Who Benefits from the Export-Import Bank Aid?*

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Abstract

We study the effectiveness of government aid to exporters by exploring an exogenous shock that affected the ability of the Export- Import Bank of the United States (EXIM) to provide aid to US exporters. We focus on Boeing, the largest individual beneficiary of aid. We find that, on average, demand for Boeing aircraft does not decline because of this shock. While airlines that face higher costs of credit or higher costs in obtaining credit, purchased fewer aircraft they account for only a small share of aircraft sales. Our results suggest that EXIM aid was not efficiently allocated across importers.

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1 Introduction

Is industrial policy effective? In the last few years, there has been a resurgence of interest in the use of industrial policy to boost economic activity.[1] In policy circles (e.g., the Draghi report in Europe) and recent empirical literature (Juhász et al., 2023; Aghion et al., 2015; Choi and Levchenko, 2021), industrial policy is described as an effective way to increase competitiveness and employment. In contrast, most of the theoretical literature (Bartelme et al., 2019; Harrison and Rodríguez-Clare, 2010) is more skeptical, arguing that industrial policy is ineffective and inefficient. The discussion focuses largely on whether governments can choose the most productive firms. Since in the United States most industrial policy is directed at exporters, we study the effectiveness of US industrial policy by focusing on government aid to exporters.

We study US aid to exporters granted by the Export-Import Bank of the United States (EXIM). The goal of this federal agency is to boost employment and increase competitiveness, and between 2000 and 2014, EXIM provided US exporters with $182 billion in aid. A large share of this is in loan guarantees to importers who wish to purchase US goods and services. These loan guarantees lower the cost of credit for importers and reduce the relative price of US goods abroad. Although most EXIM aid does not involve a direct payment from EXIM to importers, the amount of aid EXIM can provide is capped, so aid is scarce. We examine a shock to EXIM's ability to provide aid. Between June 2015 and June 2019, the bank lacked the minimum quorum of directors required to grant loan guarantees exceeding $10 million. Consequently, EXIM's total aid disbursed fell from $19 billion in 2014 to just $4 billion in 2016. Because EXIM could provide fewer loan guarantees, the relative price of US goods grew, potentially leading to a decrease in overall exports.

We focus on the largest individual beneficiary of EXIM aid – Boeing. Before 2014, aid to Boeing represented 35% of total aid and 68% of all loan guarantees. Because most aircraft purchases require credit and exceed $10 million, Boeing had a significant exposure to the cessation of EXIM's ability to provide loan guarantees to potential importers of Boeing aircraft. Other aircraft manufacturers – primarily Airbus – were not affected by the EXIM quorum lapse, so the shock increased the relative price of a Boeing aircraft. By focusing on a single large beneficiary we can directly study the efficiency of the allocation of EXIM aid across potential importers.

To study the efficiency of the allocation of EXIM aid across importers, we use data on every commercial aircraft operated by commercial airlines. For each aircraft, we observe

[1] Recent US examples include the Creating Helpful Incentives to Produce Semiconductors (CHIPS) act in the United States, which provides $39 billion in subsidies for chip manufacturing in the United States with the goal of replacing imports with domestic production, and the Inflation Reduction Act.

the model and manufacturer, the date of order, the date of delivery or expected delivery, and the airline's identity. We focus on aircraft orders as these should be more responsive to changes in relative prices. We also exploit the fact that to keep operating costs low, airlines tend to rely on aircraft produced by a single manufacturer. In our sample, 41% of airlines did not have a single Boeing aircraft in their fleet in 2014. Therefore, we use airlines that did not have Boeing aircraft before 2015 as the control group. The treated group includes all airlines that had at least one Boeing aircraft in their fleet.

Demand for Boeing aircraft, as measured by orders, does not fall after the EXIM quorum lapse. Our measure of demand, which is the likelihood that a particular aircraft order involves a Boeing aircraft, exhibits no change after 2015 for the treated airlines relative to the control group. Therefore, on average, EXIM aid did not play a significant role in boosting demand for Boeing aircraft. This result is surprising because, in 2014, Boeing sold $60 billion in commercial aircraft, of which $7 billion, or 12%, was financed with EXIM loan guarantees. Consequently, our results show that the elasticity of demand to the presence of EXIM aid is very low for the average airline.

The overall elasticity of demand for Boeing aircraft to the presence of EXIM aid can be written as the product of three quantities: (1) the elasticity of demand; (2) the share of Boeing aircraft financed by EXIM aid; and (3) the elasticity of the cost of credit faced by airlines to EXIM aid. We turn to a cross-country comparison to investigate whether the overall elasticity varies across airlines. We divide airlines into groups based on the country they are headquartered in. We split countries according to GDP per capita or IMF classification as high-income vs. emerging countries. Because airlines in developing countries face higher costs of credit, the elasticity of the cost of credit to EXIM aid should be larger for these airlines. We also split airlines based on whether any airline in their country received EXIM aid. Similarly, the overall impact of the EXIM quorum lapse should be larger for airlines in countries that received EXIM aid. We find that airlines in developed countries exhibit no change in their demand for Boeing aircraft after EXIM loses its ability to provide loan guarantees. In contrast, airlines in developing countries show an 11 percentage point drop in the likelihood of purchasing a Boeing aircraft, representing a 30% drop. Moreover, we find that only airlines in countries that had previously relied on EXIM aid exhibit a drop in demand for Boeing aircraft.

We also explore heterogeneity across airlines by focusing on a subsample of aircraft orders for which we can match airlines to their financial reports. We divide airlines into groups based on their liquidity ratio, defined as the ratio of cash to total assets and the size of their fleet in 2014. Low-liquidity airlines, defined as airlines with a liquidity ratio below the cross-sectional median, should experience a larger drop in demand for Boeing aircraft since their expected costs of credit are higher and the likelihood of obtaining credit is lower. Similarly, smaller airlines, defined as airlines with a fleet size below the cross-sectional median, should also experience a larger decline in demand for Boeing aircraft. In line with our predictions, we find that low-liquidity airlines experience a 69 percent decline in demand for Boeing aircraft, while high-liquidity airlines experience no decline. Similarly, only small airlines reduce their demand for Boeing aircraft.

Our findings indicate that EXIM aid was misallocated across airlines. Between 2007 and 2014, airlines in low-income countries accounted for half of all Boeing aircraft orders and received half of the total EXIM aid directed at Boeing. Thus, EXIM did not systematically target airlines in low-income countries. We estimate that the elasticity of demand to EXIM aid is zero for airlines in high-income countries and large but negative for airlines in low-income countries. Given the scarcity of EXIM aid, reallocating all aid from airlines in high-income countries to those in low-income countries would have increased demand for Boeing aircraft by 16 percent. Alternatively, EXIM could have reduced aid to Boeing by 50 percent and redirected it to smaller U.S. exporters without affecting demand for Boeing aircraft.

More broadly, our results suggest that EXIM aid was misallocated not only across airlines but also across U.S. exporters, with Boeing receiving excessive support. On average, EXIM aid does not induce airlines to purchase Boeing aircraft over those produced by other manufacturers. This lack of impact is unlikely to hold for other U.S. exporters. Reallocating EXIM aid away from Boeing (and from airlines in high-income countries) toward smaller U.S. exporters would therefore enhance overall U.S. exports.

The EXIM quorum lapse also affects airlines' operations. We focus on the age of the fleet, which is an important statistic for airlines. Older fleets imply increases in maintenance costs, decreases in fuel efficiency, and declines in the collateral value of aircraft. Therefore, an increase in the fleet age increases overall costs and reduces margins for airlines. To study the effect of the EXIM quorum lapse on fleet age, we aggregate our data at the airline level and focus on the aircraft stock for each airline. We find that between 2015 and 2018, the age of the fleet of treated airlines increased by 3 percent relative to airlines in the control group.

Our mechanism is driven by the ease with which airlines can substitute EXIM-backed loans for private loans. To test this, we use a dataset containing all financial transactions involving aircraft. We then compare the probability that a particular transaction is financed entirely by the private market, with no EXIM intervention, for transactions involving Boeing aircraft, using transactions not involving Boeing aircraft as the control. We find a statistically significant substitution of EXIM-backed loans by private loans –

the likelihood that a Boeing transaction is financed by the private market increases by 13 percentage points. This result is another way to say that the average airline does not decrease its demand for Boeing aircraft. If airlines still order Boeing aircraft and EXIM-backed loans are unavailable, there must be a substitution. When we compare airlines in different countries, we find that this substitution is larger for airlines in developed countries. Therefore, airlines in emerging countries decrease their demand for Boeing because they find it difficult to obtain credit or because the cost of credit is too high. We can also interpret this result as suggesting that, for airlines in developed countries, the elasticity of the cost of credit to EXIM aid is zero.

Our paper does not address whether the level of government aid directed toward Boeing is efficient or optimal. However, our findings are consistent with a misallocation of EXIM aid for a given US exporter across importers. In response to the EXIM quorum lapse, importers representing 50 percent of Boeing aircraft orders exhibit no decline in demand. Consequently, providing aid to these importers is inefficient. In contrast, an increase in EXIM aid to airlines facing a higher cost of credit would increase orders for Boeing aircraft.

Related literature. We contribute to a growing literature on industrial policy. On the theoretical side, Harrison and Rodríguez-Clare (2010) argue that industrial policy in general, and export credit in particular, have limited effects in large open countries. Similarly, Bartelme et al. (2019) argue that industrial policy is generally ineffective. Recently, a growing empirical literature contends that industrial policy may be effective, as argued by Juhász et al. (2023). Focusing on South Korea, Choi and Levchenko (2021) show that industrial policy directed toward the heavy and chemical industries has positive long-run effects. Using data from China, Aghion et al. (2015) show that industrial policy fosters competition and entry.[2] We contribute to this literature by studying one of the most common forms of industrial policy – aid to exporters – and by focusing on whether aid is efficiently allocated across importers, rather than across domestic firms or sectors.[3]

The paper closest to ours is Matray et al. (2024), who study the effect of the EXIM quorum lapse by looking at the impact across sectors rather than within exporters. They assume that EXIM acts by directly lowering the cost of credit of US firms, which is ac-

[2]There is a long literature focusing on industrial policy for East Asian countries - South Korea (Liu, 2019; Lane, 2022), Japan (Liu and Ma, 2021), and China (Thun, 2006; Bai et al., 2020). Following the EXIM quorum lapse, Kurban (2021) studies the effectiveness of EXIM aid.

[3]There is also a long literature studying the role of export credit agencies in facilitating international trade, including Badinger and Url (2013), Choi and Kim (2021), Egger and Url (2006), Moser et al. (2008), and Felbermayr and Yalcin (2013). Using data from Pakistan, Zia (2008) shows that removing subsidized loans has a larger impact on financially constrained exporters.

curate for only a small share of overall EXIM aid. They compare the evolution of total sales of US exporters who relied on EXIM aid with a control group of US exporters who did not rely on EXIM aid. They find that total sales of exporters who depended on EXIM aid declined by as much as 17% in response to the EXIM quorum lapse. This effect is large: the average exporter received received aid equal to 5% of total sales, which should be the upper bound for the effect. The authors then use the fact that this decline is more pronounced for exporters with a higher marginal productivity of capital to argue that aid was efficiently allocated across exporters. Our approach is different. We focus on a single large US exporter which was the largest beneficiary of EXIM. This allows us to sidestep the issue of finding an appropriate control group for exporters that rely on EXIM support, which may introduce biases in the results, since obtaining EXIM aid is an endogenous outcome. Moreover, we can speak directly to the efficiency of aid allocation across importers without assuming that differences in the marginal productivity of capital are driven entirely by Total Factor Productivity and not by the presence of financial frictions or different production functions.

We also contribute to the literature on the role of credit as a source of comparative advantage. Most of this literature focuses on the role of credit for exporters, as in Manova (2013), Chor and Manova (2012), Paravisini et al. (2015), and Monteiro and Moreira (2023). However, there has been little focus on the effect of credit on importers.[4] We contribute to this literature by showing that shocks to the cost of credit only affect importers who face financial constraints, high credit costs, or or difficulties in obtaining credit.

The rest of the paper is organized as follows. In section 2 we describe the institutional background. We present our data sources in Section 3. Section 4 presents our results for aircraft orders, and Section 5 presents our results for airlines. Section 6 presents evidence on the financing of aircraft. Section 7 concludes.

2 The Export-Import Bank and Boeing

2.1 The Role of the U.S. Export-Import Bank

The Export-Import Bank of the United States, or EXIM, is the official export credit agency of the US government. Its stated goal is to support the creation and maintenance of jobs in the United States by facilitating the export of US goods and services. Like other export credit agencies (ECAs) worldwide, EXIM attempts to fill the void when private lenders

[4]One exception is Muûls (2015), who studies the role of credit constraints on Belgian exporters and importers.

are unable or unwilling to provide financing to domestic exporters or foreign importers.

Between 2000 and 2019, EXIM provided US exporters with $212 billion in aid. EXIM offers four main programs: (1) loan guarantees for foreign buyers of US goods or services; (2) insurance for US exporters against buyer nonpayment; (3) direct loans to foreign buyers; and (4) working capital loans for exporters. Loan guarantees are the largest program, representing 47 percent of total aid between 2007 and 2021. In this program, EXIM offers a loan guarantee to foreign buyers who require a loan to purchase US goods or services. In turn, the foreign buyers obtain a loan from a commercial bank (usually a US bank) using the guarantee. Although the terms of the loans vary considerably, these loans typically have a maturity of up to 10 years, and the guarantee can cover up to 85 percent of the principal. The insurance program, which represents 25 percent of aid, protects US exporters against default. Under this program, EXIM provides insurance against the importers' default risk by covering up to 95 percent of sales invoices. This allows US exporters to offer trade credit to their trade partners while being insured against counterparty risk. Direct loans to foreign buyers represent 18 percent of aid. In this program, EXIM provides direct fixed-rate financing to importers who wish to buy US goods or services (up to 12 years in general and up to 18 years for renewable energy projects). The smallest program is the working capital program, which represents 11 percent of EXIM aid and under which EXIM provides a 90 percent loan-backing guarantee to US exporters.

Most of the programs EXIM offers do not imply an outward cash flow. For example, in the absence of default, an EXIM loan guarantee to a foreign buyer will not lead to any payment on the part of EXIM. However, EXIM support is scarce because it faces a hard constraint on how much aid it can provide. According to its charter, EXIM cannot provide more than $15 billion of aid annually.

Arguments in favor of EXIM. EXIM is one of many ECAs worldwide. According to the Organization for Economic Cooperation and Development (OECD), every member country has at least one ECA to support exporters and increase its competitiveness. For example, in 2014, Germany provided over $14 billion in export aid.[5] The main argument in favor of ECAs is that they help fill a void caused by market failures or inefficiencies. Exporters require credit to export, primarily because of the long time lag between production and receiving payment from an importer. However, some macro-prudential regulations, such as Basel II and Basel III, impose reserve requirements that result in a higher

[5] We present the amount of aid given by each ECA in Figure A.1.

cost of funding exports to non-OECD countries.[6] Therefore, ECAs can increase exporters' comparative advantage by reducing their cost of credit via loan guarantees. Hence, ECAs can boost exports while maintaining a low level of risk for domestic banks.

ECAs can also provide insurance. Exporters may be reluctant to export to countries with weak contractual enforcement because counterparty risk is high. The insurance programs EXIM provides mitigate this problem by limiting the exposure of domestic exporters to the risk of nonpayment. Hence, the cost of trading with emerging countries decreases, and emerging countries can obtain cheaper imports.

Although ECAs are an example of protectionism and industrial policy, they tend to be more efficient than tariffs or loans to all domestic firms. ECAs can boost employment and lower current account deficits with lower costs than tariffs by targeting exporters, who are likely to be the most productive firms.

Arguments against EXIM. EXIM aid is a form of industrial policy, and it is subject to the same criticisms as industrial policy as a whole. Industrial policy in the export market aims to lower the relative price of domestic exports. However, the effectiveness of this policy may be limited. Harrison and Rodríguez-Clare (2010) argue that industrial policy has a limited impact and is effective only for relatively small countries. Similarly, Bartelme et al. (2019) argue that industrial policy will likely yield minimal gains even for fully open economies such as that of the United States. As industrial policy works by distorting relative prices, the costs in domestic markets may be sizable. If countries provide aid to exporters, they increase the relative price of non-tradable goods at home. Moreover, since countries cannot provide aid to all firms in the tradable sector, they also introduce distortions in relative prices within sectors. Both distortions may introduce misallocation in factors of production, such as excess employment in specific sectors or certain firms.

EXIM is also criticized for providing aid for political reasons while taking on excessive risks and requiring a large budget. For example, Boeing is the largest individual recipient of aid, so critics of EXIM refer to it as "Boeing's Bank." However, aircraft are among the safest assets to use as collateral because they are easily redeployable, which suggests that the effectiveness of EXIM intervention may be very limited. Moreover, around 11 percent of EXIM aid involves loan guarantees to JPMorgan Chase. Critics of EXIM argue that large commercial banks such as JPMorgan Chase should be able to finance exports and hedge risk without government support. Finally, EXIM has explicit political goals. In its

[6] Monteiro and Moreira (2023) provide evidence that the distortion introduced by Basel III leads to a significant decline in exports to non-OECD countries.

charter, EXIM is expressly forbidden from providing aid to ”Marxist-Leninist” countries.[7] EXIM even has a program, the China and Transformational Exports Program, whose only goal is to aid US exporters facing competition from Chinese firms.[8]

The allocation of EXIM aid is also widely criticized. Like most ECAs, EXIM provides most of its aid to exporters selling in developed or high-income emerging countries. For example, in 2014, 51 percent of aid given by OECD ECAs was directed to other OECD countries or non-OECD high-income countries, as shown in Figure A.2. Moreover, most of the export aid is directed at large domestic firms. For example, in 2014, only 22 percent of EXIM aid was directed at small or medium enterprises.[9] Larger firms have, in general, greater ease in obtaining working capital loans, providing trade credit to their customers, and hedging against counterparty risk themselves - but they receive almost 80 percent of total aid.

