Wedded to Prosperity? Informal Influence and Regional Favoritism

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Abstract

This paper explores the informal influence of political leaders' spouses on the subnational allocation and effectiveness of development aid. We investigate whether regions containing the birthplaces of political leaders' spouses receive significantly more aid during their partners' tenure and whether this aid is less effective compared to other times. To examine these patterns, we construct two new global datasets: one tracking the personal characteristics of political leaders and their spouses, and another geocoding aid projects, including new data on aid from the United States and 18 European donors. Our analysis of the 1990–2020 period reveals that regions with the birthplaces of political leaders' spouses receive significantly more aid from Western bilateral donors, while political favoritism through Chinese aid shifts from the birth regions of spouses to those of the leaders themselves. We find that aid to the birth regions of spouses increases particularly before elections and is less effective there compared to aid given to the same regions at other times.

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1 Introduction

In 1979, when asked about the wealth accumulation among her family's acquaintances and allies during her husband's presidency, Imelda Marcos, wife of then-Philippine President Ferdinand Marcos, responded: "Well, some are smarter than others" (Branigin 1984). One notable beneficiary from his association with the president's wife is Herminio Disini, who at the time was married to one of Imelda Marcos's cousins. Disini obtained a virtual monopoly for his cigarette-filter business by taking advantage of a presidential decree that raised import tariffs for his foreign competitors to 100 percent (Branigin 1984). Imelda Marcos held no elected office—yet, it seems she was able to exercise substantial influence over the allocation of resources.

Anecdotal evidence abounds that illustrates the informal influence wielded by powerful politicians' unelected spouses, often shaping resource allocation outside formal institutional channels.¹ Despite such examples, there is no evidence as to whether and to what degree this influence systematically benefits individuals, companies, or even entire subnational regions associated with powerful spouses. This paper addresses this gap, analyzing the spouses of political leaders of a maximum of 123 countries over the 1990–2020 period. We focus on spousal birth regions to capture areas where we expect spouses to take particular interest in. Specifically, we test whether subnational regions where the spouse of a leader was born attract more foreign aid compared to how much aid that same region receives at other times and how a region develops once it receives the aid.

The importance of unelected spouses for policy outcomes and the lack of solid evidence on it has long been recognized. After he left the White House, U.S. President Harry S. Truman expressed the hope that "someday someone will take the time to evaluate the true role of the wife of a President" (Gonnella-Platts and Fritz 2017, 5). As Dahl (1961) points out, indirect influence of leaders' spouses is even more difficult to measure than those of elected officials. To ignore such indirect influence, however, is to exclude "what may well prove to be a highly significant" factor in answering who governs (Dahl 1961, cited in O'Connor et al. 1996, 836). According to O'Connor et al. (1996, 849), "[t]he

¹Informal influence can be used to change the allocation of resources, for example via (successful) "attempts to affect public policy, executive decision-making, or the course of a political career" (O'Connor et al. 1996, 837). One example of a first lady with well-documented informal influence is Hinda Déby of Chad, who "is also in the management of Chad's oil industry and has gained from lucrative contracts, acted as a mediator between private companies and foreign investors, and appointed relatives and members of her inner circle to strategic positions. Ahmat Khazali Acyl, for example, is Hinda Déby's elder brother and managing director of Société des Hydrocarbures du Tchad (SHT), the national oil company. Mahamat Kasser Younous, a member of her inner circle, was also a managing director in SHT, while Ibrahim Hissein Bourma, a brother-in-law, is SHT's marketing director" (Van Wyk et al. 2018, 5). A less consequential example is the wife of the Democratic Party's nominee for the 2022 South Korean presidential election, who had to apologize for using her husband's aides to run errands (see https://www.thetimes.co.uk/article/ leaders-wives-dragged-into-koreas-election-of-unlikeables-w0hw8vcsh, last accessed July 14, 2023).

failure of political scientists and historians to consider the political role of first ladies neglects the role of a key player in the president's inner circle"—a failure that we argue extends to economists as well.

Spouses can exercise political influence via a number of channels. They are important advisors to their partners. U.S. President Truman, for example, consulted his wife on whether or not to use the atomic bomb, fight in Korea, or on the European Recovery Program after World War II (O'Connor et al. 1996). Observers often attribute more power to spouses than to elected vice presidents.² They derive status from their marriage, have influence over their partner, and often control access to them (Van Wyk et al. 2018). This might make it difficult to turn down requests.³ Often, spouses develop their own political agendas and patronage networks, allowing them to deliver spoils in exchange for support.⁴ It thus seems that spouses of country leaders have the means to favor their birth regions.⁵

We expect spouses of country leaders will leverage their influence to channel resources to their home regions for a number of reasons. First, spouses could cultivate political support for their partners, especially during election periods.⁶ To maximize voter turnout in their strongholds, political leaders strategically allocate resources to these areas (Dreher et al. 2019). To the extent that regional populations affiliated with the leader's spouse extend their support to the leader, we expect the same to hold true for spouses' birth regions. Adida et al. (2016) argue that such support should be forthcoming because marriage is a credible signal of coalition building between (ethnic) regions. They identify instrumental as well as expressive reasons, highlighting how marriage serves as a signal regarding the likelihood of resource allocation to a particular region or as an end in itself. Their findings show that people who share the spouse's ethnicity express substantially

²As Hay (1988) points out, while the "vice president [is] a heart beat away (from the president) [...] the first lady can hear it" (cited in O'Connor et al. 1996, 846).

³As Uruguayan first lady Maria Julia Pou put it, "[y]ou are not a simple citizen and nobody looks at you as a simple citizen. [W]hen a first lady picks up the phone and calls somebody, it's Somebody" (cited in Gonnella-Platts and Fritz 2017, 30).

⁴As Van Wyk et al. (2018, 31) highlight, many first ladies in their study, including Hinda D'Éby, Grace Mugabe, and Janet Museveni, "have developed a public policy agenda independent of and/or parallel to that of their husbands' government." They argue that the role of first ladies as "social workers-in-chief" (Troy 2006, 142) is significant, as it provides them with unique access to resources, including networks of people and funding, often channeled through the NGOs they support.

⁵Anecdotes abound. Consider Uganda, where according to a local newspaper report first lady Janet Museveni thanked her husband in the name of the Ntungamo people during a 2020 campaign meeting: "thank you for granting Ntungamo a district status, they also commend you for the good roads of Ntungamo-Mirama hills, Kagamba-Ishaka and Ntungamo-Rukungiri that are all tarmacked." The report continues explaining that "Mrs Museveni added that the people of Ntungamo were also very happy for the pineapple factory, youth and women funds, education and health services among many development programs the NRM government has extended to them." Incidentally, Ntungamo District is Janet Museveni's birth region. See https://www.independent.co. ug/janet-thanks-museveni-for-building-roads-in-ntungamo/, last accessed July 13, 2023.

⁶Following Mrs. Museveni's praise for her husband cited in footnote 5, she assured him of solid support from the region's voters in the upcoming elections.

greater support for the leader. Second, spouses might use their role to prepare their own future political campaign (Gonnella-Platts and Fritz 2017). Well-known examples include Cristina Fernández de Kirchner (Argentina), Sonia Gandhi (India), and Hillary Clinton (United States).⁷ Again, to the extent that political support from birth regions is particularly strong, focusing resources there in order to maximize turnout at election time can be a winning strategy. Finally, just like leaders themselves, spouses might be economically privileging their home regions in anticipation of returning to these places after their partner's political career comes to an end or might be motivated by parochial altruism (Dreher et al. 2019).

Taken together, spouses have motive and opportunity. We thus investigate whether subnational regions receive more foreign aid and develop more rapidly at the time a person who originates from such regions is married to the country's political leader compared to how these regions perform at other times. Western donors exercise substantial effort to avoid the misappropriation of their funds for reasons of recipient country politics. For example, results from a conjoint experiment by Briggs (2021) reveal that World Bank Task Team Leaders perceive recipient governments as seeking to direct aid towards presidential hometowns, while simultaneously expressing resistance to such targeting. This finding helps explain why presidential birth regions do not receive more aid from the World Bank, while they do receive more aid from China, as documented by Dreher et al. (2019) and Dolan and McDade (2020).⁸ While Western donors of foreign aid seem more interested in preventing the use of their aid for within-country political purposes than China (Blair et al. 2022), it seems unlikely that they can entirely prevent such allocation (Bjørnskov 2010). To the extent they successfully prevent aid from being targeted to the leaders' birth regions, we expect part of the aid to go to the birth regions of their spouses instead.⁹ This substitution might occur because donors are less attuned to the informal influence of political leaders' spouses. Unlike leaders themselves, spouses do not typically hold formal office, and their influence on aid allocation may escape scrutiny. This reduced visibility could result in aid flowing to these regions, as donors may overlook such favoritism or deem it less politically sensitive. Additionally, informal influence may even be advantageous for donors, as it allows them to interfere with the politics of recipient countries without

⁷The list of examples is long. Spain's first lady Ana Botella later successfully campaigned for Mayor of Madrid (Gonnella-Platts and Fritz 2017). Other examples include Margarita Cedeño de Fernandez (Dominican Republic), Margarita Zavala de Calderon (Mexico), and Julia Pou (Uruguay) (Gonnella-Platts and Fritz 2017, 35). Likewise, Grace Mugabe (Zimbabwe) demonstrated a clear interest in higher office for herself (Van Wyk et al. 2018).

⁸Dreher et al. (2019) also report first evidence that Chinese aid in Africa flows more freely to regions affiliated with political leaders' spouses. In a broader context, Mueller (2024) highlights the importance of China's need to maintain domestic political stability as a key determinant of its global foreign aid allocation, rather than focusing solely on foreign policy or other objectives.

⁹Note that we do not claim that birth regions of leaders' spouses are the only or even most likely alternative to substitute for aid to leaders' birth regions. Such aid might target other places of direct interest to the leader or birth regions of other members of the governing elites (Francois et al. 2015).

attracting attention.

However, if political motives undermine the effectiveness of aid, rather than being put to better use, aid given to spouses' birth regions might be as ineffective as aid given for obvious, formal, political reasons, or even more so. This could be the case when donors carefully scrutinize their projects given to regions with obvious political connections, but apply less scrutiny when connections are harder to identify. Such lack of oversight could reduce aid effectiveness in regions tied to political leaders' spouses.

Our panel data allow us to test whether the home regions of leaders' spouses receive more aid during their partners' tenures compared to other periods. We use a binary variable equal to one when the region is the birth region of the spouse of the effective political leader. The data allow us to control for subnational region and country-year fixed effects. We are in particular interested in whether regions receive more aid in years the spouse of the country's leader was born in a region relative to the years just before. That way, we can disentangle changes in aid due to the influence of time-varying variables that affect aid and a region's political importance in tandem from the causal influence of a *Spouseregion*. This approach follows those of previous event studies in the aid allocation and effectiveness literature (Kuziemko and Werker 2006, Kaja and Werker 2010, Andersen et al. 2022) and enables us to interpret the difference in aid during these periods as causal. Overall, controlling for the birth regions of the leaders themselves, the focus on spouses allows us to test the effect of informal influence on resource allocation and investigate the contextual factors that facilitate such influence.

Our findings demonstrate that regions including the birthplaces of political leaders' spouses receive significantly more aid, particularly during election periods and when elections are more competitive. This increase in aid is driven by European donors and the United States, while World Bank aid does not exhibit similar patterns. Notably, while European donors also give more aid to the birth regions of political leaders themselves, the increase in aid to their spouses' regions is larger by an order of magnitude. By contrast, China provides less aid to spouses' regions but allocates more aid to leader regions compared to what these regions receive in the year before the leader comes from there. These results suggest that Western donors attempt to avoid channeling their aid to regions where political motives are overt, thereby leaving such regions to benefit from Chinese aid. However, rather than being free of political influence, Western aid is redirected to areas where favoritism is less visible but political interests remain equally significant. While prior research has characterized Western aid as less politically motivated than Chinese aid (Dreher et al. 2019), our findings challenge this view, highlighting that political considerations are simply obscured rather than absent.

This politicization of aid has important implications for its effectiveness. We find that aid given to a region during the tenure of a political leader whose spouse was born there is less effective in fostering economic development, as measured by nighttime light emissions, compared to aid given to these regions at other times. These results highlight the informal influence wielded by unelected spouses and its impact on the allocation of resources and developmental outcomes.

This paper contributes to three main literatures. The first investigates the influence of politicians' familial ties on political decision-making and outcomes. For example, studying voting behavior of U.S. congressmen, Washington (2008) finds that congressmen with daughters are substantially more likely to vote in line with feminist views. Similarly, McGuirk et al. (2023) show that congressmen with draft-age-sons are less likely to vote for conscription. Examining the more direct benefits of political connections for relatives, Gagliarducci and Manacorda (2020) demonstrate how family ties improve labor market outcomes in Italy. Fafchamps and Labonne (2017) show that in the Philippines, relatives of politicians are more likely to hold better paying jobs, while Cruz et al. (2017) find that politicians' relatives are politically more successful by themselves compared to people without political connections. We are however not aware of quantitative evidence on elected leaders' spouses on the allocation of resources or developmental outcomes. While this question has received some attention, previous work is qualitative and selective. Examples include studies by Gonnella-Platts and Fritz (2017) on the role of 12 first ladies from five continents, O'Connor et al. (1996) on 38 wives of U.S. Presidents, and Van Wyk et al. (2018) on wives of the 10 longest-serving African presidents. These works point to substantial influence of some of the first ladies they investigate but, due to their qualitative nature, remain necessarily selective in scope. We are thus the first to systematically evaluate the effects of politicians' unelected spouses on development aid and outcomes. We are also the first to investigate the effects of personal connections with leaders more broadly on regional outcomes.

The second strand of literature to which we contribute investigates the effect of political decision makers on the prosperity and development of favored regions. Thanks to the growing availability of data at the subnational level, scholars have assessed the extent to which country leaders favor their birth region (Mu and Zhang 2014, Burgess et al. 2015, Do et al. 2017) or ethnic region (Franck and Rainer 2012, De Luca et al. 2018). These studies have found substantial evidence of such regional preferential treatment. For instance, home regions experience higher economic growth (Hodler and Raschky 2014), receive more public goods (Kramon and Posner 2013, 2016, Burgess et al. 2015), benefit from larger government transfers, but suffer from biased taxation (Kasara 2007). Firms located in such regions receive easier access to credit and experience stronger growth in sales and employment after leaders from these regions assume office (Asatryan et al. 2022, Osei-Tutu and Weill 2024). Leader birth regions are also less likely to experience internal conflict (Kammerlander and Unfried 2022). A number of recent papers focus on foreign aid as one specific form of favoritism. They find that home regions of leading politicians receive a disproportionate amount of development aid (Briggs 2014, Dreher et al. 2019,

Bommer et al. 2022, Cruzatti et al. 2024). Contrary to this literature, we shift focus from formal political power to examine how unelected spouses leverage informal influence to redirect resources. What is more, due to data availability, the previous literature has either focused on one particular recipient country or on aid from China and the World Bank. We are the first to investigate the subnational allocation of Western bilateral donors, including the United States, across a large number of recipient countries.

Finally, and less directly, we also contribute to the literature on informal governance. This literature examines the influence of unwritten rules that modify or substitute formal provisions. Such informal influence can override or complement legal procedures, especially when important rules are unwritten (Stone 2011, 2013, Manulak 2017). This literature has focused primarily on international organizations and treaties. In this paper, we extend this analysis to a new context by investigating the informal influence of powerful spouses on governments and the environments that enable such influence. We reveal a novel dynamic in donor-recipient relationships: Western donors may strategically tolerate informal influence when it allows them to achieve political objectives while maintaining plausible deniability. This finding challenges the prevailing assumption that aid allocation is driven exclusively by formal institutional frameworks and highlights the potential significance of informal channels in shaping donor influence.

Beyond the substantive contributions to the study of formal and informal political influence, this paper introduces two novel datasets, both of which we expect to be valuable for a wide range of future research. The first is the *Political Leaders' Affiliations Database* (*PLAD*), which provides geolocated birthplaces of leaders and their spouses worldwide, along with data on their education, profession, ethnicity, and number of children, covering 176 countries over the 1989–2020 period. We thus complement existing data on political leaders that provide information on leaders' tenure, details on turnover, and ideology (Goemans et al. 2009, Licht 2022, Herre 2023, Funke et al. 2023).

The second database we introduce in this paper—the Geocoded Official Development Assistance Database (GODAD)—is a geocoded, dyadic panel dataset of development aid projects assembled from various sources. We geocode data for 18 bilateral European donors and the United States, based on raw project data that the OECD's Development Assistance Committee provides in its Creditor Reporting System (CRS). In a nutshell, CRS project titles and descriptions provide text data from which geographic entities can be identified. We collect and process data from the CRS on our 19 donors for more than 1,600,000 unique projects. We exploit project titles and descriptions to extract candidate geographical entities that can be matched to known cities, regions, or other administrative entities within the recipient country. To do so, we run a Named Entity Recognition (NER) algorithm through a (pre-trained) RoBERTa base transformer model for entity identification on the corresponding project titles or descriptions. This particular class of algorithms employs deep learning models to identify specific categories within a text, including geographic entities. We successfully geocode 217,696 projects, for which we identify 282,419 unique project-location pairs. The extracted entities undergo a series of data cleaning and cross-checking.¹⁰ We complement CRS data with data from individual recipient countries' Aid Information Management Systems and geocoded data on French aid projects provided by the Agence Française de Développement (2024).¹¹

Finally, we include data on geocoded Chinese aid commitments and World Bank projects, resulting in a first-of its kind dataset of geocoded aid projects that will hopefully serve as important input for future studies on the allocation and effects of development aid.¹² Our final sample provides granular information on 226,661 aid projects for 21 donors and 184 recipient countries. Importantly, we provide data on flows for Western bilateral aid data which amount to US\$290 billion (in constant 2014 dollars) over the 1990–2020 period with a wealth of details regarding lending arrangements and modalities.¹³

We proceed as follows. Section 2 describes the construction of PLAD and GODAD and presents descriptive statistics. In Section 3, we explain how we identify the effects of informal influence on the subnational allocation of funds. Section 4 shows our results, both for total aid and disaggregated by donor. This section also investigates heterogeneity and the consequences of informal influence on development outcomes. We conclude in Section 5.

2 Data

2.1 The Political Leaders' Affiliation Database (PLAD)

To measure the informal influence of political leaders' spouses, we build a new database with information on personal characteristics of political leaders and their spouses, including their regions of birth. The resulting *Political Leaders' Affiliation Database* (PLAD) contains information on the universe of effective political leaders of all countries worldwide, following the definitions in the Archigos Database on Political Leaders

¹⁰Appendix B explains the evaluation of the NER model accuracy on our dataset, data cleaning, and how we deal with false positives and negatives.

¹¹Appendix B.2.4 explains in detail how we integrated these data.

¹²Raw data on Chinese aid projects are available from Custer et al. (2021) and Dreher et al. (2022) for the 2000–2021 period, for which Goodman et al. (2024) provide geocodes. We clean these raw data and merge them to our administrative regions. AidData (2017) provides geocoded data for a sub-set of World Bank projects for the years 1995–2014. We merge them with project-level data from the International Aid Transparency Initiative (IATI), referring to the years 1998–2020. We thank Christopher Kilby for sharing code that helps performing this task. Data on World Bank disbursements are from Kersting and Kilby (2021).

¹³The CRS provides data from 1973 onward. However, the share of missing information is substantially larger for earlier years. While we provide more details on the full sample in Appendix B, descriptive statistics in the main text refer to the 1990–2020 period. These are the years that we can use in the econometric analysis below, restricted by the availability of PLAD.

(Goemans et al. 2009).¹⁴ Effective political leaders are typically presidents in presidential systems, prime ministers in parliamentary systems, and party chairpersons in communist states. We rely on Archigos data until 2015 and update leader information until the year 2020, relying on online libraries and databases such as the CIA World Factbook, Munzinger, Encyclopaedia Britannica, and Ethnicity of Celebs, as well as on reports from popular news services. We describe the data collection process in detail in Appendix A. Altogether, our database covers 1,081 political leaders with 1,230 terms in office from 176 countries over the 1989–2020 period.

Once we had identified the universe of effective political leaders, we used these same sources to collect detailed data on their spouses and joint offspring. Among others, we have collected information on spouses' names, dates and places of birth, as well as their educational and professional background. To distinguish informal from formal influence, we paid particular attention to spouses' political careers, documenting whether they held elected or appointed office or occupied leading positions in charities or similar organizations before, during, and after their partner's tenure. We also documented the number and gender of the couple's children, along with details on how the relationship with the leader ended (if applicable). We gathered information on all spouses a monogamous leader has had throughout their lifetime.¹⁵ For polygamous marriages, we identified what we refer to as the 'first spouse.' This designation refers to the individual holding the official or informal title of 'first lady' or 'first gentleman.' In cases where such titles are not employed, we identified the first spouse as the partner with whom the leader is most frequently observed in public or fulfilling representative functions. Table A.1 in Appendix A.2 lists all variables with their definitions and sources.

Our estimation sample contains information on spouses for 96% of the leaders in our database, totaling 558 spouses. Of these, 361 served as the spouse of a leader at some point during the leader's tenure. On average, a spouse is 'in power' for 6.5 years. The median spouse holds at least a Bachelor degree or equivalent and has three children with the respective leader.

We geocode birth regions using information from Geonames, relying on seven precision codes (Strandow et al. 2011), with the highest precision being the village or city level.¹⁶ We aggregate the birth region information for administrative regions at the first (ADM1) and second (ADM2) subnational levels.¹⁷ Specifically, we geocoded the birth regions of

¹⁴We make these data available to the public through our project website at https://www.plad.me. We currently include information on leaders only but will add spouse characteristics upon publication of this paper. We plan to update these data on a yearly basis. A future version of PLAD will also include geocoded information on birth regions of cabinet members (Asatryan et al. 2023).

¹⁵Leaders in our dataset have on average 1.3 spouses. The only monogamous leaders in our dataset that had more than four spouses are Michael Manley in Jamaica and Gerhard Schröder in Germany, both of whom had five spouses.

¹⁶See http://www.geonames.org. As a secondary source, we rely on Google Maps.

¹⁷Depending on the administrative terminology used in a specific country, ADM1 regions are provinces, states, and governorates, among others. The smaller ADM2 regions typically correspond to counties or

246 'spouses in office' (68%) to the respective ADM1 regions. Figure 1 shows a world map of the ADM1 birth regions of political leaders and their spouses, highlighting significant variation across space.¹⁸ 210 spouses (58.2%) were geocodable to the more fine-grained ADM2 region level, leading to 1,120 ADM2 region-year observations that indicate spouses' birthplaces.

We observe some overlap between the birth regions of leaders and their spouses. For 20.1% of the ADM2 region-year observations that contain the spouse birth regions, the leader also originates from that same region. The raw correlation between the two variables is 0.2. Out of the 1,120 spousal-year observations in our sample, 255 are leaderyear observations as well. Of the 143 regions that change their status as birth region at least once, 22% of the new regions are the birth region of both the leader and their spouse, while their predecessors were born in two different regions. 3.8% correspond to a matching change in leader region—e.g., while both Kolinda and her husband Jakov Kitarović were born in Rijeka, their successors as president and first spouse of Croatia (Zoran Milanovic and Sanja Musić) both originated from Zagreb.

