Online Appendix

This online appendix provides supplementary information on the empirical results presented in "Guns or Money? Defense Cooperation and Bilateral Lending as Coevolving Networks." Please note that references to tables and figures in the article are represented by roman numerals whereas references to tables and figures in this appendix are denoted by capitalized letters.

1 Data

We first overview the main data sources used for the analysis, with a particular emphasis on defining DCAs, clarifying how DCAs differ from other prominent types of defense agreements, and describing the data collection process.

1.1 Defining DCAs

Defense cooperation agreements (DCAs) are most simply defined as "formal bilateral agreements that establish institutional frameworks for routine defense cooperation" (Kinne 2018). These agreements are extensively discussed in Kinne (2017*a*,*b*, 2018), and much of the below information is drawn from these sources. As we detail further below, while alliances and nonagression pacts—the most well-known forms of defense cooperation—tend to emphasize militarized conflict and the historical contingencies that lead to such conflicts, DCAs focus overtly on *cooperative* activities, with an emphasis on establishing an institutionalized framework for routine, day-to-day cooperation. The key characteristics of DCAs include:

- **Institutional frameworks.** As framework treaties, DCAs provide the institutional framework for defense cooperation, but specific details of implementation are left to later protocols, legislation, and implementing arrangements (Matz-Lück 2009, 2014). Article IV of the 2010 DCA between Indonesia and Vietnam illustrates: "For the purpose of the implementation of this Memorandum of Understanding, the operational, administrative, and technical matters shall be subject to separate implementing arrangements to be concluded between both Parties."[1] Consequently, substantive improvements in the areas covered by DCAs typically require additional protocols, and the DCA provides the legal umbrella for these subsequent activities.
- **Coverage of multiple issue-areas.** Substantively, the issue-areas covered by DCAs typically involve some combination of (1) mutual consultation and defense policy coordination; (2) joint exercises, training, and education; (3) coordination in peacekeeping operations; (4) defense-related research and development; (5) defense industrial cooperation; (6) weapons procurement; and (7) security of classified information. Additional topics that may be covered include logistics and maintenance, military quality assurance, military medicine and health services, and so on. In their most straightforward form, DCAs cover the full range of cooperative activities in which two defense partners might engage. As stated by the 2006 France-India DCA: "This Agreement shall establish a framework which aims to cover all cooperation activities conducted by the Parties in the field of defence." This breadth distinguishes DCAs not only from alliances, defense pacts, and nonaggression treaties, but also from the hundreds of varieties of narrow, issue-specific defense agreements that countries have signed, covering everything from war cemeteries to nuclear materials to military cartography.
- **Mutual committments by signatories.** Typically, DCA obligations are symmetric; both parties commit to the same rules and standards. Indeed, the language of DCA texts favors

[1] *Memorandum of Understanding between the Government of the Republic of Indonesia and the Government of the Socialist Republic of Vietnam on Strengthening of Cooperation between Defence Officials and Its Related Activities*, signed October 27, 2010, Hanoi.

phrases such as "the Parties" and "the Signatories" in lieu of proper nouns, with extensive reference to "mutual cooperation" and "mutual consent."[2] Nonetheless, many DCAs incorporate asymmetries of some form or another, typically involving such issues as basing, military aid, and troop deployments. We employ a broad coding of DCAs, which allows for limited asymmetry in obligations, so long as the agreement maintains a focus on the core issue-areas discussed above.[3] This broader coding better reflects the myriad ways in which financial and defense cooperation influence one another. Importantly, our results are robust to more restrictive codings.

- **Long-term commitments.** The modal duration of a DCA is ten years. Over 90% of DCAs endure for at least five years. While some DCAs last as few as three years, others are indefinite. Even those agreements of relatively limited duration are nearly always eligible for renewal. This feature distinguishes DCAs from a host of other agreement types, such as (1) agreements signed during conflicts or crises, such as basing or overflight deals, which are limited to the time frame of the crisis; (2) agreements that are tied to a particular project or research program, such as joint development of a new weapon technology, which typically expire at the program's resolution; and (3) agreements that hinge upon the delivery of a particular good or service, such as arms, training, or logistical support, and which function more as contracts than formal treaties.

1.2 Differences between DCAs and other agreement types

To further emphasize the uniqueness of DCAs, we distinguish them from the most common alternative forms of defense cooperation, including alliances, nonaggression pacts, strategic partnerships, and status-of-forces agreements.

DCAs vs. alliances and nonaggression pacts. Alliances and nonaggression pacts have been extensively studied (e.g., Gibler 2009; Mattes and Vonnahme 2010; Walt 1987). The definition of alliances offered by Leeds, Ritter, Mitchell and Long (2002), which encompasses nonaggression pacts, states that alliances are "promises to aid a partner in the event of military conflict, to remain neutral in the event of conflict, to refrain from military conflict with one another." The authors further clarify that "[a]lliance partners may promise to cooperate in offensive action, to refrain from attacking one another, to remain neutral in the event the other is attacked or finds itself otherwise involved in war, or to consult regarding the use of military force." Thus, alliances are fundamentally about questions of *conflict*.

In contrast, DCAs solely address cooperation. In fact, DCAs typically contain no information on conflict or mutual defense. For example, after signing a controversial DCA with China in 2007, the defense minister of Indonesia stated: "We only want to improve our defense cooperation with China. We have no intention of signing a defense treaty with China."[4] Similarly, after signing a

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[2] For example, see *Agreement between the Government of the Republic of Indonesia and the Government of the Republic of Singapore on Defence Cooperation*, signed April 27, 2007, Tampak Siring, Bali, Indonesia.

[3] In contrast, Kinne (2018) employs a narrower coding of DCAs, where any agreement that shows evidence of asymmetry is excluded.

[4] "RI Has No Intention of Concluding Defense Pact with China," *LKBN Antara*, November 8, 2007.

DCA with Sinapore the same year, Indonesia's president referred to the deal as "not a military pact."[5]

With the exception of the North Atlantic Treaty Organization (NATO, discussed further below), few if any alliances address the issue-areas covered by DCAs. For example, according to Leeds et al. (2002), the vast majority of alliances do not require personnel of signatories to interact during peacetime. In most cases, then, DCAs and alliances can be easily differentiated by the former's focus on routine defense interactions and the latter's focus on conflict and crises. While some alliances do contain "DCA-like" provisions, these are subjugated to mutual defense provisions. The definition of DCAs used by Kinne (2017*a*, 2018), which we adopt here, overtly excludes any mention of mutual defense or nonaggression obligations.

DCAs vs. status of forces agreements. SOFAs also involve defense cooperation (Erickson 1994). However, SOFAs address questions of legal jurisdiction, such as a signatory government's jurisdiction over foreign deployed troops. Countries sometimes sign "umbrella" SOFAs, intended to cover any troops exchanged between them. When DCA partners lack such a framework, they may include limited SOFA provisions within the DCA itself. But such provisions are always secondary to the DCA's primary emphasis on substantive defense cooperation. SOFAs can thus be easily differentiated from DCAs by their singular emphasis on jurisdiction.

DCAs vs. strategic partnership agreements. While SPAs are increasingly common, they differ from DCAs in key ways. First, SPAs are typically extremely broad, covering not only defense issues but also trade, investment, health, the environment, diplomacy, and so on. Second, SPAs are often the product of unique historical circumstances. For example, the SPAs signed by the US with Iraq and Afghanistan were the direct result of wars with those two countries. Third, SPAs have an ambiguous status in international law. According to Kay (2000), "the United States and its potential peer competitors have rarely employed a term so extensively without a clear sense of its meaning or purpose." The generality, historical specificity, and legal vagueness of SPAs clearly distinguish them from DCAs.