2.2 The EXIM Shock of 2015 to 2019

Like most US government agencies, EXIM is subject to a renewable statutory charter. US Congress charters the bank as a government corporation for a specific term. The current EXIM charter, passed by Congress in December 2019, authorizes EXIM to function until December 2026.

In 2012, EXIM was chartered for a three-year term, which was then extended in September 2014 through June 30, 2015. However, due to political differences between the Republican-controlled Congress and President Barack Obama, congressional authorization for EXIM lapsed on July 1, 2015. As a result, EXIM could not provide any new aid between July and December 2015.

According to its charter, EXIM can authorize long-term financing support for transactions above $10 million only with the approval of its board and a quorum of three members. The EXIM board consists of five members: the president of the bank, the first vice president, and three additional directors. These members are appointed by the president and subject to confirmation by the Senate. In July 2015, when it had to fill one vacancy on its board, the terms of two additional members expired, leaving EXIM with only two board members. Therefore, EXIM could not approve transactions above the $10 million

[7] This prohibition is laid out in EXIM’s charter, in Section 2(b)(2).

[8] These criticisms are not unique to EXIM. China has also been accused of using its foreign aid and export credit agency as a mechanism to establish political links with emerging African countries and as a means of quelling unrest at home. For example, Mueller (2022) shows that China is more likely to provide foreign aid to countries that wish to buy goods from Chinese firms in sectors that experience labor unrest.

[9] In Figure A.7, we show that this share is high only for insurance and working capital programs. However, since these programs represent a small share of the overall value of aid, the share in total aid is small.

threshold. In January 2016, President Obama nominated a new board member, but the Senate did not move to consider the nomination. The quorum lapse lasted until July 2019, when three new board members were appointed by President Donald Trump and confirmed by the Senate, restoring EXIM's ability to provide financing to US exporters.

The quorum lapse led to a sharp decline in the number of aid projects and the value of aid EXIM could provide. In Figure 1, we plot the evolution of the value of aid granted by EXIM by program type.[10] After 2015, there was a sharp decline in total aid provided by EXIM until 2019. Even after 2019, EXIM activity did not return to its pre-2015 levels due to the Covid-19 pandemic. Before 2015, the loan guarantees program was the largest in value - for example, in 2014, it represented 56 percent of the value of all aid and only 4 percent of the number of transactions. In 2016, loan guarantees accounted for less than 3 percent of the value of total aid, and in 2019, this share was only 3 percent. The quorum lapse disproportionally affected the loan guarantees program because the transactions in this program were very large. Between 2007 and 2014, the average loan guarantee was $53 million, while the average insurance project was only $2 million.

2.3 EXIM and Boeing

Until 2014, Boeing was the largest recipient of aid from EXIM, receiving around $64 billion in aid between 2007 and 2014, representing around 35 percent of all aid granted by EXIM in this period. Most of this aid was provided under the loan guarantee program, where Boeing accounted for 68 percent of all aid. Naturally, the EXIM quorum lapse posed a significant financial shock to Boeing. In Figure 2, we plot the total value of EXIM aid, decomposed in aid given to Boeing and other exporters.

In 2016 and 2018, Boeing received no aid from EXIM. In 2017, it received aid for four projects with a total value of $19 million, representing 0.7 percent of the total aid given by EXIM that year. Because most aid to Boeing is in loan guarantees to foreign buyers, EXIM lowered the cost of credit to foreign buyers. Since most aircraft are financed with debt, EXIM effectively lowered the price of Boeing aircraft and boosted demand. In that sense, the EXIM quorum lapse represented an increase in the cost of credit for foreign buyers or, from the perspective of Boeing, a negative demand shock as the relative price of Boeing aircraft for buyers increased.

[10] In Figure A.3, we present a similar plot for the number of aid projects granted by EXIM.

3 Data

Our empirical analysis relies on four datasets, which we describe below.

EXIM transaction-level data. EXIM provides detailed data on all authorizations approved between October 1, 2006, and June 30, 2022. The data include information on the type of program, the US recipient of aid (the exporters), and the financial institution involved. In addition, EXIM provides information on the identity of the importer and its country, the value of aid, and the decision date.[11] For example, in June 2015, EXIM provided a loan guarantee to the South African airline Comair with a total value of $80 million. The loan was provided by the South African bank Needbank. In March 2021, EXIM provided the Dutch airline KLM with a loan guarantee of $376 million, and the loan was obtained from two banks. This dataset provides information on 45,310 transactions between 2007 and 2021. In our analysis, we focus on the 2013 to 2018 period, for which there are 18,865 transactions, of which 728 are loan guarantees.[12]

Aircraft orders. We use the Ascend CASE database, which contains ownership and operating information on the stock of all commercial aircraft worldwide. For every aircraft in operation in August 2020, we observe the model and manufacturer, the airline operating the aircraft, and the original operator of the aircraft. We also observe the date on which the aircraft was ordered and its delivery date. We focus on aircraft *orders*; therefore, the relevant data is the order date. We restrict the sample to commercial passenger aircraft for which we can observe the airline's country. Between 2013 and 2018, we observe 14,446 orders from 436 airlines in 121 countries.[13]

Airline data. We supplement our data with airline-level data, which we obtain from Compustat and Compustat Global. We match each airline in the Ascend CASE database with a company in Compustat. Of the 436 airlines in our sample, we can match 72 airlines to Compustat. These airlines tend to be larger and represent 40 percent of all orders in the 2012 to 2018 period. We also obtain data on country-level variables, such as GDP or GDP

[11] The data are available at data.exim.gov.

[12] We provide summary statistics of these transactions in Appendix A. In Figure A.4, we present data on the main recipients. In Figure A.5, we present evidence on the concentration of EXIM aid among a small set of US firms and sectors. In Figure A.6, we show that the direct loan and loan guarantee programs have the largest average amount by transaction.

[13] In Figure B.2, we present data on the largest airlines in terms of aircraft orders and the largest countries, also in terms of total aicraft orders.

per capita, from CEPII.[14]

Aircraft financing data. We use the Deal Tracker dataset from *Airfinance Journal*. This dataset contains information on every aircraft purchase, including the identity of the buyer and the seller, as well as information on the aircraft and the financing of the deal. In particular, we can observe whether the aircraft purchase was financed by a bank loan, a bond, equity, or aid from EXIM or any other ECA. The dataset covers around 15,000 transactions starting in 1997. We focus on transactions involving commercial airlines. Between 2013 and 2018, we observe 4,039 transactions.

Figure 3 illustrates the composition of transactions by financing type. Operating leases are the most common form of aircraft financing, accounting for 69 percent of total transactions. Commercial loans from financial institutions are also common and represent around 17 percent of all transactions. Export credit, which includes EXIM aid, represents 9 percent of all transactions. As Figure 3 shows, there is a significant decline in the number of transactions after 2012 and a sharp decline in transactions financed by export credit after 2014, consistent with the EXIM quorum lapse.

4 The Effect of the EXIM Quorum Lapse on Boeing

In this section, we estimate the impact of the lack of a quorum on the EXIM board on Boeing aircraft orders. EXIM provided loan guarantees to foreign buyers of Boeing aircraft, which lowered their cost of credit and, therefore, reduced the relative price of Boeing aircraft. Consequently, demand for Boeing aircraft declined, resulting in a drop in aircraft orders.

The decline in orders of Boeing aircraft for a given airline should depend on three quantities: (1) the elasticity of demand; (2) the share of Boeing aircraft financed by EXIM; and (3) the elasticity of the cost of credit to the EXIM loan guarantee. Airlines with a more elastic demand curve should react more, as should airlines that mainly rely on EXIM funding for their aircraft purchases. Similarly, airlines for whom EXIM aid is more effective at lowering the cost of credit should react by cutting their Boeing orders more.

In 2014, Boeing aircraft deliveries represented 38 percent of all aircraft deliveries. In 2018, this share fell to 34 percent, representing an 8 percent decline.[15] However, in 2014,

[14] CEPII, or the Center for Research and Expertise on the World Economy, provides data on a variety of aggregate variables. The data can be found here. There are some airlines for which we cannot identify the country. These airlines account for less than 5 percent of our observations, and we exclude them from our analysis.

[15] We present the decomposition of total aircraft orders by manufacturer over time in Figure B.1.

Boeing's revenues from commercial aircraft sales were $60 billion - out of which $7 billion, or 12 percent, were financed with EXIM loan guarantees.[16] The structure we lay above may explain this discrepancy. If the elasticity of the cost of credit to the presence of EXIM aid is low, then we would also expect the decline in orders to be low.

4.1 Estimation

Our goal is to obtain empirical estimates of the effect of the EXIM quorum shock on Boeing aircraft orders. Our outcome variable is an indicator variable that takes the value of one if the aircraft was produced by Boeing and zero if otherwise. Therefore, we can interpret our results as the effect on Boeing's share of orders.

The main identification challenge comes from potential changes in demand for air travel, which may be heterogeneous across airlines. To address this problem, we define treated airlines as airlines with at least one Boeing aircraft in their fleet in 2015. Our control airlines are airlines that did not have Boeing aircraft in their fleet in 2015. The use of Airbus-intensive airlines allows us to control for changes in overall demand for air travel (and aircraft) using airlines that would probably not purchase Boeing aircraft in the absence of the EXIM quorum shock. This happens because airlines, particularly smaller ones, do not wish to mix Boeing and Airbus aircraft in their fleet because of maintenance costs, as shown in Benmelech and Bergman (2008) and Benmelech and Bergman (2011a).[17]

We estimate the following regression:

$$\begin{aligned}\text{Boeing}_{jit} = \lambda_t + \alpha_i + \sum_{m=-3, m\neq -1}^{2} \delta_m \times \mathbf{1}\{m = t - 2016\} \times \mathbf{1}\{i \in \text{Treated}\} \\ + \beta X_{it} + \theta W_{\text{country},t} + \varepsilon_{ijt}, \qquad (1)\end{aligned}$$

where the outcome variable takes the value of one if aircraft j ordered by firm i in year t is produced by Boeing, and zero if otherwise. We include airline and time fixed effects and a vector of country controls. The time fixed effects allow us to capture common variation in demand for aircraft and air travel. The airline fixed effects are important because airlines differ in size, operating market, their aircraft mix, and their reliance on EXIM aid. The

[16] Incidentally, this 12 percent share also represents the maximum effect on Boeing orders if we assume that production is separable across customers. To see this note that, the largest possible impact on Boeing is a 12 percent drop in sales or orders. To obtain a larger decline, the marginal cost of selling to customers who did not rely on EXIM aid needs to depend on the amount produced for customers who relied on EXIM aid.

[17] In fact, in our sample, there is a large share of airlines that use only Boeing aircraft and a large share of airlines that use only Airbus aircraft. In Figure D.1, we plot the distribution of the share of Boeing aircraft in an airline's fleet. The distribution exhibits a spike at zero and another one at one.

country controls include the logarithm of GDP, the logarithm of population, and GDP per capita. In our main specification, we also include the logarithm of one plus the fleet size as an airline-level control.[18] The coefficients of interest are the δ_m coefficients, which identify the effect of the lack of quorum in the EXIM board m periods after 2015. Therefore, we can interpret δ_m as the change in the share of Boeing aircraft among total orders between 2015 and $2015 + m$. We cluster errors at the airline level and present our estimation results in Figure 4.

We find no statistically significant effect on Boeing orders, and this result is robust to our choice of airline controls. In the specification with no airline controls and in the specification where we use fleet size as a control, the coefficients are very similar even though the sample size varies. In the specification with no airline controls, we use 296 airlines, whereas the specification with fleet size as a control uses 214 airlines. In contrast, the results for the third specification - which uses other airline-level controls - are larger in absolute value even though they are not statistically significant (except in 2016). These larger coefficients are the result not of the controls but of the change in the sample size. None of the new airline controls are statistically significant in the third specification. However, the sample size drops by two-thirds, leaving only 69 airlines. Therefore, sample selection drives the increase in the coefficients' size. We thus rely on fleet size as our preferred specification.

Extensive margin. One concern with our estimation of equation (1) is that it mixes the extensive margin (whether or not to acquire an aircraft) with the choice of manufacturer. For example, suppose almost all airlines that purchased Boeing aircraft stop purchasing aircraft. In this case, as we only observe the choice of manufacturer for realized orders, we would estimate an average treatment effect of zero even though the EXIM shock has real effects. To address this concern, we estimate a Poisson event study where the outcome variable is the number of aircraft orders made by each airline in a given year. We estimate the following equation

$$\text{Orders}_{it} = \exp\left\{\lambda_t + \alpha_i + \sum_{m=-3, m\neq -1}^{2} \delta_m \times \mathbf{1}\{m = t - 2016\} \times \mathbf{1}\{i \in \text{Treated}\}\right\} + \varepsilon_{it}, \tag{2}$$

[18] We also present results for specifications with other controls, such as leverage or sales at the airline level. However, when we include these controls, we exclude all airlines we could not match to Compustat data. This greatly reduces the number of airlines in our sample.

and present the results in Figure D.2. We find that there is no change in the average number of aircraft orders following the EXIM shock. Therefore, our results are not driven by an asymmetric change in aircraft orders. Instead, we find that on average, Boeing orders do not change after EXIM's ability to provide loan guarantees to airlines ends. Therefore, on average, EXIM does not significantly affect Boeing's ability to sell aircraft in the global market.

Discussion. Our findings for Boeing do not necessarily generalize to other U.S. exporters receiving EXIM support. Consequently, they should not be interpreted as evidence that loan guarantees or EXIM assistance, in general, have no effect on U.S. exports. Aircraft manufacturing, unlike many other industries, involves products that are easily collateralized, as demonstrated by Benmelech and Bergman (2008) and Benmelech and Bergman (2011a). Moreover, legal procedures for seizing collateral in the event of default are relatively standardized across countries.[19] As a result, potential lenders face minimal losses in default scenarios and therefore require only a small interest rate spread, leading to relatively low borrowing costs for airlines. This implies that loan guarantees for aircraft purchases are unlikely to significantly reduce interest rates in the first place.

By contrast, a loan guarantee for foreign buyers of U.S.-produced wind turbines could be more effective. This contrast suggests that EXIM over-allocated aid to Boeing—where such support is unlikely to have a meaningful impact—resulting in a misallocation of EXIM funds across exporters. If other U.S. exporters exhibit a strictly positive elasticity of demand to EXIM financing, reallocating funds from Boeing to these firms would improve allocative efficiency.[20]

4.2 Heterogeneity Across Countries

We now turn to a cross-country comparison. We argue that the effect of the EXIM shock on a given airline is the product of three components: (1) the price elasticity of demand for aircraft; (2) the share of EXIM aid in overall purchases; and (3) the elasticity of the cost of credit faced by the airline to the presence of EXIM aid. Using our data, we test whether the last two components are significant.[21] This result is important because it allows us to

[19] For instance, the Aircraft Equipment Protocol of the Cape Town Treaty, which took effect in 2006, establishes uniform legal remedies for aircraft-related defaults, including repossession and the treatment of bankruptcy laws. Under this protocol, disputes are adjudicated in the High Court of Ireland. The treaty has been ratified by 81 parties, including the European Union, the United States, and China.

[20] If no U.S. exporters exhibit positive elasticity to EXIM funding, eliminating EXIM aid entirely would enhance efficiency.

[21] We assume that the price elasticity does not exhibit systematic variation across countries and airlines.

understand whether EXIM affects any subset of airlines.

To understand whether or not the elasticity of the cost of credit faced by the airline in relation to the presence of EXIM aid is relevant, we need to find a proxy for the elasticity. The elasticity should be larger, in absolute value, for airlines that find it difficult to access credit markets. For example, an airline in Canada will, all other things being equal, observe a lower cost of credit than an airline in Ethiopia. We thus use economic development level as a proxy for this elasticity. We do this in two ways. First, we use the International Monetary Fund's classification of a country as high-income as a proxy for countries where the elasticity should be low.[22] Therefore, for all other countries, the elasticity should be large. Second, we use the country's GDP per capita in 2015 as another proxy. We split countries according to the median GDP per capita in 2015: countries below the median are classified as having a high elasticity, and countries below the median are classified as having a low elasticity.

We also use our data on EXIM transactions to study heterogeneity across airlines. We separate airlines into two groups: (1) airlines in countries that have received EXIM support before 2015; and (2) airlines in countries that have received no EXIM support before 2015. According to our hypothesis, the effect should be larger for airlines in countries that received EXIM support. We present the results of these comparisons in Figure 5.

Our results in Panel (A) and Panel (B) are very similar. Overall, we find that airlines with easier access to credit (as proxied by airlines in wealthier countries) exhibit no change in Boeing orders after EXIM loses the ability to provide loan guarantees. In contrast, airlines in poorer countries experience a decline in orders, consistent with our hypothesis that the elasticity of the cost of credit to the presence of EXIM aid is larger for these airlines. In Panel (A), only the coefficient for 2018 for countries with a low GDP per capita is significant at a 5% level. In Panel (B), only the coefficient for 2018 for low-income countries is significant at a 5% level but the coefficient for 2016 for the same set of countries is significant at a 10% level. The effect is sizable and persistent - for airlines in countries with low GDP per capita, the average treatment effect is a drop of 11 percentage points in the likelihood of purchasing a Boeing aircraft, which represents a 30 percent drop relative to the unconditional average likelihood before 2015. Moreover, we also find that the decline in Boeing orders is present only for airlines in countries with access to EXIM funds, which shows that our results are not driven by potentially heterogeneous fluctuations in demand. In Panel (C), the coefficients for 2016 and 2018 for countries that did not rely on EXIM funds are positive and statistically significant at a 10% level

[22]The IMF and the World Bank classify countries as high-income, upper-middle-income, lower-middle-income, and low-income, based on their gross national income per capita. We use the classification in 2015.