Figure 1 – Birth regions of political leaders and their spouses, ADM1, 1990–2020



Note: The world map indicates whether an ADM1 region has been a leader birth region (in purple), spouse birth region (in green), both (in yellow), or none (in white) over the 1990–2020 period.

Table A.2 in Appendix A shows summary statistics for the whole PLAD sample.

districts. The Database of Global Administrative Areas (GADM) provides shapefiles with information on subnational administrative regions and their boundaries (Hijmans et al. 2018).

¹⁸Figure C.2 in Appendix C replicates this map at the ADM2 level for three world regions. The figure shows that birthplaces are to some extent geographically concentrated. In Africa, this is in part because leaders (and thus their spouses) tend to stay in power for a prolonged period of time. In Latin America, a comparably small number of regions are coded as (exclusive) spousal birth regions, as many spouses are born in the same regions as leaders.

On average (in the 1989–2020 period), an ADM2 region is coded as a spousal region in 0.14%—or 0.044 years. There is notable variation across continents: in Africa, an ADM2 region is coded as a spousal region in about 0.27% of all years, compared to 0.08% in the Americas. In our estimation sample, 143 ADM2 regions experience changes in their status as spousal birth regions, with some regions undergoing multiple changes. In total, there are 250 status switches. This is the variation that we will use in most of the empirical analyses below. The number of switches is lowest in Europe, with only 23 changes, and largest in the Americas with 79 changes.

2.2 Geocoded Official Development Assistance Dataset (GODAD)

In order to analyze the subnational allocation of aid for a large set of donors, we build the Geocoded Official Development Assistance Dataset (GODAD). It contains geographic information on aid projects of 19 bilateral donors from the OECD's Creditor Reporting System (CRS): the 18 European member countries of the OECD's Development Assistance Committee (DAC) and the United States.¹⁹ We complement CRS data with data from individual recipient countries' Aid Information Management Systems (AIMS), which are available for Burundi, Colombia, the Democratic Republic of Congo (DRC), Honduras, Iraq, Nepal, Nigeria, Senegal, Sierra Leone, Somalia, Timor-Leste, and Uganda, and further include geocoded data on French aid projects provided by the Agence Française de Développement (2024).²⁰ We then merge the geocoded data on Western bilateral donors with data on Chinese aid commitments available from AidData's Global Chinese Development Finance Dataset version 3.0 (Custer et al. 2021, Dreher et al. 2021, Goodman et al. 2024) for the 2000–2021 period and World Bank projects for the years 1995–2020 from AidData and IATI.²¹ The resulting database enables researchers to tackle a large set of research questions, against the backdrop of a literature that has previously been limited to investigate the allocation and effectiveness of subnational aid either only for individual recipient countries or the two donors (China and the World Bank) for which geocoded data had previously been available for a significant number of countries and years.

To geocode projects for European donors and the United States, we utilize textual information associated with projects to identify geographic entities within the recipient

¹⁹The European donor countries covered are Austria, Belgium, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom.

 $^{^{20}\}mathrm{See}$ Section B.2.4 for details.

²¹We take data until 2014 from AidData (2017) and merge project-level data from IATI, available since 1997. Our publicly available dataset includes also geocoded data on Indian aid from Asmus et al. (2023). However, since the data are restricted to the 2007–2014 period, we exclude them from the empirical analysis below.

country. The OECD's CRS data provide project-level information on OECD donors beginning in 1973 (though a small share of donors' projects has been reported in earlier years). The GODAD uses all available years. However, given the time coverage of PLAD and other geocoded data, our empirical analysis uses aid data for the 1990–2020 period only. Project numbers and descriptive statistics that we report below all refer to this shorter sample period.

The raw data contain financial information on commitments and disbursements (in US\$) as well as information on project characteristics, such as implementing agencies, scope, and project descriptions. We exploit text data on project titles and descriptions to identify and geocode projects (at least) at the ADM2 level, allowing us to study the subnational allocation and effectiveness of aid.

Project titles and descriptions provide text data from which we can identify geographical entities. As described in detail in Appendix B, we apply the following procedure for the extraction and identification of geographical entities: First, we collect raw data from the OECD CRS for our 19 donors from 1973 to 2020. For our 1990–2020 sample period, the CRS reports a total of 1,605,748 unique bilateral projects. We exclude aid sectors whose projects cannot be allocated to specific recipient regions, reducing the number to 1,328,163 projects. These include aid spent in donor countries (such as refugee assistance), general budget support, administrative costs, and debt relief. We then exploit the text descriptions of projects to extract candidate geographical entities that can be matched to known cities, regions, or administrative entities within the recipient country. CRS data provide titles, short descriptions, as well as long descriptions of aid projects, which we all use as sources of information. For each project we run a Named Entity Recognition (NER) algorithm through a (pre-trained) RoBERTa base transformer model for entity identification. This particular class of algorithms uses deep learning models to identify specific categories within a text, including geographic entities. We then pass these entities through the GoogleV3 geocoder API. Our geocoding pipeline returns subnational locational information for 217,696 projects (roughly 16% of the initial sample of considered CRS projects).²² From these, we identify 282,419 project-location pairs, as some projects are destined for more than one location.

We investigate whether or not these projects are a representative sample of all aid projects (see Appendix B.4 for details). Unsurprisingly, we find that more recently reported projects and projects in more location-dependent sectors, such as infrastructure, are more likely to be geocoded and are thus over-represented in GODAD. We also find differences with respect to donor countries and the type of financial flows. Our results

²²Note that this does not mean that the model misses 84% of the geopolitical entities in the data. The bulk of projects do not contain entities that can be geocoded, either because the nature of the project is not subnational or because the project titles and descriptions do not allow for an accurate geocoding. Appendix B provides details on the evaluation of the NER model accuracy, data cleaning, and how we deal with false positives and negatives.

reported below thus cannot necessarily be generalized to all aid from all donors but have to be interpreted with respect to the specific set of geocoded projects available to us.²³

We also test the accuracy of our final data sample by making use of a random sample of 10,000 projects, for which we manually code geographical information. Overall, we find a low incidence of errors, with only 5% of projects in this random sample containing missing or erroneous geocoded information. Errors are classified as false negatives (missed information) or false positives (erroneous geocoding). Missed information is limited, as the entity extraction model responsible for identifying candidate geographical locations has an accuracy of almost 90%. Among wrongfully geocoded entities, most of these cases occur because of semantic reasons, when the model is 'tricked' by descriptions in the text, with references to projects or organizations in a grammatically similar manner to location descriptions.²⁴ In other cases, the location may be referring to a wider geographical area (Sahara desert), which provides no proper subnational information on the aid project. Appendix B describes in detail all the steps taken to obtain the final sample, including the accuracy metrics for the NER model and the errors found in the final sample.

Table B.2 in Appendix B summarizes the number of projects available over the 1990–2020 period by showing the main descriptive statistics both before and after geocoding. As can be seen, both number and size of aid projects considerably shrink after the geocoding. To a large extent, this reduction is explained by a lack of accuracy in the CRS, which does not include the necessary information we need for geocoding. What is more, even among the sample of potentially geocodable projects, the vast majority is not earmarked for specific, subnational purposes, preventing geocoding. In terms of project size, very large loans and grants are typically countrywide aid flows or finance large infrastructure projects, which do not generally indicate their specific region. Hence, these cases drive much of the changes in the distribution of project sizes before and after geocoding. As shown in Figure B.3, however, the distribution of commitments by sectors remains overall stable before and after the geocoding.

A skeptical reader might argue that the share of projects we managed to geocode is rather low. However, when we compare our data to one of the most widely used datasets on an individual country (Uganda), the number of reported projects in GODAD compares favorably to those reported in the AIMS Geocoded Research Release (AidData 2016).²⁵ Specifically, AIMS covers 224 projects by the donors we consider in our sample, while in GODAD we include 5,970 projects. Notably, AIMS reports no World Bank projects in Uganda, whereas we include 1,122 projects from the World Bank. In sum, our dataset

²³In our empirical analysis below, we control for region and country-year fixed effects, which should mitigate these concerns. We also run separate regressions for individual donors that account for differences in geocodability across countries.

²⁴For example, the NGO "Moving to Freedom" will appear to the model as a locality named Freedom. ²⁵Examples for publications that use the Uganda data include Briggs (2018), Civelli et al. (2018) and Pickbourn et al. (2022).

offers a considerably more comprehensive view compared to previous sources utilized in the literature on aid allocation and effectiveness, even in the few cases where such data for recipient countries are available at all (see Section B.5 for details).

As a final step, we merge our new data to the existing datasets described above. As can be seen from Table B.2, to the total number of 217,696 geocoded projects (of which 181,015 are for the European bilateral donors combined and 37,216 are US projects), we add 5,290 projects for the World Bank, and 7,370 projects for China. We aggregate these to the first and second administrative regions of each aid recipient country, resulting in a panel with a maximum of 97,569 (1,446,339) region-year observations at the ADM1 (ADM2) level, respectively. Figure 2 provides a first glimpse at the data. The world maps show the (log) aid amounts in millions of US\$ at the level of ADM1 regions over the 1990–2020 period, with darker colors representing larger amounts.

To illustrate the co-location of aid and birthplaces, we display four administrative maps of the DRC in Figure 3, where each panel represents one of our four donor (groups) as indicated in the column header. The darker colored a region is the more aid it has received by the respective donor. The red markers indicate the birth regions of the DRC's leaders and their spouses, where the increasing size accounts for the various term lengths. The map also shows the birth region and tenure of different presidents and their spouses. On the far right, the red triangle corresponds to the birth region of Laurent-Désiré Kabila, leader of the country from 1997 until 2001. Shortly after, his son Joseph Kabila assumed power, staying in office until 2019. In 2006, Joseph Kabila married Olive Lembe di Sita, born in Kailo, a region marked on the center right of the map with a red diamond. As can be seen, the pattern of European aid is in line with birth-region favoritism with respect to both leader and spouse. Of course, the example presented here is purely illustrative and implies no causality. We next turn to the econometric analysis to analyze systematic patterns.



Panel A: European OECD-DAC bilateral donors

Panel C: China



Note: The world map displays for each ADM1 region the (log) amount of aid in constant 2014 US dollars it has received over the 1990–2020 period on a color scale, with darker colors indicating larger aid receipts. The panel header indicates the respective donor (group). Note that data for China (the World Bank) are available as of the year 2000 (1995) only.





Note: The map illustrates the total amount of aid received by each ADM2 region of the Democratic Republic of Congo (DRC) over the 1990–2020 period, measured in constant 2014 US dollars and represented on a color scale, with darker shades indicating higher aid amounts. Red markers indicate the birth regions of the DRC's leaders and their spouses, with the size of the markers increasing with the respective term lengths. The panel header indicates the respective donor (group). Note that data for China (the World Bank) are available as of the year 2000 (1995) only.

3 Empirical Strategy

To identify the effects of informal political influence through leaders' spouses, we explore within-region temporal variation in foreign aid flows. Our empirical strategy compares aid received by a region when it is the birthplace of a leader's spouse with aid flows to the same region when such a connection to the current national leader is absent. Our sample includes all countries that have received aid during the sample period at least once. We run our baseline regressions at the more detailed level of ADM2 regions, but show results at the ADM1 level for comparison. We estimate the following equation with ordinary least squares:

$$Aid_{c,i,t} = \beta_1 Spouseregion_{c,i,t-1} + \beta_2 Leaderregion_{c,i,t-1} + \beta_3 Pop_{c,i,t} + \sigma_i + \tau_{ct} + \varepsilon_{c,i,t}.$$
 (1)

Our main dependent variable is $Aid_{c,i,t}$, which captures the logarithm of aid in constant 2014 US\$ given to recipient region *i* of country *c* in year t.²⁶ We apply OECD definitions and thus analyze aid that qualifies as Official Development Assistance (ODA), which is government aid aimed at promoting economic development and welfare in developing countries and provided on concessional terms.²⁷ The main analysis focuses on aid aggregated over four (groups of) donors: gross aid disbursements from 18 European bilateral OECD-DAC donors, the United States (for the years 1990–2020), and the World Bank (1995–2020), as well as aid commitments from China (2000–2020).²⁸ Since geocoded World Bank aid data are unavailable before 1995, our analysis of total aid—including all 21 donors—is limited to the 1995–2020 period. Chinese aid only gained substantial traction with its "Going Global" policy and was negligible in the years prior to 2000 (Brautigam 2011). So we assign it a value of zero for those years.

We measure informal political influence at the subnational level using a binary variable $Spouseregion_{c,i,t-1}$ —referred to as Spouseregion in the text and tables below—that equals 1 if the spouse of the effective political leader of country c in year t - 1 is born in region i.²⁹ Mirroring our definition of spouse birth regions, we code a binary variable

²⁶We add a value of 1 before taking logs. Some values in the OECD-DAC's gross disbursements are negative, arguably representing coding mistakes. We set them to 1. For projects with multiple locations that spread across regions, we allocate amounts equally across locations. For example, for a project with two locations in region A and one location in region B, we allocate two thirds of disbursement amounts to A and one third to B. Data for China report outlines of project infrastructure instead of project locations. We therefore split amounts across those regions that receive parts of the project.

²⁷Our measure of World Bank aid thus covers disbursements only from the International Development Association (IDA), which is the concessional lending arm of the World Bank. We exclude Other Official Flows when measuring Chinese aid.

 $^{^{28}}$ We provide separate analyses for (groups of) donors below, excluding the years no data for the respective donor are available. Note that data on Chinese aid *disbursements* are not available. However, commitment data exist for other donors, which we use in additional analyses below for comparison.

²⁹If there is no information on spousal birth regions, we code the spouse birth region variable as zero. This substantially increases the number of observations, which allows us to use information for a larger

Leaderregion_{c,i,t-1} that takes a value of 1 if the effective political leader of country c in year t - 1 is born in region i.³⁰ Given that leaders and their spouses are often born in the same region, this variable allows us to control for leaders' formal influence.³¹ This approach ensures that any informal influence that we attribute to spouses is not simply a reflection of the formal influence of the politician in power. We lag both variables by one year to allow time for disbursements to adjust.

Our regressions control for the logarithm of a region *i*'s population size in year t (CIESIN 2018, $Pop_{c,i,t}$).³² Most of our regressions include region fixed effects to control for unobserved variables that affect a region equally at any point in time. For instance, regions containing a capital city often differ from other regions in ways that could correlate with both development aid and the likelihood of a leader's spouse being born there. Such differences may include higher infrastructure levels, more robust political networks, or concentrated economic activity. By applying subnational region fixed effects, we account for these stable, region-specific characteristics. Finally, we add country-year fixed effects to account for factors that affect aid given to the entire country in a given year.³³ Examples of these factors include national economic crises, changes in government policy, or shifts in diplomatic relations that affect aid flows uniformly across all regions within the country. We cluster standard errors at the country level, which allows for arbitrary spatial and temporal correlation among all regions within a country.³⁴

Although the fixed effects for regions eliminate the possibility that factors linked to

number of regions for which we have information for birth regions in a limited number of years only. In the rare cases leaders change spouses while they hold power, we consider the previous spouse to be in power in the transition year and the new spouse to assume the role as first spouse in the following year. For example, Bakili Muluzi, President of Malawi from 1994 to 2004, divorced his first wife, Anne Muluzi, in 1999 and married his second wife, Patricia Shanil Dzimbiri, in the same year. We code Muluzi's birth region as *Spouseregion* in 1999, and Shanil Dzimbiri's as of the year 2000.

³⁰In years in which there is a change in the country's leader, the effective leader is defined as the one who held power for the majority of that year.

 $^{^{31}\}mathrm{To}$ be precise, 10.5% of leaders in the sample are born in the same region as their spouse during tenure.

³²We do not include additional covariates. Most of the variables included in country-level aid allocation studies—such as trade, rule of law, and democracy—are captured by the country-year fixed effects or are not available at the regional level. While we thus follow the tradition of subnational studies to estimate parsimonious regressions (e.g., Briggs 2017, Dreher et al. 2019), note that our identification strategy does not rest on their inclusion.

³³De Chaisemartin and d'Haultfoeuille (2020) show that two-way fixed effects estimators with staggered treatment provide a weighted estimate of average treatment effects over periods and units of observation, where weights can turn negative so that they bias the estimates (and coefficients can even switch sign). As we discuss in more detail in Appendix D, just 3 percent of the Average Treatment Effects of the Treated receive negative weights in our baseline regression and are thus unlikely to affect our results. This finding aligns with results from Widmer and Zurlinden (2022) and Bluhm et al. (2025) in similar settings. Following their approach, we thus mainly report results from traditional two-way fixed effects estimators. Appendix D shows that our results are not affected by this choice. Also note that country-year fixed effects—while being included in most regressions—are not required for our exclusion restriction to hold, and all results below are similar if we exclude them.

³⁴Our results hold when we cluster standard errors in a number of different ways, as we show in Table C.1 in Appendix C below.

regions receiving more aid are correlated with time-invariant unobserved variables—also making it more likely a region is the birth region of the leader's spouse—our estimates may still not be causal. Time-varying factors at the subnational level could simultaneously influence aid flows to a region and the likelihood a leader's spouse was born there. To address this concern, we include a series of binary indicators capturing the temporal pattern of spousal connections: binary variables that take a value of 1 in the first or second year *before* a region becomes the birth region of a leader's spouse; a binary indicator for the year *during* which a region gains this spousal status; and binary variables for the two years *after* a region was the birth region of a leader's spouse. We obtain the following regression equation:

$$Aid_{c,i,t} = \sum_{j=-2}^{0} \alpha_{1,j} PreSpouseregion_{c,i,t-j} + \beta_1 Spouseregion_{c,i,t-1} + \sum_{k=1}^{2} \gamma_{1,k} PostSpouseregion_{c,i,t-k} + \sum_{j=-2}^{0} \alpha_{2,j} PreLeaderregion_{c,i,t-j} + \beta_2 Leaderregion_{c,i,t-1} + \sum_{k=1}^{2} \gamma_{2,k} PostLeaderregion_{c,i,t-k} + \beta_3 Pop_{c,i,t} + \sigma_i + \tau_{ct} + \varepsilon_{c,i,t}.$$

$$(2)$$

Note that these additional variables are not simple leads and lags of the birth region indicators. $PreSpouseregion_{c,i,t-j}$ with j = -2, -1, 0 indicate that region *i* will become the birth region of the leader's spouse in two years, next year, or this year, respectively. The event-time specification thus estimates two separate coefficients for the years before a region is the birth region of a leader's spouse (t + 2, t + 1) and a separate coefficient for the first year (t), which is the year a region gains its spouse status (i.e., it is a region with spousal status in just parts of this year). The year in which a region loses its status as spouse region is covered by the lagged $Spouseregion_{c,i,t-1}$ indicator. We then estimate two additional coefficients for the years that follow: $PostSpouseregion_{c,i,t-1}$ and $PostSpouseregion_{c,i,t-2}$ indicate that one and two years ago, respectively, the region lost its status as Spouseregion. Finally, we include the corresponding variables for *Leaderregion* in all regressions.

Significant effects in years just *after* a region's status as birth region changes would not be surprising. Effects on aid disbursements do not necessarily evaporate immediately after a spouse's partner leaves office. Some informal influence might remain. Aid committed earlier might be disbursed with lags, or donors might be slow to adjust the allocation of their aid. Significant coefficients in years *before* a leader's spouse originates from a region could however violate the parallel trends assumption or indicate the influence of important omitted variables. In addition to testing whether aid to birth regions develops differently compared to other times, we thus also test whether the effect of birth regions is stronger compared to the effects for the years just before the spouse's partner assumes office. In other words, even if significant coefficients of $PreSpouseregion_{t+2}$ and $PreSpouseregion_{t+1}$ suggest there are omitted variables that affect the amount of aid a region receives and the likelihood a leader whose spouse is born there assumes office soon, a significant difference in the size of the coefficients, $\beta_1 - \alpha_{1,t-1}$, would still indicate an effect of informal influence. We thus explicitly test whether the effect of birth regions is larger (rather than different), reporting results of one-sided t-tests in the regression tables below.

Our identification strategy thus relies on comparing aid flows to the same region at different points in time, specifically when it is and is not connected to a leader's spouse. Controlling for birth regions of the leaders themselves, this within-region comparison, combined with pre-treatment indicators, allows us to isolate the effect of informal political connections from other regional characteristics that might make it more likely for a region to become the spouse region and to attract aid flows. A skeptical reader might think that a potential threat to identification arises if spouse regions receive heightened scrutiny at times of political importance. We have however no reason to believe that this would affect the likelihood with which donor officials include more precise geographic information in project descriptions or titles. We nevertheless test for potential bias in Appendix B.4. If heightened scrutiny led to more detailed reporting, we would expect to find more small projects in spouse regions, while large ones will likely be included either way. This would result in a lower average project size in spouse regions. However, we find no evidence of systematically smaller project sizes in spouse regions. We also do not observe a larger share of geocoded projects among all projects during election years, which are arguably times of heightened political scrutiny in general. These findings suggest that reporting biases are unlikely to drive our results.

4 Results

4.1 Main Results

Columns 1 and 2 of Table 1 show the results for total aid using Equation (1) and the event-time specification from Equation (2), respectively, but excluding country-year fixed effects.³⁵ As can be seen, spousal regions experience a significant increase in total aid, ranging from 161 to 164 percent compared to the amounts these regions receive at other times. This effect is significantly different from zero at least at the 5-percent level. Moreover, the coefficient on *Spouseregion* in column 2 is significantly larger than the

 $^{^{35}}$ Recall that we control for (log) population as well as fixed effects for ADM2 regions. We do not show their coefficients to reduce clutter.

coefficient for the year just before a region turns into being the birth region of a leader's spouse (see p-value Prob > F Spouse reported at the bottom of Table 1). Additionally, the three PreSpouseregion coefficients—representing a region's future spousal status in one or two years and the year of the status change—are all substantially smaller and estimated imprecisely. The results further show that aid disbursements decrease to their average levels one and two years after the spouse of a leader originated from a region, but the spouse of the current leader does not. In contrast, the coefficients for regions where leaders themselves are born are much smaller and imprecisely estimated. However, the coefficient in the event-time specification is significantly larger compared to the year before the leader originates from a region (see p-value Prob > F Leader at the bottom of Table 1).

Columns 3 and 4 report results for our preferred specification (i.e., including countryyear fixed effects). Our results for *Spouseregion* remain robust but smaller in magnitude, showing increases of 88 and 97 percent respectively. In other words, an ADM2 region receives almost twice the amount of aid—about half a million US\$ more, on average during the tenure of a leader whose spouse was born there, compared to what this region receives at other times. In the event-time specification of column 4, the birth regions of spouses continue to receive larger disbursements in the first year after the leader leaves office, but this effect disappears in the subsequent year. This rapid dissipation suggests that these political dynamics do not have a permanent influence on the allocation of aid. One plausible explanation is that aid commitments made toward the end of a leader's term, anticipating the region's loss of its spousal status, are disbursed with a lag after the leader's departure. The effect of the birth regions of the leaders themselves is again substantially smaller than that of spousal regions—approximately 30 percent compared to 97 percent—and while not statistically significant at conventional levels, it significantly exceeds the amount of aid the same region received before the leader's tenure. While these findings partially align with previous research highlighting the significance of leader birth regions in attracting foreign aid, our results reveal a substantially larger and more robust effect driven by the informal influence exerted by leaders' spouses than the formal influence of leaders themselves. This is significant because it highlights a more subtle aspect of political connections that donors may be less willing to publicly acknowledge. It supports our hypothesis that donors are more cautious about directing aid to regions where domestic political motives are more obvious (i.e., leader birth regions) and prefer to allocate aid to regions where such influences are less visible, such as the birth regions of the leaders' spouses.