1.3 Collection of original DCA data

Kinne (2017*a*, 2018) discusses collection of the DCA dataset. The dataset includes all countries for the period 1980–2010. The data collection consisted of three phrases. In the first phase, data were collected from established databases, including the World Treaty Index (Bommarito, Katz and Poast 2012; Rohn 1984) and the United Nations Treaty Series (United Nations Treaty Collection 2012). Due to underreporting of signed treaties by governments, these sources provide only about 15% of the observations in the DCA dataset. In the second phase, data were collected from individual country publications, including official online or print treaty series, legislative gazettes, online databases, and informal sources, such as documents provided directly by personnel of foreign, internal, and defense ministries. These sources contribute about 60% of the observations in the dataset. In the third phase, data were collected from global newspaper and newswire archives, based on manual keyword searches in Factiva and Lexis-Nexis. These sources provide the remaining 25% of the observations in the main dataset.

[5] "Extradition, defense treaties signed in Bali," *The Jakarta Post*, April 28, 2007.

1.4 Operationalizing DCA and loan data for inferential network analysis

The DCA network is operationalized as a $T = 21$ stack of binary matrices, covering the period 1990–2010,[6] where an $x_{ij,t} = 1$ entry in a given $\mathbf{x}_t$ DCA network indicates that a DCA has been signed between i and j in either the current year or the prior four years. We use this five-year window primarily because the durations of many DCAs are not known precisely. Of those agreements with a known duration (i.e., where full treaty texts are available), over 90% endure for at least five years. Many DCAs are indefinite. The five-year window is thus conservative. Insofar as DCAs influence loans beyond five years, the model will underestimate the true strength of these effects, which biases estimates toward zero. Estimates significantly different than zero are thus especially strong evidence of network effects. At the same time, we expect the cross-network influence of DCAs to be especially pronounced in the first few years of their signature, when public and political attention is greatest. As we show below, our results are highly robust to varying the size of the five-year window.

We use lending data from the Debtor Reporting System (DRS) of the World Bank.[7] The World Bank requires all members to report detailed information on their financial positions, including information on bilateral government-to-government loans. To match the DCA dataset, we use loan data for the period 1990–2010, and we similarly operationalize the loan network as a stack of $T = 21$ matrices, where an $y_{ij,t} = 1$ entry in a given $\mathbf{y}_t$ loan network indicates that an $i \to j$ loan agreement has been signed in the current year or prior four years. As with DCAs, the cross-network impact of loans is likely greatest immediately following their signature. Indeed, a loan's influence may decline precipitously when repayment begins and governments face the financial costs of borrowing. In the loan data, the mean grace period (i.e., time to repayment) is five years. Thus, as with DCAs, the five-year window represents a higher hurdle for our analysis, as it captures only cross-network influences that materialize within the first few years of a loan agreement's signature. Note that, unlike DCAs, loans are directed from an i creditor to a j debtor. Thus, the $\mathbf{y}_t$ matrix is asymmetric, such that $y_{ij,t} \neq y_{ji,t}$.

2 The Stochastic Actor-Oriented Model (SAOM)

We first summarize the properties of the SAOM. This discussion draws heavily from Snijders (2001, 2005, 2008), Snijders, Van de Bunt and Steglich (2010), and especially Snijders, Lomi and Torló (2013). We then discuss the control variables for both the DCA and loan equations. Finally, we present summary statistics.

6 Although we have DCA data since 1980, the DCA network is extremely sparse in the 1980s, which causes convergence problems in the estimation algorithm.

7 We intentionally include government-to-government loans granted for any purpose. Some loans are designated for purchase of military equipment, but the vast majority of loans are meant to spur economic development (e.g., via infrastructure, power plants, and so on). Our theory is agnostic about the specific use of loans.

2.1 Modeling the coevolution of two networks

A standard SAOM relies upon a single nodal utility function, $f_i(\mathbf{x})$, which is assumed to apply identically to all nodes in the network $\mathbf{x}$. In creating, maintaining, and/or terminating ties in the $\mathbf{x}$ network, actors seek to maximize this function. To extend this single-equation model to the problem of coevolving networks, we consider an additional network, $\mathbf{y}$, with a separate corresponding utility function. We thus simultaneously model two utility functions, $f_i^X(\mathbf{x}, \mathbf{y})$ and $f_i^Y(\mathbf{x}, \mathbf{y})$, which effectively transforms the SAOM into a model of multiplex network coevolution (Snijders, Lomi and Torló 2013). For notational purposes, $f_i^X(\mathbf{x}, \mathbf{y})$ always refers to the DCA network, and $f_i^Y(\mathbf{x}, \mathbf{y})$ always refers to the loan network. Each function consists of a linear combination of various effects,

$$f_i^X(\mathbf{x}, \mathbf{y}) = \sum_{h=1} \beta_h^X s_{ih}^X(\mathbf{x}, \mathbf{y}) \tag{1}$$

and

$$f_i^Y(\mathbf{x}, \mathbf{y}) = \sum_{h=1} \beta_h^Y s_{ih}^Y(\mathbf{x}, \mathbf{y}), \tag{2}$$

where $s_{ih}^X(\mathbf{x}, \mathbf{y})$ represents those variables that determine the creation, maintenance, and/or termination of ties in the DCA network, and $s_{ih}^Y(\mathbf{x}, \mathbf{y})$ represents those variables that determine the creation, maintenance, and/or termination of ties in the loan network. In practice, these functions consist of one of three types of effects: (1) endogenous network influences, such as transitivity or reciprocity; (2) exogenous influences like geographic distance, regime type, or economic development; and (3) cross-network influences, such as those illustrated in Figures 1, 3, and 4 of the main paper. Each specified s_{ih}^X or s_{ih}^Y effect is weighted by a respective β_h^X or β_h^Y parameter. Typically, a negative β parameter estimate indicates that a specified effect discourages network tie formation, while a positive estimate indicates that a specified effect encourages tie formation.

Given the model's complexity, parameters must be estimated via simulation. We employ simulated method of moments estimation, as recommended by Snijders (2005). Briefly, this approach uses an iterative Robbins-Monro Markov-chain Monte Carlo algorithm to search the parameter space and locate $\hat{\beta}$ values that generate simulated networks that, according to calculated target statistics, closely resemble the observed networks (Snijders 2005). The estimation algorithm incorporates a number of fundamental assumptions. First, the network evolves continuously, one tie at a time, with potentially large numbers of tie changes occurring unobserved between observation moments. Second, nodes exercise individual agency in that they choose x_{ij} or y_{ij} ties in such a way as to maximize the payoff from their respective utility function. Third, the opportunity for actors to change their ties in either network is stochastically determined by separate rate functions, which allows for the rate of change in one network to be substantially different than in the other. Fourth, once an actor changes a tie in either the $\mathbf{x}$ or $\mathbf{y}$ network, that change is immediately reflected in the other network, which ensures that the ties between the two networks interact in a continuously evolving process.

For the loan utility function, $f_i^Y(\mathbf{x}, \mathbf{y})$, we specify a series of cross-network effects, where structures within the DCA network influence ties in the loan network. For example, to assess the effect of a tie in the DCA network on a tie in the loan network, which tests H2, we include the dyadic cross-product of the two networks, defined as

$$\text{DCA bilateral} = s_{i1}^{Y} = \sum_j y_{ij} x_{ij}. \tag{3}$$

If a given i extends a tie in the $\mathbf{y}$ network (i.e., makes a loan to a j partner), s_{i1}^{Y} equals 1 if i and that j partner also have a DCA in place and equals zero otherwise. Put differently, a y_{ij} loan tie to a state with which i also has a x_{ij} DCA tie should be preferred over a tie to a j state with which i has no x_{ij} tie, given the relatively greater contribution of the former to i's utility function.