(although only the coefficient for 2018 is significant at a 5% level), which suggests that airlines that did not rely on EXIM funds actually increase their Boeing orders. In contrast, the coefficient for 2016 for countries that relied on EXIM funds is negative and statistically significant at a 5% level, showing that airlines that relied on EXIM funds decrease their Boeing orders.

Robustness. We conduct a variety of robustness checks. One concern with the regression in equation (1) is that airlines that rely on Boeing aircraft are exposed to different shocks when compared with airlines that rely on aircraft produced by other manufacturers. For example, in the period before 2019, airlines that relied on Boeing aircraft were placing large numbers of orders because Boeing would release the 737-Max, which was announced in 2011, and which was a highly anticipated addition to the Boeing product mix.[23] In Figure D.3, we show that our results for the estimation of equation (1) are not driven by the 737-Max. If we exclude the 737-Max orders from our sample, we still do not observe a decline in the demand for Boeing aircraft. Similarly, our results in Figure 5 are also not driven by the 737-Max orders, as we show in Figure D.6.

We also consider different definitions of airlines with a high elasticity of the cost of credit to the presence of EXIM loan guarantees. In Figure D.4 we show that only airlines in countries that are not in the OECD experience a decline in demand for Boeing aircraft following the EXIM shock. Similar, as we show in Figure D.5, only airlines in countries with a high real interest reate exhibit a decrease in demand for Boeing aircraft following the EXIM shock.

Implications for Misallocation. Our findings indicate that airlines in high-income countries do not reduce their demand for Boeing aircraft in the absence of loan guarantees. These airlines account for approximately 50% of Boeing aircraft orders between 2007 and 2014 and 53% of total EXIM aid used for Boeing purchases. This pattern suggests that EXIM was not targeting airlines in low-income countries, despite aid being most relevant for these firms. Moreover, our results imply that reallocating aid from high- to low-income countries before 2014 could have increased Boeing orders. Specifically, our estimates suggest that such a shift would have raised the likelihood of an airline purchasing a Boeing aircraft by approximately 6 percentage points—a 16% increase. Given EXIM's $15 billion budget cap, this suggests that if the objective was to maximize Boeing orders, EXIM's allocation of funds was inefficient.

[23]The 737-Max was announced in August 2011, first flow in January 2016, and certified by the FAA in March 2017. It was eventually grounded between March 2019 and November 2020 as a result of two fatal accidents - the Lion Air Flight 610 in October 2018 and the Ethiopian Airlines Flight 302 in March 2019.

4.3 Heterogeneity Across Airlines

We now turn to the airlines themselves. The ease with which airlines may access credit markets and the cost of credit they are offered also depend on their characteristics. We expect that smaller airlines obtain more expensive credit than larger airlines. Similarly, we expect airlines with lower liquidity, that is, airlines with less cash as a share of total assets, to face less favorable terms when seeking financing. Therefore, the elasticity of the cost of credit to the presence of EXIM financing should be larger for smaller and less liquid airlines.

To test this, we rely on the subsample of airlines for which we observe firm-level information. We define the airline's size as the number of aircraft in its fleet in a year. We define airline liquidity as the share of cash to total assets. Using these measures for 2015, we split airlines according to size - we define large airlines as those whose size is above the cross-sectional median - and liquidity - we define liquid airlines as those whose liquidity ratio is above the cross-sectional median. We then estimate equation (1) for each subsample of airlines and present the results in Figure 6.

We find that low-liquidity airlines are far less likely to purchase Boeing aircraft once EXIM can no longer provide loan guarantees. For low-liquidity airlines, we find that the coefficients for 2016 and 2018 are negative and statistically significant at a 10% level, while all coefficients associated with high-liquidity airlines are not statistically different from zero. In Panel (B), we find that the coefficient for 2016 for small firms is negative and statistically significant at a 10% level, as is the coefficient for the same year for large firms. However, the coefficient for small firms is roughly twice the size of the coefficient for large firms. In fact, the likelihood of purchasing a Boeing aircraft declines by 27 percentage points for these airlines, or a 69 percent decline relative to the period before 2015. In contrast, high-liquidity airlines do not change their behavior. Similarly, only smaller airlines observe a decline in the likelihood of purchasing Boeing aircraft after 2015.[24]

Robustness. We show that our results are not driven by orders of the 737-Max aircraft in Figure D.9 - if we exclude the 737-Max orders, our results persist. Our findings are also robust to the definition of financial constraints for airlines. In Figure D.7, we show that only airlines with a low ratio of cash flows to sales exhibit a decline in demand for Boeing aircraft. We can also use the external financing ratio as in Rajan and Zingales (1998). The external financing ratio is the difference between the change in PP& and cash

[24]These results are not driven by the same variation as the results in Figure 5. If we repeat the exercise but consider only airlines in high-income countries, we obtain the same qualitative results. We present the result of this exercise in Figure D.10.

flows divided by lagged PPE. The ratio captures the degree to which firms rely on external funds to finance their asset purchases. If the external financing ratio is positive, the firm's internally generated cash flows are not sufficient to finance the increase in assets. In contrast, if the ratio is negative, the firm does not require external funds to purchase assets. We define airlines as unconstrained if the external financing ratio is negative, and as constrained if the external financing ratio is strictly positive. In Figure D.8 we find that only constrained airlines reduce their demand for Boeing aircraft. Therefore, unconstrained airlines, which should either rely on internal funds or should exhibit a low elasticity of cost of capital to EXIM funds, do not decrease their demand for Boeing aircraft when EXIM is no longer able to provide them with loan guarantees.

These results are again evidence of a misallocation of EXIM aid among potential Boeing customers. Large and liquid airlines do not need these funds; once they are removed, they do not change their behavior. In contrast, smaller and less liquid airlines are more sensitive to the presence of these funds and, therefore, should be allocated a larger share of aid.

5 The Effect of the EXIM Quorum Lapse on Airlines

We next examine the impact of the EXIM lapse in aid on airline operations. We focus on the quorum lapse's effect on the fleet age. The age of the fleet is important for three reasons. First, airlines with older fleets are more likely to face unexpected increases in maintenance costs. Older aircraft are more likely to require maintenance, and maintenance is more likely to be costlier. Hence, airlines may decrease their demand for Boeing aircraft at the expense of an increase in the present value of maintenance costs. Second, older aircraft have a lower resale value, which reduces their ability to serve as collateral.[25] Therefore, airlines may find it harder to source credit. Third, older aircraft also tend to be more fuel-inefficient.[26] Hence, fuel costs will be higher for airlines with older aircraft, and their carbon footprint will be larger. Because most regulators in the international aviation sector are pushing for carbon neutrality or emission caps, this may also increase costs for the airline.

We begin by aggregating our data to the airline level to understand the impact of the EXIM quorum lapse. We compute the age of the fleet as the average age of all aircraft in

[25] In general, GAAP rules state that a commercial aircraft fully depreciates between 15 and 25 years.

[26] Benmelech and Bergman (2011b) report that aircraft of older vintage are associated with lower usage, and that the lower usage is driven by higher fuel prices.

the fleet. We then estimate the following regression

$$\log \text{Age}_{it} = \lambda_t + \alpha_i + \sum_{m=-3,m\neq -1}^{2} \delta_m \times \mathbf{1}\{m = t - 2016\} \times \mathbf{1}\{i \in \text{Treated}\}$$
$$+ \beta X_{it} + \theta W_{\text{country},t} + \varepsilon_{it}, \tag{3}$$

where the outcome variable is the logarithm of the fleet age for airline i in year t. We include airline and time fixed effects, as well as a vector of time-varying country controls, which include the logarithm of GDP, the logarithm of population, and GDP per capita. We also include the logarithm of the fleet size as a control. The coefficients of interest are the δ_m coefficients, which identify the effect of the lack of quorum in the EXIM board m periods after 2015. Therefore, we can interpret δ_m as the percentage change in fleet age between 2015 and $2015 + m$. We cluster errors at the airline level and present our estimation results in Figure 7.

We find that airlines that relied on Boeing aircraft observe an increase of around 3 percent in the age of their fleet.[27] Only the coefficient for 2018 is statistically significant at at 5% level, and so the effect on age is not immediate. Since the average airline has a fleet that is 12 years old, this implies an increase of 3 months in age. If we use the depreciation schedule used for commercial aircraft, these results suggest a decrease of 1 percent in resale value.[28]

6 The EXIM Shock and the Financing of New Aircraft

So far, we have focused on the effect of EXIM's quorum lapse on Boeing orders. Our results show that for airlines that are likely to have a large elasticity of the cost of credit to the presence of EXIM aid, there is a substantial drop in the likelihood of ordering a Boeing aircraft. In contrast, airlines with a lower elasticity exhibit no change in behavior. To test this mechanism directly, we turn to the market for aircraft financing. According to our hypothesis, airlines with a larger elasticity should find it harder or more expensive to substitute EXIM-subsidized loans with regular loans, which should, in turn, drive the decrease in Boeing orders.

[27] In Figure E.1, we decompose airlines into groups based on the sovereign risk of the country in which they are headquartered. The increase in age is driven by airlines in countries with a high sovereign risk, which is associated with a higher cost of credit.

[28] To see this, note that GAAP rules state that the life-cycle of a commercial aircraft is 25 years, and so an aircraft depreciates a 4 percent per year. Since the increase in age is a quarter, this yields a decrease in resale value of around 1 percent.

In Figure 8, we decompose the number of Boeing aircraft transactions by financing type. Until 2014, export credit – including EXIM financing – plays a significant role in financing Boeing aircraft, accounting for 20 percent of transactions. Between 2006 and 2014, the most important source of financing is operating leases, which account for 55 percent of transactions. After 2015, there is a substantial decline in the share of export credit, but no equivalent decline in the number of transactions. There is an increase in the share of operating leases to 79 percent, which suggests that airlines adjust to the lack of EXIM financing by shifting towards private financing.

6.1 The Case of Ethiopian Airlines

To motivate our analysis, we focus on the case of Ethiopian Airlines, the flag carrier of Ethiopia. Because Ethiopia is a developing country, the elasticity of the cost of credit to the presence of EXIM aid is likely to be large for Ethiopian Airlines. In Table I, we decompose the number of transactions and the dollar value for Ethiopian Airlines in the 2012 to 2018 period between transactions involving EXIM funding and transactions that do not include EXIM. Within the transactions with EXIM funding, we further decompose them into transactions that involve US banks and those that do not. Within the transactions that do not involve EXIM funding, we split transactions into three groups: (1) transactions that involve US banks; (2) transactions that do not involve US banks; and (3) transactions that do not involve US banks and instead involve funding from the Aircraft Finance Insurance Consortium (AFIC), which was developed in 2017 as a private alternative to EXIM.[29]

In the years before EXIM's quorum lapse, there are 10 Boeing transactions totaling $1,768 million. Of these, six used EXIM financing. All the transactions that do not use EXIM support are financed by banks outside the United States. In contrast, almost all transactions that rely on EXIM support involve US banks, representing 97 percent of the value of transactions involving EXIM support.[30] Following 2015, the number of transactions falls to half, and the dollar value declines by almost two-thirds. However, there is also a change in the composition of these transactions. All transactions between 2016

[29] AFIC offers an insurance-based aircraft finance product and chiefly focuses on transactions involving Boeing aircraft. Since 2017, AFIC has executed transactions supporting over $6 billion in aircraft financing. AFIC's aircraft finance non-payment insurance fully protects participating banks or institutional investors from payment default under AFIC-supported aircraft financing. In the event of a failure to pay by the airline or leasing company, the lender submits a proof of loss and the AFIC insurers pay 100 percent of the missed installment. Insurers continue to make all scheduled payments to the lender until all outstanding principal and interest is repaid.

[30] This result goes beyond this specific case study. In Figure C.1, we show that while the share of transactions that involve US banks is small, the share of transactions that involve US banks if the transaction also involves EXIM aid is substantially larger.

and 2018 involve banks outside the United States and funding from AFIC. Therefore, Ethiopian Airlines reacted to EXIM's quorum lapse in two ways. First, it reduced its demand for Boeing aircraft, as evidenced by fewer transactions. Second, and more important, it substituted EXIM support with a private provider: AFIC. Because AFIC provides an insurance product, it reduces the risk lenders take when providing loans to Ethiopian Airlines and mitigates the lack of loan guarantees. However, this substitution is imperfect, and Ethiopian Airlines still reduced its demand for Boeing aircraft.

6.2 The Effect on Private Financing

We now analyze the substitution between EXIM and private financing using the Deal Tracker database from *A*irfinance Journal. We define private funding as any funding not provided by a government export credit agency, particularly EXIM. We hypothesize that airlines were, on average, able to shift away from EXIM support toward private funding. Still, this substitution is more pronounced for airlines with easier access to financial markets or facing lower funding costs.

To test the substitution, we compare the likelihood that a transaction involving a Boeing aircraft is financed with external private funds, using transactions that do not involve Boeing aircraft as the control group. We estimate the following equation using all transactions between 2013 and 2018:

$$\text{Private}_{ijt} = \lambda_{jt} + \alpha_{c(j)} + \delta W_{c(j)t} + \mu_{\text{Boeing}} + \gamma \cdot \mathbf{1}\{i \in \text{Boeing}\} \cdot \mathbf{1}\{t > 2015\} + \varepsilon_{ijt}, \quad (4)$$

where the outcome variable takes the value of one if transaction i by airline j in year t is not funded with EXIM support and zero if otherwise. Our regression specification includes airline-year and country fixed effects, as well as country macro and demographic controls, including the logarithm of GDP, the logarithm of population, and GDP per capita.[31] The country fixed effects and controls aim at capturing possible changes in demand for air travel in the different countries, as well as changes and differences in overall economic conditions. Our parameter of interest is the average treatment effect γ, which captures the likelihood that a Boeing aircraft is financed with non-EXIM funding after 2015 compared to aircraft produced by other manufacturers.

We consider two country-level measures to proxy for the ease of access to credit markets and expected financing cost. First, and as in Section 4, we split countries into two groups using their GDP per capita in 2015. Airlines in countries with a GDP per capita

[31] In this specification, we can include firm-year fixed effects because we have more firms per country when compared with our sample of aircraft deliveries.

below the median are likely to have higher costs of financing and are more likely not to find financing at all. Our second measure is sovereign risk, which we measure using Moody's sovereign risk ratings in 2015. We split countries into low-risk countries (with ratings above or equal to Aa3) and high-risk countries (with ratings below Aa3). There is some evidence that suggests that firms are unlikely to have a higher credit rating than the sovereign rating of the country in which they operate (Chen et al., 2016; Almeida et al., 2017; Drago and Gallo, 2017), and so this is a good proxy of the funding cost for airlines. We estimate equation (4) on all transactions and each of these subsamples and present the results in Table II.

If we consider the whole sample, we find that after the EXIM quorum lapse, Boeing transactions are more likely to be financed by external private funds than transactions involving aircraft produced by other manufacturers, such as Airbus. The increase in likelihood is 13 percentage points, which effectively undoes most of the gap between Boeing and other manufacturers.[32] This is because airlines choose to substitute EXIM funds with other private funding sources, such as operating leases.

If we focus on the role of sovereign risk, we find that the substitution of EXIM guarantees by private financing is more pronounced for airlines in countries with low sovereign risk, which is in line with our hypothesis and our results on Boeing orders. This may be driven by two factors: (1) these airlines face a lower cost of financing; or (2) these airlines are more likely to obtain a loan. We cannot distinguish between the two explanations. Still, if we interpret credit rationing as a situation in which the cost of credit is infinity, both explanations are driven by the credit cost gap between airlines. We find very similar results when we compare airlines in countries with different levels of GDP per capita – while airlines in high-income countries can substitute EXIM support with private financing, airlines in low-income countries display no statistically significant substitution.

6.3 The Role of Dependence on EXIM Funds

We can also test the importance of the reliance on EXIM funds in determining the substitution between EXIM funds and private funding. There should be no substitution for airlines that did not previously rely on EXIM funds. In contrast, the substitution we document should be driven by airlines that previously relied on EXIM funding. This decomposition also allows us to exclude other potential changes in credit markets as a driver for the results we present in Table II. To test this, we include a third difference in equation (4) as we compare airlines that received EXIM support for the purchase of Boeing aircraft

[32]This result is robust to a variety of different specifications, as we show in Table F.1.

before 2015 with airlines that did not receive EXIM support for Boeing purchases in the same period. We present the results of this analysis in Table III.

The results in the first column include all transactions and, therefore, coincide with the results in the first column of Table II. In the second column, we include only transactions for airlines that relied on EXIM support at least once before 2015. We find that the average treatment is larger, consistent with our hypothesis. In the third column, we also include the triple-difference. We find that there is no substitution between EXIM support for airlines that did not rely on EXIM support and private financing. This allows us to exclude other potential shocks to credit supply as the source of the substitution we document. The substitution between EXIM support and private financing is driven by airlines that previously relied on EXIM support to purchase Boeing aircraft.

