-value=0.03) and FEVD graphs report that bank failures explain roughly 14% of debtor bankruptcies. Row 3 in Column 1 illustrates that net-creditors of banks, large manufacturing firms, do not respond to an increase in bank failures. The null hypothesis that banks do not granger cause net-creditor bankruptcies cannot be rejected (p-value=0.58). A consistent pattern appears across the panels. Increases in the number of bank failures preceded increases in bankruptcies of bank-dependent firms; increases in the number of bank failures appears uncorrelated with increases in bankruptcies of firms that did not depend upon banks for access to credit. This pattern emerged in the 1920s and characterized the commercial credit cycle.

Robustness Checks

We subject the data to several robustness checks and our results do not alter significantly through each modification of the data. The first robustness check is to detrend the data through an HP filter and determine if the results change. Table B.8 shows that when we put the data through an HP filter the results do not significantly change. The second robustness check is analyzing the data in terms of the total amount of liabilities of firm bankruptcies instead of the number of firm bankruptcies. We find similar results when we analyze the data in terms of liabilities loss and the amount of bank suspended deposits. Table B.9 displayers the granger-causality tests and FEVD statistics associates with equations 1 and 2 conducted using liabilities. Third, we include other factors that may influence the commercial bank lending channel such as the Discount Rate in New York and the amount of commercial paper outstanding in the United State. Figures B.9 and B.10 display that bank failures still have a large and significant impact on net-debtors controlling for the Discount rate and commercial paper. Tables B.10 and B.11 report the granger-causality test and FEVD statistics and show that our results still hold controlling for other factors; bank suspensions precede bank-dependent firm bankruptcies, but do not precede bank-independent firm bankruptcies.

5. Discussion

Clear chronological correlations existed between failures of banks and bankruptcies of firms. Our research design – including the comparison of exogenous and endogenous shocks and the comparison of effects on treatment and control groups – enables us to identify causal relationships. These patterns indicate that failures of banks triggered failures of firms that depended on banks for credit. The pattern stems almost entirely from pronounced increase in failure of bank-dependent firms following events identified as financial panics. These statistical findings appear consistent with widespread claims by profession observers that financial crises and lenders-of-last resort influenced economic activity through what we now describe as a bank-lending channel.

Our findings help to explain the change in bank lending practices documented by Jacoby and Saulnier in their seminal study (1942). The collapse of commercial banking in the early 1930s cut merchants off from their typical source of working capital and depleted the cash reserves of manufacturers. These firms, like everyone else, suffered "the most desperate scramble for liquidity that we have ever experienced (Currie 1934 p. 124)" and "the most extreme and prolonged period of bank credit liquidation in the history of the United States (Kimmel 1939 p. 1)." From 29 June 1929 to 30 June 1933, total loans from Fed member banks decline from $25.7 billion to $12.9 billion (50%). Total loans from non-member banks declined form $9.8 billion to $3.5 billion (64%). In the decade after this crisis, short-term lending to businesses (often based upon marketable acceptances) stagnated, while medium term lending (typically direct loans from the bank to the ultimate borrow) – maturing in one to fifteen years – expanded. Jacoby and Saulnier attributed this expansion to "business demand for medium-term loans relative to the demand for short- or long-dated credit (Jacoby and Saulnier 1942 p.2) and to businesses memory of "the pressures that had been put upon them by commercial banks during the contraction period of 1929-1932 to liquidate their short-term obligations (Jacoby and Saulnier 1942 p. 16)." During the recovery, traditional lending expanded gradually. Term lending to businesses expanded swiftly. Term lending included loans repayable after more than one and in less than fifteen years, often amortized, principally used for working capital or the purchase of machinery and equipment, and almost always representing direct relationships between the lender and borrower.[22] This form of business lending arose during the 1930s, when there was a break with the orthodox theory of commercial banking relationships with business enterprises, which accepted the fact that bank loans would finance not only short-lived expansions but would also fund the acquisition of fixed assets and long-term working capita.

[22] Term lending displaced two forms of credit popular before the depression: commercial bank loans and corporate bonds. Term lending possessed many features of the former but matured on the time horizon of the latter. Jacoby and Saulnier (1942) 72 percent of the number and 57 percent of the amount of term loans were amortized.

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Appendix A.

Appendix of Chapter 1

Table A1: The determinants of intra-firm trade -ONET Child Labor Intensity Robustness Checks

Dependent Variable :	Share of U.S. intra-firm imports							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ONET Child Labor Intensity	-0.168***	-0.265**	-0.173**	-0.169**	-0.195***	-0.145***	-0.186**	-0.173**
	(0.00416)	(0.00968)	(0.00529)	(0.00509)	(0.00339)	(0.00405)	(0.00538)	(0.00500)
Capital Intensity	0.0382*	-0.180**	0.0560**	0.0587**	0.0365	0.0453*	0.0503*	0.0466*
	(0.0109)	(0.0361)	(0.0123)	(0.0123)	(0.0127)	(0.0109)	(0.0124)	(0.0117)
Skill Intensity	-0.0136	-0.129	-0.0128	-0.0138	-0.0239	-0.0171	-0.0221	-0.0104
	(0.0578)	(0.165)	(0.0740)	(0.0713)	(0.0463)	(0.0574)	(0.0753)	(0.0693)
GDP per capita	0.179***	0.272***	0.189***	0.135***	0.179***	0.164***	0.149***	0.151***
	(0.0107)	(0.0197)	(0.0164)	(0.0171)	(0.0107)	(0.0113)	(0.0131)	(0.0130)
GDP per capita * ONET Child Labor Intensity		0.0997						
		(0.00127)						
GDP per capita * Capital Intensity		0.228***						
		(0.00378)						
GDP per capita * Skill Intensity		0.124						
		(0.0208)						
Log Children in employment, total * ONET Child Labor Intensity			0.0245					
			(0.0171)					
Log Children in employment, total * Capital Intensity			-0.0271*					
			(0.0390)					
Log Children in employment, total * Skill Intensity			0.00699					
			(0.249)					
Log Children in employment, total			-0.0293					
			(0.176)					
Log Child employment in manufacturing * ONET Child Labor Intensity				0.0207				
				(0.0261)				
Log Child employment in manufacturing * Capital Intensity				-0.0286				
				(0.125)				
Log Child employment in manufacturing * Skill Intensity				0.0398				
				(0.403)				
Log Child employment in manufacturing				-0.00197				
				(0.409)				
ILO Indicator * ONET Child Labor Intensity					0.0366			
					(0.00180)			
ILO Indicator * Capital Intensity					0.00257			
					(0.00739)			
ILO Indicator * Skill Intensity					0.0188			
					(0.0257)			
ILO Indicator					0.00378			
					(0.0221)			
Log No. Articles in t * ONET Child Labor Intensity						-0.0472***		
						(0.000559)		
Log No. Articles in t* Capital Intensity						-0.0106		
						(0.00225)		
Log No. Articles in t * Skill Intensity						-0.00421		
						(0.00831)		
Log No. Articles in t-1 * ONET Child Labor Intensity						-0.0413***		
						(0.000595)		
Log No. Articles in t-1 * Capital Intensity						0.0120		
						(0.00150)		
Log No. Articles in t-1 * Skill Intensity						-0.00219		
						(0.00838)		
Log No. Articles in t						0.0287		
						(0.00674)		
Log No. Articles in t-1						0.0441***		
						(0.00560)		
Log not enrolled in school * ONET Child Labor Intensity							0.0335	
							(0.00105)	
Log not enrolled in school * Capital Intensity							-0.0391	
							(0.00406)	
Log not enrolled in school * Skill Intensity							0.0213	
							(0.0158)	
Log not enrolled in school							-0.0490	
							(0.0126)	
Log out of school * ONET Child Labor Intensity								0.00900
								(0.000928)
Log out of school * Capital Intensity								-0.0406
								(0.00355)
Log out of school * Skill Intensity								-0.0267
								(0.0141)
Log out of school								-0.0816
								(0.0110)
Observations	153,438	153,438	74,318	70,530	153,438	133,374	105,669	105,329
R-squared	0.181	0.181	0.209	0.211	0.181	0.200	0.199	0.197
P-value of F-test for joint significane of interaction terms	0.00355	6.54e-06	0.249	0.241	0.139	4.61e-08	0.465	0.267
# Clusters	85	85	85	85	85	85	85	85