In columns 5–8 of Table 1, we estimate variants of our main regression. Column 5 includes separate binary variables for each of the first five years a region is classified as a spouse region, along with an additional binary variable that captures all additional years where the spouse's "tenure" extends beyond five years. As can be seen, the

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	ADM2	ADM2	ADM2	ADM2	ADM2	ADM2	ADM2	ADM2	ADM1	ADM1
PreSpouseregion (t+2)		-0.33		-0.19	-0.20	-0.52	-0.20	-0.18		0.12
		(0.64)		(0.44)	(0.46)	(1.11)	(0.42)	(0.33)		(0.37)
PreSpouseregion (t+1)		-0.10		-0.11	-0.14	-0.41	-0.18	-0.25		0.07
		(0.21)		(0.24)	(0.30)	(0.80)	(0.38)	(0.47)		(0.21)
PreSpouseregion (t)		0.44		0.30	0.31	0.04	0.44	0.42		0.05
		(0.88)		(0.72)	(0.75)	(0.07)	(0.98)	(0.82)		(0.17)
Spouseregion	0.96^{***}	0.97^{**}	0.63^{**}	0.68^{*}		0.54	0.59	0.55	0.39^{*}	0.38
	(2.63)	(2.28)	(2.06)	(1.83)		(1.52)	(1.46)	(1.33)	(1.85)	(1.41)
Spouseregion (year 1)					0.28					
					(0.64)					
Spouseregion (year 2)					0.58					
					(1.19)					
Spouseregion (year 3)					0.95^{*}					
					(1.90)					
Spouseregion (year 4)					1.59***					
					(3.14)					
Spouseregion (year 5)					1.15**					
					(2.13)					
Spouseregion (year > 6)					0.28					
					(0.56)					
PostSpouseregion (t)					1.03**					
					(2.36)					
PostSpouseregion $(t-1)$		0.63		0.88^{*}	0.89*	0.42	1.01*	1.04*		-0.23
		(1.22)		(1.74)	(1.75)	(0.85)	(1.89)	(1.73)		(0.63)
PostSpouseregion $(t-2)$		0.14		0.34	0.34	0.19	0.52	0.51		-0.07
		(0.31)		(0.82)	(0.82)	(0.44)	(1.18)	(0.98)		(0.21)
Leaderregion	0.20	0.12	0.25	0.26	0.24	0.07	0.36	0.30	0.32**	0.02
Deaderregion	(0.89)	(0.40)	(1.14)	(1.00)	(0.89)	(0.13)	(0.67)	(0.50)	(2.16)	(0.08)
Number of countries	110	110	110	110	110	87	82	82	123	123
Number of regions	29467	29467	29467	29467	29467	168	3044	1358	2352	2352
Number of observations	717858	709673	717858	20101	712526	4090	75542	32797	58582	58074
Prob > F Spouse	.1,000	0.01	.1,000	0.03	.12020	0.02	0.04	0.06	30002	0.11
Prob > F Leader		0.09		0.09		0.34	0.22	0.28		0.48
R squared (within)	0.0216	0.0218	0.0006	0.0006	0.0007	0.0068	0.0014	0.0010	0.0005	0.0006
Number of regionsNumber of observationsProb > F SpouseProb > F LeaderR squared (within)	0.0216	23401 709673 0.01 0.09 0.0218	0.0006	23401 709673 0.03 0.09 0.0006	0.0007	4090 0.02 0.34 0.0068	75542 0.04 0.22 0.0014	32797 0.06 0.28 0.0010	58582 0.0005	$58074 \\ 0.11 \\ 0.48 \\ 0.0006$

Table 1 – Birth Regions and Total Aid, 1995–2020

Note: The dependent variable is Aid, i.e., the logarithm of aid (plus 1) given to region i of country c in year t: ODA disbursements of 18 European donors, the United States, and the World Bank's IDA, as well as ODA commitments from China (which we set to zero for the years 1995–1999). Spouseregion and Leaderregion are lagged by one year. Prob > F Spouse/Leader tests whether the coefficients of Spouseregion/Leaderregion are larger than those of PreSpouseregion_{t+1}/PreLeaderregion_{t+1}. All regressions, except columns 1, 3, and 9, control for PreLeaderregion_{t+2}, PreLeaderregion_{t+1}, PreLeaderregion_{t-1}, and PostLeaderregion_{t-2}. Each specification includes Pop, i.e., the logarithm of a region's population size. Columns 1–8 (9–10) include ADM2 (ADM1) fixed effects. Columns 3–5 and 7–10 include country-year fixed effects. Column 6 includes fixed effects for years. Standard errors are clustered at the country level.

t-statistics are reported in parentheses; * p<0.10, ** p<0.05, *** p<0.01.

coefficients on all individual Spouseregion variables are positive and reach statistical significance at conventional levels in years 3–5 of a leader's "tenure." The effects on aid remain significantly positive during the transition year and the first year the (new) leaders' spouse is no longer born in that region, as indicated by the coefficients on $PostSpouseregion_{c,i,t}$ and $PostSpouseregion_{c,i,t-1}$. Beyond this point, the effects become small and insignificant. It thus seems that spouses need time to build significant informal influence to affect foreign aid decisions.

Columns 6–8 build on the event-time specification of column 4 and change the sample that we use to estimate this regression. In column 6, we include only those ADM2 regions that register as *Spouseregion* in our sample period at least once. We take this approach to address potential concerns about the inclusion of a large number of regions in our control group that never experience a change in status.³⁶ Column 7 takes a less conservative approach by including all ADM2 regions within the same ADM1 region, as long as at least one ADM2 region in that ADM1 unit was classified as a *Spouseregion* during the sample period. Column 8 focuses on this same sample, but excludes ADM2 regions that did not receive any aid during the sample period. These modifications result in dramatic reductions in the number of observations (now ranging between 4,090–75,524) and thus unsurprisingly less precise estimates but do not change our conclusion in qualitative and quantitative terms.

Finally, in columns 9 and 10, we replicate our key specifications focusing on ADM1 regions, which are substantially larger than ADM2 regions (ADM1 regions cover 42,372 $\rm km^2$ on average, compared to 2,793 $\rm km^2$ for ADM2 regions). A priori, the expected change in the size of the birth-region effect is unclear. On one hand, the larger size of ADM1 regions might make it easier for domestic politicians to obscure the political motivations behind directing aid to specific areas, reducing the likelihood that donors or their domestic audiences detect such targeted influence. If this concern dominates, the estimated effect should be larger than for ADM2 regions. On the other hand, informal networks through spouses may be particularly effective at channeling resources to smaller, more specific communities where personal connections are strongest, leading to aid being more concentrated in ADM2 regions than in larger ADM1 regions. If this is the case, effect sizes should be smaller and less precise when now focusing on larger areas. The results suggest that the latter effect prevails, with estimated increases in aid to Spouseregions ranging between 46–48 percent. While effects for leaders' birth regions are of comparable size in column 9, this is not the case under the event-time specification in column 10. These findings indicate that the visibility of a region's political status matters more at the level of smaller ADM2 regions than at the level of larger ADM1 regions, where such influence may be less targeted.

 $^{^{36}}$ We estimate this specification with fixed effects for years rather than country-years given that the number of observations in the control group otherwise becomes small.

In summary, birth regions of leaders' spouses register substantial increases in aid, with smaller and less consistent effects for leader-associated regions. In our preferred specification, these regions nearly double their aid receipts. Further analyses show that the effect is most pronounced for economic and social infrastructure aid, with increases of 79–95 percent (see Table C.2 of Appendix C).³⁷ By comparison, the estimate for the production sector is a more modest (and less precisely estimated) increase in aid of 25–27 percent. This pattern likely reflects the more immediate visibility of infrastructure projects like hospitals, schools, and transportation networks, which provide tangible benefits that voters can directly attribute to political leadership in their region. These differential findings align with the conclusions in Dolan and McDade (2020), where sectoral choices are shown to reflect strategic considerations rather than purely developmental objectives.

4.2 Heterogeneous Effects

In Table 2, we explore potential heterogeneity of the average effect of aid. Columns 1 and 2 test electoral motives. To the extent that leaders' electoral support is particularly strong in their own birth regions and those of their spouses, they might want to increase turnout and thus steer aid to those regions, particularly at election times and when elections are competitive (Dreher et al. 2019, Jablonski 2023). However, donors might be particularly wary during election periods to ensure that aid is not misused to advance the electoral interests of incumbent leaders.³⁸ To test these hypotheses, column 1 includes interactions between the *Spouseregion* and *Leaderregion* indicators and a variable indicating whether an executive election is scheduled within the next one or two years.³⁹ Column 2 examines the influence of electoral competitiveness, incorporating an interaction with the 0–7 index of executive election competitiveness from Scartascini et al. (2021). This index combines information on electoral rules and outcomes, where higher values indicate greater competitiveness.

We find evidence that the *Spouseregion* effect strengthens in the lead-up to elections, whereas the *Leaderregion* effect weakens, with the interaction coefficient for the latter being imprecisely estimated. Notably, the coefficients of the two interactions are significantly different from each other (p-value: 0.03). On one hand, these findings

³⁷We follow the OECD's DAC in coding these sectors: Social Infrastructure & Services includes Education, Health, Population Policies/Programs & Reproductive Health, Water Supply & Sanitation, Government & Civil Society, and Other Social Infrastructure & Services. Economic Infrastructure & Services includes Transport & Storage, Communications, Energy, Banking & Financial Services, and Business & Other Services. The Production Sector includes Agriculture, Forestry, Fishing, Industry, Mining, Construction, Trade Policies & Regulations, and Tourism.

 $^{^{38}}$ Faye and Niehaus (2012) show that only recipient countries that are closely aligned with a donor receive more aid during election years.

³⁹Note that the levels of this variable, as well as others introduced below, do not vary within countries in a year and are thus absorbed by the country-year fixed effects.

suggest that recipient leaders seek to promote reelection by channeling more aid to their spouses' birth regions, which are less likely to attract donor scrutiny. On the other hand, there is weak evidence that donors are more effective at preventing aid from being redirected to leaders' own birth regions during these times of heightened scrutiny. Similar patterns emerge when electoral competitiveness is high, with the positive interaction coefficient for *Spouseregion* significantly differing from the negative (insignificant) interaction coefficient for *Leaderregion* (p-value: 0.047). In sum, these findings support the interpretation that donors generally succeed in limiting additional aid to leaders' birth regions for electoral purposes but fail to apply the same scrutiny to spouses' birth regions.

Columns 3–6 examine the role of governance by interacting birth region status with four different indicators, one at a time. It is plausible to expect that stronger governance would limit the ability of leaders' spouses to influence aid allocation for personal or political purposes. However, the same logic applies to the political leaders themselves. Consequently, strong governance might shift overt political influence by leaders to more subtle, informal influence by their spouses. This could lead to a net increase in aid giving to spouse regions with better governance. The relative strength of these opposing effects likely depends on the specific dimension of governance under study.

In column 3, we use the law and order index from PRS Group (2023), ranging from 0– 6. Column 4 uses an indicator measuring the perceived absence of corruption, taken from the same source, and measured on a 0–100 scale. Column 5 interacts with Hollyer et al.'s (2024) HRV2 Transparency Index.⁴⁰ Finally, column 6 focuses on government attempts to censor the media, on an ordinal 0–4 scale (from the Varieties of Democracy Project, Coppedge et al. 2023). Higher values imply better governance, more transparency, and less censorship.

Our results indicate that both spouse and leader regions receive less aid in countries with strong law and order and low corruption, although three of the four coefficients are estimated imprecisely. Conversely, spouse regions—but not leader regions—receive more aid in countries with greater transparency, where reporting on political favoritism is more likely (p-value of t-test for equal coefficients of the interactions: 0.06). In line with this, spouse regions benefit more in countries with less media censorship. This suggests that donors recognize obvious political motives in more transparent environments, diverting aid from leader birth regions to spouse birth regions, where political motives are less apparent. Donors appear to avoid public scrutiny of politically motivated projects in regions where such motives are more evident, while showing less concern for scrutiny in regions with less obvious favoritism.

⁴⁰HRV2 fits an item response model to 228 variables from the World Bank's World Development Indicators, focusing on non-reported data. Its sample mean is 2.95, with a standard deviation of 2.25. Note that the data end in 2015; we extrapolate them until 2020.

	(1)	(2)	(3)	(4)	(5)	(6)
Spouseregion	0.57^{*}	-1.43	1.78^{*}	1.49	0.10	0.41
	(1.71)	(1.37)	(1.94)	(1.58)	(0.25)	(1.25)
Leaderregion	0.27	0.93	1.54^{**}	0.83	0.30	0.38
	(1.23)	(1.12)	(2.57)	(1.46)	(0.97)	(1.51)
Spouse region \times Election	0.45^{*}					
	(1.75)					
Leaderregion \times Election	-0.22					
	(1.29)					
Spouseregion \times Competetiveness		0.34^{**}				
		(2.08)				
Leaderregion \times Competetiveness		-0.12				
		(0.92)				
Spouseregion × Law & order			-0.35			
			(1.36)			
Leaderregion \times Law & order			-0.43**			
			(2.24)			
Spouseregion \times Corruption			. ,	-0.35		
				(1.04)		
Leaderregion \times Corruption				-0.28		
				(1.23)		
Spouseregion \times Transparency					0.21**	
					(2.03)	
Leaderregion \times Transparency					-0.03	
					(0.36)	
Spouseregion \times Censorship					. ,	0.43**
						(2.06)
Leaderregion \times Censorship						-0.22
						(1.24)
Number of countries	109	109	88	88	102	110
Number of regions	29306	29306	27463	27463	28513	29467
Number of observations	687580	715421	671167	671167	705468	717858
R squared (within)	0.0006	0.0007	0.0007	0.0007	0.0007	0.0007

Table 2 – Birth Region Interactions and Total Aid I, ADM2, 1995–2020

Note: The dependent variable is Aid as defined in Table 1. Spouseregion and Leaderregion are lagged by one year. Column 1 interacts these variables with an indicator for whether an executive election will be held within one or two years. Column 2 uses electoral competitiveness as part of the interactions, while column 3 incorporates the law and order index, and column 4 includes the absence of corruption index (both taken from the ICRG and ranging from 0–6 and 0–100, respectively). Column 5 interacts with the HRV Transparency Index, and column 6 uses an indicator for government attempts to censor the media, measured on an ordinal 0–4 scale (from the Varieties of Democracy Project). Higher values across these governance measures indicate better governance, less corruption, greater transparency, and less censorship. All regressions include *Pop*, i.e., the logarithm of a region's population size, and ADM2 fixed effects as well as country-year fixed effects. Standard errors are clustered at the country level. t-statistics are reported in parentheses; * p<0.10, ** p<0.05, *** p<0.01. In Table 3, we explore how characteristics of spouses, rather than countries, influence aid allocation to birth regions. In columns 1–3, we test whether birth regions of spouses who wield formal influence, in addition to their informal influence through marriage, receive more aid compared to birth regions of spouses without formal influence. We distinguish between formal influence during three different time periods: before, during, and after the partner of the spouse holds office as the country's effective leader. For example, Asif Ali Zardari, the husband of the late Pakistani Prime Minister Benazir Bhutto, exemplifies all three periods. Before Bhutto's tenure, Zardari wielded formal power as a member of the national assembly; during her tenure, he served as Minister for the Environment; and after her leadership, he assumed the presidency himself.

Starting with the "before" period in column 1, we expect that spouses who held influential roles prior to the leader taking office can leverage their established networks to channel larger amounts of aid to their birth regions compared to spouses without such influence. Specifically, we interact the *Spouseregion* indicator with three binary variables, each coded as one if, at any time before the leader assumed office, the spouse (i) served as an elected politician, (ii) held a non-elected executive position in a public company or administration, or (iii) occupied a leading position in an NGO, foundation, or trade union (see Appendix A for detailed definitions). While the coefficients of the three interactions are all positive as expected, only the one for spouses with a prior leadership role in NGOs is statistically significant at conventional levels.

Column 2 tests whether spouses holding concurrent positions of power have stronger influence over aid inflows, compared to spouses with no formal role. The theoretical expectations are ambiguous. On the one hand, spouses with formal positions of power could directly intervene in the aid allocation process. On the other hand, donors might be more sensitive to potential distortions in aid flows to regions where such formal power is visible, potentially mirroring the scrutiny often directed toward leader regions. As a result, the net effect of those opposing influences could be positive, negative, or null. In our sample, 23 spouses held elected office at the same time as their partner, among them Cristina Fernández de Kirchner (Argentina), Janet Kataaha Museveni (Uganda), and Néstor Kirchner (Argentina). Additionally, 25 spouses occupied non-elected political positions during their partner's tenure, and 94 held high-ranking positions in NGOs. Our regression results show that while spouses' birth regions indeed receive less aid in case they hold elected office compared to spouses with no formal roles, the coefficient of the interaction (as well as the other two interactions) is not statistically significant at conventional levels. We interpret this as showing that the influence of spouses does not work through their own formal power, but rather only informally, via their partner's political status.

In column 3, we aim to test whether a spouse's intention to pursue positions of power in the future influences the allocation of aid to their home regions. Since intentions cannot be directly observed, we proxy them by examining whether spouses channel more aid to their birth region if they assume a position of power after their partner leaves office. As can be seen, none of the interactions is statistically significant at conventional levels. It thus seems that informal influence on aid flows reflects immediate, contemporaneous power dynamics rather than spouses' more long-term strategy to achieve own career objectives.

	(1)	(2)	(3)	(4)	(5)	(6)
	before	during	after	#spouses	#children	placebo
Spouseregion	0.29	0.73^{*}	0.64^{*}	1.67***	0.45	0.62**
	(0.86)	(1.75)	(1.93)	(3.02)	(1.06)	(2.00)
Leaderregion	0.25	0.24	0.25	0.55	0.58^{**}	0.25
	(1.15)	(1.11)	(1.13)	(1.30)	(2.10)	(1.15)
Spouse region \times Elected power	1.17	-0.20	-0.25			
	(1.48)	(0.23)	(0.26)			
Spouse region \times Non-elected power	1.35	0.19	0.61			
	(1.07)	(0.16)	(0.31)			
Spouse region \times NGO	1.79^{*}	-0.30	-0.23			
	(1.88)	(0.57)	(0.19)			
Spouseregion \times Number spouses				-0.69**		
				(2.32)		
Leaderregion \times Number spouses				-0.23		
				(0.94)		
Spouseregion \times Number children					0.07	
					(1.07)	
Leaderregion \times Number children					-0.14*	
					(1.92)	
Future spouseregion						-1.31**
						(2.17)
Number of countries	110	110	110	110	110	110
Number of regions	29467	29467	29467	29467	29467	29467
Number of observations	717858	717858	717858	717858	717858	717858
R squared (within)	0.0007	0.0006	0.0006	0.0007	0.0007	0.0006

Table 3 – Birth Region Interactions and Total Aid II, ADM2, 1995–2020

Note: The dependent variable is Aid as defined in Table 1. Spouseregion and Leaderregion are lagged by one year. Columns 1–3 interact these variables with indicators for whether the spouse held elected power, non-elected power, or a key position in an NGO or charity, either before the leader assumed office (column 1), during their time in office (column 2), or after leaving office (column 3). Column 4 interacts with the number of spouses a leader has, and column 5 with their number of children. Column 6 presents a placebo regression using a (lagged) indicator for regions where a future spouse of the country's leader is born. All specifications control for Pop, i.e., the logarithm of a region's population size, and include ADM2 fixed effects as well as country-year fixed effects. Standard errors are clustered at the country level. t-statistics are reported in parentheses; * p<0.10, ** p<0.05, *** p<0.01.

Columns 4 and 5 of Table 3 investigate whether aspects of the first couple's marital relationship influence the birth-region effect. To this end, we interact the *Spouseregion*

and *Leaderregion* indicators with the number of spouses a leader has concurrently (column 4) and the number of children they have (column 5). A larger family could imply that multiple informal networks compete for influence. We thus expect the effect of a region's *Spouseregion* status to weaken when it is shared with more individuals, either due to a higher number of spouses or children. The results show that individual spouse regions benefit less when a leader has multiple spouses, while leader regions receive less aid when the leader has more children.

The final column 6 reports results from a placebo regression, where we include an indicator for regions where a future spouse of the country's leader is born, but the spouse of the current leader is born elsewhere. The results show that regions of future spouses receive less aid rather than more, suggesting that any omitted variable bias affecting both current and future spouse regions equally biases our estimates for *Spouseregion* downwards.⁴¹ This is reassuring as it suggests that the observed positive effects of *Spouseregion* on aid patterns are likely not driven by confounding factors but rather reflect genuine patterns of informal political influence.

Table C.3 in Appendix C explores additional heterogeneity. First, we find that the *Spouseregion* effect does not differ significantly across world regions.⁴² Second, there is no evidence of differential benefits to spouse regions or leader regions in countries with higher political risk. Third, leveraging Crombach and Smits's (2024) Subnational Corruption Database, we include measures of corruption at the level of ADM2 regions rather than entire countries, controlling for the level of these variables. Corruption is defined as "the abuse of entrusted power for private gain," which Crombach and Smits (2024) extract from a number of sources. They measure it on a 0–100 scale, with higher values indicating less corruption. While we do not observe significant differential effects of birth region status in more corrupt subnational regions overall, we find that both spouse and leader birth regions with higher levels of "grand" corruption—defined as the "abuse of high-level power" (but available for a smaller sample only)—receive significantly more aid during the leader's tenure.

Fourth, we find no evidence that leader or spousal birth regions benefit more in countries with more democratic elections, stronger national parties, higher levels of formal education among leaders or their spouses, or where leaders are eligible for re-election.⁴³ Finally, we test interactions between the birth regions of leaders and their spouses. While aid might be expected to increase if both leaders and their spouses are born in the same region, our results provide no evidence in support of this.⁴⁴

⁴¹Note however that the number of future birth regions is small—just 24 region-year observations with eight unique region-spouse observations.

 $^{^{42}}$ Note that there are insufficient changes in regional status in Oceania to estimate a coefficient.

 $^{^{43}\}mathrm{We}$ take these variables from PRS Group (2023), Coppedge et al. (2023), and the PLAD data we introduce with this paper. The notes in Table C.3 and Appendix A provide details.