We show that, in response to the cessation of the EXIM loan guarantee program, which helped some airlines finance their purchase of Boeing aircraft, airlines shifted towards private external funds (e.g., operating leases or commercial loans). This substitution is more pronounced for airlines that are more likely to face lower credit costs or have access to credit markets. These results align with our findings relative to Boeing orders, since airlines that are more likely to face lower credit costs also do not exhibit a decrease in the demand for Boeing aircraft. All of our results in this section are driven by airlines that had previously relied on EXIM support – suggesting that our results are driven by the drying up of EXIM funds rather than an unrelated move of airlines towards private funds.

7 Conclusion

In this paper, we study the effectiveness of US industrial policy for exporters by focusing on EXIM aid to exporters. We examine a shock to EXIM's ability to provide aid. Between June 2015 and June 2019, the bank lacked the minimum quorum of directors required to grant loan guarantees exceeding $10 million. We focus on the largest individual beneficiary of EXIM aid: Boeing.

We use data on commercial aircraft to investigate the effects on demand for Boeing aircraft. We find that, on average, there is no decline in demand for Boeing aircraft. Therefore, on average, EXIM aid did not play a significant role in boosting demand for Boeing aircraft. We find that airlines in developed countries exhibit no change in their demand for Boeing aircraft after EXIM loses its ability to provide loan guarantees. In contrast, airlines in developing countries show an 11 percentage point drop in the likelihood of purchasing a Boeing aircraft, representing a 30 percent drop. We also find that low-liquidity airlines experience a 69 percent decline in demand for Boeing aircraft, while high-liquidity airlines experience no decrease. Similarly, only small airlines reduce their demand for Boeing aircraft. Our results suggest that EXIM aid was misallocated across airlines. Given that EXIM aid is scarce, had EXIM shifted all aid from airlines in high-income countries to airlines in low-income countries, demand for Boeing aircraft would have increased by 16 percent. Our mechanism is driven by the ease with which airlines can substitute EXIM-backed loans for private loans. When we compare airlines in different countries, we find that this substitution is larger for airlines in developed countries. Therefore, airlines in emerging countries decrease their demand for Boeing because they find it difficult to obtain credit or because the cost of credit is too high.

Our paper does not address whether the level of government aid directed toward Boeing is efficient or optimal. This is a crucial question for policymakers, particularly as governments increasingly turn to industrial policy to increase competitiveness. We leave this question for future research.

References

Aghion, Philippe, Jing Cai, Mathias Dewatripont, Luosha Du, Ann Harrison, and Patrick Legros, "Industrial policy and competition," *American economic journal: macroeconomics*, 2015, *7* (4), 1–32.

Almeida, Heitor, Igor Cunha, Miguel A. Ferreira, and Restrepo Felipe, "The real effects of credit ratings: The sovereign ceiling channel," *Journal of Finance*, 2017, *72* (1), 249–290.

Badinger, Harald and Thomas Url, "Export credit guarantees and export performance: Evidence from Austrian firm-level data," *The World Economy*, 2013, *36* (9), 1115–1130.

Bai, Jie, Panle Jia Barwick, Shengmao Cao, and Shanjun Li, "Quid pro quo, knowledge spillover, and industrial quality upgrading: Evidence from the Chinese auto industry," Technical Report, National Bureau of Economic Research 2020.

Bartelme, Dominick G, Arnaud Costinot, Dave Donaldson, and Andres Rodriguez-Clare, "The textbook case for industrial policy: Theory meets data," Technical Report, National Bureau of Economic Research 2019.

Benmelech, Efraim and Nittai K Bergman, "Liquidation values and the credibility of financial contract renegotiation: Evidence from US airlines," *The Quarterly Journal of Economics*, 2008, *123* (4), 1635–1677.

_ and _ , "Bankruptcy and the collateral channel," *The Journal of Finance*, 2011, *66* (2), 337–378.

_ and _ , "Vintage capital and creditor protection," *Journal of Financial Economics*, 2011, *99* (2), 308–332.

Chen, Sheng-Syan, Hsien-Yi Chen, Chong-Chuo Chang, and Shu-Ling Yang, "The relation between sovereign credit rating revisions and economic growth," *Journal of Banking and Finance*, 2016, *64*, 90–100.

Choi, Hyelin and Kyunghun Kim, "Effect of export credit insurance on export performance: an empirical analysis of Korea," *Asian Economic Journal*, 2021, *35* (4), 413–433.

Choi, Jaedo and Andrei A Levchenko, "The long-term effects of industrial policy," Technical Report, National Bureau of Economic Research 2021.

Chor, Davin and Kalina Manova, "Off the cliff and back? Credit conditions and international trade during the global financial crisis," *Journal of International Economics*, 2012, *87* (1), 117–133.

Drago, Danilo and Raffaelle Gallo, "The impact of sovereign rating changes on the activity of European banks," *Journal of Banking and Finance*, 2017, *85*, 99–112.

Egger, Peter and Thomas Url, "Public export credit guarantees and foreign trade structure: Evidence from Austria," *World Economy*, 2006, *29* (4), 399–418.

Felbermayr, Gabriel J and Erdal Yalcin, "Export credit guarantees and export performance: An empirical analysis for Germany," *The World Economy*, 2013, *36* (8), 967–999.

Harrison, Ann and Andrés Rodríguez-Clare, "Trade, foreign investment, and industrial policy for developing countries," *Handbook of development economics*, 2010, *5*, 4039–4214.

Juhász, Réka, Nathan Lane, and Dani Rodrik, "The new economics of industrial policy," *Annual Review of Economics*, 2023, *16.*

Kurban, Danny, "Does Public Financing Support Increase Exports?: Evidence from a Quasi-experiment at the US Export-import Bank," Working Paper 2021.

Lane, Nathan, "Manufacturing revolutions: Industrial policy and industrialization in South Korea," Technical Report 2022.

Liu, Ernest, "Industrial policies in production networks," *The Quarterly Journal of Economics*, 2019, *134* (4), 1883–1948.

_ **and Song Ma**, "Innovation networks and r&d allocation," Technical Report, National Bureau of Economic Research 2021.

Manova, Kalina, "Credit constraints, heterogeneous firms, and international trade," *Review of Economic Studies*, 2013, *80* (2), 711–744.

Matray, Adrien, Karsten Müller, Chenzi Xu, and Poorya Kabir, "EXIM's exit: The real effects of trade financing by export credit agencies," *NBER Working Paper*, 2024, *32019.*

Monteiro, Joao and Pedro Moreira, "The Impact of a Higher Cost of Credit on Exporters: Evidence from a Change in Banking Regulation," Working Paper 2023.

Moser, Christoph, Thorsten Nestmann, and Michael Wedow, "Political risk and export promotion: evidence from Germany," *World Economy*, 2008, *31* (6), 781–803.

Mueller, Joris, "China's Foreign Aid: Political Determinants and Economic Effects," Working Paper 2022.

Muûls, Mirabelle, "Exporters, importers and credit constraints," *Journal of International Economics*, 2015, *95* (2), 333–343.

Paravisini, Daniel, Veronica Rappoport, Philipp Schnabl, and Daniel Wolfenzon, "Dissecting the effect of credit supply on trade: Evidence from matched credit-export data," *The review of economic studies*, 2015, *82* (1), 333–359.

Rajan, Raghuram and Luigi Zingales, "Financial development and growth," *American Economic Review*, 1998, *88* (3), 559–586.

Thun, Eric, *Changing lanes in China: Foreign direct investment, local governments, and auto sector development*, Cambridge University Press, 2006.

Zia, Bilal H, "Export incentives, financial constraints, and the (mis) allocation of credit: Micro-level evidence from subsidized export loans," *Journal of Financial Economics*, 2008, *87* (2), 498–527.

Table and Figures

Figures

FIGURE 1: Evolution of Total Aid Given by EXIM

This Figure plots the evolution of total aid given by EXIM to US exporters between 2007 and 2019. We decompose the aid into four categories: (1) loan guarantees to foreign firms importing US goods and services; (2) insurance for US exporters against accounts receivable risk; (3) direct loans to foreign firms; and (4) working capital loans to US firms.

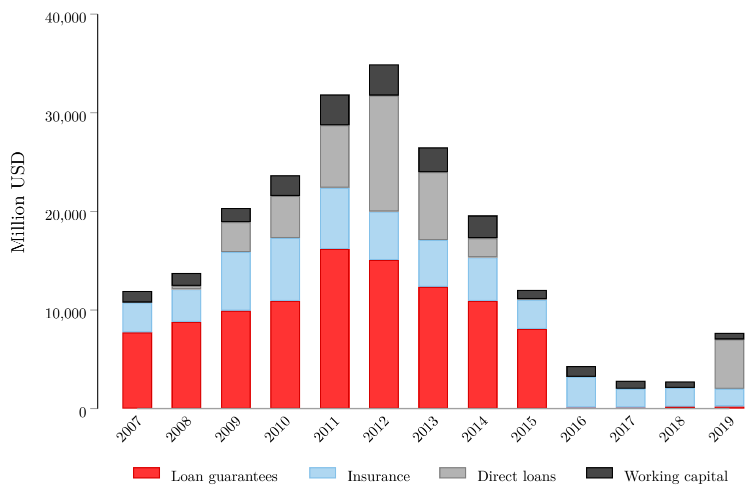


FIGURE 2: Evolution of Aid Given by EXIM to Boeing

This figure plots the evolution of total aid given by the Export-Import Bank to US exporters between 2007 and 2019. We decompose aid into two categories: (1) aid given to Boeing; and (2) aid given to all other firms.

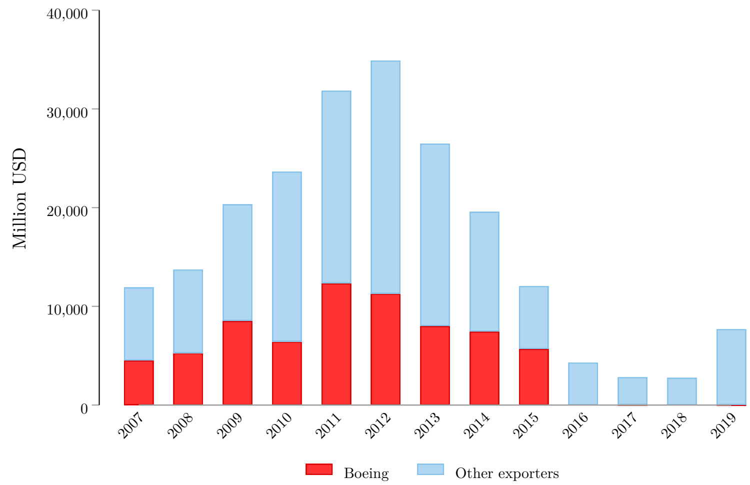


FIGURE 3: Decomposition of the number of transactions by financing type

This figure presents a decomposition of the number of transactions involving commercial airlines by source of financing every year between 2006 and 2019. We consider eight types of financing: (1) commercial loans (mostly from financial institutions); (2) bond issuance; (3) equity issuance; (4) export credit (aid from export credit agencies such as EXIM); (5) operating leases; (6) other sources of financing (mostly internal funds); (7) structured operating leases (operating leases with additional characteristics, such as a call option); and (8) tax leases.

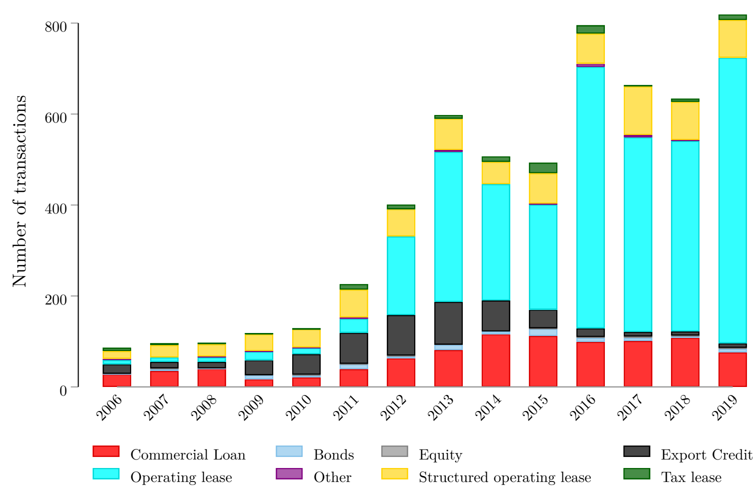


FIGURE 4: Effect on Boeing orders

This Figure presents the results of estimating equation (1) on a sample of 11,500 aircraft orders and 296 airlines between 2013 and 2018. The outcome variable takes the value of one if the aircraft ordered is produced by Boeing and zero if otherwise. We include year fixed effects, airline fixed effects, and a vector of country controls (logarithm of GDP, logarithm of population, and GDP per capita). We compare two groups of airlines: the treated airlines are airlines that had at least one Boeing aircraft in their fleet in 2015, and the control aircraft are airlines that did not have any Boeing aircraft in their fleet in 2015. We present the average treatment effects over time, where we compare treated vs. control airlines, using 2015 as the base year. Therefore, the coefficient for the year $2015 + m$ can be interpreted as the average treatment effect on the share of Boeing orders between 2015 and $2015 + m$. We consider three specifications, where we vary the airline controls: (1) no airline controls; (2) including the logarithm of one plus the fleet size; and (3) including also the logarithm of total assets, the ratio of cash flows to sales, leverage, liquidity (ratio of cash to total assets), and collateral (ratio of PPE to total assets). We cluster errors at the airline level and display 95% confidence intervals.

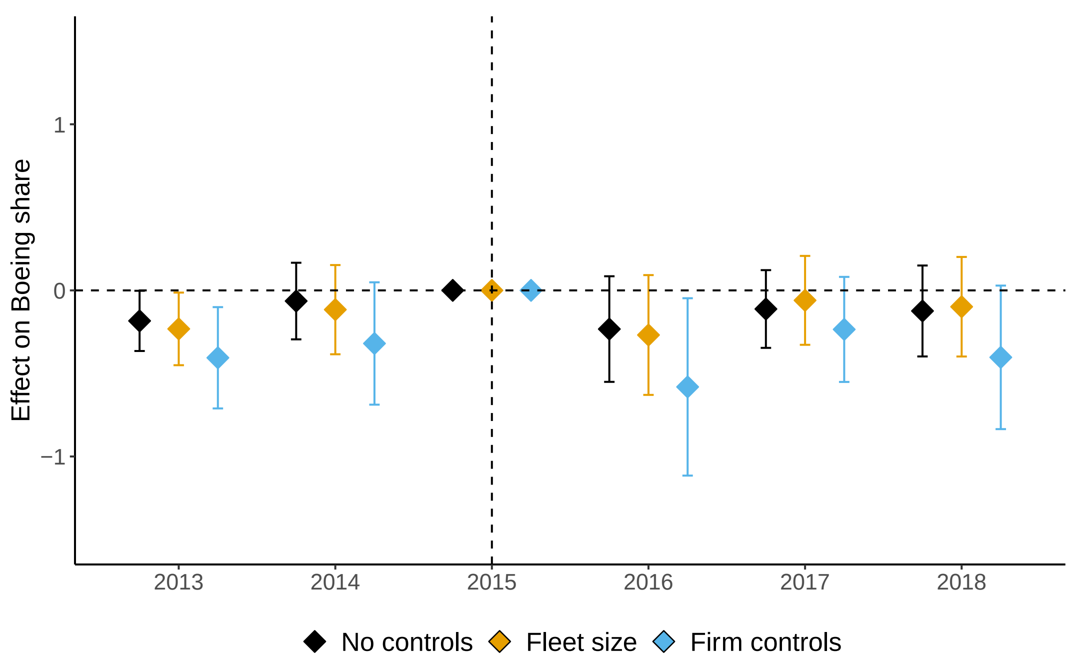
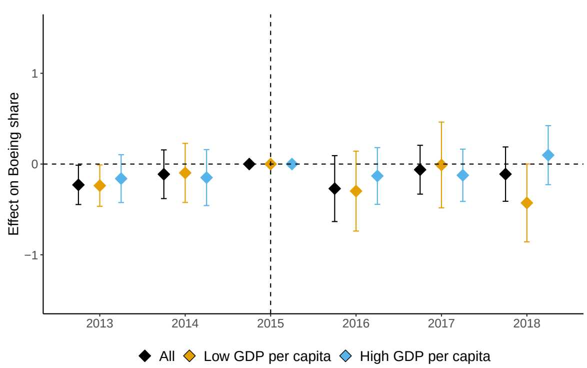


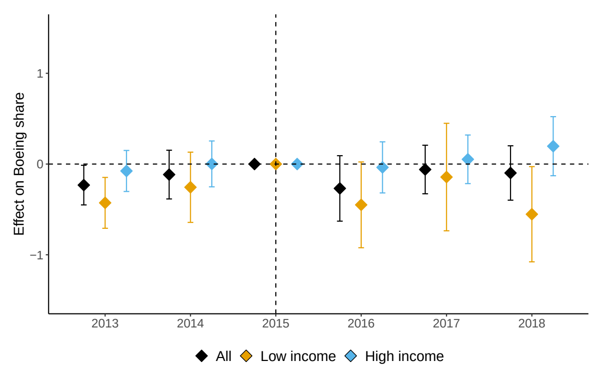
FIGURE 5: Effect on Boeing orders - role of country characteristics

This Figure presents the results of estimating equation (1) on a sample of 11,500 aircraft orders and 296 airlines between 2013 and 2018. The outcome variable takes the value of one if the aircraft ordered is produced by Boeing and zero if otherwise. We include year fixed effects, airline fixed effects, a vector of country controls (logarithm of GDP, logarithm of population, and GDP per capita), and the logarithm of one plus the fleet size as a time-varying airline control. We compare two groups of airlines: the treated airlines are airlines that had at least one Boeing aircraft in their fleet in 2015, and the control aircraft are airlines that did not have any Boeing aircraft in their fleet in 2015. We present the average treatment effects over time, where we compare treated vs. control airlines, using 2015 as the base year. Therefore, the coefficient for the year $2015 + m$ can be interpreted as the average treatment effect on the share of Boeing orders between 2015 and $2015 + m$. We split countries into two groups using their GDP per capita in 2015: countries below the median are classified as low-income, and countries above the median are classified as high-income. We also split countries into low- and high-income using the 2015 IMF classification. Finally, we also split countries in two groups using their previous reliance on EXIM funds. In Panel (A), we present the results for the full sample and the two subsamples created using GDP per capita. In Panel (B), we present the results for the full sample for the two sub-samples created using the IMF classification. In Panel (C), we present the results for the full sample and for the two subsamples created using the previous reliance on EXIM funds We cluster errors at the airline level and display 95% confidence intervals.