The dependent variable is the share of intra firm imports. An observation is a NAICS4-country pair. Standardized 'beta' coefficients are reported.
Standard errors clustered at the 4-digit NAICS industry level appear in parenthesis. All regressions include Country and Year Fixed Effects.
*** p<0.01, ** p<0.05, * p<0.1

Table A2: The determinants of intra-firm trade- ILAB Child Labor Intensity Robustness Checks

Dependent Variable :	Share of U.S. intra-firm imports							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ILAB Child Labor Intensity	-0.0210***	0.0365	-0.0136	-0.000808	-0.0203***	-0.0188*	-0.0200*	-0.0219**
	(0.0332)	(0.159)	(0.0627)	(0.0612)	(0.0338)	(0.0461)	(0.0513)	(0.0451)
Capital Intensity	0.0598**	-0.154*	0.0799***	0.0830***	0.0584**	0.0654***	0.0744***	0.0690***
	(0.0118)	(0.0399)	(0.0129)	(0.0127)	(0.0138)	(0.0113)	(0.0131)	(0.0123)
Skill Intensity	0.132***	0.121	0.137***	0.134***	0.143***	0.115***	0.135***	0.137***
	(0.0295)	(0.105)	(0.0366)	(0.0356)	(0.0282)	(0.0295)	(0.0394)	(0.0349)
GDP per capita	0.181***	0.255***	0.190***	0.137***	0.181***	0.166***	0.153***	0.154***
	(0.0106)	(0.0176)	(0.0164)	(0.0171)	(0.0106)	(0.0112)	(0.0130)	(0.0130)
Log Children in employment, total * ILAB Child Labor Intensity			0.000433					
			(0.253)					
Log Children in employment, total * Capital Intensity			-0.0328*					
			(0.0401)					
Log Children in employment, total * Skill Intensity			-0.0204					
			(0.135)					
Log Children in employment, total			-0.0409					
			(0.149)					
GDP per capita * ILAB Child Labor Intensity		-0.0594						
		(0.0200)						
GDP per capita * Capital Intensity		0.224***						
		(0.00403)						
GDP per capita * Skill Intensity		0.0134						
		(0.0120)						
Log Child employment in manufacturing * ILAB Child Labor Intensity				-0.0131**				
				(0.443)				
Log Child employment in manufacturing * Capital Intensity				-0.0395*				
				(0.129)				
Log Child employment in manufacturing * Skill Intensity				0.00968				
				(0.246)				
Log Child employment in manufacturing				-0.0164				
				(0.385)				
ILO Indicator * ILAB Child Labor Intensity					-0.000669			
					(0.0414)			
ILO Indicator * Capital Intensity					0.00186			
					(0.00689)			
ILO Indicator * Skill Intensity					-0.0190			
					(0.0118)			
ILO Indicator					-0.00705			
					(0.0169)			
Log No. Articles in t * ILAB Child Labor Intensity						0.00459		
						(0.0112)		
Log No. Articles in t * Capital Intensity						-0.00554		
						(0.00213)		
Log No. Articles in t * Skill Intensity						0.0584***		
						(0.00487)		
Log No. Articles in t-1 * ILAB Child Labor Intensity						-0.00645		
						(0.0122)		
Log No. Articles in t-1 * Capital Intensity						0.0151*		
						(0.00159)		
Log No. Articles in t-1 * Skill Intensity						0.0506***		
						(0.00478)		
Log No. Articles in t						0.0524***		
						(0.00568)		
Log No. Articles in t-1						0.0625***		
						(0.00509)		
Log not enrolled in school * ILAB Child Labor Intensity							-0.00238	
							(0.0168)	
Log not enrolled in school * Capital Intensity							-0.0448	
							(0.00412)	
Log not enrolled in school * Skill Intensity							-0.00806	
							(0.00920)	
Log not enrolled in school							-0.0553	
							(0.0112)	
Log out of school * ILAB Child Labor Intensity								-0.000230
								(0.0113)
Log out of school * Capital Intensity								-0.0418
								(0.00364)
Log out of school * Skill Intensity								-0.0245
								(0.00791)
Log out of school								-0.0731
								(0.00979)
Constant								
	(0.0956)	(0.164)	(0.161)	(0.167)	(0.0965)	(0.102)	(0.120)	(0.118)
Observations	153,438	153,438	74,318	70,530	153,438	133,374	105,669	105,329
R-squared	0.174	0.175	0.202	0.204	0.174	0.193	0.192	0.190
P-value of F-test for joint significane of interaction terms	0.00379	2.55e-06	0.309	0.139	0.263	6.50e-06	0.593	0.325
# Clusters	85	85	85	85	85	85	85	85

The dependent variable is the share of intra firm imports. An observation is a NAICS4-country pair. Standardized 'beta' coefficients are reported. Standard errors clustered at the 4-digit NAICS industry level appear in parenthesis. All regressions include Country and Year Fixed Effects.
*** p<0.01, ** p<0.05, * p<0.1

Appendix B.

Appendix of Chapter 3

Data Sources

Bank Suspensions. Data on bank suspensions comes from FRB 37, Dun's Review, NBER Macrohistory.

Business Failures: Data on business failures comes from Dun's Review. See Gou and Richardson (2014) for details.

Bank Suspensions: The data that we examine on bank failures originated with two sources: bank regulators and the financial press. Regulators of state and national banks reported changes in bank status – such as suspensions, mergers, and terminations – to their supervisors, who published these materials periodically. The financial press reported many of these events within days of their occurrence in daily publications like the Wall Street Journal and New York Times. The financial press also compiled information about these events which was published periodically in volumes such as Rand McNally Bankers Directory or R.G. Dun's Bank and Quotation Record. During the 1920s and 30s, the Federal Reserve Board's Division of Bank Operations compiled information from all of these sources to create data on the number of bank suspensions and amount of deposits of suspended banks. The Federal Reserve published aggregate tabulations from this endeavor in its monthly bulletin in September 1937. Richardson (2006, 2007, 2008) and Chung and Richardson (2007) recovered this microdata and used it to construct the data series analyzed in this essay. These series consists of counts of failures of banks from regulators original reports that have been checked repeatedly by experts over the intervening decades. Data on monthly bank failures from 1921 to 1932 is used to estimate our monthly vector autoregressions.

Quarterly bank failure data is gathered from the National Bureau of Economic Research Macrohistory database which originates from R.G. Dun and Co.. Aggregate data on quarterly bank failures from 1894 to 1924 is gathered from this source. These data are merged with the monthly data to construct a consistent series of quarterly bank failures from 1895 to 1937. Data on quarterly bank failures from 1900 to 1932 is used to estimate quarterly vector autoregressions.

Banking Panic Data: We identify banking crises whose origins appear to lie within the dynamics of the financial system in two ways. Richardson (2007a) identifies local and national banking panics from examiners' reports of the causes of bank suspensions. Panics are defined as events where the bulk of the banks that suspended operations possessed portfolios that examiners deemed sufficient prior to the crisis but were forced out of business by what examiners deemed to be sudden, sizeable, and unexpected demands by depositors or financial counterparties such as correspondent banks. Andrew Jalil (2010) identifies panics as clusters of bank suspensions reported in the financial press. For years when Jalil and Richardson's series overlap, the different methods yield identical results (Table 5 shows the quarters when banking panics occurred).

Business Data: Data on bankruptcies of firms comes from publications of R.G. Dun and Company (a predecessor of today's Dun and Bradstreet Corporation). We process these sources to create accurate, consistent, and high-frequency data on failures of firms and banks from 1895 through 1933 (Richardson and Gou, 2011). Our series begins in 1895, the first year for which R.G. Dun published monthly data on bankruptcies disaggregated by branch of business. Dun's collected this information by establishing a reporting network which collected information on court filings in every county in the United States during each month of the year. Dun's defined branches of business according to classifications devised by the census bureau in the early 1890s. Dun's defined a business failure as the involvement of a firm in a court proceeding or voluntary action which was likely to end in loss to creditors (and in most cases involved the destruction of the organization). Personnel bankruptcies of profession individuals such as doctors, dentists, and lawyers were excluded. These data include all bankruptcy proceedings filed under the Bankruptcy Act of 1898.

Dun's tabulated data about bankruptcies in several ways. Dun's classified firms into economic sectors of manufacturing and trading. Within those sectors, Dun's classified firms by branch of business and as large (revenues above $5,000 per year) or small (revenues below $5,000) starting in 1900. Dun's classifications separate firms into the types that we described in the previous section: wholesalers and retailers, manufacturers, large firms, small firms, large wholesalers and retailers, large manufacturers, small wholesalers and retailers, and small manufacturers. Monthly data from 1922 to 1932 is used in our monthly vector autoregressions. We aggregate the monthly data to quarterly data for the years 1900 to 1932 to analyze our quarterly vector autoregressions.