⁴⁴We have also tested whether regional heterogeneity affects the magnitude of the birth region effects. To minimize the risk of endogeneity, we interact birth regions with variables measured in the first year of

In summary, the evidence suggests that electoral motives and institutional quality shape the *Spousereqion* effect. The effect strengthens before (competitive) elections, underscoring the role of electoral motives, and intensifies in weaker institutional environments where informal rules prevail over formal institutions. More transparent countries experience larger increases in aid to the birth region of leaders' spouses, but not to those of the leaders themselves. Conversely, our findings show no evidence that the Spouseregion effect is influenced by whether leaders and their spouses are from the same subnational region, the world region of the recipient country, or the educational background of the leaders and their spouses. Additionally, there is no evidence that the formal influence of spouses holding elected or appointed office drives these results. Overall, these findings shed light on the multifaceted interplay between electoral incentives, institutional frameworks, and informal governance structures in shaping aid allocation to the birth regions of the leader's spouse. This raises critical questions about how aid can be more effectively safeguarded from political manipulation, particularly in contexts with weak formal oversight mechanisms and where informal networks dominate decision-making.

4.3 Consequences of Informal Influence

Having established the presence and patterns of informal influence in aid allocation, we turn to examining the potential consequences of spouses' informal influence. To fully evaluate the implications of increased aid to spousal regions, one would need to compare the effectiveness of aid in such regions to its opportunity costs. This entails assessing whether aid rerouted for political reasons is less effective than it would have been if allocated to another country or a different region within the same country. Alternatively, if the aid is additional, its benefits in spouse regions must be weighed against potential alternative uses of these funds in the donor country. Instead of addressing these broader opportunity costs, we focus exclusively on the direct consequences of aid in the birth regions of leaders' spouses. Regardless of the motivations for providing aid, donors may ensure that the aid is utilized effectively, particularly when directed toward politically sensitive regions or times. It is however equally plausible that such aid is wasted or even hurts development. For example, it may empower elites at the expense of broader populations, exacerbate inequality, or even trigger unrest or outright conflict.

Table 4 investigates effects of a region's status as a birthplace of the leader's spouse on

our sample (or the first year these data are available): a region's road density, (log) nightlight, population size, geographical size of a region, a binary variable that indicates the presence of ports in a region, binary indicators for the availability of oil or gas in a region as well as for the presence of mines, and a dummy that captures capital regions. There is little evidence that these variables mediate the magnitude of the birth region effects, with some exceptions: We find that *Leaderregions* benefit less if they host oil and gas, while the *Spouseregion*-effect turns stronger in regions with ports and weaker in regions with denser road networks. Details are available on request.

development, over the range of aid volumes these regions receive. Our first measure for development is $Light_{c,i,t}$, which measures the logarithm of average nightlight emissions in an ADM2 region *i* of country *c* in year t.⁴⁵ It is the sum of emissions of all pixels in a region weighted by the fraction of each cell that falls within a specific polygon. In order to cover as many years as possible in our panel, we rely on Li et al. (2020), who combine data from the Defense Meteorological Satellite Program (DMSP) and DMSP converted Visible Infrared Imaging Radiometer Suite (VIIRS). These data provide a useful proxy for regional GDP estimates in parts of the world where data coverage is spotty and cover almost all countries in our sample starting in 1992. Following Hodler and Raschky (2014), our measure then corresponds to the log of the average nighttime light intensity in a region and year.⁴⁶

We investigate the potential role of aid in how birth regions affect development by summing the amount of aid received over three years, including it in our regressions with a lag of one year, and interacting aid with the two birth region indicators. If donors are aware of the politically sensitive nature of a leader's birth region they might subject aid projects in these regions to greater scrutiny. If donors ensure the effectiveness of aid directed toward regions of obvious political importance, such as *Leaderregions*, but neglect to apply the same scrutiny to less visible *Spouseregions*, we would expect differing outcomes. Specifically, aid given to a region during a period when it holds spouse-region status should be less effective, while aid to leader regions could be equally effective—or even be more effective—compared to aid allocated to these regions at other times.

 $^{^{45}}$ We add 0.01 before taking logs in order to not lose zero observations.

⁴⁶As Hodler and Raschky (2014) point out, we thus measure nightlight intensity per area. They prefer this measure over light per capita mainly due to concerns regarding the quality of subnational population data. Note that the inclusion of fixed effects for regions is likely to make this choice inconsequential.

	(1)	(2)	(3)	(4)	(5)	(6)
	Light	Light	Mortality	Mortality	Corruption	Corruption
PreSponseregion $(t+2)$	8	0.159**		1.038	0 000 oF 0000	0.057
		(2.37)		(0.13)		(0.40)
PreSpouseregion $(t+1)$		0.094		-10.021		0.078
		(1.37)		(1.66)		(0.49)
PreSponseregion(t)		0.036		-0.958		-0.020
		(0.47)		(0.10)		(0.11)
Spouseregion	0.126^{*}	0.127^{*}	-22.336	-20.802	-0.088	-0.087
. 0	(1.96)	(1.82)	(0.90)	(0.90)	(0.44)	(0.40)
Aid	-0.000	-0.000	0.043^{*}	0.044^{*}	0.002	0.002
	(0.55)	(0.56)	(1.84)	(1.85)	(1.00)	(1.00)
Spouseregion \times Aid	-0.007**	-0.007**	0.729	0.730	-0.005	-0.004
	(2.49)	(2.35)	(1.25)	(1.26)	(0.77)	(0.72)
PostSpouseregion $(t-1)$	× ,	-0.052	~ /	43.163	· · · ·	0.009
		(0.90)		(0.88)		(0.05)
PostSpouseregion $(t-2)$		-0.084		-5.744		-0.084
		(1.21)		(0.56)		(0.51)
Leaderregion	0.108^{*}	0.213***	-11.326	1.651	0.357^{**}	0.146
	(1.90)	(2.86)	(1.02)	(0.15)	(2.62)	(0.99)
Leaderregion \times Aid	-0.002	-0.002	0.184	0.080	-0.006	-0.006
	(0.98)	(0.97)	(0.76)	(0.35)	(1.58)	(1.65)
First year	1998	1998	1998	1998	1998	1998
Last year	2020	2020	2017	2017	2020	2020
Number of countries	110	110	56	56	104	104
Number of regions	29467	29467	5660	5659	28851	28851
Number of observations	633939	628770	70400	69701	622787	617701
R squared (within)	0.0022	0.0022	0.0001	0.0003	0.0007	0.0008

Table 4 – Birth Regions and Development, ADM2

Note: The dependent variable in columns 1–2 is log(lights), defined as the log of mean nightlight emissions in region *i* of country *c* in year t (+0.01). Columns 3–4 use *infant mortality*—the rate of infants dying before reaching one year of age, per 1,000 live births. Columns 5–6 use the absence of corruption, defined as "the abuse of entrusted power for private gain" (Crombach and Smits 2024), with higher values representing less corruption, on a 0–100 scale. Aid is the logarithm of aid (plus 1): ODA disbursements of 18 European donors, the United States, and the World Bank's IDA, as well as ODA commitments from China. Spouseregion and Leaderregion are lagged by one year. Even columns control for PreLeaderregion_{t+2}, PreLeaderregion_{t+1}, PreLeaderregion_t, PostLeaderregion_{t-1} and PostLeaderregion_{t-2}. Each specification includes Pop, i.e., the logarithm of a region's population size, ADM2 fixed effects, and country-year fixed effects. Standard errors are clustered at the country level.

t-statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01.

Column 1 and the event-time specification of column 2 show that nightlight emissions increase in the birth regions of spouses compared to how these regions develop at other times, conditional on the coefficient of the interacted variable being zero (i.e., when no aid is received). The coefficient indicates that nightlight emissions in these regions increase by 13.5 percent when the leader's spouse originates from there. This effect is similar to that observed for leader birth regions, where the coefficient is also positive and significant, implying an increase in nightlight emissions of between 11.5 and 24 percent when these regions do not receive any aid. Furthermore, aid itself has no significant effect on nightlight emissions in regions without formal and informal influence (i.e., when *Spouseregion* and *Leaderregion* are zero).

The coefficient of the interaction between *Spouseregions* and aid is negative and significant. This finding aligns with two potential interpretations. First, aid allocated for political reasons may be sufficiently less effective than aid allocated for other reasons, resulting in a lower overall impact of aid on regional growth when the leader's spouse is from that region compared to its effect at other times (Dreher et al. 2021). Second, even the aid a region would have received regardless of its political salience may become less effective at times a leader's spouse is born there. This could occur if project implementation is less carefully vetted or if oversight and supervision become lax. The insignificant coefficients of the interaction between aid and *Leaderregion* suggests that donors might more carefully scrutinize aid projects allocated to these regions, recognizing their political importance. However, while being imprecisely estimated, the coefficients of the interactions are negative as well, and not statistically different from those of the interaction with *Spouseregion*.

To illustrate the magnitude of the estimated coefficients, Figure 4 plots the marginal effects of *Spouseregion* and *Leaderregion* over the range of aid these regions receive. The figure shows that regions where a country's leader or their spouse was born develop better when they receive no aid, compared to how they develop at other times. As the amount of aid increases, the positive effect of being a birth region diminishes, although it remains positive except when aid is very high. In sum, being a birth region is beneficial, but the advantage decreases as aid increases. While the additional aid a *Spouseregion* receives as a consequence of its political status harms these regions' development outcomes, the harm is typically not sufficient to overturn the overall positive effect the spouse region status exerts on these regions.

Columns 3 and 4 of Table 4 replicate the analysis focusing on an alternative indicator of development—infant mortality—measured as the rate of infants dying before reaching one year of age, per 1,000 live births.⁴⁷ The results indicate that mortality is lower

⁴⁷Data on infant mortality are from Cruzatti et al. (2023), who combine data from 92 Demographic and Health Surveys (DHS) across 53 countries and nearly 55,000 sub-national locations (enumeration areas) from 2002 to 2014. We aggregate their data to the level of ADM2 regions.



Figure 4 – Effects of Birth Regions on Light Conditional on Aid, ADM2

Note: The figure plots the marginal effects and 95% confidence intervals of *Spouseregion* and *Leaderregion* conditional on the value of (log) total aid, corresponding to column 1 of Table 4. The histogram plots (log) total aid for values larger than zero. The non-normal distribution arises because we plot the sum of aid received over the past three years for each region-year observation. The first mode primarily corresponds to region-year observations where aid was received in only one of the three years, the second mode to those receiving aid in two years, and the third to region-year observations receiving aid in all three years.

in *Spouseregions* when they receive no aid, although the coefficients are estimated imprecisely, likely due to the smaller sample size.⁴⁸ While the coefficients of the interactions with *Spouseregion* and *Leaderregion* show that such regions experience worse outcomes when they receive substantial amounts of aid, none of these coefficients are statistically significant at conventional levels.

Finally, columns 5 and 6 examine corruption as our subnational measure of development. We again use data from Crombach and Smits's (2024) Subnational Corruption Database, which measures corruption on a scale of 0–100, with higher values indicating less corruption. We find no significant effects of aid on corruption when *Spouseregion* and *Leaderregion* are zero. Similarly, we do not find significant interactions between birth region status and aid, though all coefficients have the expected sign, and the negative coefficient on the interaction term with *Leaderregion* narrowly misses significance at the ten-percent level.

Overall, the additional aid a region receives due to its informal political significance appears to be less effective in promoting broad development outcomes than aid allocated to the same regions at other times. The results for mortality and corruption are weaker, and while the effects for *Leaderregions* follow a similar pattern, they are also less pronounced and imprecisely estimated. While politically motivated aid is generally less effective than aid that is not influenced by political considerations, informal political influence may be even more harmful, as these connections are less visible and harder to monitor, further reducing the overall impact of aid.

4.4 Donor-specific Effects

Table 5 returns to the study of aid allocation patterns, focusing now on different (groups of) donors individually rather than aggregate amounts of aid. Columns 1 and 2 analyze aid disbursements from the group of 18 European donors, while columns 3 and 4 examine aid from the United States, both covering the period from 1990 to 2020. Results reported in columns 5 and 6 refer to IDA disbursements in the years 1995–2020. Columns 7 and 8 show our findings for Chinese ODA commitments between 2000 and 2020. We do not lag the *Spouseregion* indicator when we estimate its effect on commitments, expecting that they will change faster than disbursements, on average. This implies that the year of a region's change in status is covered by the birth region indicators, while the year in which regions lose their status is not, and we therefore control for it. What is more, we continue to estimate two coefficients after we define regions as birth region and thus

⁴⁸The coefficients imply that infant mortality would be lower in birth regions that receive no aid by more than 20 infants per 1,000 births in *Spouseregions*. For comparison, Widmer and Zurlinden (2022) find that infant mortality in leader birth regions is eight deaths lower per 1,000 live births, in a sample of 36 African countries, with coefficients also estimated imprecisely.
exclude $PostSpouseregion_{c,i,t-2}$ and $PostLeaderregion_{c,i,t-2}$.⁴⁹

Column 1 shows that aid from the 18 European donors combined increases substantially when a region is the birth region of a leader's spouse. According to our estimates, European aid to those regions increases by 164%, which is statistically significant at the one-percent level.⁵⁰ Importantly, there is no evidence of pre-trends in aid prior to a region attaining spouse-region status, though European aid begins to increase modestly in the first year of a leader's tenure. Aid flows remain significantly higher compared to the year immediately before a region gains spouse-region status and continue to be elevated in the years following the end of a leader's tenure.⁵¹ Turning to the results for political leaders, we find that while the coefficient for leader birth regions is also positive, it is much smaller in magnitude and less precisely estimated. However, the event-time specification in column 2 shows that aid does increase compared to the year before a leader originates from the region. Overall, these weaker effects suggest that European donors mitigate the direct use of their aid for the benefit of leaders to some extent, but not entirely, while significantly larger amounts of aid flow to the birth regions of leaders' spouses.

Columns 3 and 4 show very similar results for US aid. According to the estimates of column 3, US aid to spouse birth regions increases by 105%, a statistically significant effect at the five-percent level, whereas the birth regions of leaders themselves do not see an increase in aid—these regions even exhibit small, negative coefficients. The eventtime specification in column 4 further supports these findings, showing that aid to spouse regions increases significantly compared to what these same regions received just before they gained their birth region status, while aid to leader regions remains unchanged.

In line with previous findings for Africa over a shorter time frame (Dreher et al. 2019), World Bank aid does not differ significantly at times the country's leader or their spouse originate from a region, compared to what the same region receives at other times though coefficients on *Spouseregion* itself are positive and only marginally insignificant at the ten-percent level. In contrast, as shown in column 6, World Bank aid to spouse regions increases significantly and substantially in the years following a leader's tenure. This pattern suggests that World Bank aid compensates for reduction in aid from other donors once a region loses its (informal) political influence.

Columns 7 and 8 present the results for Chinese aid commitments. Column 7 shows a decrease in Chinese aid to regions that include the birthplaces of leaders' spouses, but an increase in aid to regions that include leaders' own birthplaces. The coefficients for *Spouseregion* and *Leaderregion* are similar in absolute size, suggesting shifts in aid

 $^{^{49}\}mathrm{This}$ decision does not affect our results.

⁵⁰This effect is somewhat larger in magnitude when compared to that of leader birth regions on China's aid in Africa, reported in Dreher et al. (2019). Results are very similar when we do not lag birth regions by one year or lag by two years instead.

⁵¹Aid fades out eventually. When we add a further lag, the coefficient is small and insignificant.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Europe	Europe	USA	USA	WB	WB	China	China
PreSpouseregion $(t+2)$		0.200		-0.662*		0.302		0.732**
		(0.48)		(1.90)		(0.87)		(2.02)
PreSpouseregion (t+1)		-0.203		-0.120		0.476		0.333
		(0.48)		(0.33)		(1.29)		(1.15)
PreSpouseregion (t)		0.692		0.035		0.365		
		(1.61)		(0.10)		(1.16)		
Spouseregion	0.971^{***}	1.063^{***}	0.717^{**}	0.722^{*}	0.345	0.500	-0.279^{*}	-0.191
	(3.03)	(2.85)	(2.00)	(1.82)	(1.32)	(1.57)	(1.72)	(1.10)
PostSpouseregion (t)								0.277
								(0.89)
PostSpouseregion $(t-1)$		0.816		0.233		0.605^{*}		-0.186
		(1.64)		(0.61)		(1.87)		(0.52)
PostSpouseregion $(t-2)$		0.986^{**}		0.426		0.591^{*}		
		(2.32)		(1.13)		(1.88)		
Leaderregion	0.168	0.374^{*}	-0.044	-0.097	0.000	0.034	0.186	0.168
	(1.01)	(1.66)	(0.22)	(0.42)	(0.00)	(0.14)	(1.50)	(1.32)
First year	1990	1990	1990	1990	1995	1995	2000	2000
Last year	2020	2020	2020	2020	2020	2020	2020	2020
Number of countries	110	110	110	110	110	110	110	110
Number of regions	29467	29467	29467	29467	29467	29467	29467	29467
Number of observations	847135	834787	847135	834787	717858	709673	584428	584428
Prob > F Spouse		0.00		0.02		0.47		0.04
Prob > F Leader		0.02		0.37		0.30		0.02
R squared (within)	0.0010	0.0010	0.0007	0.0008	0.0001	0.0002	0.0002	0.0005

Table 5 – Birth Regions and Aid by Donor Group, ADM2

Note: The dependent variable is Aid, i.e., the logarithm of aid (plus 1) given to region *i* of country *c* in year *t*: ODA disbursements of 18 European donors (columns 1–2), the United States (columns 3–4), and the World Bank's IDA (columns 5–6), as well as ODA commitments from China (columns 7–8). Except for columns 7–8, Spouseregion and Leaderregion are lagged by one year. Prob > F Spouse/Leader tests whether the coefficients of Spouseregion/Leaderregion are larger than those of PreSpouseregion_{t+1}/PreLeaderregion_{t+1}. Columns 2, 4, 6, and 8 control for PreLeaderregion_{t+2}, PreLeaderregion_{t+1}, PreLeaderregion_t, and PostLeaderregion_{t-1}. Columns 2, 4, and 6 also control for PostLeaderregion_{t-2}. Each specification includes Pop, i.e., the logarithm of a region's population size, ADM2 fixed effects, and country-year fixed effects. Standard errors are clustered at the country level.

t-statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01.

of approximately 20–24 percent. While the coefficient for *Leaderregion* is imprecisely estimated, it is statistically different from that of *Spouseregion*, with a p-value of 0.035. One possible interpretation is that recipient countries request less aid from China for spouse regions, relying on their ability to redirect resources from other donors to those areas. Instead, they might channel Chinese aid to leader regions, where Western donors are more likely to impose restrictions on their funds. Alternatively, China might perceive spouse regions as less in need of aid due to the increase in aid from other donors. Column 8 further reveals that these changes in Chinese aid are significantly different from the amounts received in the year prior to a region becoming the birthplace of a leader and their spouse.⁵²

Figure 5 summarizes the effects of the event-time specification for total aid and the individual (groups of) donors.⁵³ The figure shows no significant pre-trends in aid from any donor before an ADM2 region becomes the birthplace of a leader's spouse (*PreSpouseregion* (t + 2), *PreSpouseregion* (t + 1)). It also highlights significant increases in total aid, primarily driven by contributions from Western bilateral donors. Aid disbursements from European donors and the United States rise significantly when a leader's spouse is born in a region. In contrast, aid commitments from China decrease during this period.⁵⁴

When examining individual European donors using the event-time specification (Table C.5 in Appendix C), we find that 16 out of 18 European donors display positive coefficients on *Spouseregion*, indicating a broadly consistent pattern of informal political influence. However, the reduced number of non-zero aid observations leads to less precise estimates for many countries. Nevertheless, we find significant increases in aid to spouse birth regions for Germany, Ireland, and Spain. Moreover, seven donors show significantly larger aid flows compared to pre-tenure levels: Germany, Greece, Iceland, Ireland, the Netherlands, Spain, and Switzerland. This suggests that the spouse-region effect represents a broad pattern across European donors.

In summary, our results demonstrate that both the birth regions of leaders and their spouses benefit from increased aid inflows, though donor behaviors vary significantly. Chinese aid predominantly flows to leader birth regions, mirroring a shift away from

 $^{^{52}}$ Results for *Leaderregion* are in line with results previously reported in Dreher et al. (2019) for Africa. When we re-run our regressions with China's more commercially-oriented Other Official Flows, our results show that birth regions do not receive less or more compared to what they get at other times. 53 See Figure C.1 in Appendix C for the analogous figure of *Leaderregion* effects.

⁵⁴We have also tested whether the use of disbursements vs. commitments drives these differences. While data on Chinese aid disbursements are unavailable, Table C.6 in Appendix C replicates the analysis for commitment amounts for all (groups of) donors as well as using a binary variable indicating that a project has been committed in a year. Again, European donors and the United States give more aid to *Spouseregions*, while China gives more generously to *Leaderregions* and spend their aid more parsimoniously in *Spouseregions* (note that according to the binary indicator World Bank aid to *Spouseregions* increases significantly, but not differentially compared to what these regions received in the year just before).



Figure 5 – Effects of Spouse Birth Regions on Aid, ADM2

Note: The figure displays the coefficients and 90% confidence intervals for *Spouseregion*, along with all *PreSpouseregion* and *PostSpouseregion* variables. The results are based on column 4 of Table 1 and columns 2, 4, 6, and 8 of Table 5.

Spouseregions. In contrast, aid from European donors and the United States increases substantially for spouse regions. European donors also direct more aid to leader birth regions, though the magnitude of the increase is considerably smaller than for spouse regions. This is in line with the expectation that Western donors, to some extent, mitigate the use of aid for overtly political purposes when such motives are evident. Conversely, when these motives are less apparent, aid increases substantially, either because donors fail to recognize the political significance of spousal regions or because they are less concerned about allocating aid to such regions, knowing that audiences in donor countries are less likely to scrutinize them.⁵⁵

Our findings challenge the conclusions of earlier work. While previous studies observed that Chinese aid often flows abundantly to the birth regions of political leaders, these findings led to expectations that aid from Western donors would be more effectively allocated.⁵⁶ However, our results reveal that, rather than being directed toward more productive uses, Western aid is also diverted for political purposes, though it tends to flow to regions where such motives are less apparent.⁵⁷ This contrast between Western and Chinese donors highlights the role of informal versus formal governance in shaping aid allocation. The increased aid to leader birth regions from China reflects a stronger influence of formal political ties on Chinese aid. By contrast, aid from European donors and the United States follows a different pattern, suggesting that informal governance structures—where political motives are less obvious but still influential—play a significant role in shaping aid flows.

5 Conclusions

This study presents the first systematic analysis of how informal influence on political leaders shapes regional development flows and outcomes. We provide novel evidence that the birth region of a leader's spouse receives significantly more foreign aid inflows during

⁵⁵Audience costs should be more relevant at times of heightened political scrutiny. When we interact the birth region variables with indicators for upcoming elections in *donor* countries, we find some evidence in line with this. Belgium, Denmark, Germany, Italy, and Switzerland give less aid to leader birth regions when elections are imminent at home compared to other years. Belgium and Switzerland do the same in spouse regions as well. Detailed results are available on request.

⁵⁶For example, while Kersting and Kilby (2014) emphasize donors' preferences for promoting democratic governance, our findings suggest that informal domestic political dynamics also play a significant role in shaping the allocation of aid from Western donors.