To assess higher-order impacts of the DCA network on the loan network, we include the following two additional statistics:

$$\text{DCA degree}_j = s_{i2}^{Y} = \sum_j y_{ij}(x_{j+} - \bar{x}) \tag{4}$$

$$\text{DCA closure} = s_{i3}^{Y} = \sum_{j \neq k} y_{ij} x_{ik} y_{kj} \tag{5}$$

The statistic s_{i2}^{Y} captures the influence of a potential loan partner's position in the DCA network on i's probability of making a loan, which tests H3. A negative parameter estimate indicates that as j's DCA ties increase, it becomes less attractive as a debtor. s_{i3}^{Y} incorporates i and j's mixed DCA-loan ties to relevant k third parties, which tests H4. A positive estimate for this effect indicates that the more of i's defense partners that make loans to j, the more likely i is to make a loan to j.

For the $f_i^X(\mathbf{x}, \mathbf{y})$ DCA equation, where DCA ties are the dependent variable of interest, we include the following effects:

$$\text{Loan bilateral} = s_{i1}^{X} = \sum_j x_{ij} y_{ij}. \tag{6}$$

$$\text{Loan outdegree}_j = s_{i2}^{X} = \sum_j x_{ij}(y_{j+} - \bar{y}) \tag{7}$$

$$\text{Loan similarity} = s_{i3}^{X} = \sum_j x_{ij} \left(\frac{\sum_k y_{ki} y_{kj}}{y_{+i} + y_{+j} - \sum_k y_{ki} y_{kj}} \right) \tag{8}$$

The statistic s_{i1}^{X}, which tests H1, is the cross-product of the two networks, operationalized with DCAs instead of loans as the dependent variable. The statistic s_{i2}^{X} operationalizes the overall lending activity or "outdegree" of states in the loan network, which tests H5. Finally, s_{i3}^{X} measures the similarity of i and j's respective borrowing portfolios, which tests H6.

2.2 Control variables

As discussed in the main text, we employ a battery of control variables for both the loan and DCA equations. Here, we detail the motivations behind these controls and provide context for the estimates. As we show below, the model is highly robust to inclusion/exclusion of the controls.

2.2.1 DCA equation

The selection of control variables for the DCA equation follows Kinne (2018), who shows that exogenous influences on DCA creation largely stem from a combination of (1) an interest in military modernization, (2) a need to respond to mutual security threats, and (3) a desire to establish cohesive groups of like-minded defense collaborators, i.e., "security communities." The control variables used to capture these incentives can be generally grouped into military, political, and economic influences.

Military factors

- CINC: the Correlates of War CINC score of the potential initiator, as well as the interaction of the initiator's and target's CINC scores (Singer, Bremer and Stuckey 1972). The empirical relationship between power and defense cooperation is complex. On the one hand, powerful states should make for more attractive defense partners, given that their comparative advantage in military resources can help their partners modernize their militaries. On the other hand, powerful states are potentially a source of threat themselves. We thus anticipate that, in general, governments should prefer to sign DCAs with powerful partners. However, *mutually powerful* states should be unlikely to sign agreements with one another.

- NATO members: a dummy variable that equals one if i and j are both members of NATO in the current year. Prima facie, we might expect a positive relationship between NATO membership and DCAs. However, due to its unusually broad mandate, NATO in fact often overlaps with the same issue areas addressed by DCAs, such as joint exercises, defense-related R&D, training and education, information exchange, and so on. Further, NATO members often sign subsidiary defense agreements, which accomplish similar goals as DCAs but, not being standalone legal instruments, are not counted as such. We thus anticipate a negative correlation between NATO membership and DCAs.

- NATO-PfP members: a dummy variable that equals one if either i or a j is a full NATO member and the other is a member of NATO's partnership for peace (PfP) program. Anecdotal evidence reveals that NATO states often use DCAs as a way to tighten relations with and "recruit" potential NATO members (Kinne 2018). We thus anticipate a positive correlation between this variable and DCAs.

- Alliance (non-NATO): a dummy variable that equals one if i and j share a defense pact other than NATO (Gibler 2009). In general, alliances reflect shared interests. Further, becaused most alliances, with the above-noted exception of NATO, do not address the sort of routine, substantive defense cooperation encouraged by DCAs, we anticipate a positive correlation between non-NATO alliances and DCAs.

- Terrorism: the number of annual fatal terrorist attacks in the potential initiator, as well as the interaction of the initiator's terrorist attacks and the potential target's terrorist attacks (START 2016). Because DCAs focus on mutual security threats, we expect a positive correlation between these variables and DCAs.

- Common enemy: a count of the number of third-party states with whom i and j fought a militarized interstate dispute (MID) in the past five years (Palmer, D'Orazio, Kenwick and Lane 2015). Given that DCAs are motivated, in part, by the need to address shared security threats, we tentatively expect a positive correlation between this variable and DCAs

(Bueno de Mesquita 1975; Signorino and Ritter 1999). On the other hand, countries that exhibit a proclivity toward use of militarized force may pose security threats of their own, which suggests an insignificant or even significantly negative estimate for this variable.

Political factors

- Polity: the Polity score of the potential "initiator" of defense cooperation, on a 21-point scale, as well as the interaction between the Polity scores of the initiator and the target (Marshall and Jaggers 2002). While we might expect democracies to be more active in defense cooperation—and/or more active in cooperating with other democracies—the empirical record with regard to regime type and defense cooperation is somewhat ambiguous (Lai and Reiter 2000; Leeds 1999; Siverson and Emmons 1991). We nonetheless tentatively anticipate a positive correlation between both of these measures and DCAs.

- UNGA affinity: the S statistic applied to voting data in the United Nations General Assembly, which varies between -1 and 1 (Bailey, Strezhnev and Voeten 2015; Signorino and Ritter 1999). Higher values indicate more similar voting patterns, which in turn indicate affinity in foreign policy preferences. We anticipate a positive correlation between this variable and the probability of a DCA.

- Former colony: a dummy variable that equals one if i or j is a former colony of the other (Hensel 2014). Historically, colonizing powers are more likely to sign defense agreements with their former colonies, either to protect their interests there directly or as a form of extended deterrence. In practice, because defense agreements signed with former colonies tend to be highly asymmetric (e.g., they include provisions on basing, troop deployments, and military aid), they are generally not included in the dataset. We nonetheless anticipate a positive correlation between former colonial ties and the probability of a DCA.

- Distance: the log-transformed distance between i and j's capital cities, in kilometers (Weidmann, Kuse and Gleditsch 2010). We anticipate that more geographically proximate countries are more likely to partner with one another.

Economic factors

- Per-capita GDP: the per-capita gross domestic product of the potential initiator, as well as the interaction of the initiator's and target's per-capita GDPs, in log-transformed current year dollars (World Bank 2017). As with power, wealthy countries should generally be preferred as defense partners, given that they are better equipped, ceteris paribus, to contribute to joint projects and modernization efforts. Further, since we separately control for military power (which positively correlates with wealth), we do not anticipate that mutually wealthy countries should be averse to cooperation. We thus anticipate that both variables are positively correlated with DCAs.

- Bilateral trade: a continuous measure of total annual trade flows between i and j, in log-transformed constant dollars (Barbieri and Keshk 2012). Because bilateral trade reflects shared economic interests, we anticipate a positive correlation between trade and DCAs.

- Arms trade match: a dummy variable that equals one if i or j is a net arms importer while the other is a net arms exporter (Holtom, Bromley, Wezeman and Wezeman 2013). While arms trade itself does not increase the probability of a DCA, historical evidence shows that states nonetheless sign DCAs in anticipation of weapons deals. We thus expect this variable to increase the probability of DCAs.

2.2.2 Loan equation

The control variables account for several exogenous factors that shape the likelihood of signing new loan agreements. Note that, because the loan network is directed, we are able to separately control for creditor (i) and debtor (j) monadic effects. Specifically, we account for a country's motivation to lend, a country's need for new loans, and a potential debtor's economic and political attractiveness for creditors.