Commercial Paper Data: Data on commercial paper outstanding comes from the banking and monetary statistics 1914-1941. We collect these data for the years available 1918 to 1940.

Discount Rate Data: Data on Discount Rates outstanding comes from the banking and monetary statistics 1914-1941. We collect these data for the years available 1914 to 1940.

Tables

Table B.1: Firms' Relationships with Banks in 1926

Size of Net Income	**Manufacturers**					**Traders**				
	#	Deposits $ million	Loans $ million	Assets $ million	Ratio D/L	#	Deposits $ million	Loans $ million	Assets $ million	Ratio D/L
No Net Income	32,401	319	1,543	11,813	0.21	34,647	172	890	4,093	0.19
Under $5,000	26,042	98	287	2,115	0.34	42,881	145	428	2,731	0.34
$5,000 to $10,000	6,112	55	126	1,099	0.44	8,543	66	167	1,103	0.40
$10,000 to $50,000	11,723	237	416	4,466	0.57	10,912	198	445	3,239	0.44
$50,000 to $100,000	3,228	153	210	2,884	0.73	1,878	93	188	1,507	0.50
$100,000 to $250,000	2,595	267	260	4,343	1.03	1,014	122	197	1,760	0.62
$250,000 to $500,000	1,039	217	174	3,815	1.25	298	70	78	1,036	0.90
$500,000 to $1,000,000	569	248	157	4,363	1.58	119	52	55	870	0.95
$1,000,000 to $5,000,000	439	584	311	10,321	1.88	91	124	122	1,821	1.02
Over $5,000,000	103	1,347	541	19,511	2.49	12	121	6	981	21.63
Total Firms Reporting Net Income	51,850	3,208	2,481	52,914	1.29	65,748	991	1,684	15,048	0.59
Total All Firms	84,251	3,527	4,024	64,727	0.88	100,395	1,164	2,574	19,140	0.45

Source: IRS (1929) Table 18. Notes: Columns for deposits indicate the sum of firms' holdings of bank deposits and notes. Loans indicates firms' notes payable to commercial banks. Assets indicates firms' total assets. Ratio D/L indicates deposits divided by loans. Ratios below 1 indicate firms that were net borrowers from banks. Ratios above 1 indicate firms which were net creditors of banks.

Table B.2: Credit Difficulties Reported in Survey of National Industrial Conference Board, 1932.

Size	Employees (1929)	#	Bank Borrower %	Credit Difficulty %	Credit Rating % High + Good	Capital (1932) in $1,000	#	Bank Borrower %	Credit Difficulty %	Credit Rating % High + Good
Very Small	1 to 100	587	65.2	31.1	47.1	< 50	176	71.6	41.3	50.0
Small	101 to 250	872	68.0	21.8	45.7	50 to 500	1,350	67.3	22.2	63.9
Medium	251 to 500	486	55.3	19.0	41.2	500 to 1,000	328	60.0	12.5	72.7
Large	501 to 1,000	239	49.4	10.2	66.7	Over 1,000	1,124	50.5	9.7	80.0
Very Large	Over 1,000	446	48.0	6.5	64.3					
Unclassifiable		808	66.7	26.2	53.2	Unknown	350	71.7	49.4	11.3
Total		3,438	61.5	22.0	48.9	Total	3,438	61.5	22.0	48.9

Notes: Bank borrowers indicates fraction of firms that reported regularly borrowing working capital from commercial banks. Credit difficulty indicates fraction of bank-borrowing firms that report refusals, restrictions, or difficulties acquiring bank credit which they would have received in normal times. Credit rating column indicates the percentage of firms reporting credit difficulties in each size bracket which had either a high or good rating in Dun's credit reports in 1932.

Source. National Industrial Conference Board, 1933, Tables 17, 19, and 37

Table B.3: **Credit Sources and Difficulties Among Small Manufacturers, 1934**

	Working Capital		Longer Term Requirements	
Typical Source of Capital	% of Firms	% in Credit Difficulty	% of Firms	% in Credit Difficulty
Banks	85.9	43.7	18.1	57.6
Other Financial Institutions	4.1	61.5	1.9	55.6
Bonds or Stocks	2.4	60.2	17.0	61.3
Total # of Firms	4,089		1,877	

Notes: The total number of firms is the number of firms which reported their customary sources of working or long-term capital. Approximately 300 firms reported customarily raising working capital from multiple sources. The categories reported in the table, therefore, need not be mutually exclusive. Other financial institutions include factors, finance companies, trust companies, and merchant creditors. The columns % of firms indicates the percent of respondents indicating that the customarily in 1929 relied on that source for either working capital, longer-term capital, or both. The columns % in credit difficult indicate the fraction of firms that reported using source x for capital y which faced credit difficulties. Source: Department of Commerce (1935) Table 26

Table B.4: **Credit Difficulties, Firm Quality, and Size of Establishment Among Small Manufacturers, 1934**

		Percent in Credit Difficulties Weighted by			Percent of Firms in Credit Difficulties whose		
Wage Earners Per Establishment	# Borrow	# of Firms	Value of Manufacturing Production	Annual Pay Roll	Current Ratio > 2	Equity-debt Ratio > 2	Current Ratio > 2 Equity-debt Ratio > 2 Credit Rating High or Good
21 to 50	1364	50.9	41.5	47.3	57.4	60.2	9.2
51 to 100	1715	43.7	35.9	40.2	63.4	66.5	9.2
101 to 250	1308	39.8	33.9	36.7	63.7	68.8	8.3

Notes: Number of borrowers is the total number of firms in survey reporting to be borrowers of working capital. The percent of firms in credit difficulties is the number of firms in credit difficulties divided by the number of firms borrowing working capital calculate without weights (# of firms) or by weighting the firms by value of manufacturing production or annual pay roll. The current ratio is the current assets including cash, inventories, and receivables divided by current liabilities including short-term obligations to banks and all other liabilities payable within 1 year. The equity to debt ratio equals net worth (current assets plus fixed assets minus total liabilities) divided by total liabilities. Source: Department of Commerce (1935) Tables 7, 8, 9, 10, 19, and 25.

Table B.5: Panic Quarters defined by Jalil from 1900-1929 and Richardson from 1929-1933.

Year	Quarters	Source and Notes
1907	4	Jalil
1908	1	Jalil
1920	3,4	Jalil
1921	1	Jalil
1926	3	Jalil
1927	1	Jalil
1929	3	Jalil, Richardson
1930	4	Richardson
1931	2, 4	Richardson. Q1 and Q3 near to inclusion.
1932	1	Richardson. Q3 near to inclusion.

Source: See Jalil (2010) and Richardson (2006, 2007, 2008) and Chung and Richardson (2007).

Table B.6. Variable Availability and Stationarity, Quarterly

	Date		Dickey-Fuller	Mean	Median	Max	Min	Std
	Begin	End	Test Statistics					Dev
Bank Suspensions	1895	1936	**-10.8**	89	30	1055	0	137
Business Failures	1895	1940	-2.66	4076	3696	9141	1393	1583
Large[a]	1900	1935	-1.90	117	82	453	12	87
Small[a]	1900	1935	**-3.14**	4086	3698	8688	539	1585
Manufacturing Failures	1895	1940	-2.28	986	927	1932	409	373
Large[a]	1900	1933	-2.71	59	45	210	8	38
Small[a]	1900	1933	-2.44	973	930	1744	141	347
Trading Failures	1895	1940	**-2.93**	2897	2579	6705	874	1131
Large[a]	1900	1935	-2.68	40	22	179	2	38
Small[a]	1900	1935	**-3.53**	2929	2581	6530	352	1173

Note: **Boldface** indicates a rejection of the null hypothesis of stationarity by the DF test at the 5% level. (a) The data starts in First Quarter 1900

Sources: For 1893 to 1920, quarterly data on bank suspensions comes from the NBER Macrohistory database and originates from R.G. Dun and Co., Dun's Review.

For 1921 to 1932, Quarterly data on bank suspensions comes from the Federal Reserve Bulletin, September 1937.