(a) GDP Per Capita



(b) IMF Income Groups



(c) Reliance on EXIM

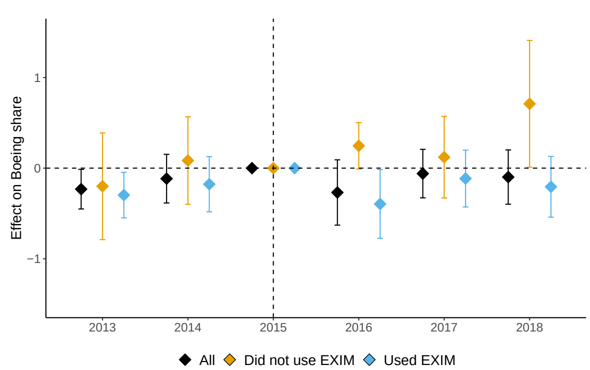


FIGURE 6: Effect on Boeing orders - role of firm characteristics

This Figure presents the results of estimating equation (1) on a sample of 11,500 aircraft orders and 296 airlines between 2013 and 2018. The outcome variable takes the value of one if the aircraft ordered is produced by Boeing and zero if otherwise. We include year fixed effects, airline fixed effects, a vector of country controls (logarithm of GDP, logarithm of population, and GDP per capita), and the logarithm of one plus the fleet size as a time-varying airline control. We compare two groups of airlines: the treated airlines are airlines that had at least one Boeing aircraft in their fleet in 2015, and the control aircraft are airlines that did not have any Boeing aircraft in their fleet in 2015. We present the average treatment effects over time, where we compare treated vs. control airlines, using 2015 as the base year. Therefore, the coefficient for the year $2015 + m$ can be interpreted as the average treatment effect on the share of Boeing orders between 2015 and $2015 + m$. We split firms into groups based on their liquidity (share of assets in total assets) in 2015 and on their fleet size in 2015. Firms below the cross-sectional median of liquidity are classified as low-liquidity and firms above the median are classified as high-liquidity. Firms below the cross-sectional median of fleet size are classified as small and firms above the cross-sectional median of fleet size are classified as large. In Panel (A), we present the results for the full sample and the two subsamples created using firm liquidity. In Panel (B), we present the results for the full sample for the two subsamples created using fleet size. We cluster errors at the airline level and display 95% confidence intervals.

(a) Liquidity

(b) Fleet size

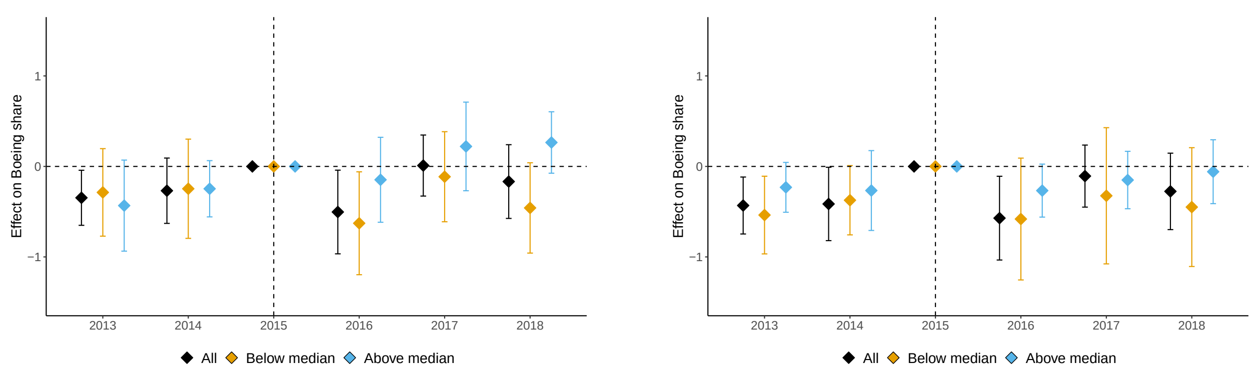


FIGURE 7: Effect on fleet age

This Figure presents the results of estimating equation (3) on a sample of 260 airlines between 2013 and 2018. The outcome variable is the logarithm of the average age of the fleet. We include year fixed effects, airline fixed effects, a vector of country controls (logarithm of GDP, logarithm of population, and GDP per capita), and the logarithm of one plus the fleet size as a time-varying airline control. We compare two groups of airlines: the treated airlines are airlines that had at least one Boeing aircraft in their fleet in 2015, and the control aircraft are airlines that did not have any Boeing aircraft in their fleet in 2015. We present the average treatment effects over time, where we compare treated vs. control airlines, using 2015 as the base year. Therefore, the coefficient for the year $2015 + m$ can be interpreted as the average treatment effect on fleet age between 2015 and $2015 + m$. We cluster errors at the airline level and display 95% confidence intervals.

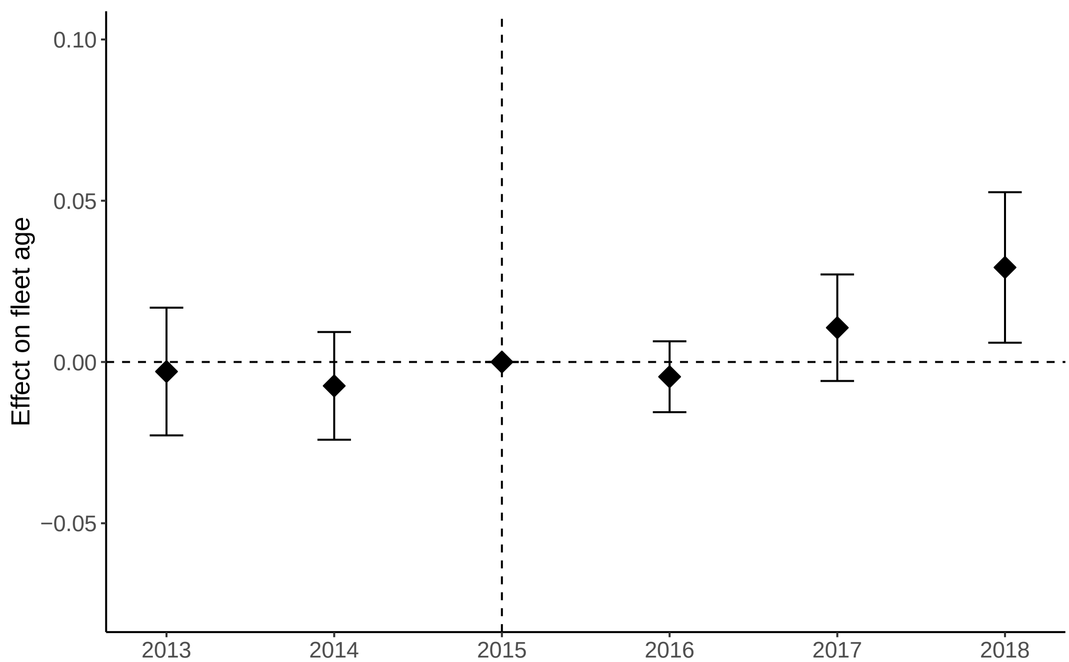
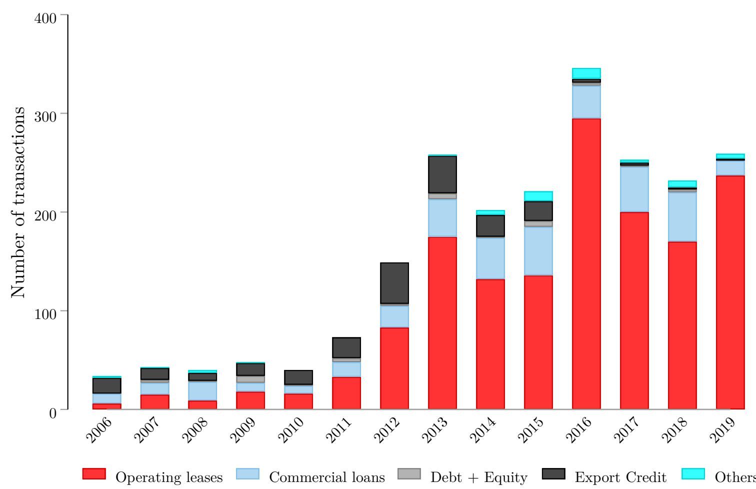


FIGURE 8: Decomposition of the number of transactions by financing type for Boeing

This figure presents a decomposition of the number of transactions involving Boeing aircraft by source of financing every year between 2006 and 2019. We consider five types of financing: (1) operating leases; (2) commercial loans; (3) debt and equity issuance; (4) export credit; and (5) other means of financing.



Tables

TABLE I: Number of transactions for Ethiopian Airlines

This table presents the decomposition of the number of transactions and the total amount in million USD conducted by Ethiopian Airlines to purchase Boeing aircraft between 2014 and 2018. We include only transactions for which we can identify the lender or lenders. We split the transactions into two groups: (1) transactions involving financing by EXIM via loan guarantees; and (2) transactions that rely only on external private funds. Within transactions financed by EXIM, we split transactions depending on whether they involve at least one US bank or no US bank at all. For transactions involving external private funds, we consider three classifications: (1) involving at least one US bank; (2) involving no US bank and no aid from AFIC; and (3) involving no US banks and with aid from AFIC.

	Number of transactions		Amount (million USD)	
	2012–2015	2016–2018	2012–2015	2016–2018
EXIM Financing				
US banks	5	0	1,357	0
Non-US banks	1	0	41	0
External private financing				
US banks	0	0	0	0
Non-US banks	4	0	370	0
Non-US banks and AFIC	0	5	0	669

TABLE II: Effects on Substitution of EXIM aid by Private Funds

This table presents the results of estimating equation (4) on all aircraft transactions between 2013 and 2018 and where the outcome variable takes the value of one if the transaction is not funded by EXIM, and zero if otherwise. We compare transactions involving Boeing aircraft (the treated group) with transactions involving aircraft produced by other manufacturers (the control group). We include airline-year fixed effects and a vector of country controls that includes the logarithm of GDP, the logarithm of population, and GDP per capita. We cluster errors at the airline level. We split countries into two groups using GDP per capita and sovereign risk. We split countries into two groups using their GDP per capita in 2015. We also split countries into low-risk countries (with ratings above or equal to Aa3) and high-risk countries (with ratings below Aa3). We present the estimates for the average treatment effect. *** ,** , and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Base	Sovereign risk		GDP per capita	
	All	Low	High	Low	High
Boeing $\times$ (Post-2015)	0.129**	0.131**	0.120*	0.173	0.124**
	(0.039)	(0.047)	(0.057)	(0.091)	(0.044)
Firm $\times$Year FE	✓	✓	✓	✓	✓
Country controls	✓	✓	✓	✓	✓
Number of countries	141	38	76	67	74
Number of airlines	662	329	330	213	473
Observations	4,005	2,327	1,592	865	3,140

TABLE III: Effects on Substitution of EXIM aid by Private Funds: The Role of EXIM Dependence

This table presents the results of estimating equation (4) on all aircraft transactions between 2013 and 2018 and where the outcome variable takes the value of one if the transaction is not funded by EXIM, and zero if otherwise. We compare transactions involving Boeing aircraft (the treated group) with transactions involving aircraft produced by other manufacturers (the control group). We include airline-year fixed effects and a vector of country controls that includes the logarithm of GDP, the logarithm of population, and GDP per capita. We cluster errors at the airline level. We also include a third difference and compare airlines that received EXIM support for Boeing purchases before 2015 with airlines that did not receive EXIM support for Boeing purchases in the same period. We present the estimates for the average treatment effects. We consider three specifications: (1) estimating equation (4) on all aircraft transactions between 2012 and 2018; (2) estimating equation (4) on all aircraft transactions between 2012 and 2018 for airlines in countries that relied on EXIM funds; and (3) estimating equation (4) with the third difference on all aircraft transactions between 2012 and 2018. *** ,** , and * denote significance at the 1%, 5%, and 10% levels, respectively.

	All	Used EXIM Funds	All
Boeing × (Post-2015)	0.129**	0.160**	0.033
	(0.039)	(0.037)	(0.019)
Boeing × (Post-2015) × Used EXIM			0.163**
			(0.049)
Country FE	✓	✓	✓
Firm ×Year FE	✓	✓	✓
Country controls	✓	✓	✓
Number of countries	141	46	141
Number of airlines	662	401	662
Observations	4,005	2,865	4,005

A Summary Statistics for EXIM transactions

FIGURE A.1: Total Aid to Exports by ECAs in 2014

This figure plots total medium- and long-term aid to exports by ECAs for the largest ECAs in the world for 2014.

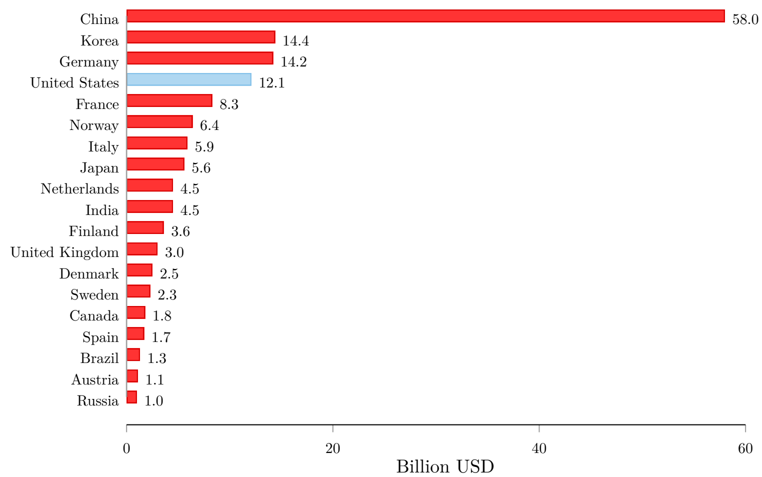


FIGURE A.2: Decomposition of Total Aid by OECD ECAs by Destination of Exports

This figure decomposes total aid given by all reporting ECAs in the OECD by the country of destination of the exports. Destinations are split into six groups: (1) OECD countries; (2) high-income countries that are not OECD members; (3) upper-middle-income countries; (4) lower-middle-income countries; (5) low-income countries; and (6) other countries for which there are no data for the level of income.

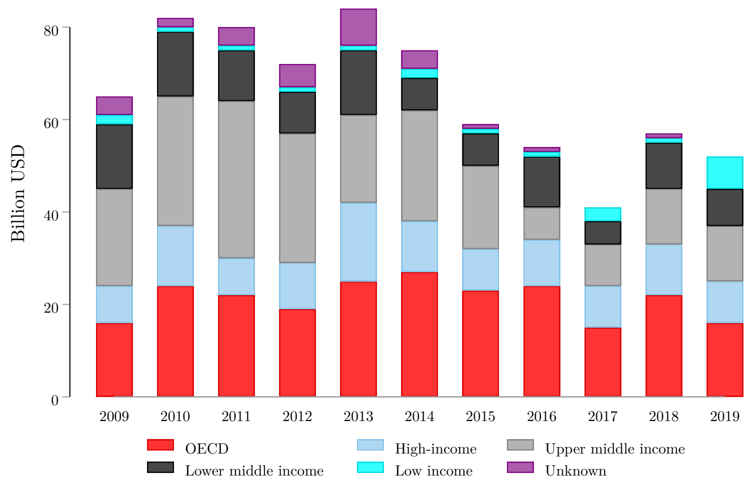


FIGURE A.3: Evolution of Number of Transactions

This figure plots the evolution of the total number of transactions of aid by EXIM between 2007 and 2021. We decompose aid into four categories: (1) loan guarantees; (2) insurance against risk in accounts receivable; (3) direct loans; and (4) working capital loans.