Creditor motivations

- Per-capita GDP (i): a measure of the country's overall wealth, obtained from the World Bank (2017). We expect that richer countries are more likely to be creditors, for two reasons. First, they are more likely to have the monetary resources available to provide loans. Second, richer countries are more likely interested in exerting influence over other countries.
- Current account (i): a measure of short-term availability of monetary resources available to lend (World Bank 2017). In contrast to per-capita GDP, the current account is significantly more volatile, as it can be positive in one year and negative in another. We expect countries with positive current account balances to be more likely to lend.
- Multilateral propensity (i): a propensity score capturing the likelihood that a country makes contributions to multilateral institutions, such as the World Bank or IMF, based on the methodology introduced in Copelovitch (2010). We anticipate that countries emphasizing multilateral lending are less likely to lend bilaterally.

Debtor Motivations

- Per-capita GDP (j): captures the recipient's overall level of prosperity (World Bank 2017). A priori, however, the expected effect is not clear. On the one hand, poorer countries are in more need of loans, which would imply that low GDP per capita should be associated with increased loans. On the other hand, very poor countries are unattractive debtors, which would imply the opposite direction of the effect.
- Current account (j): a measure of short-term availability of monetary resources, obtained from the World Bank (2017). We expect countries with positive current account balances to be in less need of a loan.
- Multilateral propensity (j): a propensity score capturing the likelihood that a country obtains loans from the World Bank or IMF, based on the methodology introduced in Copelovitch (2010). This variable controls for the expected supply of multilateral loans, as a country decides to borrow bilaterally. As multilateral loans provide capital to recipient countries, they become more attractive debtors as the chances for repayment increase. Therefore, we anticipate a positive effect on bilateral lending.

- Private propensity (j): a propensity score capturing the likelihood that a country obtains loans from the private capital market, either through issuing bonds or obtaining commercial bank credit. As above, this variable controls for the expected supply of private loans, as a country decides to borrow bilaterally. We expect that countries able to access private capital markets are more attractive debtors.

Economic attractiveness of debtors

- Credit rating (j): average rating of three ratings agencies—Fitch, Standard and Poor's, and Moody's. Data obtained from the Bloomberg Terminal (Bloomberg 2015) and converted to a 21 point scale. Credit ratings measures the economic capacity of debtors to repay loans. This information, however, might already be captured by observable economic indicators, such as GDP. In addition, credit ratings are created with private bond investors in mind, not government officials deciding on government-to-government loans. Therefore, we do not expect credit ratings to have a statistically significant effect.

- Debt, banking, or currency crisis (j): dummy variables indicating whether a country experienced a debt, banking, or currency crisis (Reinhart and Rogoff 2009). Generally, we would expect crises to have a negative effect on the likelihood of obtaining bilateral loans. However, some scholars argue that debt crises can incentivize donors to provide bail-out packages (Copelovitch 2010; Stone 2004), in which case we should observe a positive effect of debt crises (but not necessarily banking or currency crises).

- Bilateral imports and exports: measure exports to creditors from debtors, and imports obtained by debtors from creditors, in millions of current US dollars, log transformed (IMF 2015). We expect that trade with potential creditors increases the likelihood of loans. This is particularly relevant for export-dependent creditors intent on selling their products abroad.

- Oil reserves (j): a continuous measure of existing oil reserves, log transformed (EIA 2015). Creditors might give preference to debtors with proven oil reserves to gain access to debtors' natural resources (Caceres and Ear 2013). For this reason, we would expect a positive and significant effect.

- Exposure (j): aggregate total investment by private foreign banks in debtor economy, log transformed. Data come from the BIS (2013). The higher the share of investment projects funded directly by private banks, the lower the need for governments to borrow money to finance these projects themselves. For this reason, we expect a negative effect.

Political attractiveness of debtors

- Polity similarity: measures the similarity of debtor's and creditor's polity scores (Marshall and Jaggers 2002). Following the argument of *Democratic Advantage* (Schultz and Weingast 2003), democracies might be attractive debtors, particularly for democratic creditors. However, the same might be the case for autocratic creditors. For this reason, we do not expect similarity in regime type to have a significant effect.

- UNGA affinity: measure of affinity in foreign policy preferences, derived from voting patterns in the United Nations General Assembly (Bailey, Strezhnev and Voeten 2015). We anticipate that shared ideological positions facilitate lending.

- Former colony: a dummy variable that equals one if i or j is a former colony of the other (Hensel 2014). Former colonial powers might give preference to former colonies when making lending decisions, either to protect their interests there directly or as a form of rehabilitation. Thus, we expect a positive effect of this variable on the likelihood of new loans.

- Distance: the log-transformed distance between i and j's capital cities, in kilometers (Weidmann, Kuse and Gleditsch 2010). Unlike security cooperation, financial cooperation can occur over great distances without additional transaction costs. In fact, because most rich creditor nations are comparatively removed from their debtors, we expect geographical distance to be negatively associated with new loans.

- Alliance: a dummy variable that equals one if i and j are both are members of a military alliance (Gibler 2009). We expect a positive relationship, as creditors are likely more inclined to provide loans to allies than non-allies.

2.3 Summary statistics

Table A provides the summary statistics for the variables in the DCA equation, and Table B provides the summary statistics for the variables in the loan equation.

Table A: Descriptive statistics for DCA network data

	N	Min.	Max.	Mean	Var.
Bilateral DCAs	275424	0.00	1.00	0.02	0.02
Arms match	262058	0.00	1.00	0.74	0.19
Common enemy	262058	0.00	12.00	0.06	0.17
Affinity	243786	-1.00	1.00	0.68	0.08
Trade (ln)	216003	0.00	13.26	2.25	6.36
NATO members	262058	0.00	1.00	0.01	0.01
NATO-PfP members	262058	0.00	1.00	0.03	0.03
Non-NATO alliance	262058	0.00	1.00	0.05	0.05
Distance (ln)	262058	2.25	9.90	8.69	0.60
Colony	262058	0.00	1.00	0.01	0.01
Polity	253710	0.00	20.00	11.08	47.28
GDP/cap (ln)	257753	4.19	11.63	7.94	2.63
CINC (ln)	265009	-23.85	-13.49	-18.60	3.44
Terror attacks	265009	0.00	57.00	0.46	5.39

2.4 Endogenous network influences

In addition to the control variables and the cross-network influences, each equation further includes a series of "intra-network" terms. These terms capture effects that are strictly limited to endogenous influence *within* the respective loan and DCA networks. For example, Kinne (2018) finds that if a given i and j both have DCA ties to common k third parties, they are more likely to sign a direct ij DCA. At the same time, governments prefer to sign DCAs with partners that are more central in the DCA network, ceteris paribus. These *transitivity* and *preferential attachment* effects are enormously influential in the global proliferation of DCAs and must be accounted for in order to avoid omitted variable bias. Further, as we argue in the main paper, these effects reflect the macro-level, network interests of governments; their parameter estimates thus help clarify the underlying

Table B: Descriptive statistics for loan network data

	N	Min.	Max.	Mean	Var.
Bilateral loans	550848	0.00	1.00	0.02	0.02
Distance	524116	2.25	9.90	8.69	0.60
Affinity	487572	-1.00	1.00	0.68	0.08
Colony	524116	0.00	1.00	0.01	0.01
Alliance	524116	0.00	1.00	0.06	0.06
Imports (ln)	436126	0.00	26.60	10.28	58.66
Exports (ln)	436126	0.00	26.60	9.92	60.33
Credit rating	369684	1.00	21.00	11.90	26.08
Polity	504974	0.00	20.00	12.79	45.62
Corruption	373596	-2.06	2.59	-0.12	1.04
GDP/cap (ln)	507256	4.19	11.63	7.68	2.68
Oil reserves (ln)	529098	0.00	9.35	2.72	8.42
Exposure (ln)	522578	0.00	16.20	7.36	12.26
Debt crisis	529098	0.00	1.00	0.08	0.07
Banking crisis	529098	0.00	1.00	0.30	0.21
Currency crisis	529098	0.00	1.00	0.35	0.23
Current account (% GDP)	501877	-242.19	60.27	-2.51	129.16
Borrower multi. propensity	492097	0.40	0.80	0.55	0.01
Borrower priv. propensity	512635	0.47	0.80	0.63	0.01
Lender multi. propensity	520133	0.29	0.80	0.62	0.01

logic of our hypotheses. The significantly positive estimate for *Transitivity* in the DCA equation (Figure 5 in the main paper) confirms that, as hypothesized, triadic closure is an important local process in the generation of the DCA network's topology. The significantly positive estimate for the *Degree (j)* term in the model reflects a simultaneous tendency toward preferential attachment, which indicates that, although governments pursue closure in their defense relations, they also favor ties to partners that sign large numbers of DCAs. Possibly, these two effects interact in interesting ways, such that, for example, in forming groups of like-minded collaborators, states focus on high-profile defense partners. We leave this intriguing possibility for future exploration. Finally, the DCA equation also includes an *Isolate* term, which controls for the relative sparsity of the DCA network.