Table B.7. Variable Availability and Stationarity, Monthly

	Date		Dickey-Fuller test statistic		Summary Statistics				
	Begin	End	Begin to End	1922 to 1932	Mean	Median	Max	Min	S Dev
Bank Suspensions	1921	1936	**-12.8**	**-4.90**	78	58	522	12	73
Business Failures	1895	1940	**-3.67**	-0.78	1987	1924	3458	1226	406
Large	1900	1935	-2.31	-2.18	70	59.5	161	33	28
Small	1900	1935	-2.54	-0.81	1917	1837	3302	1175	387
Manufacturing Failures	1895	1940	-2.30	**-3.15**	484	481	688	324	76
Large	1900	1933	**-2.90**	-2.32	33	29.5	76	16	12
Small	1900	1933	-2.11	**-3.33**	451	452	628	297	68
Trading Failures	1895	1940	**-4.01**	-1.06	1394	1323	2595	828	326
Large	1900	1935	-2.70	-2.41	27	23	74	7	13
Small	1900	1935	**-2.89**	-0.74	1375	1290	2529	812	315
Quantity Indices									
Industrial Production	1919	1940	-2.30	-1.61	97	102	127	58	15.7

Retail Trade Index	1919	1939	-1.79	0.33	98.8	101	113	66	11.1
Wholesale Index	1919	1940	-2.13	0.23	90.5	94.4	104.4	63	11.6
Price Series									
Baa-Aaa	1919	1940	-2.10	**-4.37**	1.83	1.46	6.27	0.86	1.1
NY Discount Rate	1914	1940	-1.64	-1.94	3.7	4	6	1.5	.97
NY Acceptance Rate	1917	1940	0.65	-1.67	3.2	3.4	5.5	0.4	1.2
Credit Series									
Dollar Acceptances	1925	1940	-1.87	-1.64	1012	975	1732	555	313
Commercial Paper	1918	1940	-1.64	-0.05	555.5	578	925	81	242

Note: **Boldface** indicates a rejection of the null hypothesis of stationarity by the DF test at the 5% level. The beginning and ending dates indicates the year that the series began. Series began in January and ended in December, except for business failures, which ended in November, and the NY Discount and Acceptance Rates, which began in November and August respectively.

Table B.8: Impact of Bank Failures on Firm Bankruptcies

Variables in System		1	2		3		4	
Response of What Type of Firms		All	Trade	Manuf.	Small	Large	Debtors	Creditors
A. t-12 Differenced								
Monthly, 1922-1932	Granger P-Value	0.01	0.06	0.24	0.02	0.18	0.03	0.58
	Variance Decomp	30.5	16.4	9.0	17.4	2.2	13.9	0.6
Quarterly, 1895-1932	Granger P-Value	0.01	0.01	0.47	0.07	0.04	0.08	0.06
	Variance Decomp	54.3	52.2	26.9	43.6	46.5	47.3	46.1
B. HP-Filtered								
Monthly, 1922-1932	Granger P-Value	0.01	0.00	0.08	0.00	0.19	0.00	0.17
	Variance Decomp	29.5	31.2	16.6	28.4	9.0	29.5	4.57
Quarterly, 1895-1932	Granger P-Value	0.00	0.00	0.02	0.00	0.04	0.00	0.00
	Variance Decomp	21.5	22.1	13.3	16.4	13.7	24.6	23.7
D. HP-Filtered, SA								
Monthly, 1922-1932	Granger P-Value	0.24	0.09	0.36	0.12	0.51	0.11	0.96
	Variance Decomp	10.3	18.3	11.8	8.2	0.6	12.8	0.88
Quarterly, 1895-1932	Granger P-Value	0.01	0.00	0.15	0.03	0.00	0.00	0.02
	Variance Decomp	25.6	27.7	14.5	29.5	26.4	31.0	16.9

Table B.9: Impact of Bank Failures on Firm Bankruptcies, Liabilities

Variables in System		1	2		3		4	
Response of What Type of Firms		All	Trade	Manuf.	Small	Large	Debtors	Creditors
A. t-12 Differenced								
Monthly, 1922-1932	Granger P-Value	0.11	0.03	0.85	0.02	0.05	0.05	0.18
	Share of R2	7.7	10.6	0.35	17.2	7.3	10.9	4.1
Quarterly, 1895-1932	Granger P-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.01
	Variance Decomp	68.8	82.3	61.8	66.3	56.1	80.8	46.9
B. HP-Filtered								
Monthly, 1922-1932	Granger P-Value	0.03	0.00	0.14	0.0	0.27	0.0	0.17
	Variance Decomp	10.9	20.7	5.6	17.7	5.6	18.9	4.6
Quarterly, 1895-1932	Granger P-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Variance Decomp	25.7	30.9	13.0	23.2	15.8	26.6	9.9
D. HP-Filtered, SA								
Monthly, 1922-1932	Granger P-Value	0.78	0.15	0.51	0.04	0.98	0.14	0.70
	Variance Decomp	2.3	8.7	1.2	9.5	0.2	8.9	1.2
Quarterly, 1895-1932	Granger P-Value	0.00	0.00	0.00	0.00	0.01	0.00	0.01
	Variance Decomp	29	36.6	11.4	38.3	21.7	24.4	8.4

Table B.10: Impact of Bank Failures on Firm Bankruptcies, controlling for discount rate and commercial paper, Monthly 1922-1932

Variables in System	1	2		3		4	
Response of What Type of Firms	All	Trade	Manuf.	Small	Large	Debtors	Creditors
A. t-12 Differenced							
Granger P-Value							
Including Discount Rate	0.00	0.02	0.14	0.02	0.15	0.03	0.46
Including Commercial Paper	0.02	0.08	0.19	0.03	0.18	0.07	0.45
Including Discount Rate and Commercial Paper	0.01	0.04	0.14	0.05	0.14	0.11	0.33
Variance Decomp							
Including Discount Rate	30.6	13.5	15.4	12.8	6.54	10.0	3.06
Including Commercial Paper	30.9	16.2	10.0	17.5	2.85	14.1	0.92
Including Discount Rate and Commercial Paper	29.1	13.3	11.1	9.74	3.40	6.50	2.00
B. HP-Filtered							
Granger P-Value							
Including Discount Rate	0.00	0.00	0.06	0.00	0.11	0.00	0.06
Including Commercial Paper	0.14	0.07	0.31	0.01	0.30	0.03	0.19
Including Discount Rate and Commercial Paper	0.07	0.04	0.25	0.00	0.17	0.01	0.09

Variance Decomp							
Including Discount Rate	30.7	31.2	19.7	28.9	11.9	29.3	6.3
Including Commercial Paper	24.4	26.0	12.4	23.8	7.46	25.3	4.3
Including Discount Rate and Commercial Paper	25.1	25.9	13.9	25.1	10.5	24.5	6.6

Table B.11: Impact of Bank Failures on Firm Bankruptcies, controlling for discount rate and commercial paper, Monthly 1922-1932, Liabilities

Variables in System	1	2		3		4	
Response of What Type of Firms	All	Trade	Manuf.	Small	Large	Debtors	Creditors
A. t-12 Differenced							
Granger P-Value							
Including Discount Rate	0.05	0.01	0.91	0.00	0.00	0.01	0.00
Including Commercial Paper	0.06	0.05	0.74	0.02	0.02	0.06	0.04
Including Discount Rate and Commercial Paper	0.01	0.03	0.77	0.00	0.00	0.02	0.00
Variance Decomp							
Including Discount Rate	11.6	8.47	0.27	22.3	10.3	14.2	7.66
Including Commercial Paper	8.80	9.98	0.39	19.3	7.66	19.1	5.17
Including Discount Rate and Commercial Paper	13.2	7.87	0.46	18.6	11.4	12.2	8.82
B. HP-Filtered							
Granger P-Value							
Including Discount Rate	0.01	0.00	0.02	0.00	0.13	0.00	0.05
Including Commercial Paper	0.09	0.01	0.09	0.03	0.30	0.03	0.15
Including Discount Rate and Commercial Paper	0.03	0.01	0.02	0.01	0.15	0.01	0.05

Variance Decomp							
Including Discount Rate	14.1	24.7	7.5	22.0	6.9	23.2	5.6
Including Commercial Paper	10.6	21.1	5.8	18.2	5.7	18.4	4.7
Including Discount Rate and Commercial Paper	13.5	23.3	8.02	21.4	6.9	19.8	6.1