⁵⁷In line with this interpretation, our above results have shown that the effect of *Spouseregions* on aid indeed becomes stronger prior to elections and in more corrupt regions, and that aid given to *Spouseregions* is less effective compared to aid given at other times. The latter is mainly driven by aid from Western bilateral donors, as we show in Table C.4. Aid from the World Bank is also less effective in increasing nightlights when allocated to the birth region of a leader's spouse. In contrast, Chinese aid proves to be more effective in reducing corruption during such times, compared to aid given to the same regions at other times. This suggests that Chinese projects most susceptible to corruption may be redirected elsewhere during the tenure of the spouse's partner.

the leader's tenure, demonstrating a distinct form of regional favoritism that operates outside formal governance structures. This introduces a fundamental challenge to aid effectiveness: even when donors implement safeguards against overt political interference, subtle personal networks can redirect aid in ways that undermine its development impact. Thus, aid that appears free from obvious political interference may still produce similarly ineffective outcomes, as political motivations manifest in more nuanced and subtle ways.

Through the rich heterogeneity of our aid data, we show that the observed patterns of regional favoritism vary by donor. Our findings reveal that while Western donors manage to avoid obvious political targeting in their aid allocation, they may inadvertently channel resources through less visible political connections. Specifically, European donors and the United States direct disproportionately more aid to spousal birth regions during the tenure of their partner, arguably as a result of informal political networks and connections. Notably, regions associated only with the leaders themselves do not receive such a preferential treatment from the same Western donors: there are no increases in U.S. aid to the birth regions of leaders during their tenure, and the increase in European aid is much less pronounced than for spouse regions. We argue that this is because these Western donors try to avoid (the impression) that their aid is used for political purposes. While the political significance of a leader's birth region is obvious, their spouse's birthplace presents a less conspicuous channel for political influence. In line with this interpretation, we find the increase in aid to spousal regions to be particularly pronounced at election time and when elections are competitive. Conversely, aid to leaders' own regions decreases during these periods of heightened public scrutiny, although the coefficients are less precisely estimated in this case.

The pattern for China differs, showing a decrease in aid flows to the birth regions of leaders' spouses, with reductions similar in magnitude to the additional aid that leader birth regions receive from China. One possible interpretation is that recipient governments redirect China's aid from spouse regions to leader regions as other donors are already providing aid to the regions where a leader's spouse was born, but not to the leader's birthplace. In line with previous work for Africa (Dreher et al. 2019), we find that Word Bank aid does not increase at times a region is politically influential. Interestingly, however, such aid increases after a region loses its status as a spouse region, potentially compensating for the shortfall in aid from bilateral donors once a region loses its informal political connections.

Our results also show that aid given to a region is less effective in improving development outcomes when it is provided to the birthplaces of the spouse—or, less robustly, to the birthplaces of leaders themselves—during the leader's tenure, compared to aid given to the same regions at other times. These findings put previous work into perspective. While much of the literature suggests that political motives make aid less effective (e.g., Dreher et al. 2018, Kilby 2024) and that preventing obvious

political interference should enhance aid outcomes (Minoiu and Reddy 2010), our findings challenge this conventional wisdom: Even when donors avoid overtly political aid allocation, the funds may simply be channeled through less detectable political pathways. Thus, aid that appears free from obvious political interference may still produce similarly ineffective outcomes, as political motivations manifest in more nuanced and subtle ways.

To carry out our analyses, we introduce two new global datasets: the Political Leaders' Affiliation Database (PLAD) and the Geocoded Official Development Assistance Dataset (GODAD). PLAD provides comprehensive data on political leaders and their families, enabling researchers to study how personal characteristics and family networks influence political decision-making worldwide. GODAD offers unprecedented detail on subnational aid allocation across donors and recipients, allowing for systematic analysis of aid effectiveness. Together, these datasets create opportunities for addressing fundamental questions about political influence, family networks, and development outcomes.

Above the research and data contribution, our findings bear important policy implications. One interpretation of our findings could be that aid projects can be designed in ways that prevent recipient country politicians from engaging in political favoritism. Notably, we did not detect evidence of political favoritism in the allocation of World Bank aid projects. It is however important to note that World Bank aid differs in several respects from bilateral aid, and these differences could explain the variation in our results, rather than suggesting that the World Bank is actively preventing favoritism in aid allocation.⁵⁸

Another interpretation of our results suggests that preventing favoritism in the allocation of aid is complicated by the presence of multiple, indirect channels. In fact, our results show that Western aid benefits the birth regions of leaders' spouses more than the birth regions of the leaders themselves. While it is conceivable that such favoritism could be mitigated if donors increased scrutiny, it seems more likely that aid diverted from benefiting the birth regions of leaders' spouses would simply be redirected to other regions or purposes—less visible but equally politically motivated and potentially just as ineffective.

As such, we argue that donors should prioritize greater transparency across all aspects of their aid programs—including geographic targeting and beneficiary selection more broadly. Improvements in donor transparency would help ensure that potential distortions in the allocation of aid are minimized and, as a result, enhance the effectiveness of aid projects.

⁵⁸For instance, the World Bank's project appraisal procedures are generally more rigorous compared to those of bilateral donors. The varying project preparation cycles may cause benefits to flow to key regions with delays that are either shorter or longer than the ones we tested here. Previous studies indicate that political favoritism plays a significant role when investigating projects or recipient countries (Dreher et al. 2009, Kilby 2009, 2013, Kaja and Werker 2010, Clark and Dolan 2021, Andersen et al. 2022).

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Appendix

A Constructing PLAD

A.1 Introduction

The Political Leaders' Affiliation Database (PLAD) contains information on the birthplaces and ethnicities of the effective leaders of 176 countries around the world in the 1989–2020 period. The dataset is at the political leader level and reports information on 1,081 effective leaders who served 1,230 terms, indicating some leaders held multiple terms in office. It follows the definitions in the Archigos database on Political Leaders (Goemans et al. 2009). PLAD codes ethnicities and georeferences birthplaces of effective leaders, with highest precision being the village or city level.⁵⁹ We provide the same information for the birth regions of leaders' spouses, covering 276 spouses "in power" (32.8% percent of the leader-years in the database). The following Section A.2 describes the dataset and its variables. Section A.3 contains a detailed description of the precision codes and the data collection procedure.

A.2 Variables and data set description

The following table describes the variables included in the dataset:

Variable	Description				
idacr	Code of the country that the leader governs based on the				
	Correlates of War Project (source until 2015: Archigos)				
leader	Name of the leader (source until 2015: Archigos)				
plad_id	Unique leader identification code				
comments_spouse_general	General comments on the leader's relationships that do not				
	refer to a specific spouse				
polygamous	A dummy variable equal to 1 if the leader had multiple				
	spouses simultaneously				
multifirstspouse	A dummy variable equal to 1 if more than one spouse share				
	the official role of first spouse during the leader's tenure (in				
	the case of polygamous relationships)				
nr_spouse	Total number of spouses that leaders had during their life				
	Continued on next page				

 $^{^{59}}$ We link leaders' ethnicity to the definitions of the GeoEPR database (Vogt et al. 2015).

Variable	Description
year_spouse_change	This variable is the year a new spouse becomes the
	first gentleman/lady (either by government change or new
	marriage) [Note: If we do not know the exact year of marriage,
	we code the year when the leader's tenure starts.]
name_spouse*	Name of the spouse of the leader
$birthdate_spouse^*$	Birthdate or year of birth of the spouse
$profession_spouse^*$	Profession of the spouse
$categorized_profession_spouse^*$	Category of the profession of the spouse
$categorized_education_spouse^*$	Spouse's subject of education
$education_level_spouse^*$	Spouse's level of education/degree
$education_level_isced_spouse^*$	Spouse's level of education/degree following the ISCED
	classification [Source: UNESCO]
$political_power_{before/after/$	Spouse's level of political power before, during, or after the
$during$ _spouse*	leader's tenure
$marriage_start_spouse^*$	Start year of marriage with the spouse
$marriage_end_spouse^*$	End year of the marriage with the spouse (e.g., due to divorce
	or death of either spouse) [Note: If the couple is still together,
	"Present" is entered.]
$total_children_spouse^*$	Total number of children of the leader with the spouse [Note:
	If there is no clear statement available on the number of
	children, the number of children is coded as ".".]
female_children_spouse*	Total number of female children of the leader with the spouse
male_children_spouse*	Total number of male children of the leader with the spouse
adm1_spouse*	First-order administrative birth region of the spouse
adm2_spouse*	Second-order administrative birth region of the spouse
lat_spouse*	Latitude of the spouse's birthplace
long_spouse*	Longitude of the spouse's birthplace
$geoname_spouse^*$	Name of the spouse's birthplace used to identify coordinates
	using geonames.org [Note: The coordinates were retrieved
	using Google Maps when the place is not referenced on
	geonames.org. These rare cases are indicated in the
	comments.]
geonamesid_spouse*	ID of the spouse's birthplace from geonames.org
precision_spouse*	Precision of the spouse's birthplace
	Continued on part page

Table A.1 – continued from previous page $% \left({{{\rm{A}}_{\rm{B}}}} \right)$

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Variable	Description				
official_spouse*	Dummy variable equal to 1 if the spouse holds the official title				
	of first spouse (in the case of polygamous relationships)				
foreignborn_spouse*	Dummy variable equal to 1 if the spouse is born abroad				
divorce_spouse*	Categorical variable equal to 1 if the couple				
	divorced/separated/estranged, 2 if either the spouse or				
	the leader died, 0 if the couple is still together, "." if no				
	information could be obtained				
source1_spouse*	Source from which the information on the spouse was found				
source2_spouse*	Second source verifying and/or adding information on the				
	spouse, when possible				
$comments_spouse^*$	Further notable information on the spouse				
archigos_id	Unique identification code corresponding to Archigos variable				
	"leadid" (available until 2015) [Source: Archigos]				
startdate	Date of entry to office [Source until 2015: Archigos]				
enddate	Date of exit from office [Source until 2015: Archigos]				
startyear	Year of entry to office [Source until 2015: Archigos]				
endyear	Year of exit from office [Source until 2015: Archigos] [Note:				
	We code exit dates for leaders still in office on December 31,				
	2020 with this date.]				
adm0	Country in which the birthplace of the leader is located [Note:				
	It may differ from the country variable if the leader was born				
	abroad. Countries are identified based on the GADM dataset				
	(version 3.6, Hijmans et al. 2018)]				
adm1	First administrative division in which the birthplace of the				
	leader is located [Note: The first administrative division is				
	identified based on the GADM dataset (version 3.6)]				
adm2	Second administrative division in which the birth place of the				
	leader is located [Note: The second administrative division is				
	identified based on the GADM dataset (version 3.6)]				
country	Name of the country that the leader governs				
continent	Continent in which the country governed by the leader is				
	located				
latitude	Latitude of the leader birthplace				
longitude	Longitude of the leader birthplace				
	Continued on next page				

Table A.1 – continued from previous page

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Variable	Description			
geoname	Search term used in Geonames to geolocate birth place 60			
geo_precision	Precision of birthplace information on a scale of 1–6 (see			
	Section 3.2)			
foreign_leader	Dummy variable equal to 1 if the leader was not born in the			
	country of government			
ethnicity1	First ethnic group a leader belongs to as stated in the source			
ethnicity2	Second ethnic group a leader belongs to as stated in the source			
ethnicity_geoepr1	First ethnic group corresponding to the names of groups in			
	the GeoEPR dataset			
ethnicity_geoepr2	Second ethnic group corresponding to the names of groups in			
	the GeoEPR dataset			
ethnicitysource1	First source used to retrieve the leader's ethnicity			
ethnicitysource2	Second source used to retrieve the leader's ethnicity			
ethnicity_precision	Precision of the information on the leader's ethnicity on			
	scale of $1-4$ (see Section 3.3)			
entry	Type of entry [Source: Archigos]			
exit	Type of exit [Source: Archigos]			
gender	Leader's gender [Source until 2015: Archigos]			
yrborn	Year of leader birth [Source until 2015: Archigos]			
birthdate	Birthdate of leader [Source until 2015: Archigos]			
uid	Object ID from GADM dataset (version $3.6)^{61}$			
id_0	Numerical ID for country from GADM dataset (version 3.6)			
	(ADM0 layer)			
id_1	Numerical ID for the first administrative division from GADM			
	dataset (version 3.6) (ADM1 layer)			
id_2	Numerical ID for the second administrative division from			
	GADM dataset (version 3.6) (ADM2 layer)			
	Continued on next page			

Table A.1 – continued from previous page

⁶⁰When the place is not referenced on Geonames.org, we retrieved coordinates using Google Maps. In this case, geoname corresponds to the search term used to locate the birthplace on Google Maps. These rare cases are indicated in the comments. For some rare cases (Bosnia and Herzegovina, Eritrea), we adapted some of the administrative regions provided in the GADM manually, as their data did not correspond to the actual administrative regions.

⁶¹Object IDs are from the GADM polygons. We only provide them for leaders whose birth region we could identify at least at the second administrative level (precision code 3), as we merged our data with the GADM dataset at the second administrative level. We advise users who would like to merge the dataset on the first administrative layer via object IDs to carry out an individual geo-merge with the GADM data via the latitude and longitude data.

	1 10					
Variable	Description					
gid_0	String ID for country from GADM dataset (version 3.6) [Note					
	ISO 3166-1 alpha-3 country code when available (ADM0					
	layer)]					
gid_2	String ID for the second administrative division from GADM					
	dataset (version 3.6) (ADM2 layer)					
edu_name	Name of the education degree/training obtained by the leader					
	and the field of study					
edu_r	Leader's level of education summarized in eight categories					
	[Source until 2012: Yu and Jong-A-Pin 2020]					
birthplace_comment	Notes on controversial cases and additional information on					
	the leader's birthplace					
$ethnicity_comment$	Notes on controversial cases and additional information on					
	the leader's ethnicity					

Table A.1 – continued from previous page

* These variables are not yet included in the public version of our dataset.

A.3 Details on the data collection process

A.3.1 General information

The Political Leaders' Affiliation Database is a manually compiled dataset. We collected information by structured internet searches. As sources, we mainly rely on online libraries and databases such as CIA World Factbook, Munzinger, Encyclopaedia Britannica, and Ethnicity of Celebs, as well as on reports from popular news services such as BBC News, The Guardian, and The Washington Post.

The dataset provides information on the birthplaces of leaders and their spouses if at least two reliable sources report the same location of birth. In most cases, the determination of birthplaces is clear and uncontroversial. As information on ethnicity is not reported as frequently as birthplaces, we provide a leader's ethnicity if at least one source is available and state the sources used in the dataset. Given the scarcity of data, we do not report data on spouses' ethnicity.

We ensured data accuracy through three validation steps:

- 1. A second coder reviewed all information.
- 2. We checked for consistency by comparing our data with those of Dreher et al. (2019), Bommer et al. (2022), and Berlin et al. (2023).
- 3. The lead researchers randomly selected and screened 25% of all leaders' entries again as quality assurance.

A.3.2 Information on birthplaces

To georeference the birthplaces of national leaders and their spouses, we identify their places of origin based on biographical information about where they were born. If sources stated contradictory places, we noted this in the column *birthplace_comment*. To identify the birthplaces, we used the online encyclopedias Encyclopedia Britannica and Wikipedia⁶² and complemented this information with resources focusing on bibliographic accounts, for example, CIDOB, The Famous People, and Munzinger. After identifying the birthplaces, we obtained the respective coordinates using Geonames (https://www.geonames.org/). We provide the search term used to retrieve the coordinates in the variable geonames.⁶³ The variables longitude and latitude contain the coordinates, differs substantially between different leaders, the variable geo_precision contains information on how accurate the coordinates are. The categories of geo_precision are based on Strandow et al. (2011):

- 1 = The coordinates correspond to an exact location, such as a populated place (villages, cities) or a hill.⁶⁴
- 2 = The location is mentioned in the source as being "near," in the "area" of, or up to 25 km away from an exact location. The coordinates refer to that adjacent, exact, location.
- 3 = The location is, or is analogous to, a second-order administrative division (ADM2), such as a district, municipality, or commune.
- 4 = The location is, or is analogous to, a first-order administrative division (ADM1), such as a province, state, or governorate.
- 5 = The location can only be related to estimated coordinates, such as when a location lies between populated places; along rivers, roads, and borders; more than 25 km away from a specific location; or when sources refer to parts of a country greater than ADM1 such as a National Park which spans across several provinces (e.g., Foret Classee de Gongon in Benin).

 $^{^{62}{\}rm While}$ we prefer non-editable sources, Wikipedia offers comprehensive and well-structured information on leader characteristics.

⁶³Oftentimes, the capital city shares its name with the administrative divisions in which it is located, at the first and second level. When it is unclear whether leaders were born in the city itself or in the broader administrative division, we take a conservative approach. We assume they were born within the first-order or second-order administrative division encompassing the capital city that shares its name.

⁶⁴Sometimes we could identify a precise birthplace, but the GADM data did not provide information on ADM2 regions. In this case, we add a note in the variable *birthplace_comment*.

- 6 = The location can only be related to an independent political entity, meaning the pair of coordinates that represent a country. This includes leaders that were born in larger areas that cannot be georeferenced at a more precise level.
- 7 = Unclear. No coordinates are entered to reflect that sub-country information is unavailable. Furthermore, the names of the first and second administrative region can be found in *adm1* and *adm2*, respectively. The variable *foreign_leader* shows if a national leader was born in a foreign country. It takes a value of one if the leader was not born in the country they govern and is zero otherwise. The variable *birthplace_comment* gives further information on the birthplace and explains decision-making in controversial cases.

A.3.3 Information on (leaders') ethnicity

The concept of ethnicity is rooted in the belief in a common culture and ancestry, making it inherently subjective (Weber 1976). For our purposes, we draw on a commonly used classification proposed by Vogt et al. (2015), who suggest a classification of common culture and ancestry based on the following features: (i) language, (ii) beliefs/religion, or (iii) phenotypical characteristics. The salience of those features may differ by world region since ethnic distinctions in Latin America often align with skin color, whereas in Africa, they are more commonly defined by linguistic differences. This also relates to the varying levels of ethnic distinction, where some countries only know two ethnic groups and in other countries ethnicity is a very complex concept with several sub-groups. We rely on the ethnic concepts as mentioned in the sources and the main groups given in Vogt et al. (2015). Although the level of ethnic differentiation varies across countries, it represents the salience within each country and is thus relevant for addressing questions in political economy.⁶⁵ Furthermore, similar ethnic groups may be named rather heterogeneously across countries; for example, terms like "Afro-American," "Afro-Haitian," or "Black" are used to refer to people of African descent. In those cases, we stick to the ethnicity name used by the source or by Vogt et al. (2015) to minimize interpretation biases. We also draw from previous databases on leader characteristics (e.g., Fearon et al. 2007, Parks 2013) and encyclopedias such as CIDOB, The Famous People, Munzinger, Encyclopaedia Britannica, and Ethnicity of Celebs. If sources named contradictory ethnicities, we note this in column *ethnicity_comment*.

Note that the availability of information on leaders' ethnicity depends on the country context. Information is less likely to be available in countries where ethnicity is less

⁶⁵Due to differing relevance of ethnic affiliation across countries, sometimes it was harder to find data and we had to base information regarding ethnicity on related concepts (nationality, skin color, or family ties). We coded the *ethnicity_precision* in those cases as 3 and added in column *ethnicity_comment* the note "Assessment of ethnicity is based on nationality/skin color" or provided a reference to the family's linkages (e.g., "parents were farmers with long ancestry in the region").

salient, e.g., in less ethnically fractionalized societies. Data availability also depends on whether ethnicity is determined by language, phenotypical factors, or religion. Therefore, the quality and quantity of sources differ strongly across contexts. For countries that are less represented on major encyclopedias, we draw on country-specific resources like books or webpages of the parliament but also country-specific webpages like Afghan Bios for Afghanistan, Banglapedia for Bangladesh, or BiographyBD for India and Pakistan. What is more, some sources just provide indirect information on the ethnicity of leaders based on the individual's ancestry. Here, we also offer users the option to filter with the following precision codes (variable *ethnicity_precision*):

- 1 = Two sources state the ethnicity directly.
- 2 =Only one direct source or one of the sources is Wikipedia.
- 3 = No direct mentioning of ethnicity. Attribution via characteristics mentioned in the text or phenotypical factors in picture.

A.3.4 Information on (leaders' and spouses') education

Data on leaders' education level are taken from Yu and Jong-A-Pin (2020) for the period up to 2012 and have been updated to include leaders up to the year 2020. Leaders' level of education is summarized in the categorical variable edu_r , based on the eight-level classification outlined in Ludwig (2002):

- 1 =Illiterate (no formal education)
- 2 = Literate (no formal education)
- 3 = Elementary/primary school education or tutors
- 4 = High/finishing/secondary/trade school
- 5 = Special training (beyond high school, such as mechanical, nursing, art, music, or military training)
- 6 = College-educated
- 7 =Qualifications from a graduate or professional school (e.g., master's degree)
- 8 = Doctorates (e.g., Ph.D.)

Military training programs that do not lead to a bachelor degree are considered to be category 5. When it is known that a leader attended college, but there is uncertainty on whether they graduated or the level at which they graduated, we code their education level as category 6. If the leader is known to be a lawyer or a medical doctor, we rank the education level as category 7, as these professions require at least a master's degree in most countries. We supplement the data from Yu and Jong-A-Pin (2020) with the variable edu_name , which reports the name of the highest degree obtained by the leader, complemented with their field of study, when such information is available.

We collected data on spouses' education level in a similar way.

A.3.5 Information on (spouses') profession

We categorized spouses' professions into ten categories: Activism, Art/Entertainment, Business, Education (e.g., professors, educators, teachers, lecturers, academics), Health (e.g., pediatricians, cardiologists, nurses, physicians), Politics, Sciences/Researcher, Social Work (e.g., philanthropists, charity workers, counselors, social project managers, humanitarian workers, and volunteers), Law, and Other. Some spouses have more than one profession. In these cases, all categories are listed and separated by a comma.

A.3.6 Information on (spouses') political power

We categorized spouses' political power into the following categories:

- 0 = No political power, where spouses are explicitly mentioned as having no political power, are in exile or jail, or are deceased
- 1 = Elected political positions at the national or subnational level, including indirectly elected roles such as serving as a minister in the government or as a member of parliament
- 2 = Non-elected political positions, including leadership positions in public administration, state-owned companies, or international organizations, as well as roles such as ambassadors or leaders of influential political parties (e.g., opposition leaders).
- 3 = High positions in NGOs, foundations, charities, or trade unions

We collect information on spouses' political power for three time periods: before, during, and after the leader's tenure. A spouse is considered to have no political power if their profession is explicitly non-political, such as being a medical practitioner, teacher, or artist, and no information on political activities is available.

A.3.7 Descriptive statistics

Tables A.2 and A.3 show summary statistics.⁶⁶ On average, during the 1989-2020 period, a region-year (ADM2) observation is coded as a spousal region in about 0.23% of cases.

 $^{^{66}}$ Note that we provide statistics for the entire database here, rather than the estimation sample used in the main part of the paper.