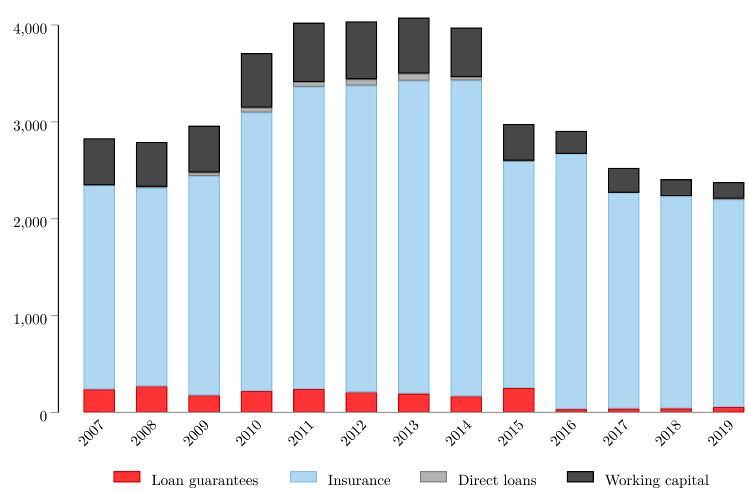
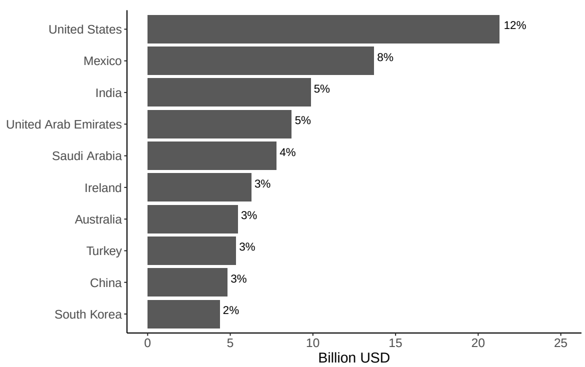


FIGURE A.4: Main recipients of EXIM aid

This figures presents the main recipients of EXIM aid for all programs until 2014. Panel A presents the countries of the customer of the US firm receiving aid. Panel B presents the US exporter associated with the transaction.

(a) Countries



(b) US exporters

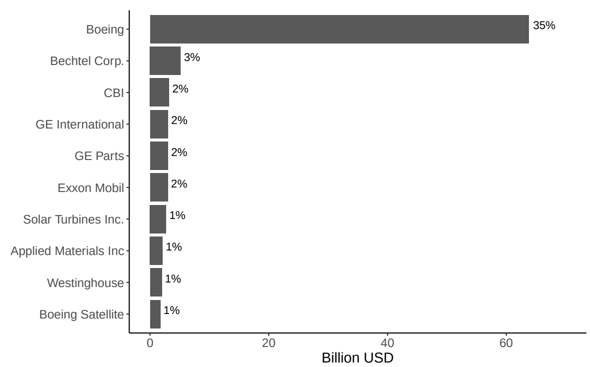
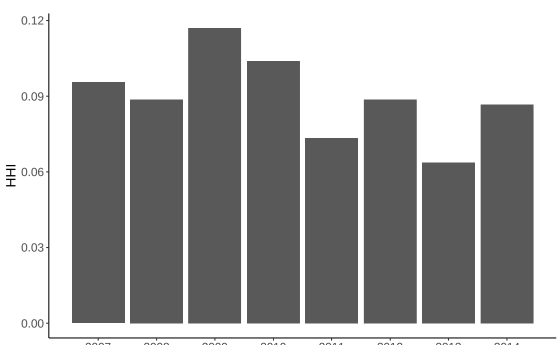


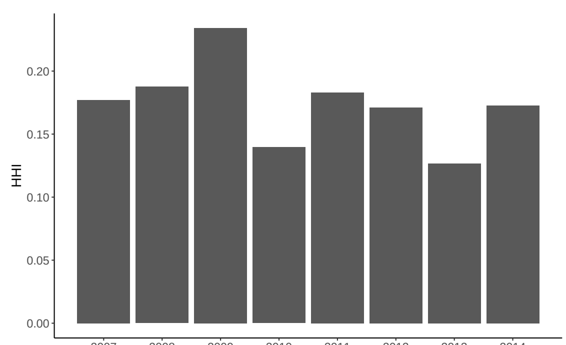
FIGURE A.5: Concentration of EXIM Aid

This figure presents the HHI of EXIM aid for all programs. We compute the HHI across countries, exporters, and sectors.

(a) Countries



(b) Exporters



(c) Sectors

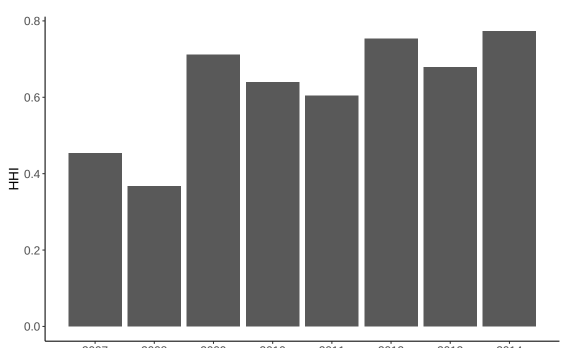


FIGURE A.6: Average Aid Amount by Program

This figure presents the average approved amount in EXIM transactions by type of program.

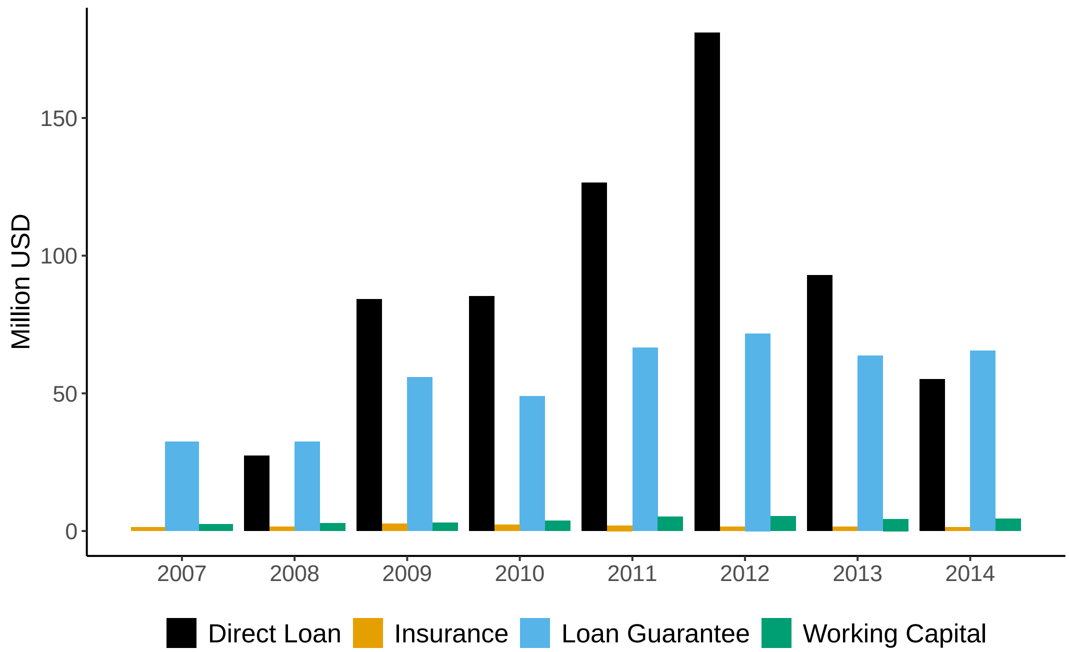
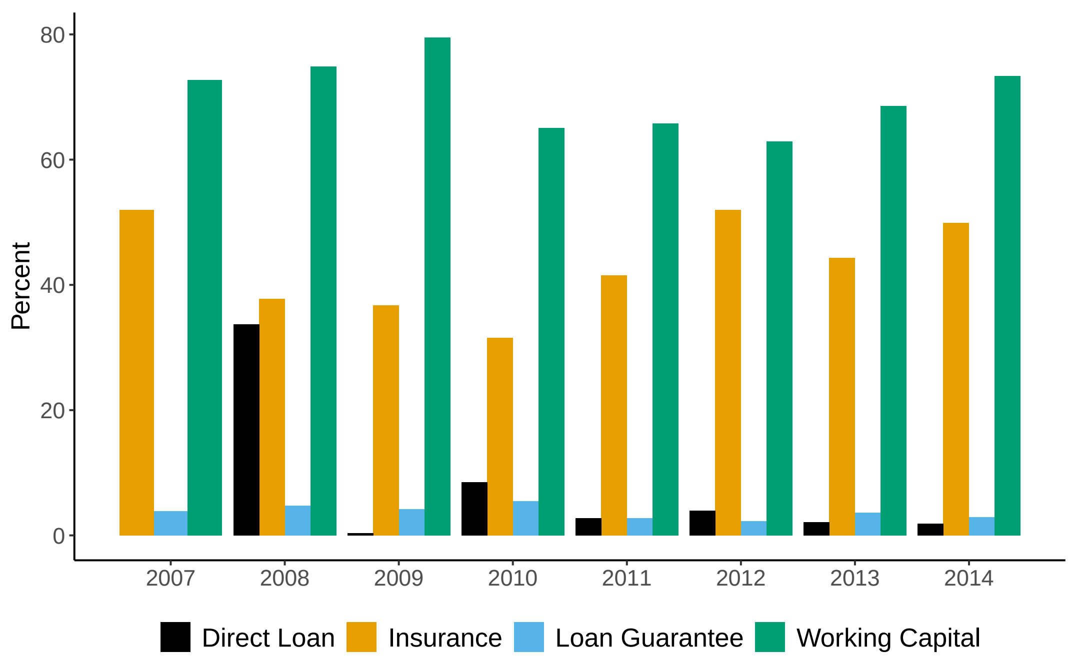


FIGURE A.7: Share of EXIM Aid Direct to SMEs

This figure presents the share of total EXIM aid that is directed at small and medium enterprises by type of program.



B Summary Statistics for Aircraft Orders

FIGURE B.1: Number of Aircraft Orders by Manufacturer

This figure presents the number of aircraft orders by manufacturer. We consider three manufacturers: Boeing, Airbus, and all other aircraft manufacturers.

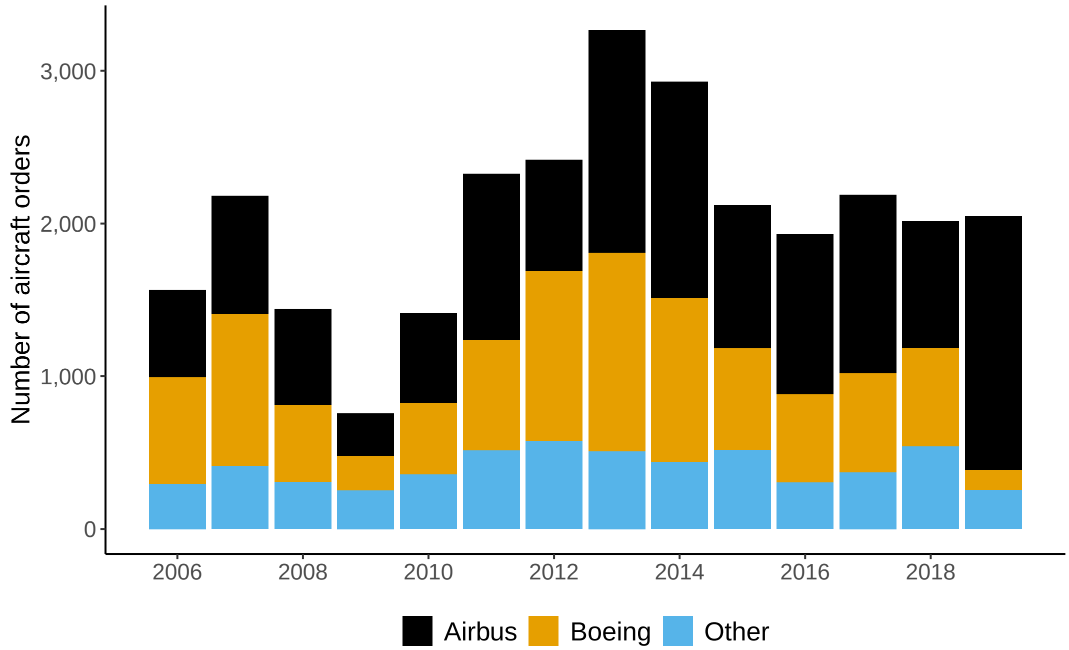
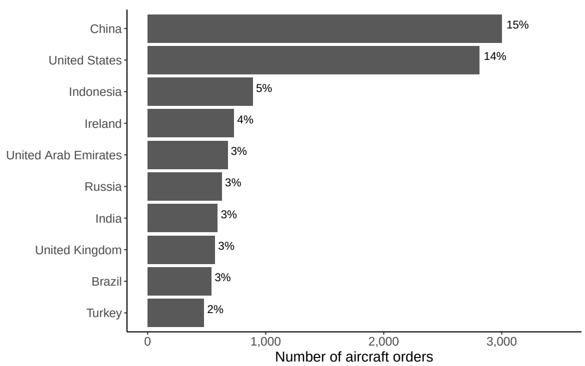


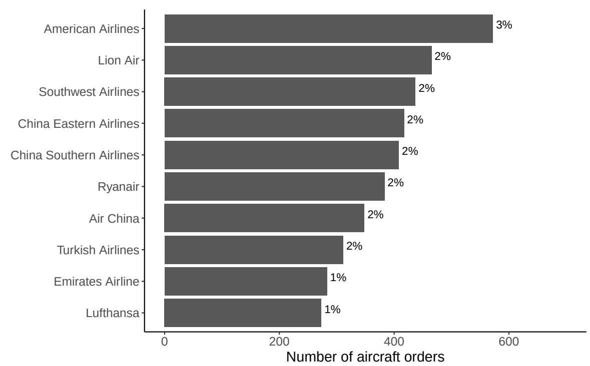
FIGURE B.2: Decomposition of Aircraft Orders

This figures presents the number of aircraft orders to the main countries and airlines. In Panel (A), we plot the number of orders by the country of the airline, along with the share of total orders. In Panel (B), we plot the number of orders by airline, along with the share of total orders

(a) Countries



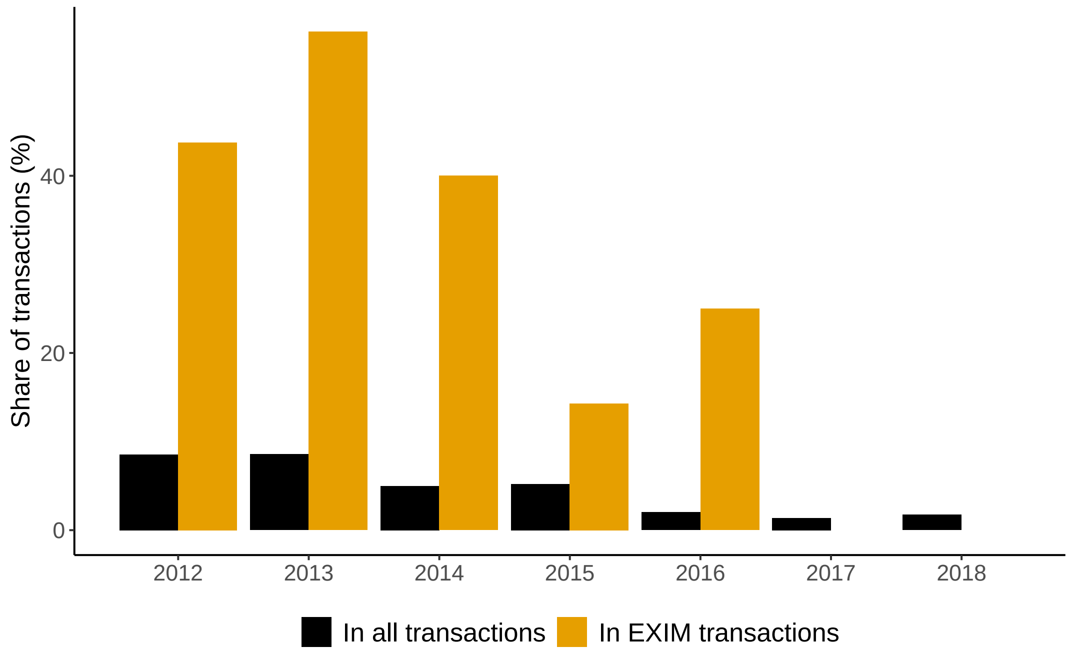
(b) Airlines



C Summary Statistics for Aircraft Financing

FIGURE C.1: Share of US Banks in Aircraft Transactions

This figure presents the share of aircraft transactions that involve a US-based bank. We compute this share for the entire sample of transactions and for a subsample of transactions that also involve EXIM aid.



D Additional Results for Boeing Orders

FIGURE D.1: Distribution of Share of Boeing Aircraft in Fleet

This figure presents the the distribution of the Boeing share of aircraft in an airline's fleet in 2014.

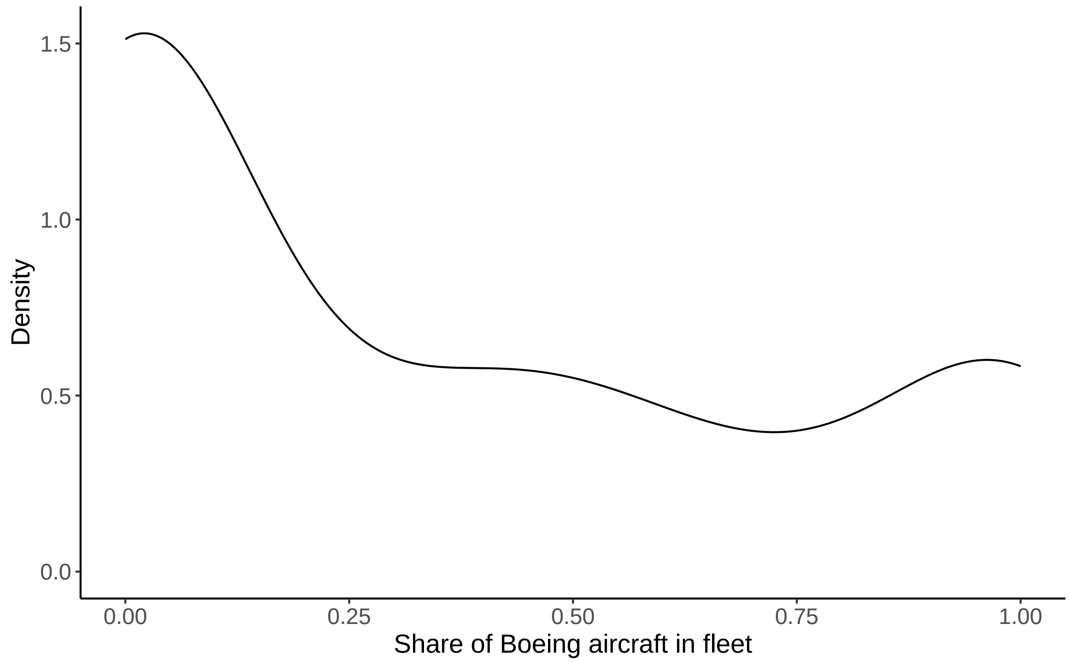


FIGURE D.2: Effect on aircraft orders

This Figure presents the results of estimating equation (2) on a sample of 436 airlines between 2013 and 2018. The outcome variable is the number of aircraft orders made by each airline in each year. We include year fixed effects and airline fixed effects. We compare two groups of airlines: the treated airlines are airlines that had at least one Boeing aircraft in their fleet in 2015, and the control aircraft are airlines that did not have any Boeing aircraft in their fleet in 2015. We present the average treatment effects over time, where we compare treated vs. control airlines, using 2015 as the base year. Therefore, the coefficient for the year $2015 + m$ can be interpreted as the average treatment effect on the number of aircraft orders between 2015 and $2015 + m$. We cluster errors at the airline level and display 95% confidence intervals.