Figures

Figure B.1: Manufacturing and Trading Firms as Bank Creditors and Debtors

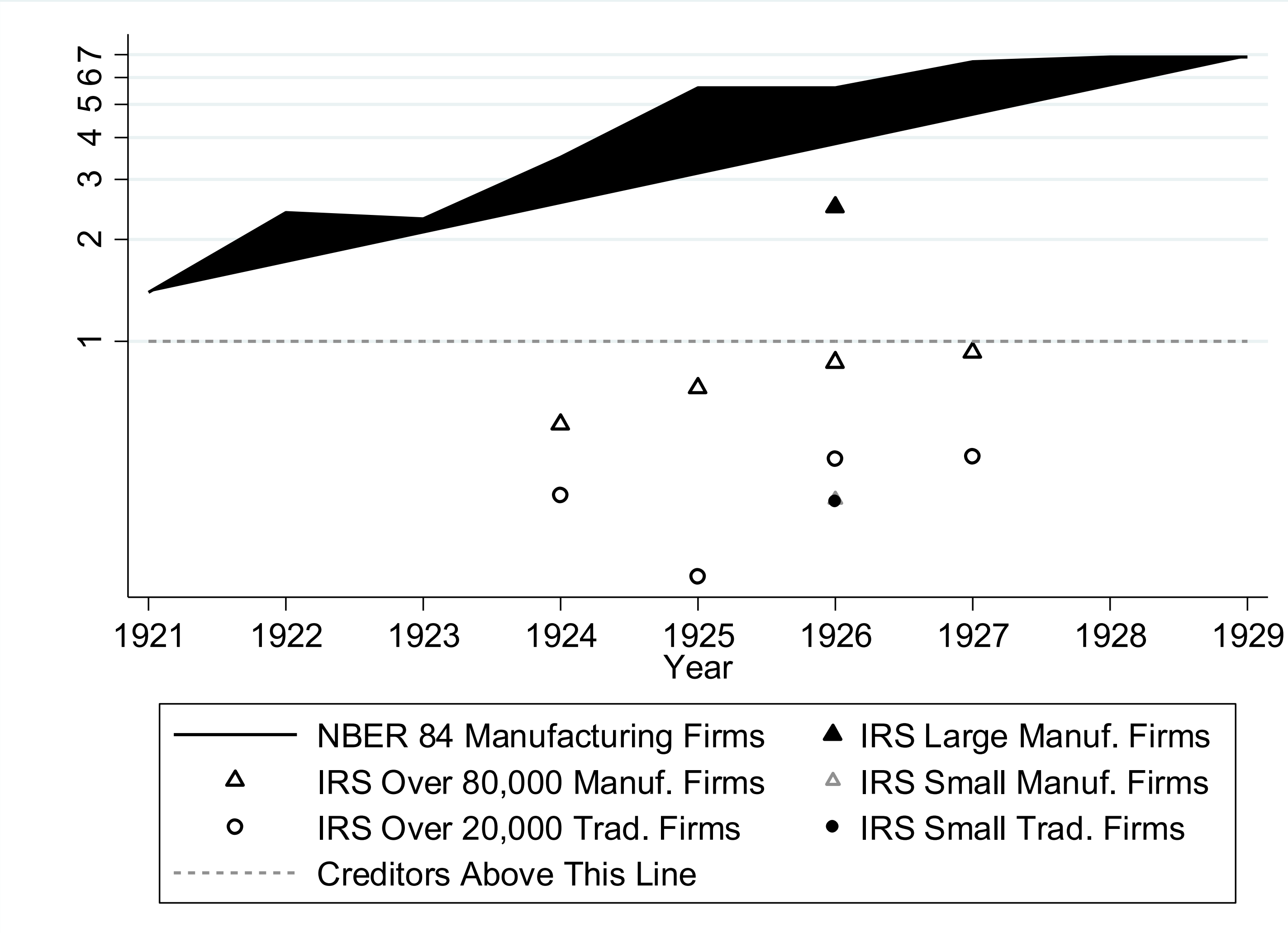

Figure B.2: The Commercial Credit Cycle

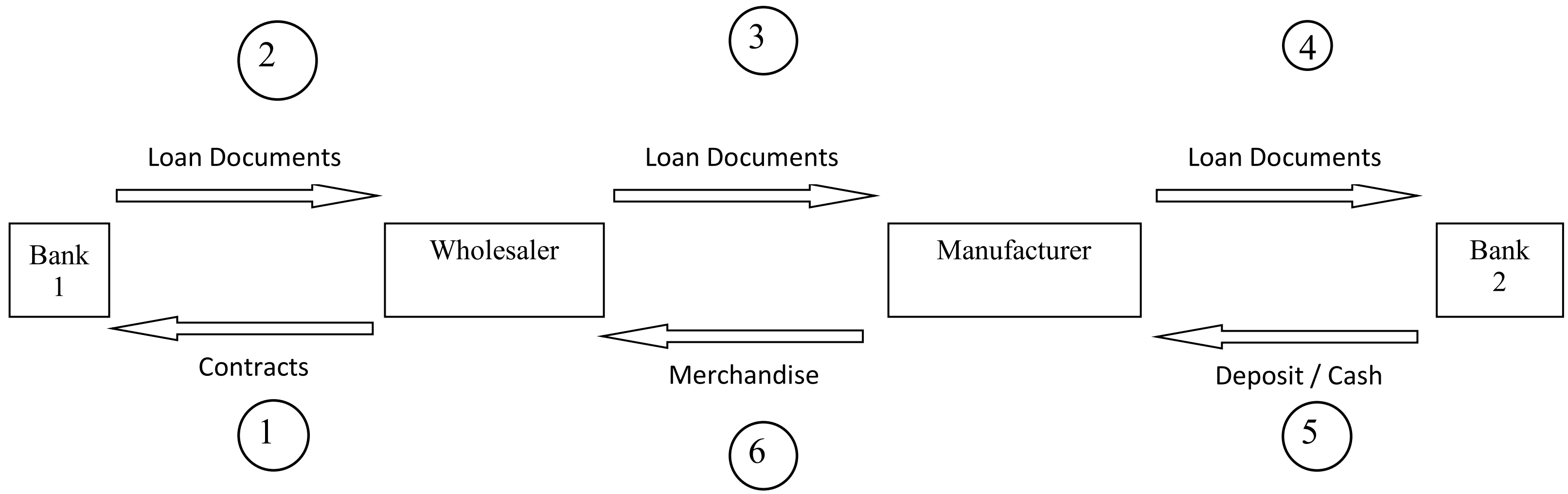

Figure B.3: Acceptance Market Completes Commercial Credit Cycle