This is equivalent to 0.07 years - or about a month - across all regions. Conditional on being a spousal region, the average (uninterrupted) duration of a spousal region is 5.6 years. There is some variation across continents: an ADM2 region is coded on average as a spousal region in about 0.27% of all years in Africa and 0.08% in the Americas. An average spousal region spell lasts 7.6 years in Africa and 4.1 years in Oceania.

262 ADM2 regions change their status as spousal birth region at least once. This value is lowest in Oceania, with only nine changes, and highest in Europe with 85 changes. Considering within-region changes, we observe the highest number of spouse region switching in Bagmati, Nepal (8 changes).

It is important to note the substantial overlap between the birth regions of leaders and their spouses (see Figure 1 in the main text). The raw correlation between the two variables is 0.219. Out of the 2,063 spouse-year observations in our sample, 484 are leader-year observations as well. Of the 262 ADM2 regions that change their status as spousal birth region at least once, 3.4% correspond to a matching change in leader region—e.g., while both Kolinda and her husband Jakov Kitarović were born in Rijeka, their successors as president and first spouse of Croatia (Zoran Milanovic and Sanja Musić) both originated from Zagreb.

Table A.2 – Descriptive Statistics Birth Regions (ADM2, 1989–2020)

	Mean	Std.Dev.
Spouse		
Spouse birthregion dummy	0.14	3.74
Change spouse birthregion	0.04	1.94
Leader		
Leader birthregion dummy	0.31	5.53
Change leader birthregion	0.08	2.79
Both		
Spouse and leader birthregion dummy	0.03	1.83
Change of spouse and leader birthregions	0.01	0.98

Note: Descriptive statistics at the ADM2 level refer to the full sample of the PLAD and show percentage shares (i.e., variables range from 0–100).

	Spouses				Leaders			Both		
	Mean	Std.Dev.	Obs	Mean	Std.Dev.	Obs	Mean	Std.Dev.	Obs	
Africa										
Birthregion dummies	0.2678	5.1680	201642	0.6717	8.1685	203202	0.0327	1.8089	201642	
Americas										
Birthregion dummies	0.0775	2.7824	512424	0.1483	3.8477	503153	0.0257	1.6014	502921	
Asia										
Birthregion dummies	0.1495	3.8630	356636	0.3086	5.5465	363262	0.0411	2.0269	355216	
Europe										
Birthregion dummies	0.1543	3.9246	359137	0.2860	5.3406	375822	0.0399	1.9964	358654	
Oceania										
Birthregion dummies	0.1376	3.7072	28340	0.4342	6.5752	30170	0.0000	0.0000	28340	

Table A.3 – Descriptive Statistics Birth Regions by Macro Region (ADM2, 1989–2020)

Note: Descriptive statistics at the ADM2 level refer to the full sample of the PLAD and show percentage shares (i.e., variables range from 0–100).

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B Constructing GODAD

B.1 Introduction

The Geocoded Official Development Assistance Dataset (GODAD) that we introduce with this paper provides newly georeferenced aid data on 18 European bilateral donors and the United States for the period between 1973–2020. We geocode these data in two steps. First, we extract relevant geographic information from project records in the OECD's Creditor Reporting System (CRS). These candidate locations for each project are then passed on to a geocoder that returns a matched location and coordinates.





Note: Visualization of the steps in the geocoding pipeline, from raw CRS data to entity extraction to geocoding.

Figure B.1 provides a schematic overview of the data pipeline in use. This appendix serves to explain this data pipeline from construction to final sample. Section B.2 describes the raw CRS data, the initial data selection, the models used to identify project location names, the methods used to geocode them, and the final data cleaning. Section B.3 then evaluates the final geocoded data, reporting descriptive statistics and robustness tests aimed at assessing their accuracy. We finally carry out two benchmarking exercises: First, in Section B.4, we compare the final geocoded sample to the original CRS data to assess its representativeness. Second, in Section B.5, we compare our data to an existing source for geocoded aid data, the Aid Information Management System (AIMS) data for Uganda.

B.2 The data pipeline

B.2.1 Raw data and sample selection

We extract data for 19 bilateral donors from the OECD's CRS, which provides detailed information on individual aid projects at the project level for the period 1973–2020. The CRS data provide information about projects across multiple dimensions, including donor and recipient countries, donor agencies, channels of delivery (government, NGO, institutes), flow types (grants, loans, other official flows), aid sectors and sub-sectors, as well as commitment and disbursement amounts. For most projects, the data also include project titles and descriptions, which we use to extract information to geolocate the projects. Table B.1 provides some examples of these raw data.

DonorName	RecipientName	ProjectTitle					
Germany	Afghanistan	Building a skateboarding facility in Kabu					
		to engage youth throughout Afghanistan,					
		building technical skills, confidence and life					
		opportunities					
Netherlands	Afghanistan	BBC Kunduz					
United Kingdom	Afghanistan	Helmand Alternative Livelihoods					
		Programme (HALP)					
Italy	D.R.C	Renovation of the toilets of the Notre Dame					
		College of Mbasa-Mboma					
Norway	D.R.C	LIKATI AGRICULTURAL PROGRAM					
Italy	D.R.C	Costruzione di una scuola nel quartiere					
		periferico di Motumbe					
Italy	D.R.C	Agricultural production in the territories of					
		Aketi					
Italy	D.R.C	Support for the medical faculty of the					
		University of the Uele					
Norway	D.R.C	DNB-Education Lower-Bas-Uele					

Fable B.1 –	CRS	Raw	Data	Example
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The CRS vintage we use includes over 1.6 million aid projects from the 19 donors combined, covering the period from 1973 to 2020.⁶⁷ We focus on bilateral projects and thus exclude cases where the recipient is either a macro region ("Africa") or is not specified. While we include all available years in our publicly accessible database, the statistics, figures, and tables below refer to the 1990–2020 period, which are the years included in the empirical analysis of this paper.

The raw data we start from to compile our regression sample consists of 1,605,748 bilateral aid projects spanning the entire period. As a first step, we filter out non-geocodable elements from the data. We drop projects that donors provide to the central government or those that remain in the donor country, such as budget aid, donors' costs for administration or hosting refugees, or debt relief. We also exclude entries that aggregate various smaller expenses and thus cannot be attributed to specific aid-recipient regions. We also filter out a set of non-geocodable activities. In particular, we exclude projects where both titles and descriptions are missing, as there is no candidate text for the geographical entity extraction. Furthermore, we identify project

⁶⁷At the time of extraction (January 2023), data for 2021 were only partially complete and thus not included in this version of the data. The files in raw text format are available at https://stats.oecd.org/DownloadFiles.aspx?DatasetCode=CRS1.

titles and descriptions that represent thematic or regional grouping of smaller, individual activities and therefore cannot be geocoded. This includes examples such as "Technical Cooperation Aggregated Activities" or "Chiesa Cattolica 8xMille." These steps reduce the number of aid projects available for geocoding to 1,328,163 for the 1990–2020 period.⁶⁸

B.2.2 Entity extraction

To extract geographic entities from the data, the first step consists in utilizing the Spacy library for natural language processing tools; specifically, the (pre-trained) Spacy core English transformer pipeline with the Named Entity Recognition (NER) model. These models are typically used to identify within text pieces of information such as names, actions, or geopolitical entities. The advantage of this specific pipeline is in its speed, flexibility, and method of processing text data. Transformer models process all inputs bidirectionally, unlike traditional recurrent neural networks which process sequentially. This allows for greater parallelization in computations, and hence speed, and improved accuracy because the model learns to interpret sentences, or pieces of string, from multiple directions. Furthermore, this parallelization has allowed the models to be trained on massive datasets, resulting in greater accuracy. The underlying model is the RoBERTabase model, trained on the entire English language Wikipedia and the online book corpus, a large online collection of digitalized books. The NER feature of this pipeline is run on the different sources of original text information (as well as translated information where available) for each project: the title, the short description, and the long description. Figure B.2 shows a stylized example of what the model would identify. The NER model shows at least one entity for a total of 424,207 projects.

To correct some of the potential shortcomings of the NER model, we implement a fuzzy string matching-based algorithm.⁶⁹ In the first part, we split the text (i.e., the project title or descriptions) into chunks and filter out "noisy" words based on the frequency of words in the full dataset. The algorithm then matches one by one the remaining candidate words with a hierarchical dataset of location names from the GeoNames database. This database consists of a set of organized text files, with lists of all administrative units, cities, and localities for each country. The procedure is essentially a record-linkage approach, which returns a closeness score for each matched candidate word. We keep only the match that is ranked as most precise and consider it as a candidate geo-entity to be passed to the geocoder when the precision is sufficiently high and the NER output did not return suitable candidate words. The advantage is that the algorithm always extracts at least one match for each string. This additional entity extraction method is particularly useful

 $^{^{68}}$ We translate 122,000 of the total raw projects into English using Google Translate API and use the English text as additional input for the entity extraction model. These projects are predominantly Spanish (44,409), French (26,293), and German (21,855).

⁶⁹Specifically, we use a Term Frequency–Inverse Document Frequency (TF–IDF) algorithm with k-Nearest Neighbor (KNN) matching.

in cases where the project description is short but the geographical entity is clear (e.g., "Dam restoration, Cairo"). Of all the projects considered for geo-entity extraction, the fuzzy matching algorithm was used to supplement the NER output for 103,781 projects.

Figure B.2 – NER Model Geo-tag Example

Project title:								
Skateboarding hall	Kabu)	GPE						
Project descripti	on:					_		
Build a skateboardin	g facility	y in	Kabu)	GPE	to engage youth throughout	Afghanistan	GPE	, building technical skills, confidence and life opportunities

Note: Figure shows stylized example of Named Entity Recognition (NER) model output.

B.2.3 Geocoding

We geocode the extracted entities with the GoogleV3 geocoding API. The choice of the geocoder is relevant when systematically checking the coordinates for a large number of cross-country locations. First, although the performance of Google Maps may vary by country, overall, it provides results of consistent quality across the sample. Unlike other popular (free) geolocating services, which essentially match locations to multiple geodatabases of locations, Google Maps API can leverage more sophisticated ranking algorithms in combination with an immense amount of lower-level GPS, WIFI, network, and other data. Second, the geocoder can be set up to restrict its search to the recipient country. This ranking algorithm for matching locations results in substantially fewer errors with respect to geocoders that rely on matching algorithms. The aforementioned geocoding process returned a total of 624,598 locations with coordinates, spread out among 415,260 projects. This represents the raw output prior to data cleaning, which we explain in the following section.

B.2.4 Data cleaning and integration

Following the geocoding, we implement a series of data cleaning procedures. First, we dropped project-locations with no subnational information.⁷⁰ When the model extracts more than one location, we check whether these entities are distinct project locations or entities that are nested in each other, such as a city located in a larger administrative region. For example, a project description may contain references to both cities in a province as well as a reference to the province itself. We then exclude the more aggregated administrative units to avoid double counting. For example, the same project could reference both "Lashkargah, Helmand, Afghanistan" as well as "Helmand, Afghanistan,"

⁷⁰Google Maps API returns the country centroid when the geolocation precision is very low, meaning that it was unable to return anything more than the search country it was assigned.

which in turn would both be tagged by the NER model. In this case, we would only keep "Lashkargah." In other cases, the project might reference "Lashkargah, Helmand province, and Kabul province." In this case, we would keep both Lashkargah and Kabul province as distinct entities.

Finally, we supplement the data with two main sources of external data: geocoded projects from a set of AIMS platforms of the recipient countries and geocoded projects from a donor country agency. While CRS is the most comprehensive and centralized source of granular aid data, we integrate it with these additional sources in order to provide a more complete picture of subnational aid activities. Specifically, we incorporate data from AIMS platforms of Burundi, Colombia, the Democratic Republic of Congo (DRC), Honduras, Iraq, Nepal, Nigeria, Senegal, Sierra Leone, Somalia, Timor-Leste, and Uganda. Additionally, we include geocoded data on French aid projects provided by the Agence Française de Développement (AFD).

Given the potential overlap between our main data source—CRS—and these additional data sources, we match across datasets based on observable project characteristics, such as the donor, recipient, titles, descriptions, and project IDs. Where projects from external sources (AIMS, AFD) are matched to CRS projects that lack locational information, we supplement the CRS data with geocodes from these external sources. This adds 647 additional geocodes from AIMS but none from AFD, as all projects with geocodes provided by AFD for the projects included in the CRS had already been geocoded by us. The final sample thus consists of 217,696 geocoded projects, and 282,419 project-location combinations, of European and U.S aid projects between 1990 and 2020.⁷¹

B.3 Evaluating the dataset

In this section, we provide an evaluation of the proprietary geocoding pipeline in its two main stages—the entity extraction model and the geocoding output. We therefore focus on quantifying the potential limitations of the processes described in Section B.2, excluding the additional data from AIMS or AFD which is integrated as a final step.

As described in Section B.2.4, the final output of the geocoding pipeline consists of geographic information for 217,696 unique projects (and 282,419 project-location combinations). This corresponds to about 16% of the original 1,328,163 bilateral projects considered. However, it is important to note that this does not indicate a failure of the data pipeline to geocode the majority of projects. The denominator includes CRS projects of interest based on the reported donor and aid sector, but not all of these projects are expected to have a subnational geographic scope, making them non-geocodable.

 $^{^{71}\}mathrm{AIMS}$ (AFD) includes an additional 2,738 (1,532) projects for the donors included in our sample that we could not match to CRS projects. Our dataset includes those projects with the prefix "AIMS" and "AFD."

First, it includes projects that contain geographic entities and are also successfully geocoded—for example, a 2008 grant of US\$1.29 million from the Spanish Ministry of Foreign Affairs and Cooperation to provide health services in Afar and Amhara, Ethiopia. Second, it includes projects that reference subnational geographic entities in their description but are not successfully geocoded. Third, it encompasses projects that *imply* a subnational objective but lack explicit geographic details. For example, a generic project described as "providing clean water infrastructure for rural villages in Morocco" would not be geocodable, as the description does not contain a specific project location. Section B.3.1 provides some further descriptives on these raw data. Finally, there are cases of projects that fit our initial filtering (bilateral, from our set of donors, within one of our sectors of interest), but have nothing to do with subnational objectives. However, they may often be large loans for sectoral support in the health sector (US\$113 million loan to Bolivia from the French Development Agency during the COVID-19 pandemic) or countrywide grants under partnerships for broad projects (US\$ 129 million grant from the UK as part of an initiative to eradicate polio in India). Sections B.3.2 and B.3.3 cover issues of the geocoding pipeline in more detail.

Table B.2 provides an overview of the final data by showing the main descriptive statistics both before and after geocoding. On average, projects are worth US\$8 million, though there is significant variation. Similar to the examples above, very large loans and grants are typically countrywide aid flows or are part of larger initiatives, such as the Iraq Relief and Reconstruction programs under United States funding in 2004. This series of projects in key infrastructure was financed by large grants, with electricity and oil infrastructure projects requiring US\$1.7 billion and US\$900 million, respectively. However, more precise information in the project descriptions, which could indicate the specific locations of these projects, is missing. These cases drive much of the changes in the distribution of project sizes before and after geocoding. Finally, Figure B.3 shows the average commitments by aid sectors for the pre- and post-geocoded sample. In general, the distribution remains stable, indicating that the geocoding process did not introduce major distortions.

	Pre-geocode			Post-geocode		
	N	Mean	S.D	N	Mean	S.D
Number of projects	1,328,163			217,784		
Commitments	1,069,789	0.8	6.7	217,784	0.5	5.2
Disbursements	$1,\!156,\!371$	0.53	4.5	217,784	0.4	3.1

 Table B.2 – GODAD EU and US Sample Description

Note: Table shows the sample of projects before and after geocoding for the years 1990–2020. Values are in millions (constant 2014) US\$.



Figure B.3 – Pre and Post Geocoding Commitments by Sector

Note: Figure shows the average size of project commitments across the main aid sectors: economic infrastructure, production, social infrastructure, multisector, commodity, and emergency aid.

We divide the evaluation of the dataset in three parts: Section B.3.1 describes the raw data—namely project titles and descriptions—from which the project locations are extracted. Section B.3.2 evaluates the first stage of the data pipeline—the entity extraction from the project titles and descriptions. Section B.3.3 evaluates the final geocoded dataset.

B.3.1 CRS raw data descriptives

The data pipeline begins with the project titles and descriptions from the CRS data. Consequently, the quality of the geocoded data depends in large part on the quality of the raw data. This section provides additional descriptive statistics on the text used to extract and geolocate project locations. All reported CRS projects considered in our initial sample contain text data in form of project titles and/or project descriptions. The availability of information varies across donors. Figure B.4 reports the total amount of tokens—or pieces of text—available for processing, within each donor's reported project titles and descriptions. These values reflect verbosity of donors in their project documentation. As the figure shows, the U.S. and Spain have longer project titles and descriptions, allowing for greater text data to be leveraged in the geocoding pipeline. Among all donors, the average project title includes 56 characters, while descriptions include 291 characters on average. The length of these varies across donors, with countries like Belgium, Finland, and Spain providing more detailed descriptions, while smaller donors such as Greece or Luxembourg tend to provide less wordy descriptions.



Figure B.4 – Total Text by Donor

Note: Figure shows the total number of tokens by donor for both reported project titles and descriptions.

B.3.2 Evaluating the Named Entity Recognition (NER) model accuracy

To evaluate the accuracy of the first-stage entity extraction model, we use a random sample of 1,000 hand-coded projects to compare the model output with human coding. We run the project descriptions and titles of this random sample through the NER model, and compare the resulting output to the hand-coded data. Equation (B.1) shows how we compute an accuracy metric for this output, defined as the share of correctly predicted entities for each project:

$$Accuracy = \frac{|Y_i \cap Z_i|}{|Y_i \cup Z_i|},\tag{B.1}$$

where Y represents the set of true (hand-coded) entities and Z the model's predicted entities. The metric thus captures the overlap between the true and predicted entities on a scale from 0 to 1, where 1 means that the model prediction and the true entities match perfectly. This metric is therefore not a binary measure of whether the individual project geocoding was correct. Over the entire random sample of 1,000 projects, total accuracy—defined as the average of the project-level measures—reaches 89%. In terms of individual projects, the model produced errors in 145 cases out of 1,000.

Figure B.5 shows the distribution of these 145 cases by error type. The largest sources of errors are syntax issues and non-English language of titles and descriptions, corresponding to around 34% and 29% (49 and 42 total) of all errors, respectively. Syntax issues are errors deriving from poorly structured text, such as short sentences or improper grammar. Language models, such as the one we employ here for entity extraction, rely on learned probabilities about the distribution of elements of a sentence (parts of speech, prefixes, suffixes, punctuation, etc.) to identify entities in a text. Poorly structured sentences, such as a project title which may not contain a verb or punctuation but for which the location can be inferred ("Hydroelectric Dam, Giza"), will increase the likelihood that the model fails to extract an entity. The abundance of available English language text suitable for training these models with respect to other languages implies that these models will perform more consistently on English text. In both these cases of syntax and language, the errors correspond almost always to instances of false negatives, where the model does not return a true location. 24% of the errors (35 projects) included cases where the extracted entity was not a real geographical entity (false positive). In these cases, the model may be "tricked" by phrases such as "Moving to Freedom," which refers to the name of an NGO project and not a city called Freedom. In other cases, the model may extract geopolitical qualifiers which are not true locations ("Kyrgyz administrative systems"). In some instances the model fails to extract either all locations (12 cases) or some of the locations in the text (7 cases) for no reason attributable to the above categories. These errors are marginal categories (8% and 4% of the cases)respectively).

B.3.3 Final output evaluation

This section analyzes the quality of the final geocoded data. The goal is to evaluate the final output rather than the individual steps. There are two main assumptions that need to be made before evaluating the quality of the geocoding process. First and most importantly, we exclusively focus on feasibly geolocatable entities. Projects at times may reference numerous, extremely small localities (neighborhoods, small villages, etc.) as beneficiaries. However, to the best of our knowledge, there is no geocoding API which will return consistently correct coordinates, across all countries, for these small localities. Our geocoder of choice (GoogleV3) almost always identifies administrative regions (provinces, municipalities, regions) or cities. Finally, most project descriptions include locations that allow us to reliably geocode at the ADM2 level, usually referencing large cities or municipalities. Geocoding at the level of smaller administrative entities, such as villages, isolated localities, or neighborhoods, would require human validation of the output.

The geocoding pipeline identifies explicitly mentioned geographical entities, but not



Figure B.5 – Share of Missing Values in Raw Text Data

Note: Figure shows the distribution of the Named Entity Recognition model errors based on a hand-coded dataset of 1,000 projects. "Syntax errors" relate to grammar or length. "Language" refers to issues of non-English text. "Not geoentity" errors are false positive model errors. "Model fail" and "Partial fail" are false negative errors.

those whose locations can only be inferred. For example, some projects may reference an allocation of funds to the University of Guadalajara for a collaboration. While the university is geocodable, the entity extraction in the first stage of the data pipeline has been tailored to identify strictly geographical entities and therefore may not tag the project to be placed in Guadalajara. The geocoded dataset provided thus reflects the allocation of funds for place-based development projects, as opposed to the transfer of funds to subnational non-geographic entities.

We evaluate the final dataset by checking a random sample from each CRS-defined recipient macro region (Caribbean and Central America, South America, North of Sahara, South of Sahara, Middle East, South and Central Asia, Far East Asia, and Oceania), which we sample under two conditions. First, each macro region's random sample contains at least 1,000 projects which mimic the share of projects by donors in the region. In other words, if in South America Spain accounts for 30% of the projects in the data, then the random sample is composed of 30% Spanish projects. However, a minimum of 100 projects are considered for each donor. We do the sampling at the project level and not the observation level as each project may contain multiple locations with different errors. Finally, the random sample goes through the standard data cleaning done in the pipeline.

Table B.3 presents a scheme for the main errors considered. Broadly, errors can be classified into two types: false positives and false negatives. False positives refer to locations which have been wrongly assigned to a project, while false negatives refer to locations missed by the geocoding process. These error types in turn can be separated into three main categories: common names in project descriptions, failure of the geocoder, and NER model errors.

"Common names" appear exclusively as false positive type errors. In these cases, the geolocated entity does not correspond to the intended project location. For example, if the project describes funds allocated from the municipality of Cordoba (Spain) to Colombia, the project may be associated to the location of Cordoba, Colombia. In the cases classified as "geocoder fail," most errors are also false positives, where the geocoder received the correct input but was not able to provide a specific location. These false positives however are easy to detect, as the geocoder returns the geometric centroid of the country for the majority of these cases. Other examples include projects which describe ethnic territories or historical names of locations. Humanitarian aid projects for the Sahawari refugee camps on the border between Western Sahara and Algeria are almost always described with Morocco being the recipient country, but the project description references the camps on the Algerian side. The geocoder, calibrated to search within Morocco, may not return anything for these cases. At times the geocoder may fail to return coordinates because of nomenclature differences for geographical locations between the donor and recipient country. This is separate from the case where the entity was not tagged in the string because of language limitations in the NER model. For example, the first stage entity extraction may correctly identify the Muskitia coast in Honduras as a location, but the geocoder may not recognize it because it expects the spelling "Mosquito Coast."