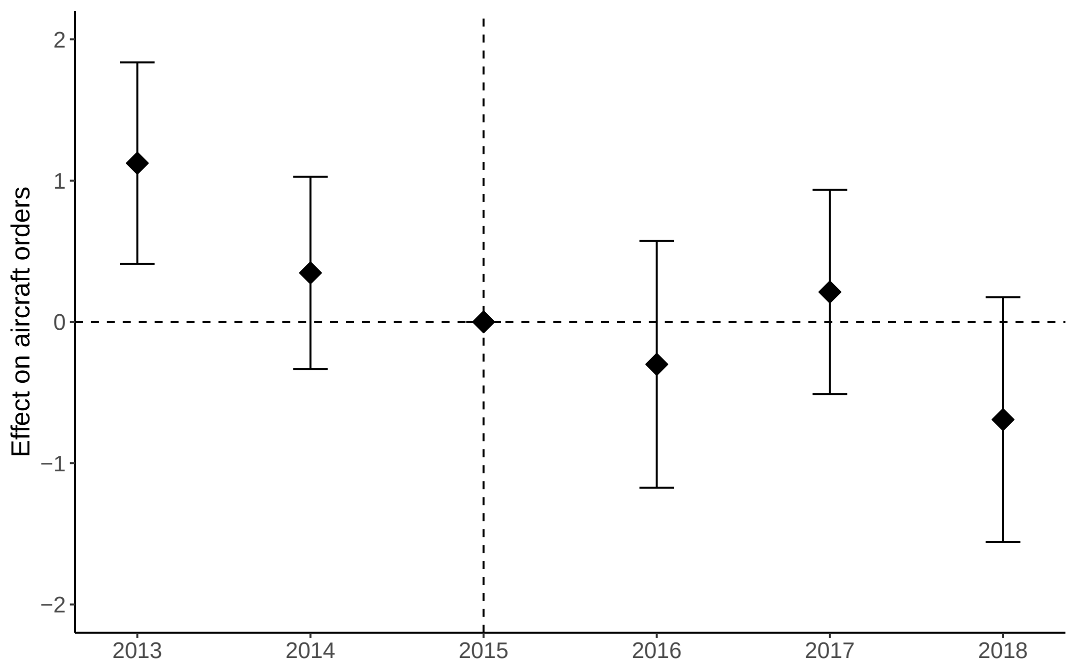


FIGURE D.3: Effect on Boeing orders

This figure presents the results of estimating equation (1) on a sample of 11,500 aircraft orders and 296 airlines between 2013 and 2018, excluding the 737-Max. The outcome variable takes the value of one if the aircraft ordered is produced by Boeing and zero if otherwise. We include year fixed effects, airline fixed effects, and a vector of country controls that includes the logarithm of GDP, the logarithm of population, and GDP per capita. We compare two groups of airlines: the treated airlines are airlines that had at least one Boeing aircraft in their fleet in 2015, and the control aircraft are airlines that did not have any Boeing aircraft in their fleet in 2015. We present the average treatment effects over time, where we compare treated vs. control airlines, using 2015 as the base year. Therefore, the coefficient for the year $2015 + m$ can be interpreted as the average treatment effect on the share of Boeing orders between 2015 and $2015 + m$. We consider three specifications, where we vary the airline controls: (1) no airline controls; (2) including the logarithm of one plus the fleet size; and (3) including also the logarithm of total assets, the ratio of cash flows to sales, leverage, liquidity (ratio of cash to total assets), and collateral (ratio of PPE to total assets). We cluster errors at the airline level and display 95% confidence intervals.

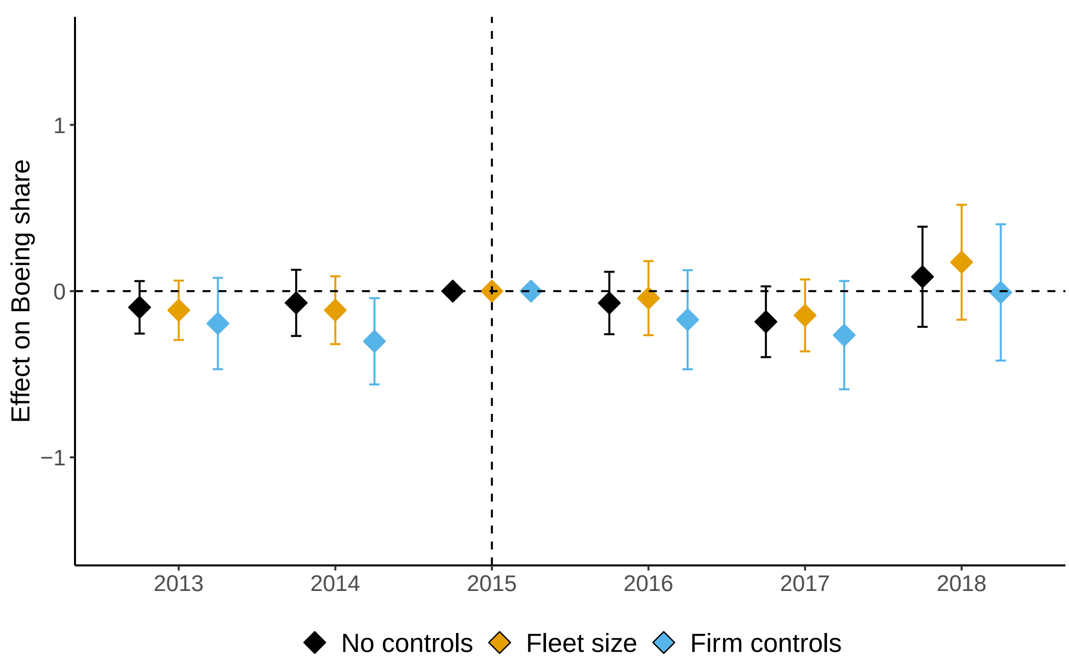


FIGURE D.4: Effect on Boeing orders - role of OECD membership

This Figure presents the results of estimating equation (1) on a sample of 11,500 aircraft orders and 296 airlines between 2013 and 2018. The outcome variable takes the value of one if the aircraft ordered is produced by Boeing and zero if otherwise. We include year fixed effects, airline fixed effects, a vector of country controls (logarithm of GDP, logarithm of population, and GDP per capita), and the logarithm of one plus the fleet size as a time-varying airline control. We compare two groups of airlines: the treated airlines are airlines that had at least one Boeing aircraft in their fleet in 2015, and the control aircraft are airlines that did not have any Boeing aircraft in their fleet in 2015. We present the average treatment effects over time, where we compare treated vs. control airlines, using 2015 as the base year. Therefore, the coefficient for the year $2015 + m$ can be interpreted as the average treatment effect on the share of Boeing orders between 2015 and $2015 + m$. We estimate the regression for the full sample, for airlines in countries in the OECD, and for airlines in countries that are not members of the OECD. We cluster errors at the airline level and display 95% confidence intervals.

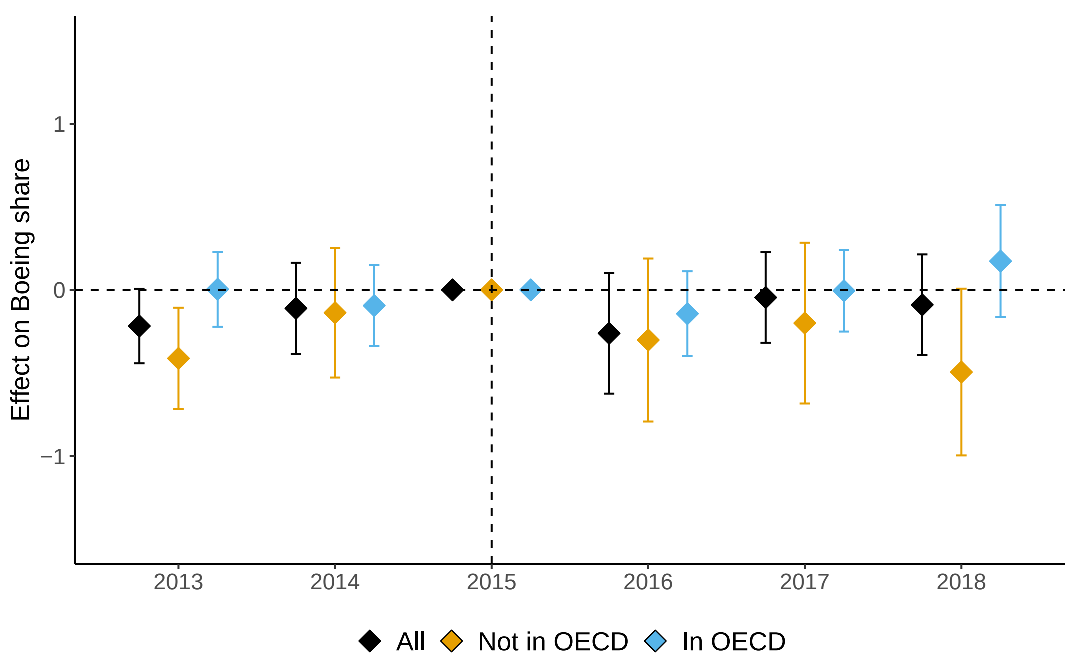


FIGURE D.5: Effect on Boeing orders - role of interest rates

This Figure presents the results of estimating equation (1) on a sample of 11,500 aircraft orders and 296 airlines between 2013 and 2018. The outcome variable takes the value of one if the aircraft ordered is produced by Boeing and zero if otherwise. We include year fixed effects, airline fixed effects, a vector of country controls (logarithm of GDP, logarithm of population, and GDP per capita), and the logarithm of one plus the fleet size as a time-varying airline control. We compare two groups of airlines: the treated airlines are airlines that had at least one Boeing aircraft in their fleet in 2015, and the control aircraft are airlines that did not have any Boeing aircraft in their fleet in 2015. We present the average treatment effects over time, where we compare treated vs. control airlines, using 2015 as the base year. Therefore, the coefficient for the year $2015 + m$ can be interpreted as the average treatment effect on the share of Boeing orders between 2015 and $2015 + m$. We divide countries into groups according to the real interest rate in 2015. We classify countries with a real interest rate above the median as having a high real rate, while the remaining countries have a low real rate. We estimate the regression for the full sample, for airlines in countries with low real rates, and for airlines in countries with high real rates. We cluster errors at the airline level and display 95% confidence intervals.

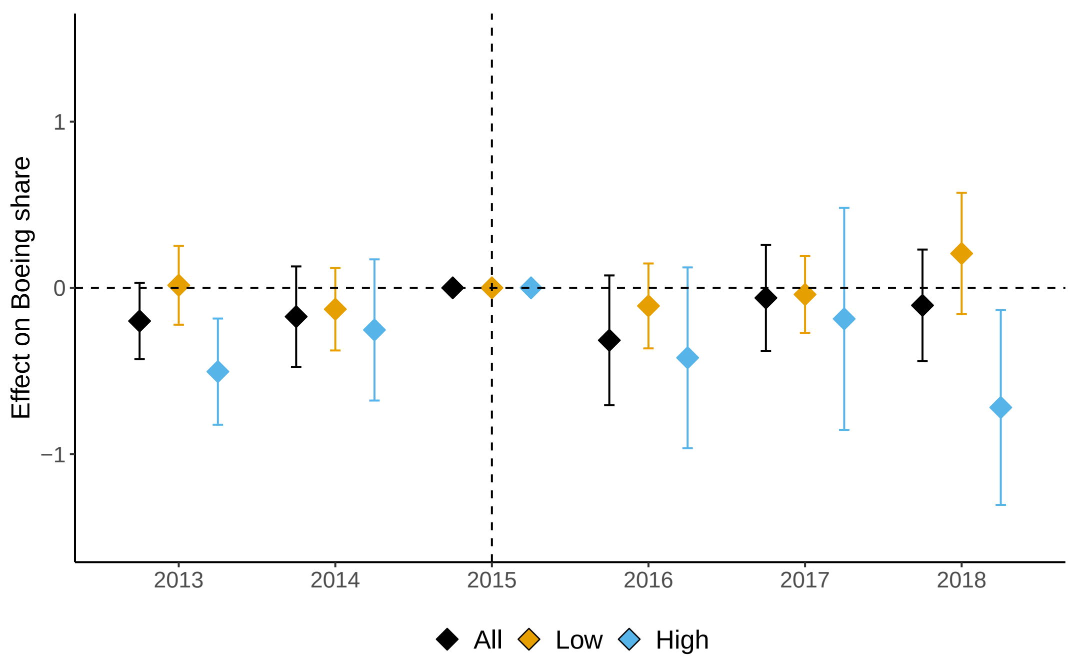
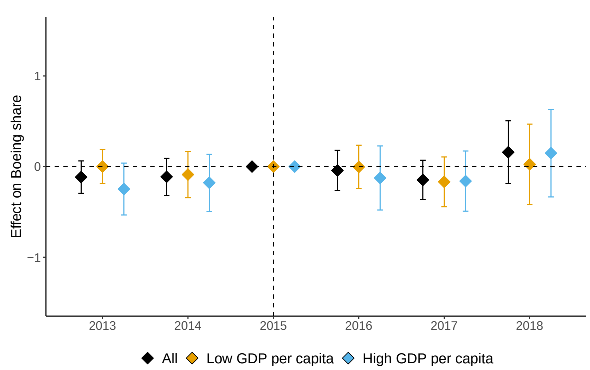


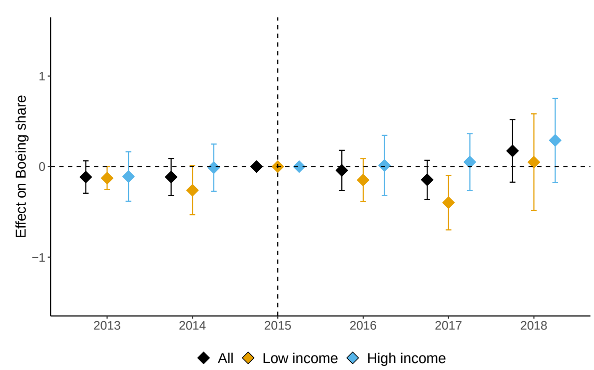
FIGURE D.6: Effect on Boeing orders - role of country characteristics

This figure presents the results of estimating equation (1) on a sample of 11,500 aircraft orders and 296 airlines between 2013 and 2018, excluding the 737-Max. The outcome variable takes the value of one if the aircraft ordered is produced by Boeing and zero if otherwise. We include year fixed effects, airline fixed effects, a vector of country controls (logarithm of GDP, logarithm of population, and GDP per capita), and the logarithm of one plus the fleet size as a time-varying airline control. We compare two groups of airlines: the treated airlines are airlines that had at least one Boeing aircraft in their fleet in 2015, and the control aircraft are airlines that did not have any Boeing aircraft in their fleet in 2015. We present the average treatment effects over time, where we compare treated vs. control airlines, using 2015 as the base year. Therefore, the coefficient for the year $2015 + m$ can be interpreted as the average treatment effect on the share of Boeing orders between 2015 and $2015 + m$. We split countries into two groups using their GDP per capita in 2015: countries below the median are classified as low-income, and countries above the median are classified as high-income. We also split countries into low- and high-income using the 2015 IMF classification. Finally, we also split countries in two groups using their previous reliance on EXIM funds. In Panel (A), we present the results for the full sample and the two subsamples created using GDP per capita. In Panel (B), we present the results for the full sample for the two sub-samples created using the IMF classification. In Panel (C), we present the results for the full sample and for the two sub-samples created using the previous reliance on EXIM funds We cluster errors at the airline level and display 95% confidence intervals.