Bunte and Kinne (2017) find that triadic closure and preferential attachment also matter in the loan network, but in a fundamentally different way than in the DCA network. The significantly negative *Transitivity* estimate in the loan equation in Figure 5 reveals that governments are averse to triadic closure in loans. Creditors tend not to make loans to the debtors of their own debtors. Indeed, governments that act as both debtors and creditors are empirically uncommon in the first place. This is understandable: Upon observing that its debtor j is itself a creditor to a third party k, the initial creditor j may cut off i from future loan supply it clearly has sufficient resources itself. Anticipating this, debtor j will not lend resources itself. At the same time, the significantly positive estimates for *Outdegree* and *Indegree* suggest a tendency to form ties with highly central nodes. Combined with the aversion to transitivity, these estimates indicate that the formation of hierarchically oriented ties, with little cooperation between or among loan partners, is an important local process in generating the loan network's topology. These empirical phenomena fit well with our argument that creditors' network strategy in the loan network intends to impose authority over its debtors.

3 Main Results and Goodness of Fit

Here, we present the estimates from the main paper in the more traditional tabular format, and we provide a series of goodness-of-fit diagnostics, focusing in particular on out-of-sample prediction.

3.1 Main results and convergence diagnostics

The main paper presents the results of the coevolution model as a forest plot, with estimates rescaled and standard errors standardized for ease of plotting. Table C provides those same estimates in their original tabular form, along with convergence diagnostics for each estimate. The "t-ratios" used to assess convergence are based on the deviations between simulated network statistics and the observed values of those statistics (i.e., in the real-world network). The general guideline, as recommended by Ripley, Snijders and Preciado (2012), is that, for individual estimates, t-ratios below 0.1 indicate excellent convergence. For the model as a whole, t-ratios below 0.25 indicate excellent convergence. As Table C illustrates, the t-ratios for each individual estimate, as well as for the model as a whole, exceed this standard.

3.2 Model fit

As noted in the main paper, we assessed the SAOM's goodness of fit using pairwise out-of-sample prediction (Kinne 2013). Specifically, we calibrated the model using a training set for the period 1990–2009, and we validated the model on data for 2010. We compare the coevolutionary SAOM to two other specifications: (1) two separate logit regression models, one for DCAs and one for loans, each with an AR1 autocorrelation term to account for temporal dependence; and (2) two separately estimated SAOMs, which model network evolution in isolation and ignore *co*evolution between the two networks. By considering logit regression, we wish to compare the SAOM to the most widely used alternative model. By considering the separately estimated SAOMs, we wish to determine the "value added" of the coevolutionary model—i.e., where the two networks do not evolve independently, but in concert with one another.

Figure A illustrates the results using a series of receiver operating characteristic (ROC) and precision-recall (PR) curves. The left panel focuses on defense agreements as the dependent variable, and the right panel focuses on loans. ROC curves compare the true positive rate (TPR) of a model's predictions to the false positive rate (FPR) for successively larger prediction thresholds. An area under the curve (AUC) closer to one—as reflected by a curve that pushes toward the top-left corner of the graph—indicates better performance. For DCAs, for example, the area under the combined SAOM's curve is 0.967, which is much higher than the area under the logit model's ROC curve (0.851). That is, the logit model's out-of-sample predictions yield fewer true positives and more false positives. For the separately estimated DCA SAOM, the AUC of the ROC curve, at 0.934, also shows a worse fit than the combined SAOM.

That said, ROC curves may be inappropriate for sparse networks or rare-events data, as a high AUC may simply reflect the relative ease of predicting zero values. We thus also fit PR curves, which compare positive predictive value (PPV) or "precision" to the TPR. The PPV is defined