Finally, there are a set of errors attributable to the first stage of the data pipeline—the entity extraction phase (these specific issues were explained in detail in Section B.3.2). When the entity extraction fails to extract the location, typically because of syntax or language, it results in false negatives. In these cases, the geocoder will receive no input and return no location. In other cases, the NER model may tag some arbitrary entities in the project descriptions which are not geographic entities, resulting in false positives.

Figure B.6 shows the error rates across different categories. In the random sample of over 10,000 projects, about 5% of the projects exhibited one of the errors described in Table B.3. Among all errors, 45% (313) fall under the "common names" category. In these instances, the geocoding pipeline returns locations that are not strictly related to the geographic scope of the project, as described above. "Geocoder fail" and "NER model fail" together are relatively less important error categories (around 25% each, or specifically 174 and 187 errors). When we further decompose these error categories into the share of error type (false positive vs. false negative), we find that, as previously explained, common names correspond to false positive errors. Aside from this, false positives also occur when the geocoder fails due to nomenclature differences or contested territories. False negatives, or instances where the geocoding pipeline fails to extract and

	False positives	False negatives
	Similar names in donor and recipient	
Common names	Sub-national entity not target of project	
	Mountains, lakes, etc.	
Geocoder fail	Antiquated nomenclature	Geocoder fail (no output)
	Contested or ethnic territories	Nomenclature differences
	Error in reported recipient country	
	Nomenclature differences	
NER model fail		Syntax
	Not geo entity	Language
		NER model failure

Table B.3 – Geocoding Pipeline Errors

Note: Table shows examples of different error categories occurring in the geocoding pipeline.

then geocode a location, are a small category in absolute value, totaling just 187.

When we focus on individual donors rather than aggregates, the error rate is below 10% for most countries. Exceptions are Finland, Iceland, and Spain with an error rate between 11% and 12%. When we disaggregate the error rate by recipient region rather than donors, no region stands out. The exception is the small region of Oceania, with an error rate of less than 1%.

Figure B.7 shows the final decomposition of errors in the geocoding pipeline, given as the share of errors by category and donor over the total number of donor projects. The figure is useful to highlight the outliers in the error rates (measured by the number of projects of a donor with a given error over total donor projects) among donor countries. In the case of Finland, common names in project descriptions determine most of the errors. For Iceland, the geocoder experienced a significantly higher failure rate compared to the average for other donors. The error rate determined by geocoder failure in Iceland is almost 9%, compared with the mean of 2%. Both Iceland and Finland are relatively minor donors in terms of total commitments. NER model failures, which determine most missed cases of locations (false negatives), are rare across all donors, with an average error rate of 1% and with some countries like Ireland, Iceland, or Netherlands having none of these issues in the random sample.



Figure B.6 – Decomposition of Pipeline Errors

Panel A: Error rate by macro-recipient region

Panel C: Error by type

Panel D: False positives and negatives



Note: The figure shows a decomposition of the pipeline errors in different classifications: by recipient macro region, by donor, by type, and by type and category. We calculate the error rate for projects as the share of projects with at least one error in the geocoding output, based on a random sample of hand-coded 10,000 projects.


$Figure \ B.7 - {\rm Donor-error} \ {\rm Heatmap}$

Note: The figure shows the error rate matrix for donors and error type. Cells show error rates, computed as the share of projects of a donor with at least one error, over the total number of donor projects. Darker colors indicate a greater error rate.

B.4 Comparison of geocoded projects with CRS data

In order to get a better understanding of the representativeness of the final geocoded sample, we compare characteristics of the geocoded and non-geocoded projects. Specifically, the inclusion of a potential subnational location within the project title or description depends on various factors. For example, an infrastructure project is more likely to be tied to a specific location. Additionally, donor-specific procedures for planning, implementing, and documenting of aid activities might influence reporting quality.

To test this, Table B.4 regresses a binary variable equal to one when the project is geocoded on five project characteristics: the year of reporting, the project size (measured as total commitments), donor country, project sector, type of financial flow, and indicators of reporting quality. Additionally, we include recipient-country fixed effects to account for time-invariant characteristics at the country level that might influence the likelihood of a project being geocoded (e.g., the difficulty of the spelling of location names). The results of this specification in column 1 show that projects reported in more recent years are more likely to be geocoded, suggesting increasing geographical precision in project reporting over time. We find no statistically significant difference with respect to project size.

The likelihood of a project being geocoded depends on the donor country, its sector, and type of financial flow. Relative to the U.S.—the largest donor country—projects donated by seven European countries (Austria, Belgium, Finland, Germany, Iceland, Italy, and Norway) are significantly more likely to be geocoded. Conversely, projects from France, Greece, and Sweden are significantly less likely to be geocoded compared to the United States. Relative to projects in the education sector (our baseline category), projects in the health, government, infrastructure, and agriculture sectors, as well as emergency aid, are more likely to be geocoded. Conversely, projects in business, finance, and services are less likely to be geocoded. These differences likely reflect the varying degrees of location dependence across sectors. For instance, infrastructure projects are inherently more location-specific compared to other sectors. Finally, when analyzing flow type, we find that equity investments and other official flows are less likely to be geocoded, while ODA loans are more likely to be geocoded compared to ODA grants, which remain the most frequent flow type.

In columns 2–5, we progressively incorporate additional fixed effects and interactions among project characteristics. Specifically, in column 2, we replace recipient fixed effects with recipient-year fixed effects, which does not substantially alter the results. In column 3, we add sector-year fixed effects to account for sector-specific aid cycles, such as surges in humanitarian aid flows in certain years. Finally, in columns 4 and 5, we include a complete set of donor-sector and donor-flow type interactions, respectively. After accounting for all these factors in column 5, the likelihood of a project being geocoded no longer shows a statistically significant difference between ODA loans and ODA grants. Similarly, there is no longer a statistically significant difference for Austria and Norway relative to the United States. However, for Germany, Ireland, Luxembourg, Portugal, Switzerland, and the UK, the coefficients become statistically significantly negative, indicating a lower likelihood of geocoding compared to the United States.

Finally, in column 6, we account for differences in the overall reporting quality with the inclusion of an indicator variable that captures whether the full source of text data (project title, short project description, and long project description) used in the geocoding process is reported in the CRS data. As expected, projects with more extensive reporting are more likely to be geocoded. The inclusion of the reporting quality indicator does not substantially affect the results for most other variables. However, some changes can be observed in the donor variables. For instance, Belgian projects become significantly more likely to be geocoded relative to the United States once we account for reporting quality.

In summary, more recent projects and projects in more location-dependent sectors may be over-represented in GODAD; projects from some donor countries are more likely to be included in the GODAD compared to others. However, GODAD represents the CRS data well with respect to project size. These insights are relevant when interpreting results of statistical models based on these data. Since our empirical analysis on spouse favoritism focuses on ODA, the reduced geocodability of equity investment projects and other official flows is not a concern for our study.

$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$				Geo-codeo	l project		
Year 0.011^{+++} Commitment in USS, In -0.003 -0.003 -0.003 0.017 0.020 -0.003 Austria 0.0391 0.149 0.1431 -0.0423 -0.0433 -0.0423 -0.0433 -0.0423 -0.0433 -0.0423 -0.0433 -0.0423 -0.0433 -0.0423 -0.0433 -0.0423 -0.0433 -0.0423 -0.0433 -0.0423 -0.0433 -0.0423 -0.0433 -0.0423 -0.0433 -0.0423 -0.0433 -0.0		(1)	(2)	(3)	(4)	(5)	(6)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Year	0.011^{***}					
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Commitment in US\$, ln	(21.30) -0.003 (0.75)	-0.003	-0.003	0.001	-0.000	-0.001
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	Austria	(0.75) 0.093^{***}	(0.89) 0.100^{***}	(0.91) 0.102^{***}	-0.041	(0.02) -0.042	(0.35) -0.030
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Belgium	(4.34) 0.080^{***}	(5.45) 0.090^{***}	(5.53) 0.092^{***}	(1.58) 0.030	(1.62) 0.030 (1.85)	(1.16) 0.065^{***}
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	Denmark	(4.60) -0.018 (1.12)	(5.90) -0.015 (1.12)	(6.15) -0.014 (0.07)	(1.36) -0.030	(1.37) -0.030	(2.94) -0.023
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Finland	(1.13) 0.224^{***}	(1.13) 0.227^{***} (12.07)	(0.97) 0.228^{***}	(0.85) 0.265^{***}	(0.87) 0.266^{***}	(0.00) 0.270^{***}
$ \begin{array}{c} (4.22) & (4.31) & (3.31) & (3.32) & (0.11) & (0.13) \\ (4.37) & (0.37) & (0.37) & (0.33) & (0.31) & (0.32) & (0.11) & (0.43) & (0.33) \\ (4.37) & (0.37) & (0.38) & (0.38) & (0.43) & (0.44) & (0.43) & (0.44) & (0.43) & (0.44) & (0.4$	France	(12.02) -0.056***	(15.97) -0.050***	-0.049***	(9.05) -0.116***	(9.10) -0.122***	(9.24) -0.101***
$ \begin{array}{c} (4.3.1) + (-3.8.1) + (-1.8.3) + (-1.8.4) + (-1.$	Germany	(4.25) 0.077^{***}	(4.94) 0.083^{***}	(4.81) 0.082^{***}	(5.82) -0.041*	(0.17) -0.041*	(0.13) -0.032
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Greece	(4.57) -0.042**	(5.87) -0.035**	(5.78) -0.036**	(1.84) -0.104***	(1.84) - 0.105^{***}	(1.43) -0.114***
	Iceland	(2.14) 0.449^{***}	(2.30) 0.453^{***}	(2.36) 0.453^{***}	(3.79) 0.490^{***}	(3.85) 0.491^{***}	(4.24) 0.499^{***}
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Ireland	(0.30) -0.002 (0.05)	-0.023	(0.00) -0.022 (0.00)	(9.87) -0.081***	(9.85) -0.081***	(10.05) -0.066^{***}
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	Italy	0.187***	(0.89) 0.194^{***}	(0.90) 0.195^{***}	(3.44) (0.083^{***})	(3.44) (0.082^{***})	(2.82) 0.088^{***}
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	Luxembourg	-0.013	(12.57) -0.010	(12.75) -0.009	(3.78) -0.062**	(3.75) -0.062**	(4.01) -0.013
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Netherlands	(0.74) 0.011	(0.65) 0.015	(0.58) 0.015	(2.22) 0.001	(2.25) 0.001	(0.47) -0.000
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Norway	(0.72) 0.039^{**}	(1.17) 0.044^{***}	(1.19) 0.044^{***}	(0.02) 0.037	(0.04) 0.037	(0.02) 0.040
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Portugal	(2.45) 0.037	(3.33) 0.050**	(3.36) 0.051^{**}	(1.38) - 0.067^{**}	(1.37) -0.069***	(1.49) -0.067***
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Sweden	(1.55) -0.040***	(2.22) - 0.036^{***}	(2.26) - 0.036^{***}	(2.60) - 0.107^{***}	(2.68) - 0.107^{***}	(2.61) - 0.088^{***}
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Switzerland	(2.76) -0.011	(3.12) -0.004	(3.05) -0.004	(4.71) - 0.102^{***}	(4.74) - 0.103^{***}	(3.78) -0.064***
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	United Kingdom	(0.75) -0.017	(0.33) -0.015	(0.36) -0.015	(4.53) -0.106***	(4.59) -0.106***	(2.86) -0.109***
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Health	(0.97) (0.114^{***})	(1.08) (0.112^{***})	(1.01)	(2.98)	(2.99)	(3.06)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Government	(16.51) $(0.022)^{***}$	(17.02) 0.022^{***}				
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Infrastructure	(2.61) 0.057^{***}	(2.74) 0.054^{***}				
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Business, finance and services	(10.59) -0.043***	(10.67) -0.043***				
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Agriculture	(5.48) (0.151^{***})	(5.53) 0.148^{***}				
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Industry	(14.42) -0.002	$(14.51) \\ 0.000$				
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Food and commodity assistance	(0.17) -0.021*	(0.01) -0.008				
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Emergencies	(1.66) 0.026^{**}	(0.64) 0.034^{***}				
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Other	(2.24) 0.056^{***}	(3.44) 0.054^{***}				
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Equity Investment	(6.11) -0.135***	(6.57) -0.138***	-0.140***	-0.140***	-0.144***	-0.127***
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	ODA Loans	(4.56) 0.054^{**}	(4.52) 0.050^*	(4.54) 0.051^*	(4.49) 0.054^{**}	(4.09) -0.022	$(3.64) \\ 0.001$
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Other Official Flows (non Export Credit)	(1.99) -0.197***	(1.87) -0.183***	(1.93) -0.172***	(2.08) -0.177***	(0.77) -0.149**	(0.04) -0.134*
Recipient FE Recipient-Year FEYesYesYesYesYesSector-year FE Donor-sector Interactions Donor-flow interactionYesYesYesYesYesDonor-sector Interactions Donor-flow interaction1,049,0511,048,9051,048,9051,048,9051,048,9051,048,905	All text columns filled-in	(5.50)	(5.17)	(4.88)	(5.21)	(1.99)	$(1.80) \\ 0.120^{***} \\ (19.27)$
Accupient real r EresresresresresresSector-year FEYesYesYesYesDonor-sector InteractionsYesYesYesYesDonor-flow interaction1,049,0511,048,9051,048,9051,048,9051,048,905Observations1,049,0511,048,9051,048,9051,048,9051,048,9051,048,905	Recipient FE Recipient Year FE	Yes	Vec	Vec	Voc	Vec	Vcc
Donor-flow interaction Yes Yes Observations 1,049,051 1,048,905 1,048,905 1,048,905 1,048,905 1,048,905	Sector-year FE Donor-sector Interactions		168	Yes	Yes	Yes	Yes
	Donor-flow interaction Observations	1,049,051	1,048,905	1,048,905	1,048,905	Yes 1,048,905	Yes 1,048,905

Table B.4 – Factors Correlated with Geocoded Projects

Note: The dependent variable is a binary indicator that is one if a project is geocoded and zero otherwise, using project-year level data. Regressions include year and country fixed effects as well as continent-specific time trends. Reference categories: Donor=U.S.; Sector=Education; Flow: ODA Grants. Reporting quality refers to the reporting of project title, short description, and long description that we used for the geo-coding process. We chose the most frequent category as reference category. Fixed effects included as indicated in the table. Standard errors clustered at the country level.

Based on these observations, it is important to discuss the extent to which differences in project characteristics between GODAD and CRS data could bias our results regarding the birth regions of spouses and leaders. We have no reason to believe that a region's status as birth region would affect the likelihood with which donor officials will include more precise geographic information in the project description or title. It seems unlikely that the project location is more likely to be reported in the project title or its description when the project is located in the birth region of the current leader or spouse. However, if such a bias were to exist, projects located in those regions would be more likely to be geocoded and thus over-represented among the GODAD projects. We could then falsely conclude that more aid is distributed to the birth regions of leaders or spouses during their time in office, while instead, the increase in aid might be driven by the over-representation of projects in those regions in our dataset.

First of all, it is reassuring that the results in Table B.4 show no evidence for a difference in project size between GODAD and CRS data on average. Second, with the inclusion of region and country-year fixed effects in all our regressions we account for differences in several project characteristics that influence the likelihood of a project to be geocoded. While country-year fixed effects absorb improvements of reporting quality over time and changes in the donor-recipient composition, region fixed effects account for the average propensity of projects to be geocodable per region that might be related to the number of projects received, their sector, or difficulty of location names, among others.

Lastly, we can test whether a larger number of projects is geocoded during times of heightened political scrutiny compared to other times. If this were the case, our estimated positive effect of *Spouseregion* on aid might be spurious. Ideally, we would want to observe the share of geocoded projects at the regional level and compare those of spouses' birth regions during their "tenure" relative to other times. However, we are, by definition, unable to observe the number of non-geocodable projects at such a granular geographical level. To address this limitation, we aggregate the data to a country-year panel and analyze whether the share of geocoded projects varies relative to the year of election or—independent of how leaders assumed office—relative to the year the leader or spouse "takes office." Arguably, political scrutiny is most intense during election years. If the share of geocoded projects were to increase in election years, this would cast doubts about the causal interpretation of the findings related to leader and spousal birth regions above.

Table B.5 presents the results. In column 1, we regress an indicator variable identifying the years of legislative elections and several lags and leads on the share of geocoded projects. In column 2, we consider executive elections. Columns 3 and 4 shift the analysis by replacing the year of election with the year in which a leader or spouse enters office, regardless of whether their assumption of office resulted from an election. All regressions include country and year fixed effects and control for continent-specific time trends.

According to our results, the share of geocoded projects is, if anything, lower rather than higher in election years (although the corresponding coefficients are imprecisely estimated). Similarly, the share is also lower, rather than higher, in the year when the tenure of leaders or their spouses begins (and weakly statistically significant). Potentially, administrations are more occupied with other duties than the exact reporting of aid projects at election time or violence related to taking office exacerbates the gathering of information. Either way, there is no evidence that geocoded projects are more likely to be "found" in our data at times of heightened political scrutiny. While we cannot directly test whether the same is true in spouse regions, this finding suggests that the positive effects on aid we report above rather represent a lower bound. What is more, recall that we do not find differences in the average project size between the CRS database and GODAD. Given that large (geocodable) projects are likely to receive scrutiny at any time, and small projects might be more likely to be scrutinized at times of political salience, it seems unlikely that our results can be explained by a larger share of geocoded projects rather than an increase in the number of projects.

Table B.5 – Share of Geocoded Projects Relative to the Timing of Elections and Inauguration

Dependent: Share of geocoded projects	Legislative election	Executive election	Leader taking office	Spouse taking office
	(1)	(2)	(3)	(4)
5 years before	0.005	-0.001	0.001	0.008*
4 years before	(1.16) 0.004 (2.52)	(0.23) -0.001	(0.20) -0.001	(1.81) 0.003
3 years before	(0.59)	(0.14)	(0.19)	(0.62)
	0.005	0.005	-0.006	-0.005
2 years before	(0.62)	(0.49)	(1.07)	(0.88)
	-0.001	0.003	-0.003	-0.000
1 year before	(0.07)	(0.22)	(0.51)	(0.01)
	-0.007	0.000	-0.005	-0.006
Year of election/office start	(0.78)	(0.03)	(0.96)	(1.18)
	-0.010	-0.003	-0.008*	-0.010*
1 year after	(1.18)	(0.25)	(1.76)	(1.88)
	-0.012	-0.002	-0.002	-0.001
2 year after	(1.55)	(0.19)	(0.32)	(0.09)
	-0.014**	-0.010	-0.004	-0.006
3 year after	(2.04)	(1.08)	(0.70)	(1.40)
	-0.012**	-0.011	-0.005	-0.005
4 year after	(2.05) -0.004	(1.49) -0.012*	$(0.99) \\ -0.000$	(1.22) -0.002
5 year after	(0.73)	(1.86)	(0.04)	(0.43)
	-0.005	-0.009*	0.002	-0.000
	(1, 20)	(1.83)	(0.36)	(0.07)
Country FE	Yes	Yes	Yes	Yes
Continent time trend	Yes	Yes	Yes	Yes
	2 286	2 286	2.321	2 321
R^2	0.744	0.743	0.742	0.742

Note: The dependent variable is the share of geocoded projects in all projects in a country-year panel. Regressions include year and country fixed effects as well as continent-specific time trends. Standard errors are clustered at the country level. t-statistics in parentheses; * p < 0.10, ** p < 0.05, *** p < 0.01.

B.5 Comparison with existing geocoded data

GODAD represents a significant milestone as the first comprehensive cross-country compilation of geocoded aid data, spanning across 184 recipient countries and 21 donors.

To highlight the value added of our dataset compared to existing sources, we provide an illustrative example by comparing our data to Uganda's Aid Management Platform. We use AidData's Uganda AIMS Geocoded Research Release (AidData 2016), which includes more than US\$12 billion in aid commitments for 565 geocoded projects during the 1978–2014 period.⁷² Among the geocoded projects, 120 pertain to budget support and are not included in the following statistics.⁷³ Considering the donors we include in the GODAD, the Uganda AIMS geocoded dataset comprises 224 projects. We show this number in column 1 of Table B.6, where the additional rows report project numbers for individual donors. Column 2 shows the number of AIMS projects that can be merged to the CRS raw data and, for comparison, column 3 reports the number of projects in the CRS. Not all projects included in AIMS can be merged to CRS projects.⁷⁴ In total, for the Western bilateral donors in the CRS sample, AIMS includes 197 projects, 144 of which are also included in the CRS.⁷⁵

Column 4 shows data from the GODAD. As can be seen, when compared to AIMS, the GODAD contains a substantially larger number of aid projects in Uganda (5,970 in total). When we restrict the sample period to those years that are covered in AIMS (in column 5), the GODAD still includes 3,777 projects, compared to the 224 projects (197 from Western donors plus 27 from China) included in AIMS (and 21,257 projects in the CRS, see column 6.). By definition, all (Western bilateral) GODAD projects are also included in the CRS, exceeding the number of projects reported in AIMS by an order of magnitude. Overall, the GODAD thus improves substantially on previously available data, even for the few recipient countries where such data exist at all.

References

- AidData (2016). Uganda AIMS Geocoded Research Release Level 1 v1.4.1. Williamsburg, VA and Washington, DC: AidData.
- Blair, R. A., R. Marty, and P. Roessler (2022). Foreign Aid and Soft Power: Great Power Competition in Africa in the Early Twenty-first Century. British Journal of Political Science 52(3), 1355–1376.
- Briggs, R. C. (2019). Receiving Foreign Aid Can Reduce Support for Incumbent Presidents. Political Research Quarterly 72(3), 610–622.

⁷²We focus on Uganda because these data have been used in a number of research articles (e.g., Briggs 2019, Blair et al. 2022) and are among the most comprehensive single-recipient datasets.

⁷³AIMS codes 113 of these projects at the country level (i.e., their designated location is "Uganda") so that they cannot be used for within-country analyses.

⁷⁴The two datasets lack uniform project identifiers and may exhibit disparities in project titles attributable to the use of acronyms or different syntax. Consequently, we identified projects that appear in both datasets through keyword analysis within project titles and descriptions, start and end dates, as well as commitment volumes.

⁷⁵AIMS includes 26 projects that are supported by multiple contributors that therefore cannot be attributed to single donors. An example is the following combination of donors: Denmark, United Kingdom, Austria, Netherlands, Ireland, as well as Denmark, European Union, United Nations Development Programme, Sweden, Austria, Ireland, Belgium, and Norway.