(a) GDP Per Capita



(b) IMF Income Groups



(c) Reliance on EXIM

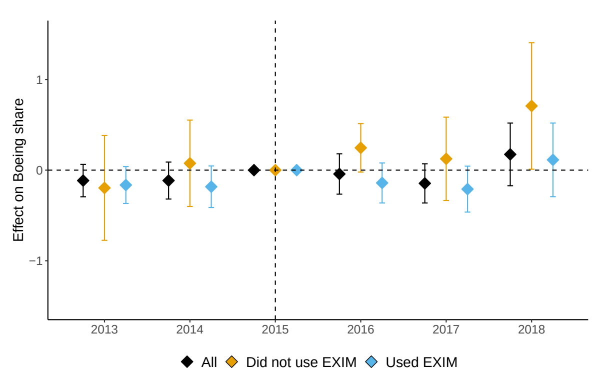


FIGURE D.7: Effect on Boeing orders - role of cash flows

This Figure presents the results of estimating equation (1) on a sample of 11,500 aircraft orders and 296 airlines between 2013 and 2018. The outcome variable takes the value of one if the aircraft ordered is produced by Boeing and zero if otherwise. We include year fixed effects, airline fixed effects, a vector of country controls (logarithm of GDP, logarithm of population, and GDP per capita), and the logarithm of one plus the fleet size as a time-varying airline control. We compare two groups of airlines: the treated airlines are airlines that had at least one Boeing aircraft in their fleet in 2015, and the control aircraft are airlines that did not have any Boeing aircraft in their fleet in 2015. We present the average treatment effects over time, where we compare treated vs. control airlines, using 2015 as the base year. Therefore, the coefficient for the year $2015 + m$ can be interpreted as the average treatment effect on the share of Boeing orders between 2015 and $2015 + m$. We divide airlines into groups according to their cash flow to sales ratio in 2015. We classify airlines with a cash flow to sales ratio above the median as having high cash flows, while the remaining airlines have a low cash flow. We estimate the regression for the full sample, for airlines with low cash flows, and for airlines with high cash flows. We cluster errors at the airline level and display 95% confidence intervals.

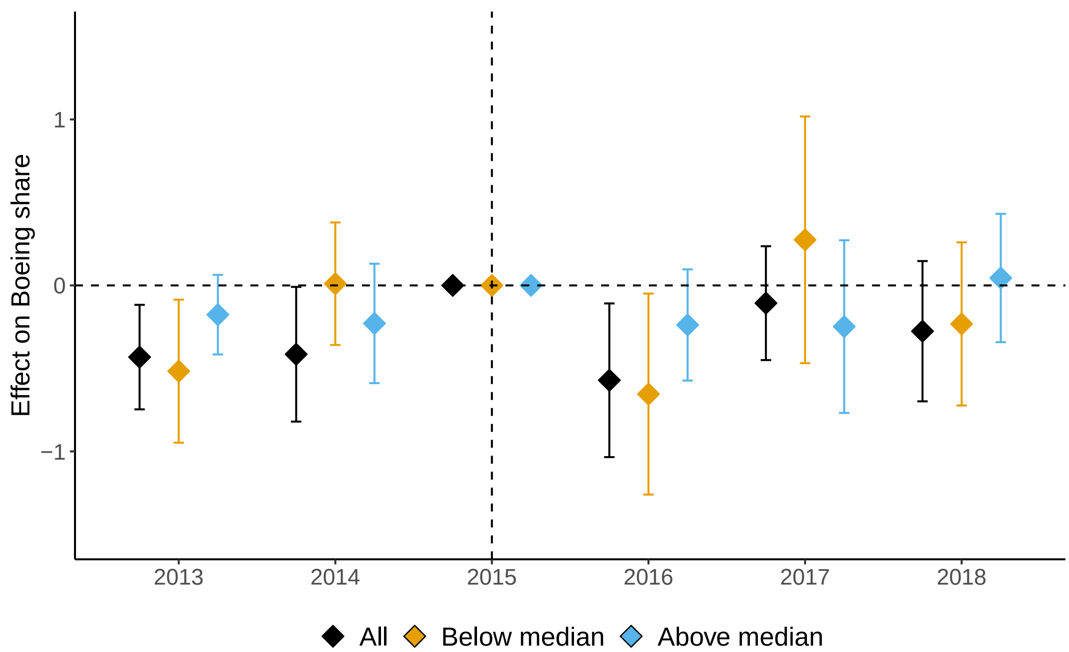


FIGURE D.8: Effect on Boeing orders - role of dependence in external financing

This Figure presents the results of estimating equation (1) on a sample of 11,500 aircraft orders and 296 airlines between 2013 and 2018. The outcome variable takes the value of one if the aircraft ordered is produced by Boeing and zero if otherwise. We include year fixed effects, airline fixed effects, a vector of country controls (logarithm of GDP, logarithm of population, and GDP per capita), and the logarithm of one plus the fleet size as a time-varying airline control. We compare two groups of airlines: the treated airlines are airlines that had at least one Boeing aircraft in their fleet in 2015, and the control aircraft are airlines that did not have any Boeing aircraft in their fleet in 2015. We present the average treatment effects over time, where we compare treated vs. control airlines, using 2015 as the base year. Therefore, the coefficient for the year $2015 + m$ can be interpreted as the average treatment effect on the share of Boeing orders between 2015 and $2015 + m$. We divide airlines into groups according to their external financing ratio in 2015. The external financing ratio is defined as in Rajan and Zingales (1998) - the difference between the change in PP&E and cash flows divided by lagged PP&. We classify airlines with a positive external financing ratio as financially constraint, while the remaining airlines are unconstrained. We estimate the regression for the full sample, for unconstrained airlines, and for constrained airlines. We cluster errors at the airline level and display 95% confidence intervals.

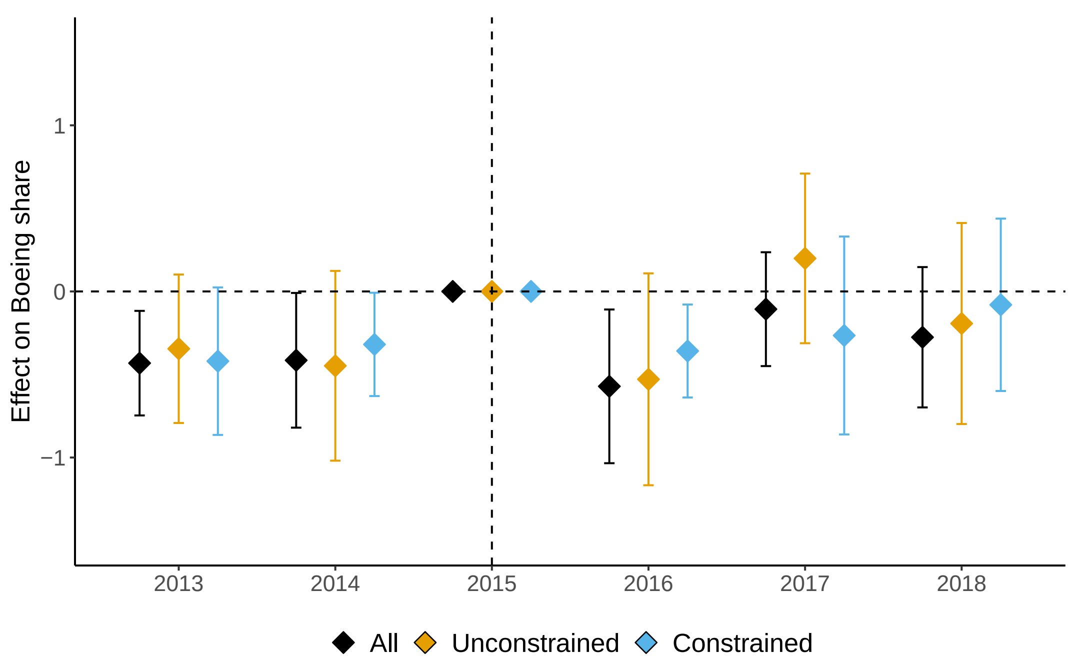


FIGURE D.9: Effect on Boeing orders - role of firm characteristics

This figure presents the results of estimating equation (1) on a sample of 11,500 aircraft orders and 296 airlines between 2013 and 2018, excluding the 737-Max. The outcome variable takes the value of one if the aircraft ordered is produced by Boeing and zero if otherwise. We include year fixed effects, airline fixed effects, a vector of country controls (logarithm of GDP, logarithm of population, and GDP per capita), and the logarithm of one plus the fleet size as a time-varying airline control. We compare two groups of airlines: the treated airlines are airlines that had at least one Boeing aircraft in their fleet in 2015, and the control aircraft are airlines that did not have any Boeing aircraft in their fleet in 2015. We present the average treatment effects over time, where we compare treated vs. control airlines, using 2015 as the base year. Therefore, the coefficient for the year $2015 + m$ can be interpreted as the average treatment effect on the share of Boeing orders between 2015 and $2015 + m$. We split firms into groups based on their liquidity (share of assets in total assets) in 2015 and on their fleet size in 2015. Firms below the cross-sectional median of liquidity are classified as low-liquidity, and firms above the median are classified as high-liquidity. Firms below the cross-sectional median of fleet size are classified as small, and firms above the cross-sectional median of fleet size are classified as large. In Panel (A), we present the results for the full sample and the two subsamples created using firm liquidity. In Panel (B), we present the results for the full sample for the two subsamples created using fleet size. We cluster errors at the airline level and display 95% confidence intervals.

(a) Liquidity

(b) Fleet size

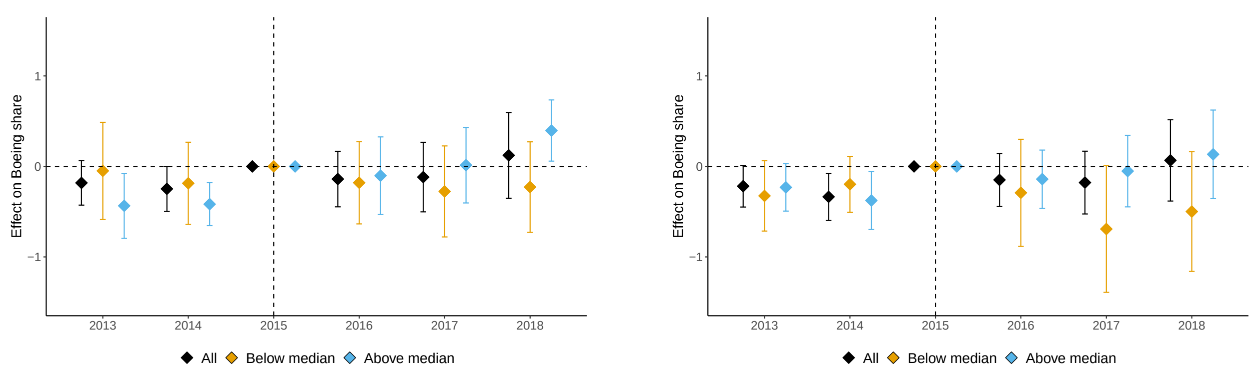
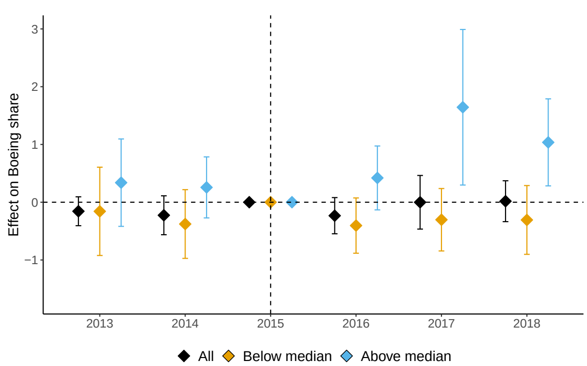


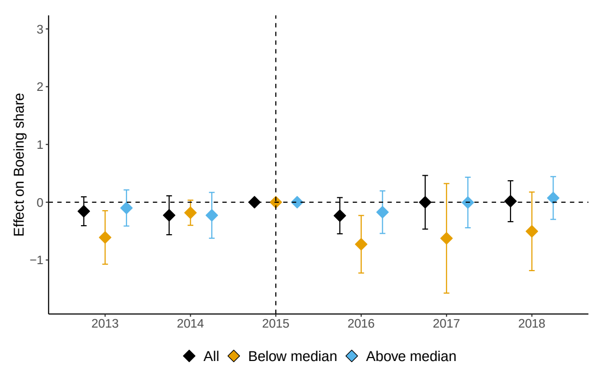
FIGURE D.10: Effect on Boeing orders - role of firm characteristics

This figure presents the results of estimating equation (1) including only airlines in high-income countries. The outcome variable takes the value of one if the aircraft ordered is produced by Boeing and zero if otherwise. We include year fixed effects, airline fixed effects, a vector of country controls (logarithm of GDP, logarithm of population, and GDP per capita), and the logarithm of one plus the fleet size as a time-varying airline control. We compare two groups of airlines: the treated airlines are airlines that had at least one Boeing aircraft in their fleet in 2015, and the control aircraft are airlines that did not have any Boeing aircraft in their fleet in 2015. We present the average treatment effects over time, where we compare treated vs. control airlines, using 2015 as the base year. Therefore, the coefficient for the year $2015 + m$ can be interpreted as the average treatment effect on the share of Boeing orders between 2015 and $2015 + m$. We split firms into groups based on their liquidity (share of assets in total assets) in 2015 and on their fleet size in 2015. Firms below the cross-sectional median of liquidity are classified as low-liquidity, and firms above the median are classified as high-liquidity. Firms below the cross-sectional median of fleet size are classified as small, and firms above the cross-sectional median of fleet size are classified as large. In Panel (A), we present the results for the full sample and the two subsamples created using firm liquidity. In Panel (B), we present the results for the full sample for the two subsamples created using fleet size. We cluster errors at the airline level and display 95% confidence intervals.

(a) Liquidity



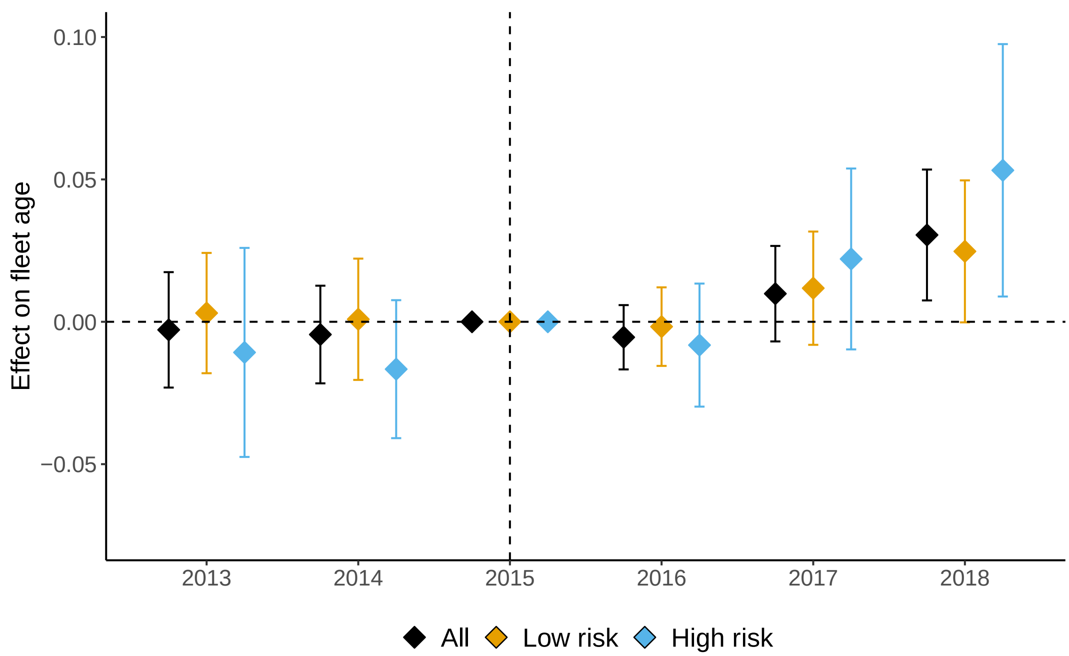
(b) Fleet size



E Additional Results for Fleet Age

FIGURE E.1: Effect on fleet age - decomposition by sovereign risk

This figure presents the results of estimating equation (3) on a sample of 260 airlines between 2013 and 2018. The outcome variable is the logarithm of the average age of the fleet. We include year fixed effects, airline fixed effects, a vector of country controls that includes the logarithm of GDP, the logarithm of population, and GDP per capita, and the logarithm of one plus the fleet size as a time-varying airline control. We compare two groups of airlines: the treated airlines are airlines that had at least one Boeing aircraft in their fleet in 2015, and the control aircraft are airlines that did not have any Boeing aircraft in their fleet in 2015. We present the average treatment effects over time, where we compare treated vs. control airlines, using 2015 as the base year. Therefore, the coefficient for the year $2015 + m$ can be interpreted as the average treatment effect on fleet age between 2015 and $2015 + m$. We also split countries into low-risk countries (with ratings above or equal to Aa3) and high-risk countries (with ratings below Aa3). We cluster errors at the airline level and display 95% confidence intervals.



F Additional Results for Aircraft Financing

TABLE F.1: Effects on Substitution of EXIM aid by Private Funds

This table presents the results of estimating equation (4) on all aircraft transactions between 2013 and 2018 and where the outcome variable takes the value of one if the transaction is not funded by EXIM, and zero if otherwise. We compare transactions involving Boeing aircraft (the treated group) with transactions involving aircraft produced by other manufacturers (the control group). We include airline-year fixed effects and a vector of country controls that includes the logarithm of GDP, the logarithm of population, and GDP per capita. We cluster errors at the airline level. We present the estimates for the average treatment effect. *** ,** , and * denote significance at the 1%, 5% ,and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Boeing × (Post-2015)	0.139***	0.132***	0.128**	0.129**
	(0.026)	(0.026)	(0.039)	(0.039)
Year FE	✓	✓		
Firm FE	✓	✓		
Firm ×Year FE			✓	✓
Country controls		✓		✓
Number of countries	150	141	141	141
Number of airlines	680	662	662	662
Observations	4,039	4,005	4,005	4,005