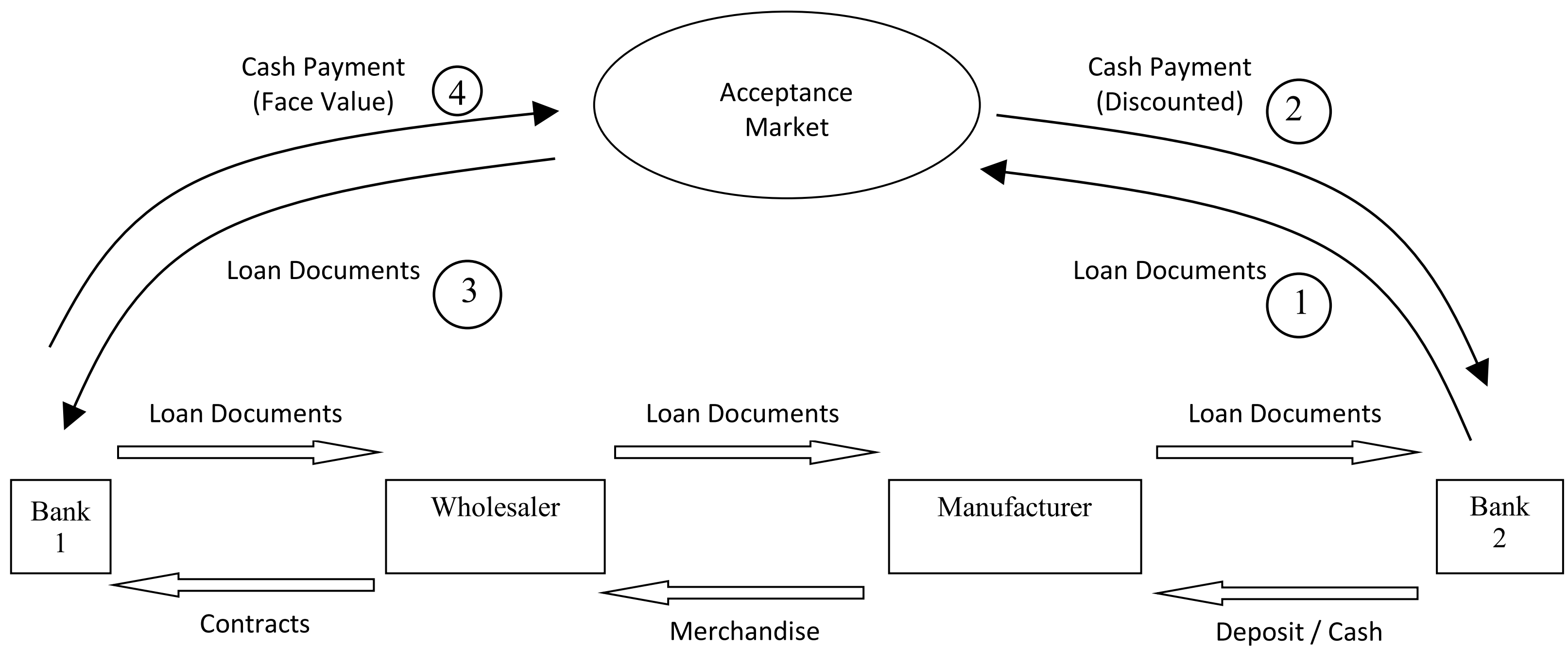

Figure B.4: Retailers' Role in the Commercial Credit Cycle

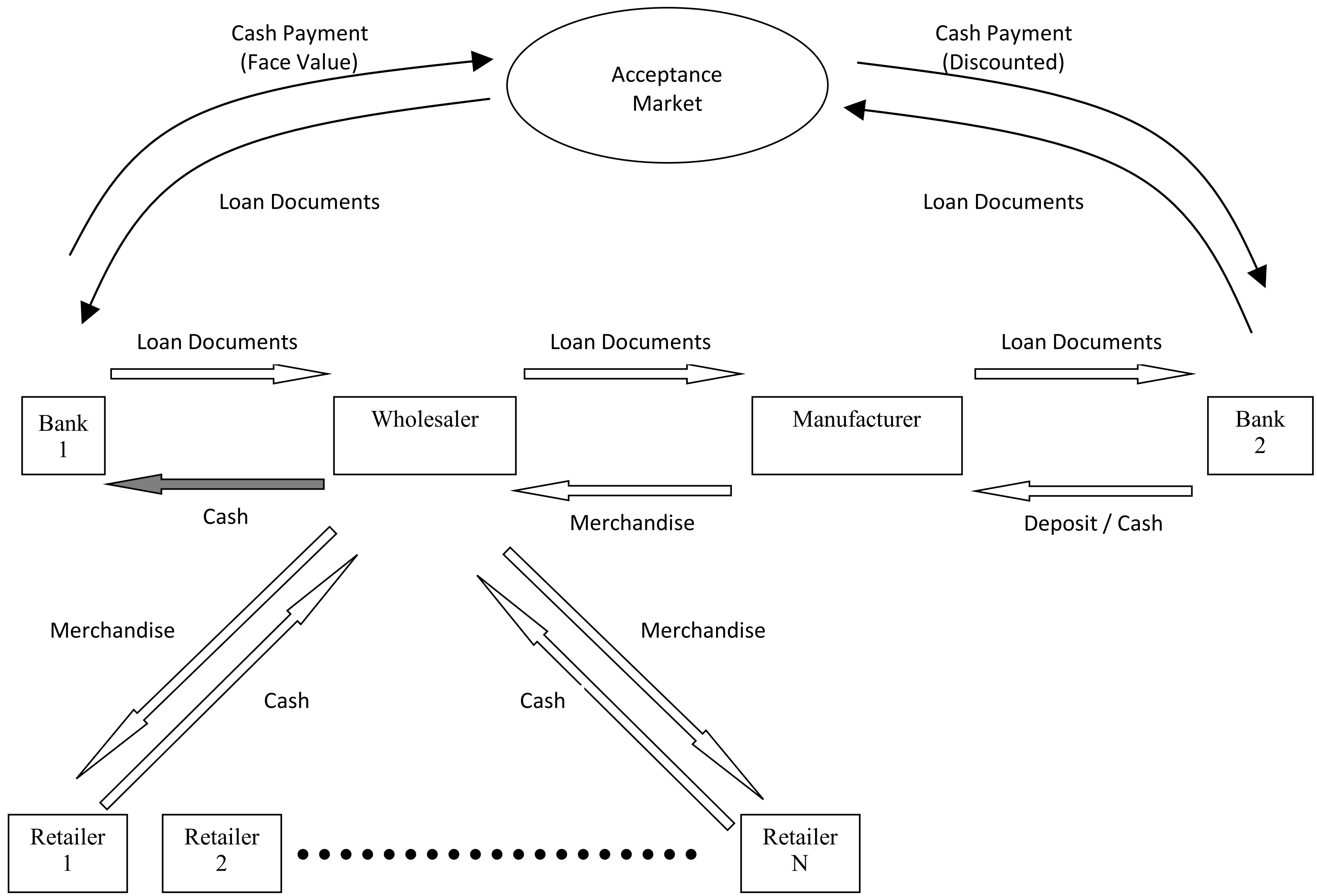

Figure B.5

VAR: Bank Suspensions and Firm Bankruptcies

Quarterly, 1900 to 1932, Data differenced t-4, 4 Lags

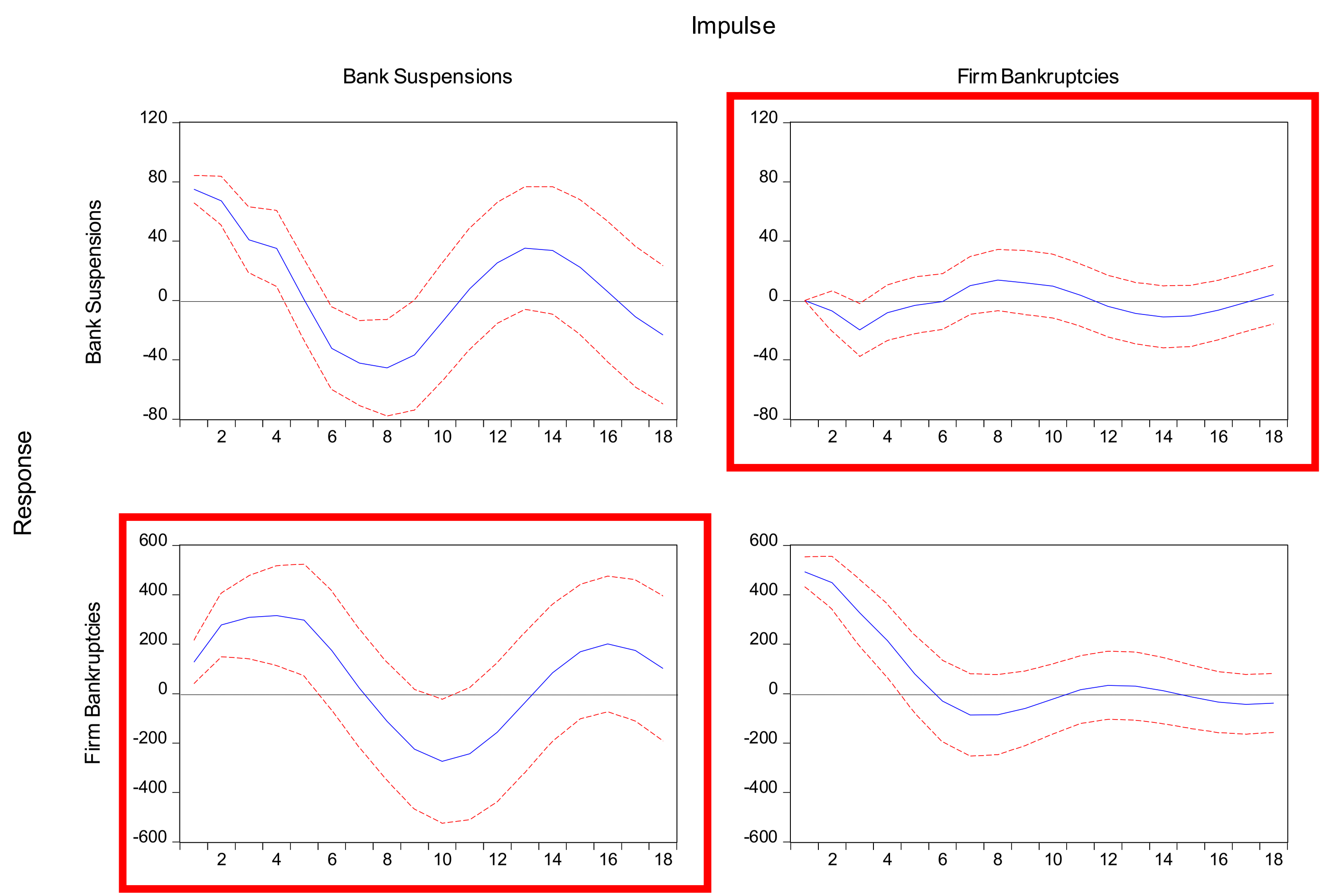

Figure B.6:

VAR: Bank Suspensions, Net Debtors, Net Creditors

Quarterly, 1900 to 1932, Data differenced t-4, 4 Lags

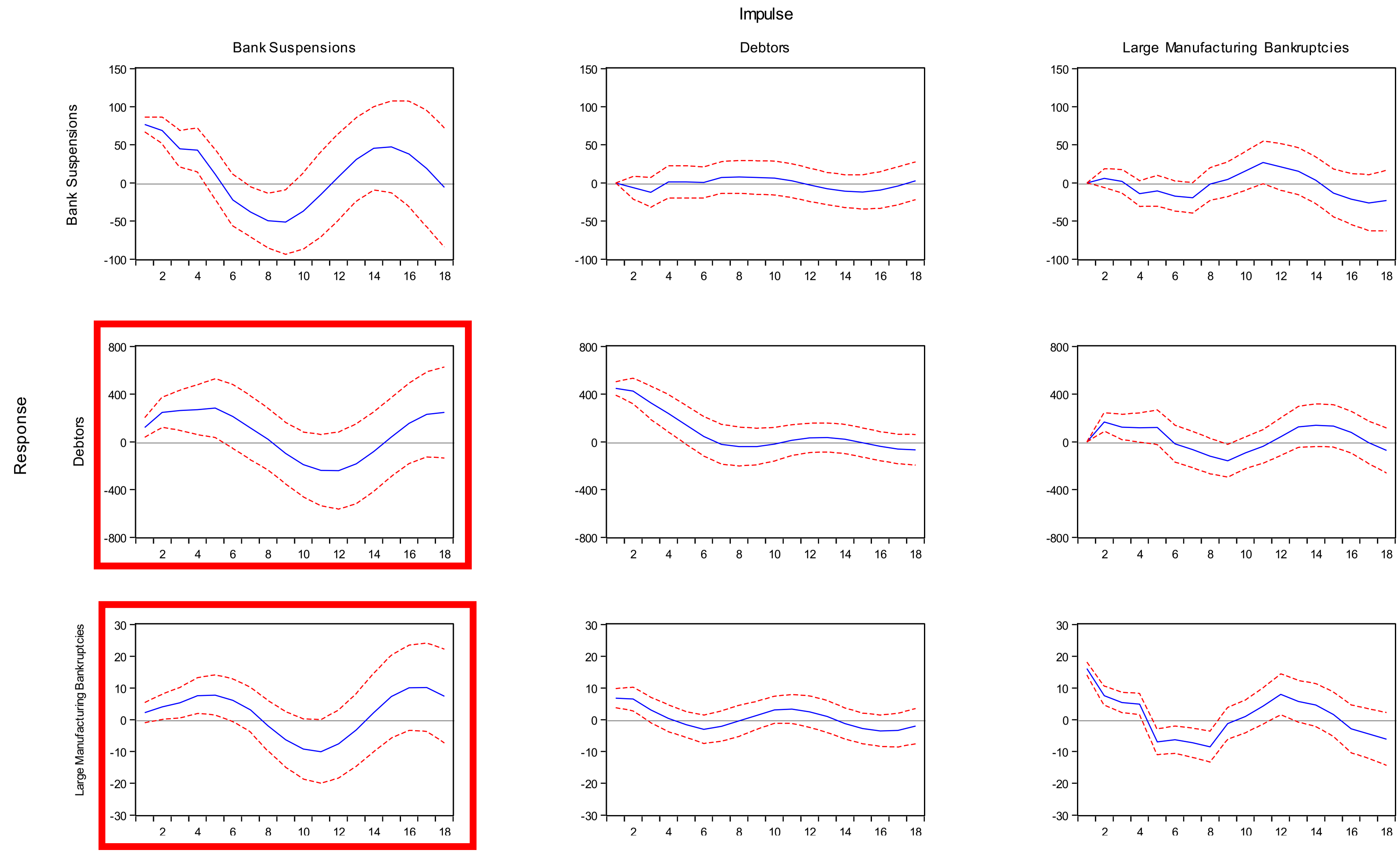

Figure B.7:

VAR: Non-Panic Bank Suspensions, Panic Bank Suspensions, Net Debtors, Net Creditors

Quarterly, 1900 to 1932, Data differenced t-4, 4 Lags

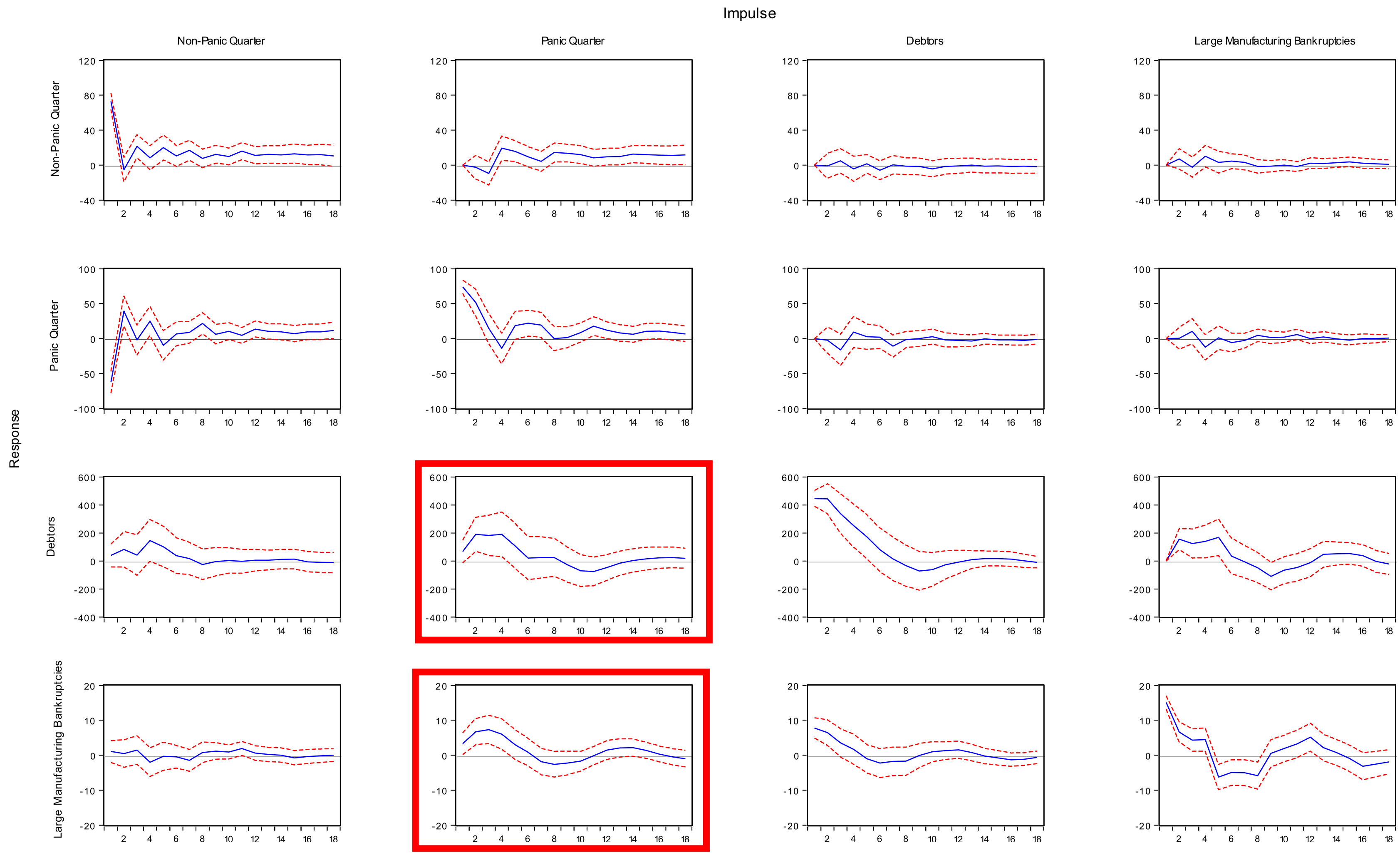

Figure B.8:

VAR: Bank Suspensions, Net Debtors, Net Creditors

Monthly, 1922 to 1932, Data differenced t-12, 2 Lags

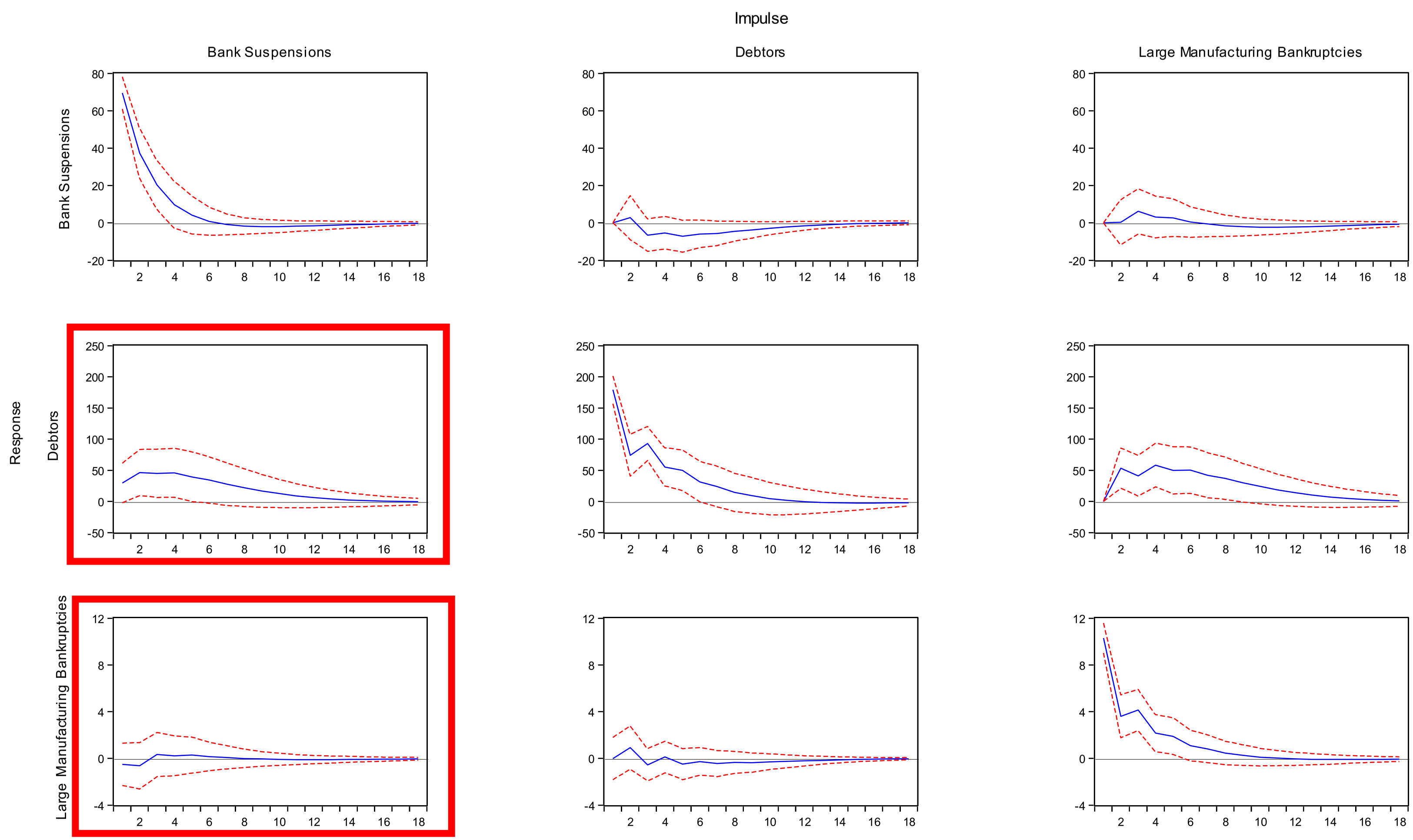

Figure B.9:

VAR – 1922 to 1932, monthly Data, differenced t-12, 2 lags. Five Equations (1) Discount Rate, (2) Bank Suspensions, (3) Commercial Paper, (4) Trading Bankruptcies, (5) Manufacturing Bankruptcies Result: Bank Suspensions ➔ Trading Failures …… Trading Failures ➔ Manufacturing Failures

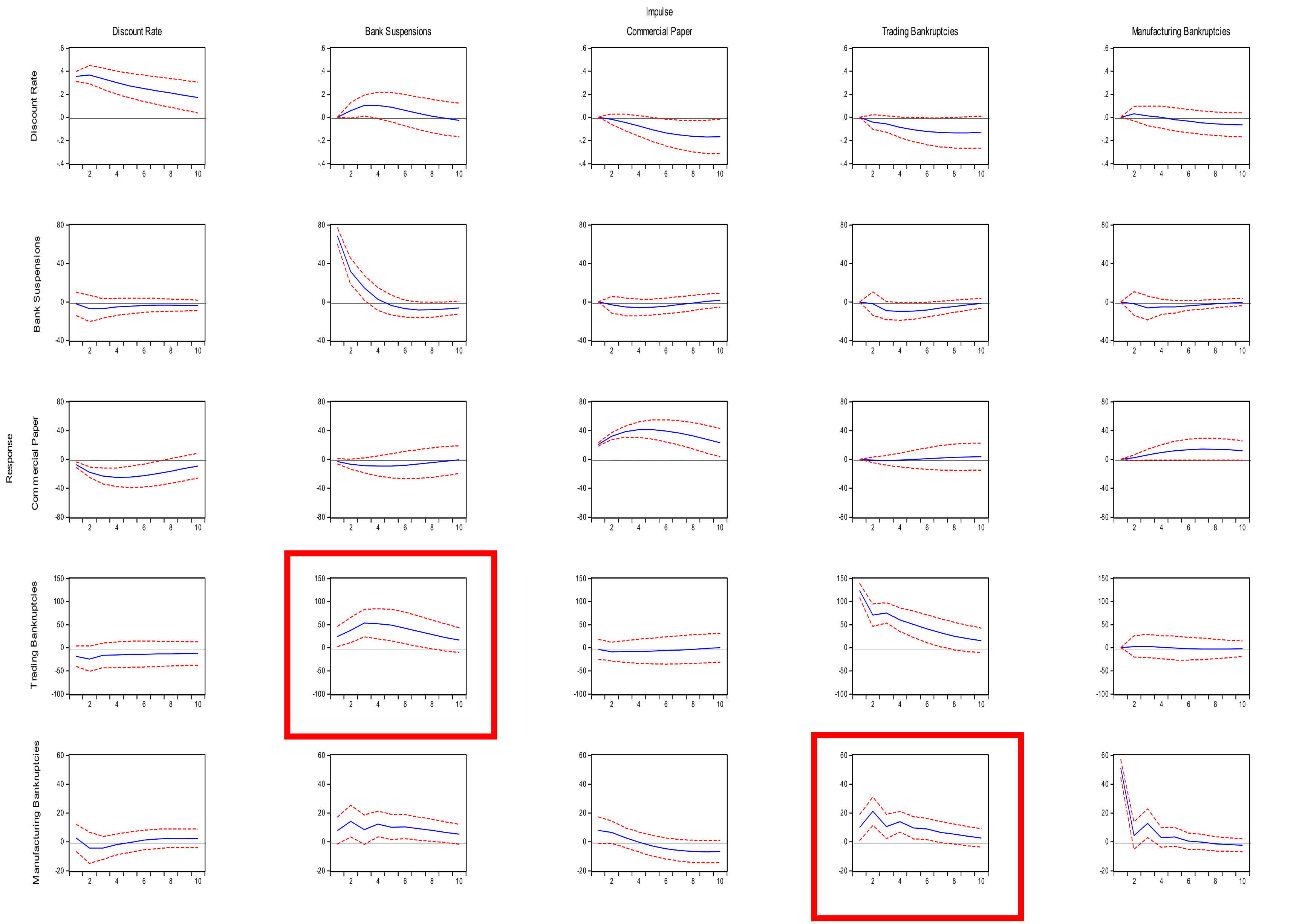

Figure B.10:

VAR – 1922 to 1932, monthly Data, differenced t-12, 2 lags

Five Equations (1) Discount Rate, (2) Bank Suspensions, (3) Commercial Paper, (4) Net Debtors, (5) Net Creditors