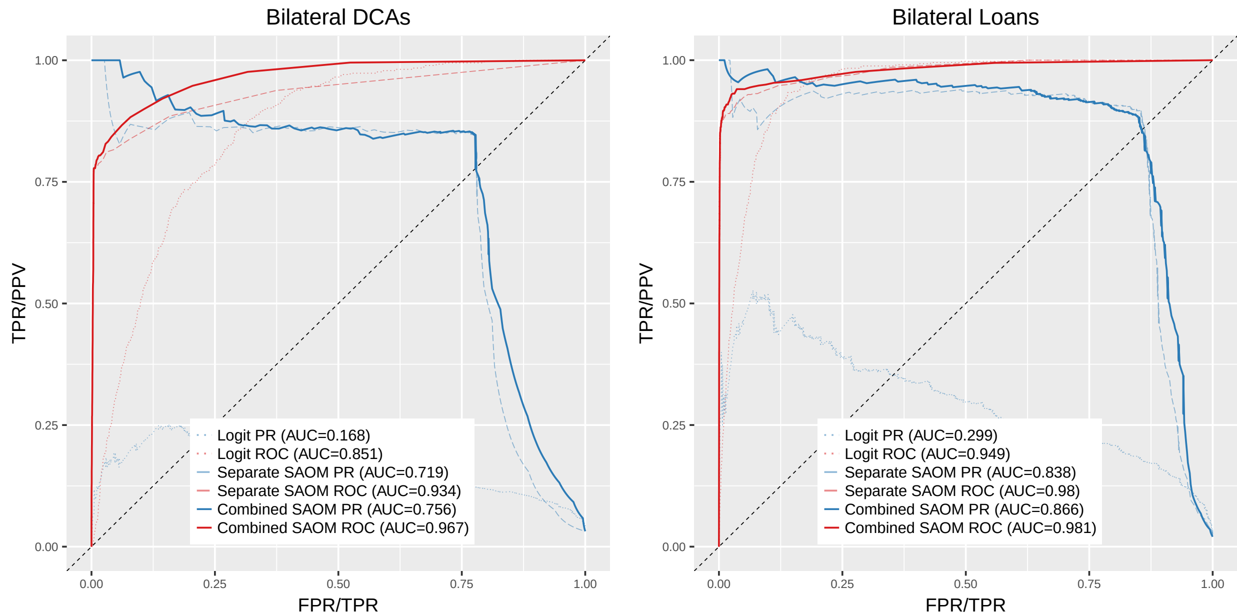
Table C: Main Results

	$\hat{\beta}$	s.e.	Convergence
DCA Equation			
Density	-1.803	(0.042)	0.007
Transitivity	0.114	(0.027)	0.020
Degree$_j$	0.042	(0.003)	0.026
Isolate	3.797	(0.210)	0.019
Colony	0.297	(0.077)	0.022
Distance (ln)	-0.369	(0.020)	-0.009
Alliance (non-NATO)	0.094	(0.058)	-0.006
Affinity	0.210	(0.062)	0.021
NATO members	-0.881	(0.093)	-0.005
NATO-PfP members	0.002	(0.053)	0.018
Bilateral trade (ln)	0.027	(0.010)	0.024
Common enemy	-0.055	(0.023)	0.018
Arms trade match	0.047	(0.034)	-0.055
Polity	0.021	(0.004)	-0.026
Pol × Pol	0.001	(0.000)	-0.001
GDP/capita	0.014	(0.021)	0.011
GDP × GDP	0.004	(0.007)	0.014
CINC	0.293	(0.027)	0.024
CINC × CINC	-0.021	(0.006)	-0.011
Terrorism	-0.006	(0.007)	0.021
Terrorism × Terrorism	-0.003	(0.004)	0.002
Loan bilateral	0.290	(0.099)	-0.028
Loan outdegree	0.002	(0.016)	-0.002
Loan similarity	0.323	(0.143)	0.018
Loan Equation			
Density	-7.932	(0.121)	0.015
Reciprocity	0.000	(fixed)	–
Transitivity	-0.178	(0.025)	-0.006
Indegree$_j$	0.725	(0.034)	0.011
Outdegree$_j$	0.477	(0.013)	0.015
Distance (ln)	-0.534	(0.031)	-0.001
Colony	0.529	(0.142)	-0.001
Affinity	0.525	(0.136)	0.016
Alliance	0.279	(0.086)	-0.001
Imports (ln)	0.066	(0.007)	-0.012
Exports (ln)	0.016	(0.006)	-0.012
Credit rating$_j$	-0.035	(0.010)	0.005
Polity similarity	0.127	(0.088)	-0.008
GDP$_j$ (ln)	-0.147	(0.037)	-0.017
GDP$_i$ (ln)	0.575	(0.037)	0.003
Oil reserves$_j$	0.059	(0.010)	-0.007
Exposure$_j$	-0.100	(0.012)	-0.012
Debt crisis$_j$	0.259	(0.074)	0.002
Banking crisis$_j$	-0.251	(0.050)	-0.015
Currency crisis$_j$	-0.058	(0.049)	-0.008
Current account$_j$	-0.011	(0.002)	-0.022
Current account$_i$	0.019	(0.005)	-0.030
Multilateral propensity$_j$	-3.144	(0.726)	0.002
Private propensity$_j$	1.995	(0.442)	-0.009
Multilateral propensity$_i$	3.072	(0.389)	0.007
DCA bilateral	0.570	(0.117)	-0.023
DCA degree$_j$	-0.169	(0.022)	-0.015
DCA closure	0.195	(0.025)	-0.010

Overall maximum convergence = 0.1974

$N = 164$; iterations $\beta = 9475$; iterations s.e. = 3000

Figure A: Goodness of Fit, SAOM vs Logistic Regression



Note: An area under the curve (AUC) closer to one indicates better fit. Logit fits derived from two separate models of DCAs and loans, respectively, with AR1 term. Separate SAOM fits derived from separately estimated single-equation DCA and loan models. Combined SAOM fits derived from multi-equation coevolutionary model. All methods use 2010 as the out-of-sample validation set, with 1990–2009 as the training set.

simply as $\frac{\text{true positives}}{\text{true positives+false positives}}$, or the ratio of the model's correctly predicted positive values to the model's total predicted positive values. A high PPV indicates that the model classifies outcomes with high precision, which is especially beneficial for sparse networks, where positive outcomes are difficult to predict. As the left panel of Figure A illustrates, the combined DCA SAOM sharply improves the precision of out-of-sample predictions. The logit model yields a PR AUC of only 0.168, which indicates extremely poor performance; the vast majority of the logit model's positive predictions are in fact false positives. In contrast, the SAOM increases the area under the PR curve to 0.756, which is also an improvement over the separately estimated DCA SAOM (PR AUC = 0.719).

The right panel of Figure A illustrates the goodness-of-fit for loans. As with DCAs, the separately estimated loan SAOM sharply improves over the performance of the logit model, and the combined SAOM further improves fit over both the logit and the separate SAOM.

4 Robustness Checks and Sensitivity Analysis

We employ a battery of robustness checks and sensitivity analyses to ensure that the results shown in the main paper are not artifacts of model specification. We estimate models with only network effects and no control variables. We vary the size of the five-year moving window. We stimate models that distinguish between creation and termination of network ties. And we estimate models that differentiate between "cheap" and "expensive" loans.

4.1 Estimation without control variables

In the main paper, each of the DCA and loan equations contains large numbers of control variables, consistent with the emerging literatures on DCAs and loans (Bunte and Kinne 2017; Kinne 2018). However, network effects may be correlated with these influences. For example, monadic characteristics like power, regime type, and wealth often covary with nodal degree. In some cases, network effects and individual attributes may coevolve (Kinne 2016; Warren 2016). An exhaustive exploration of these possibilities is far beyond the scope of this paper. Nonetheless, we wish to at least consider the robustness of the results to a stripped-down model, devoid of covariates (Achen 2002). We thus estimated the same model as in the main paper, but with all exogenous covariates excluded. That is, we include only intra-network and cross-network effects. Figure D illustrates the results.

Table D: Model with all exogenous covariates excluded

	$\hat{\beta}$	s.e.	Convergence
DCA Equation			
Density	-1.543	(0.035)	-0.009
Transitivity	0.246	(0.029)	-0.008
Degree$_j$	0.058	(0.002)	-0.011
Isolate	4.422	(0.186)	-0.004
Loan bilateral	0.412	(0.094)	-0.015
Loan outdegree	0.094	(0.011)	-0.006
Loan similarity	0.622	(0.118)	-0.009
Loan Equation			
Density	-7.230	(0.115)	-0.021
Reciprocity	0.000	(fixed)	–
Transitivity	-0.245	(0.022)	-0.019
Indegree$_j$	0.748	(0.030)	-0.024
Outdegree$_j$	0.537	(0.013)	0.002
DCA bilateral	1.189	(0.123)	0.000
DCA degree$_j$	-0.112	(0.020)	-0.017
DCA closure	0.231	(0.023)	-0.009

Overall maximum convergence = 0.1303.
Iterations β = 6529. Iterations s.e. = 3000.

The results are generally consistent with those in the main paper, with one exception. The effect of *Loan outdegree* on bilateral DCA ties, which we hypothesized to be negative but which turned out to be statistically indistinguishable from zero, is *significantly positive* here, indicating that governments prefer to sign DCAs with governments that are highly active in the loan network. Closer examination reveals that this effect is due to the high correlation between *Loan outdegree* and such nodal attributes as wealth and military power. Ceteris paribus, governments prefer to sign DCAs with countries that are wealthy and powerful, as these countries offer the easiest path to military modernization. Once we control for Correlates of War CINC scores and per-capita gross domestic product, as in the main paper, the puzzlingly positive estimate for *Loan outdegree* becomes indistinguishable from zero. Overall, then, the estimates are robust to the exclusion of covariates.

4.2 Sensitivity of five-year window

In the main paper, we define both the DCA and loan networks in terms of five-year moving windows; that is, ties are presumed to exist for five years upon creation. The practical motivation for this specification is that (1) loans do not necessarily have an easily quantifiable duration, given that they are subject to cancellations and rescheduling, and (2) the duration of many DCAs is not precisely known, as we do not possess full treaty texts for all DCAs. In practice, of DCAs where duration is known, over 90% last at least five years; the five-year window is thus conservative (and potentially underestimates DCAs that remain influential beyond the five-year mark). Further, the mean grace period, before a loan enters repayment, is five years. The substantive motivation for the five-year window is that, even when ties endure beyond the five-year mark, we anticipate that they exert their strongest impact shortly after their creation, when the attention of policymakers, analysts, journalists, and the international community remains piqued.

Of course, we must assess the robustness of the five-year specification. We thus estimated two additional models. In the first, we used a three-year window, where ties endure in the loan and DCA networks for three years upon creation. In the second, we used a seven-year window. As the estimates in Tables E and F show, the results are generally robust to these alternate specifications.

4.3 Effect of cross-network influences on tie creation

A potential complication with the SAOM is that, in estimating parameters, the estimation algorithm considers both the creation and termination of ties. Thus, a tie that is not terminated (i.e., is maintained) may be just as informative as a newly created tie. This feature of the model carries two potential complications. First, because we use a five-year "moving window" when specifying ties in the loan and DCA networks, the termination of ties is exogenously imposed. We have strong theoretical reasons for using the five-year range, and we showed above that the model's results are robust to alternative time spans. Nonetheless, because the model treats tie termination as informative, the five-year approach risks biased parameter estimates. A second, more nuanced complication is that because the SAOM treats maintained ties as being as equally informative as newly created ties, the parameter estimates may simply reflect the mutual presence of ties in both networks; that is, they do not necessarily reflect the probability of transition, where, for example, having a DCA in place increases the probability of a transition in the loan network, from no tie to a loan tie.[8]

Vijayaraghavan, Noél, Maoz and D'Souza (2015) develop a Markov-chain model that specifically estimates the probability of transition, and which promises exciting new causal insights on the question of multiplex dynamic spillover. Nonetheless, in its present formulations, this model poses a number of nontrivial challenges. For example, it is purely "bivariate" and does not allow for control variables, which creates an unavoidable risk of omitted variable bias. It is also strictly bilateral in the sense that it only assesses the probability of a bilateral tie in one network influencing the

[8] We thank an anonymous reviewer for emphasizing the importance of this feature of the SAOM.

Table E: Three-year moving window

	$\hat{\beta}$	s.e.	Convergence
DCA Equation			
Density	-1.916	(0.039)	0.023
Transitivity	0.081	(0.023)	0.049
Degree$_j$	0.053	(0.005)	0.015
Isolate	3.566	(0.202)	0.030
Colony	0.250	(0.070)	0.042
Distance (ln)	-0.318	(0.018)	-0.052
Alliance (non-NATO)	0.107	(0.052)	0.018
Affinity	0.182	(0.053)	0.011
NATO members	-0.633	(0.079)	0.047
NATO-PfP members	-0.012	(0.048)	0.004
Bilateral trade (ln)	0.030	(0.009)	0.029
Common enemy	-0.036	(0.020)	0.073
Arms trade match	0.059	(0.030)	-0.010
Polity	0.014	(0.003)	0.092
Pol × Pol	0.001	(0.000)	0.028
GDP	0.081	(0.026)	0.037
GDP × GDP	-0.006	(0.012)	0.006
CINC	0.279	(0.025)	0.009
CINC × CINC	-0.020	(0.006)	0.025
Terrorism	-0.002	(0.006)	0.031
Terrorism × Terrorism	-0.000	(0.003)	-0.020
Loan bilateral	0.357	(0.103)	0.060
Loan outdegree	-0.037	(0.017)	-0.007
Loan similarity	0.299	(0.137)	-0.011
Loan Equation			
Density	-7.765	(0.100)	-0.013
Reciprocity	0.000	(fixed)	–
Transitivity	-0.383	(0.041)	-0.052
Indegree$_j$	0.855	(0.031)	-0.031
Outdegree$_j$	0.308	(0.014)	-0.010
Distance (ln)	-0.528	(0.024)	-0.008
Colony	0.291	(0.056)	0.020
Affinity	0.642	(0.106)	0.001
Alliance	0.157	(0.071)	0.012
Imports (ln)	0.035	(0.006)	-0.017
Exports (ln)	0.003	(0.005)	0.006
Credit rating$_j$	0.003	(0.008)	0.014
Polity similarity	0.007	(0.077)	-0.013
GDP$_j$ (ln)	-0.130	(0.033)	-0.059
GDP$_i$ (ln)	0.588	(0.034)	-0.000
Oil reserves$_j$	0.043	(0.009)	-0.036
Exposure$_j$	-0.089	(0.012)	-0.039
Debt crisis$_j$	0.231	(0.062)	0.018
Banking crisis$_j$	-0.059	(0.042)	0.053
Currency crisis$_j$	0.029	(0.043)	-0.055
Current account$_j$	-0.011	(0.002)	-0.031
Current account$_i$	0.035	(0.005)	0.004
Multilateral propensity$_j$	-5.769	(0.540)	0.007
Private propensity$_j$	1.418	(0.387)	0.043
Multilateral propensity$_i$	1.066	(0.228)	0.006
DCA bilateral	0.533	(0.115)	-0.004
DCA degree$_j$	-0.186	(0.022)	-0.059
DCA closure	0.079	(0.033)	-0.054

Overall maximum convergence = 0.1921.
Iterations $\beta = 9724$. Iterations s.e. = 3000.

Table F: Seven-year moving window

	$\hat{\beta}$	s.e.	Convergence
DCA Equation			
Density	-1.748	(0.044)	0.011
Transitivity	0.190	(0.033)	-0.007
Degree$_j$	0.033	(0.003)	-0.009
Isolate	3.841	(0.245)	0.011
Colony	0.353	(0.080)	0.042
Distance (ln)	-0.415	(0.022)	-0.038
Alliance (non-NATO)	0.095	(0.066)	-0.061
Affinity	0.309	(0.068)	-0.010
NATO members	-1.154	(0.097)	0.001
NATO-PfP members	0.044	(0.058)	-0.005
Bilateral trade (ln)	0.011	(0.010)	-0.005
Common enemy	-0.073	(0.027)	-0.016
Arms trade match	0.073	(0.036)	0.007
Polity	0.027	(0.004)	-0.008
Pol $\times$ Pol	0.001	(0.000)	0.017
GDP	0.079	(0.029)	-0.008
GDP $\times$ GDP	-0.011	(0.014)	0.003
CINC	0.339	(0.029)	-0.002
CINC $\times$ CINC	-0.025	(0.007)	-0.010
Terrorism	-0.003	(0.007)	0.005
Terrorism $\times$ Terrorism	-0.002	(0.003)	-0.001
Loan bilateral	0.324	(0.096)	0.008
Loan outdegree	0.000	(0.017)	-0.038
Loan similarity	0.345	(0.149)	0.043
Loan Equation			
Density	-7.897	(0.130)	0.046
Reciprocity	0.000	(fixed)	–
Transitivity	-0.187	(0.020)	0.034
Indegree$_j$	0.771	(0.035)	0.050
Outdegree$_j$	0.318	(0.017)	0.020
Distance (ln)	-0.603	(0.030)	-0.003
Colony	0.346	(0.071)	0.009
Affinity	0.682	(0.145)	-0.044
Alliance	0.280	(0.087)	0.021
Imports (ln)	0.029	(0.007)	0.025
Exports (ln)	0.008	(0.007)	-0.010
Credit rating$_j$	-0.015	(0.010)	-0.004
Polity similarity	0.022	(0.094)	0.046
GDP$_j$ (ln)	-0.102	(0.040)	-0.013
GDP$_i$ (ln)	0.522	(0.041)	0.005
Oil reserves$_j$	0.077	(0.012)	-0.065
Exposure$_j$	-0.159	(0.015)	-0.061
Debt crisis$_j$	0.337	(0.079)	-0.022
Banking crisis$_j$	-0.203	(0.055)	-0.015
Currency crisis$_j$	0.005	(0.051)	0.002
Current account$_j$	-0.013	(0.002)	-0.025
Current account$_i$	0.042	(0.005)	0.014
Multilateral propensity$_j$	-5.693	(0.623)	-0.056
Private propensity$_j$	2.129	(0.457)	-0.030
Multilateral propensity$_i$	2.378	(0.364)	-0.046
DCA bilateral	0.213	(0.115)	0.040
DCA degree$_j$	-0.121	(0.023)	-0.068
DCA closure	0.073	(0.022)	0.032

Overall maximum convergence = 0.1799.
Iterations $\beta = 9397$. Iterations s.e. = 3000.

corresponding bilateral tie in the other network; it cannot accommodate the higher-order cross-network features that comprise the bulk of our theory. For these reasons, we do not consider the approach of Vijayaraghavan et al. (2015) to be applicable to our current questions and hypotheses.

We instead estimate an alternative SAOM, where we separate out the impact of DCAs and loans on the *creation* of new ties in the opposing network. In this case, the parameter estimates tell us not merely whether bilateral DCAs are correlated with bilateral loans, but whether the presence of a tie in the DCA network increases the probability of a *newly created tie* in the loan network (and vice versa). This approach addresses the first problem discussed above by excising any influence on parameter estimates from termination of ties. And it addresses the second problem because the creation of new ties directly reflects transition, where dyads that previously lacked ties now have them.[9]

Because this specification increases the risk of non-convergene, we estimate a creation effect for each of our six variables of interest separately, i.e., in six separate models. Table G collects and summarizes the results across the six models.[10] The results are generally consistent with the results from the main paper. The hypothesized network effects increase the probability of *newly created ties* in the opposing network; i.e., they encourage a state transition. The one exception is the effect of bilateral DCAs on bilateral loans. In the main paper, we found that bilateral DCAs increase the probability of bilateral loans. Here, we find an insignificant estimate for this effect. Substantively, the difference between these two estimates means that DCAs do not necessarily increase the probability that a loan will be created de novo, but they do increase the probability that a loan will be maintained. The remaining higher-order cross-network influences of DCAs remain hugely influential. Ceteris paribus, new loans are less likely to be created with countries that sign many DCAs, and new loans are *more likely* to be created in unison with one's defense partners. Regarding the influence of the loan network on creation of DCAs, we find that bilateral loans and similarity in borrowing profiles greatly increase the probability of a new DCA, while the loan centrality of the partner, as in the main paper, has no significant effect.

Table G: Effect of cross-network influences on tie creation

	β	s.e.	Convergence
DCA Equation			
Loan bilateral (tie creation effect)	1.288	(0.116)	-0.030
Loan outdegree$_j$ (tie creation effect)	0.019	(0.015)	0.023
Loan similarity (tie creation effect)	6.275	(0.263)	0.091
Loan Equation			
DCA bilateral (tie creation effect)	-0.132	(0.165)	-0.024
DCA degree$_j$(tie creation effect)	-0.175	(0.028)	-0.044
DCA closure (tie creation effect)	0.364	(0.043)	-0.094

Estimates from six separately estimated models. Estimates for exogenous covariates suppressed. All models maximum convergence < 0.25. All models iterations s.e. = 3000.

[9] See Kinne (2013) for a similar implementation.

[10] Each of the six models includes a full array of endogenous network effects, cross-network effects, and exogenous covariates. For ease of presentation, estimates for these effects are not shown. They are nearly identical to those from the main model.

4.4 Cheap loans versus expensive loans

Our argument suggests that governments coordinate their foreign economic and security policies. For instance, with H1 we argue that creditors may provide loans as side payments and/or bargaining chips in the context of issue linkage in order to convince the debtor to sign a DCA. We find strong evidence in support of this hypothesis. However, our models so far have assumed that all loans, irrespective of their characteristics, have similar effects on the likelihood of security cooperation. Yet, this may not be the case, as governments provide different types of loans. Most commonly noted is the distinction between loans provided in the context of international assistance and those related to trade promotion. The former are typically extremely cheap, with concessional interest rates below 2%. In contrast, the latter often carry significantly higher, non-concessional interest rates. Considering these differences in the price of borrowing, it is possible that debtors accept only inexpensive loans as side payments in the context of negotiating a DCA. In other words, expensive loans may not purchase any "political goodwill," and, consequently, our argument may not apply to expensive loans.

We investigate this possibility by re-operationalizing the loan network to include only expensive loans (i.e., those with an interest rate higher than 2%). If expensive loans indeed undermine the strategic intentions of creditors, we should find that they do not increase the likelihood of DCAs. In contrast, we would expect loans to increase the probability of signing a DCA if expensive loans still provide debtors with economic benefits. For example, non-concessional loans often fund large infrastructure projects in the recipient country. If the debtor uses parts and services from companies located in the creditor country, this loan promotes trade. At the same time, the return on investment of this project—a hydroelectric power dam providing the country with much needed electricity, for example—may be significantly higher than the interest rate on the loan. Thus, despite non-concessional interest rates, such loans can provide value to recipients.

Table H illustrates the findings. The results show that, as anticipated by our theory, even expensive loans increase the likelihood of signing a DCA.

Table H: Loan network restricted to expensive loans

	β	s.e.	Convergence
DCA Equation			
Density	-1.784	(0.043)	-0.002
Transitivity	0.116	(0.026)	-0.013
Degree$_j$	0.041	(0.003)	-0.029
Isolate	3.773	(0.206)	-0.021
Colony	0.300	(0.078)	0.027
Distance (ln)	-0.371	(0.020)	0.010
Alliance (non-NATO)	0.115	(0.059)	0.036
Affinity	0.240	(0.061)	-0.013
NATO members	-0.886	(0.093)	-0.017
NATO-PfP members	-0.008	(0.053)	-0.021
Bilateral trade (ln)	0.023	(0.010)	0.012
Common enemy	-0.057	(0.023)	0.021
Arms trade match	0.052	(0.033)	0.025
Polity	0.021	(0.004)	0.012
Pol $\times$ Pol	0.001	(0.000)	-0.020
GDP	0.055	(0.027)	0.006
GDP $\times$ GDP	-0.013	(0.013)	0.033
CINC	0.294	(0.029)	-0.032
CINC $\times$ CINC	-0.022	(0.006)	0.016
Terrorism	-0.006	(0.007)	-0.022
Terrorism $\times$ Terrorism	-0.003	(0.004)	0.022
Loan bilateral	0.268	(0.109)	0.007
Loan outdegree	0.007	(0.018)	0.005
Loan similarity	0.304	(0.149)	0.028
Loan Equation			
Density	-8.464	(0.140)	-0.028
Reciprocity	0.000	(fixed)	–
Transitivity	-0.843	(0.117)	0.003
Indegree$_j$	0.980	(0.042)	-0.044
Outdegree$_j$	0.397	(0.023)	-0.011
Distance (ln)	-0.586	(0.032)	-0.040
Colony	0.271	(0.078)	0.030
Affinity	1.031	(0.155)	-0.009
Alliance	0.241	(0.094)	0.005
Imports (ln)	0.026	(0.008)	-0.032
Exports (ln)	0.004	(0.007)	-0.013
Credit rating$_j$	0.008	(0.011)	0.009
Polity similarity	-0.001	(0.100)	-0.077
GDP$_j$ (ln)	-0.177	(0.043)	0.020
GDP$_i$ (ln)	0.609	(0.045)	0.002
Oil reserves$_j$	0.059	(0.013)	0.008
Exposure$_j$	-0.150	(0.016)	-0.026
Debt crisis$_j$	0.264	(0.082)	0.023
Banking crisis$_j$	-0.027	(0.058)	-0.050
Currency crisis$_j$	-0.075	(0.056)	-0.002
Current account$_j$	-0.013	(0.002)	0.014
Current account$_i$	0.038	(0.006)	0.035
Multilateral propensity$_j$	-5.042	(0.721)	0.002
Private propensity$_j$	1.215	(0.514)	0.021
Multilateral propensity$_i$	2.052	(0.348)	0.034
DCA bilateral	0.306	(0.134)	-0.056
DCA degree$_j$	-0.168	(0.026)	0.002
DCA closure	0.093	(0.034)	-0.078

Overall maximum convergence = 0.2103.
Iterations $\beta = 9754$. Iterations s.e. = 3000.

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