	(1)	(2)	(3)	(4)	(5)	(6)
	AIMS	Merged	CDS	CODAD	GODAD	CRS
	Uganda	projects	UND	GODAD	(1978-2014)	(1978-2014)
Total	224	144	30988	5970	3777	21257
Austria	35	25	1493	416	266	927
Belgium	4	3	1079	223	138	786
Denmark	31	18	1105	116	91	888
Finland	-	-	469	156	87	262
France	-	-	625	88	26	376
Germany	5	3	2404	679	368	1625
Greece	-	-	40	1	1	34
Iceland	1	-	71	50	15	23
Ireland	17	14	3877	551	409	3051
Italy	-	-	1254	509	361	966
Luxembourg	-	-	85	2	2	31
Netherlands	-	-	1028	119	112	971
Norway	60	45	2450	328	281	1917
Portugal	-	-	2	-	-	-
Spain	1	-	381	150	103	267
Sweden	11	9	2449	248	138	1741
Switzerland	-	-	417	33	11	180
United Kingdom	12	10	1881	236	145	1188
United States	20	17	9878	799	319	6024
World Bank	-	-	-	1122	796	-
China	27	-	-	144	108	-

Table B.6 - Number of Projects by Donors, AIMS Uganda, CRS, GODAD

C Additional Tables and Figures



Figure C.1 – Effects of Leader Birth Regions on Aid, ADM2

Note: The figure displays the coefficients and 90% confidence intervals for *Leaderregion*, along with all *PreLeaderregion* and *PostLeaderregion* variables. The results are based on column 4 of Table 1 and columns 2, 4, 6, and 8 of Table 5.



Figure C.2 – Leader and Spouse Birth Region, ADM2, 1990–2020

Note: The maps indicate whether an ADM2 region has been a leader birth region (in purple), spouse birth region (in green), both (in yellow), or none (in white) over the 1990–2020 period.









Figure C.4 – World Bank aid by macro region, ADM2, 1990–2020





Figure C.5 – EU aid by macro region, ADM2, 1990–2020

 $\it Note:$ The maps indicate the amount of log aid of 18 European donors per ADM2 region over the 1990–2020 period.

Figure C.6 – US aid by macro region, ADM2, 1990–2020



 $\it Note:$ The maps indicate the amount of log US aid per ADM2 region over the 1990–2020 period.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ADM2	ADM2	с-у	с-у	HAC	HAC	DK	DK
PreSpouseregion $(t+2)$		-0.19		-0.19		-0.19		-0.19
		(0.48)		(0.49)		(0.49)		(0.41)
PreSpouseregion (t+1)		-0.11		-0.11		-0.11		-0.11
		(0.27)		(0.29)		(0.29)		(0.25)
PreSpouseregion (t)		0.30		0.30		0.30		0.30
		(0.78)		(0.85)		(0.82)		(0.62)
Spouseregion	0.63^{**}	0.68^{*}	0.63^{***}	0.68^{***}	0.63^{***}	0.68^{***}	0.63^{***}	0.68^{**}
	(2.10)	(1.94)	(3.87)	(3.75)	(2.95)	(2.83)	(3.05)	(2.38)
PostSpouseregion $(t-1)$		0.88^{**}		0.88^{**}		0.88^{**}		0.88^{*}
		(1.99)		(2.18)		(2.17)		(1.82)
PostSpouseregion $(t-2)$		0.34		0.34		0.34		0.34
		(0.85)		(0.88)		(0.90)		(0.89)
Leaderregion	0.25	0.26	0.25^{**}	0.26	0.25	0.26	0.25	0.26
	(1.20)	(0.98)	(2.11)	(1.10)	(1.62)	(1.07)	(1.61)	(1.08)
Number of countries	110	110	110	110	110	110	110	110
Number of regions	29467	29467	29467	29467	29467	29467	29467	29467
Number of observations	721238	713053	721238	713053	721238	713053	721238	713053
Prob > F Spouse		0.03		0.02		0.02		0.00
Prob > F Leader		0.09		0.08		0.09		0.15
R squared (within)	0.0006	0.0006	0.0006	0.0006	0.0006	0.0006	0.0006	0.0006

Table C.1 – Birth Regions and Total Aid with Clustering Options, 1995–2020

Note: The dependent variable is Aid, i.e., the logarithm of aid (plus 1) given to region i of country c in year t: ODA disbursements of 18 European donors, the United States, and the World Bank's IDA, as well as ODA commitments from China (which we set to zero for the years 1995–1999). Spouseregion and Leaderregion are lagged by one year. Prob > F Spouse/Leader tests whether the coefficients of Spouseregion/Leaderregion are larger than those of PreSpouseregion_{t+1}/PreLeaderregion_{t+1}. Columns 2, 4, 6, and 8 control for PreLeaderregion_{t+2}, PreLeaderregion_{t+1}, PreLeaderregion_t, PostLeaderregion_{t-1}, and PostLeaderregion_{t-2}. Each specification includes Pop, i.e., the logarithm of a region's population size. Columns 1–2 include country fixed effects. Columns 3–10 include country-year fixed effects. Standard errors are clustered as indicated in the column header: at the ADM2 level, at the country-year level, using heteroskedasticity-consistent (HAC) estimators, and employing Driscoll-Kraay (DK) corrections.

	(1)	(2)	(3)	(4)	(5)	(6)
	Econ	Econ	Social	Social	Prod	Prod
PreSpouseregion $(t+2)$		-0.20		0.04		-0.29
		(0.50)		(0.10)		(0.83)
PreSpouseregion (t+1)		0.03		0.02		-0.25
		(0.07)		(0.05)		(0.65)
PreSpouseregion (t)		0.06		0.09		-0.02
		(0.13)		(0.26)		(0.06)
Spouseregion	0.58	0.65	0.59^{*}	0.67^{*}	0.24	0.22
	(1.54)	(1.50)	(1.84)	(1.77)	(0.83)	(0.66)
PostSpouseregion $(t-1)$. ,	0.85^{*}	. ,	0.83^{*}	. ,	-0.14
		(1.69)		(1.78)		(0.35)
PostSpouseregion $(t-2)$		0.52		0.78**		0.38
, ,		(1.10)		(1.99)		(0.93)
Leaderregion	0.07	-0.10	0.20	0.31	0.29	0.32
	(0.33)	(0.37)	(0.96)	(1.15)	(1.38)	(1.07)
Number of countries	110	110	110	110	110	110
Number of regions	29467	29467	29467	29467	29467	29467
Number of observations	717858	709673	717858	709673	717858	709673
Prob > F Spouse		0.06		0.06		0.13
Prob > F Leader		0.46		0.01		0.28
R squared (within)	0.0002	0.0003	0.0005	0.0006	0.0001	0.0001

Table C.2 – Birth Regions and Aid by Sector, 1995–2020

Note: The dependent variable is Aid in a particular sector, i.e., the logarithm of aid (plus 1) given to region i of country c in year t: ODA disbursements of 18 European donors, the United States, and the World Bank's IDA, as well as ODA commitments from China (which we set to zero for the years 1995–1999). Our sectoral definitions follow the OECD-DAC: Social Infrastructure & Services includes Education, Health, Population Policy/Programs & Reproductive Health, Water Supply & Sanitation, Government & Civil Society, and Other Social Infrastructure & Services. Economic Infrastructure & Services includes Transport & Storage, Communications, Energy, Banking & Financial Services, and Business & Other Services. The Production Sector includes Agriculture, Forestry, Fishing, Industry, Mining, Construction, Trade Policies & Regulations, and Tourism. Spouseregion and Leaderregion are lagged by one year. Prob > F Spouse/Leader tests whether the coefficients of Spouseregion/Leaderregion are larger than those of $PreSpouseregion_{t+1}/PreLeaderregion_{t+1}$. Columns 2, 4, and 6 control for $PreLeaderregion_{t+2}$, $PreLeaderregion_{t+1}$, $PreLeaderregion_t$, $PostLeaderregion_{t-1}$, and $PostLeaderregion_{t-2}$. Each specification includes Pop, i.e., the logarithm of a region's population size. All regressions include ADM2 fixed effects and country-year fixed effects. Standard errors are clustered at the country level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
INTER:		PRS	Subn. Corr	Grand	Democ	Control	Educ	Leaderregion	Reelection
Spouseregion	1.14**	1.52	1.78	3.37**	-0.19	0.70**	-0.44	0.71**	1.06^{***}
	(2.02)	(0.63)	(0.95)	(2.39)	(0.27)	(2.17)	(0.31)	(2.32)	(2.76)
Leaderregion	0.24	1.42	0.74	2.27^{*}	0.67	0.22	0.31	0.28	-0.20
	(0.77)	(1.12)	(0.79)	(1.93)	(1.08)	(1.01)	(0.34)	(1.22)	(0.51)
Spouse region \times Africa	-0.75								
	(0.97)								
Spouse region \times Asia	-0.52								
	(0.68)								
Spouse region \times Europe	-1.41								
	(1.06)								
Spouse region \times INTER		-0.01	-0.02	-0.07**	1.68	-0.20	0.09	-0.34	-0.47
		(0.36)	(0.61)	(2.18)	(1.24)	(0.69)	(0.39)	(0.50)	(1.14)
Leader region \times INTER		-0.02	-0.01	-0.05*	-0.87	0.07	0.01		0.39
		(0.99)	(0.61)	(1.79)	(0.79)	(0.42)	(0.09)		(0.99)
Number of countries	110	88	104	74	110	110	70	110	104
Number of regions	29467	27463	28851	24116	29467	29467	21485	29467	28891
Number of observations	717858	671167	705258	135367	717858	717858	299755	717858	695375
R squared (within)	0.0006	0.0006	0.0006	0.0007	0.0006	0.0006	0.0004	0.0006	0.0006

Table C.3 – Birth Regions and Total Aid, 1995–2020, Additional Interactions

Note: The dependent variable is Aid, i.e., the logarithm of aid (plus 1) given to region i of country c in year t: ODA disbursements of 18 European donors, IDA, and the U.S. and ODA commitments from China (which we set to zero for the years 1995-1999). Spouseregion and Leaderregion are lagged by one year. All regressions control for the logarithm of a region's population size. The omitted category in column 1 is the Americas; note that we also interact Leaderregion with the same continents. PRS is corruption, taken from the PRS Group's International Country Risk Guide, ICRG, and ranging from 0–6, with higher values indicating less corruption. Subn. Corr and Grand measure sub-national corruption, taken from Crombach and Smits (2024). Corruption is "the abuse of entrusted power for private gain," "grand" corruption is the "abuse of high-level power," both on a scale of 0–100, with higher values measuring less corruption. Democ measures to what extent the ideal of electoral democracy is achieved, on a score from 0–1. Control measures whether party control of the national government is unified, ranging from 0–2. These variables are taken from the Varieties of Democracy Project—higher values measure more democracy and unified control. Educ an indicator for higher education (see text for details). Leaderregion is a binary indicator for leader birth regions. Reelection is taken from Scartascini et al. (2021). It is a binary measure indicating whether or not the head of government is eligible for reelection. All regressions include ADM2 fixed effects, country-year fixed effects, and the logarithm of a region's population size. Interacted variables that vary at the ADM2 level are included in levels as well. Standard errors are clustered at the country level.

		Europe			USA			World Ba	nk		China	
	Light	Mortality	Corruption	Light	Mortality	Corruption	Light	Mortality	Corruption	Light	Mortality	Corruption
Spouseregion	0.111*	-7.335	-0.054	0.060	-4.224	-0.114	0.048	-13.463	-0.245	-0.006	-16.326	-0.304
	(1.83)	(0.54)	(0.25)	(1.15)	(0.41)	(0.82)	(0.85)	(0.67)	(1.63)	(0.08)	(0.79)	(1.65)
Leaderregion	0.191^{***}	-7.351	0.343^{***}	0.131^{***}	-7.119	0.296^{***}	0.051	-5.960	0.175	0.109^{*}	3.365	0.195^{*}
	(4.30)	(1.09)	(2.99)	(3.24)	(1.31)	(2.81)	(1.06)	(0.68)	(1.50)	(1.96)	(0.61)	(1.70)
Aid	-0.003***	0.073^{***}	0.001	-0.007***	0.027	0.001	0.000	0.058^{**}	0.002	-0.008***	0.188^{*}	0.000
	(4.25)	(2.87)	(0.69)	(5.81)	(0.48)	(0.31)	(0.18)	(2.09)	(0.93)	(3.45)	(1.68)	(0.08)
Spouse region \times Aid	-0.010***	0.540	-0.009	-0.016***	0.887^{*}	-0.014	-0.007**	0.534	0.003	-0.010	-0.141	0.019^{**}
	(2.90)	(1.28)	(1.23)	(2.63)	(1.78)	(1.52)	(2.12)	(1.09)	(0.44)	(1.54)	(0.26)	(2.06)
Leader region \times Aid	-0.009***	0.064	-0.008*	-0.012**	0.287^{*}	-0.014***	0.000	-0.004	0.003	-0.006	-0.154	-0.005
	(3.45)	(0.30)	(1.75)	(2.59)	(1.86)	(2.66)	(0.14)	(0.02)	(0.79)	(1.23)	(0.43)	(0.73)
First year	1992	1995	1995	1992	1995	1995	1998	1998	1998	2003	2003	2003
Last year	2020	2017	2020	2020	2017	2020	2020	2017	2020	2020	2017	2020
Number of countries	110	57	104	110	57	104	110	56	104	110	55	104
Number of regions	29467	5692	28851	29467	5692	28851	29467	5660	28851	29467	4931	28851
Number of observations	788771	85359	702430	788771	85359	702430	633939	70400	622787	496701	44190	487699
R squared (within)	0.0043	0.0001	0.0002	0.0050	0.0001	0.0003	0.0022	0.0001	0.0007	0.0038	0.0001	0.0012

Table C.4 – Birth Regions and Development by Donor Group, ADM2

Note: The dependent variable in columns "Light" is log(lights), defined as the log of mean nightlight emissions in region *i* of country *c* in year *t* (+0.01). Columns "Mortality" use *infant mortality*—the rate of infants dying before reaching one year of age, per 1,000 live births, columns "Corruption" use the absence of corruption, defined as "the abuse of entrusted power for private gain" (Crombach and Smits 2024), with higher values representing less corruption, on a 0–100 scale. Aid is the logarithm of aid (plus 1): ODA disbursements of 18 European donors ("Europe"), the USA, IDA ("World Bank"), and ODA commitments from China ("China"). Spouseregion and Leaderregion are lagged by one year. All regressions include ADM2 fixed effects, country-year fixed effects, and the logarithm of a region's population size. Standard errors are clustered at the country level. t-statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	AUT	BEL	DEN	FIN	FRA	GER	GRE	ICE	IRE	ITA	LUX	NED	NOR	POR	ESP	SWE	CHE	UK
PreSpouseregion $(t+2)$	-0.005	0.036	0.013	0.280	0.285	-0.541	0.041	-0.015	0.044	-0.087	-0.072	-0.135	0.025	-0.072	-0.056	-0.033	-0.367**	-0.599**
	(0.02)	(0.12)	(0.08)	(1.22)	(0.94)	(1.54)	(0.60)	(1.25)	(0.30)	(0.32)	(0.37)	(0.87)	(0.09)	(1.02)	(0.25)	(0.17)	(2.06)	(2.51)
PreSpouseregion (t+1)	-0.033	-0.197	0.033	0.309	0.033	-0.755**	-0.068*	-0.046**	-0.128	0.093	0.061	-0.196	0.109	-0.075	-0.075	-0.069	-0.324	0.049
	(0.17)	(0.82)	(0.22)	(1.49)	(0.11)	(2.16)	(1.87)	(2.31)	(1.28)	(0.30)	(0.28)	(1.35)	(0.40)	(1.09)	(0.27)	(0.28)	(1.39)	(0.23)
PreSpouseregion (t)	-0.062	0.284	0.039	0.659^{***}	0.301	-0.169	-0.092^{*}	0.136	-0.054	0.478	-0.019	-0.099	0.015	0.029	0.099	0.120	-0.033	-0.316
	(0.36)	(1.24)	(0.28)	(2.72)	(0.95)	(0.52)	(1.71)	(1.24)	(0.45)	(1.34)	(0.09)	(0.66)	(0.05)	(0.33)	(0.32)	(0.54)	(0.14)	(1.42)
Spouseregion	0.189	0.047	0.074	0.209	0.157	0.577^{*}	-0.004	0.032	0.155^{*}	0.109	0.166	0.081	0.181	0.009	0.522^{**}	-0.162	0.180	0.260
	(1.27)	(0.25)	(0.62)	(1.15)	(0.77)	(1.72)	(0.11)	(1.37)	(1.68)	(0.44)	(0.92)	(0.57)	(0.85)	(0.21)	(2.29)	(1.03)	(1.02)	(1.29)
PostSpouseregion $(t-1)$	0.079	-0.256	0.207	-0.012	0.009	0.191	-0.080*	0.069	-0.020	-0.179	-0.102	-0.148	0.158	0.057	0.136	0.108	0.217	0.033
	(0.38)	(1.10)	(1.07)	(0.04)	(0.03)	(0.36)	(1.74)	(0.78)	(0.19)	(0.52)	(0.56)	(0.72)	(0.55)	(0.58)	(0.52)	(0.42)	(0.61)	(0.14)
PostSpouseregion $(t-2)$	-0.127	-0.134	0.076	-0.010	0.261	0.554	-0.098	0.098	-0.060	-0.002	-0.108	-0.189	0.131	-0.005	0.810^{***}	0.033	0.145	0.433^{*}
	(0.64)	(0.55)	(0.53)	(0.04)	(0.86)	(1.31)	(1.51)	(0.97)	(0.55)	(0.01)	(0.64)	(0.95)	(0.43)	(0.07)	(2.75)	(0.12)	(0.49)	(1.66)
Leaderregion	0.161	0.002	-0.019	-0.072	0.002	-0.149	-0.070	-0.031*	-0.037	-0.301**	-0.152	0.063	0.076	0.140^{*}	0.129	0.321^{**}	0.003	0.256^{*}
	(1.21)	(0.01)	(0.21)	(0.51)	(0.01)	(0.75)	(1.15)	(1.85)	(0.89)	(2.07)	(1.53)	(0.62)	(0.42)	(1.84)	(0.78)	(2.06)	(0.02)	(1.76)
Number of countries	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110
Number of regions	29467	29467	29467	29467	29467	29467	29467	29467	29467	29467	29467	29467	29467	29467	29467	29467	29467	29467
Number of observations	834787	834787	834787	834787	834787	834787	834787	834787	834787	834787	834787	834787	834787	834787	834787	834787	834787	834787
Prob > F Spouse	0.15	0.12	0.39	0.32	0.27	0.00	0.09	0.02	0.01	0.48	0.30	0.07	0.40	0.11	0.04	0.35	0.04	0.20
Prob > F Leader	0.25	0.07	0.33	0.43	0.43	0.31	0.14	0.04	0.11	0.04	0.24	0.33	0.36	0.18	0.29	0.10	0.43	0.19
R squared (within)	0.0002	0.0003	0.0003	0.0003	0.0002	0.0007	0.0002	0.0002	0.0002	0.0004	0.0004	0.0004	0.0004	0.0002	0.0005	0.0002	0.0004	0.0005

Table C.5 – Birth Regions and Aid by European Donor Country, ADM2, 1990–2020

Note: The dependent variable is the logarithm of ODA disbursements from one of 18 European donors (plus 1) given to region *i* of country *c* in year *t*: (1) Austria, (2) Belgium, (3) Denmark, (4) Finland, (5) France, (6) Germany, (7) Greece, (8) Ireland, (9) Iceland, (10) Italy, (11) Luxembourg, (12) Netherlands, (13) Norway, (14) Portugal, (15) Spain, (16) Sweden, (17) Switzerland, and (18) United Kingdom. Spouseregion and Leaderregion are lagged by one year. Prob > F Spouse/Leader tests whether the coefficients of Spouseregion/Leaderregion are larger than those of PreSpouseregion_{t+1}/PreLeaderregion_{t+1}. All regressions control for PreLeaderregion_{t+2}, PreLeaderregion_{t+1}, PreLeaderregion_t, PostLeaderregion_{t-1}, and PostLeaderregion_{t-2}. Each specification includes Pop, i.e., the logarithm of a region's population size, ADM2 fixed effects, and country-year fixed effects. Standard errors are clustered at the country level. t-statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01.

	(1) (2)		(3)	(4)	(5)	(6)	(7)	(8)
	Euro	pe	US	SA	World	Bank	Chin	ıa
	Commitm	Dummy	$\operatorname{Commitm}$	Dummy	$\operatorname{Commitm}$	Dummy	$\operatorname{Commitm}$	Dummy
PreSpouseregion $(t+2)$	-0.322	0.016	-0.741**	-0.074***	-0.126	0.016	0.732^{**}	0.037^{*}
	(0.72)	(0.46)	(2.02)	(2.76)	(0.41)	(0.61)	(2.02)	(1.69)
PreSpouseregion $(t+1)$	-0.353	-0.019	0.058	-0.002	-0.095	0.041	0.333	0.057^{**}
	(0.77)	(0.53)	(0.16)	(0.06)	(0.31)	(1.60)	(1.15)	(2.21)
PreSpouseregion (t)		0.023		0.014		0.024		
		(0.69)		(0.50)		(1.02)		
Spouseregion	0.480	0.055^{**}	0.391	0.062^{**}	0.115	0.027	-0.191	-0.018
	(1.54)	(2.10)	(1.14)	(2.06)	(0.57)	(1.24)	(1.14)	(1.37)
PostSpouseregion (t)	0.161		-0.114		0.898^{**}		0.277	0.035
	(0.39)		(0.30)		(2.19)		(0.89)	(1.23)
PostSpouseregion $(t-1)$	0.126	0.053	0.301	0.045	-0.170	0.045^{**}	-0.186	0.004
	(0.26)	(1.35)	(0.82)	(1.45)	(0.48)	(2.04)	(0.52)	(0.17)
PostSpouseregion $(t-2)$		0.040		0.037		0.033		
		(1.15)		(1.22)		(1.48)		
Leaderregion	0.136	0.013	-0.042	0.003	0.166	0.005	0.168	0.017^{**}
	(0.91)	(0.69)	(0.22)	(0.16)	(1.24)	(0.25)	(1.32)	(2.00)
First year	1990	1990	1990	1990	1995	1995	2000	2000
Last year	2020	2020	2020	2020	2020	2020	2020	2020
Number of countries	110	110	110	110	110	110	110	110
Number of regions	29467	29467	29467	29467	29467	29467	29467	29467
Number of observations	855774	834787	855774	834787	718813	709673	584428	584428
Prob > F Spouse	0.03	0.02	0.17	0.02	0.28	0.23	0.04	0.00
Prob > F Leader	0.40	0.26	0.17	0.39	0.44	0.24	0.02	0.02
R squared (within)	0.0005	0.0007	0.0005	0.0009	0.0001	0.0001	0.0005	0.0006

Table C.6 – Birth Regions and Aid, ADM2, Event Study, Alternative Definition of Aid

Note: The dependent variables are Aid, i.e., the logarithm of aid (plus 1) given to region i of country c in year t: ODA commitments, or a binary variable indicating at least one new project, of 18 European donors (columns 1–2), the United States (columns 3–4), the World Bank's IDA (columns 5–6), and China (columns 7–8). Spouseregion and Leaderregion are lagged by one year in column 2, 4, and 6, which are based on disbursements. Prob > F Spouse/Leader tests whether the coefficients of Spouseregion/Leaderregion are larger than those of $PreSpouseregion_{t+1}/PreLeaderregion_{t+1}$. Columns 2, 4, and 6 control for $PreLeaderregion_{t+2}$, $PreLeaderregion_{t+1}$, $PreLeaderregion_{t+2}$, $PreLeaderregion_{t+1}$, $PreLeaderregion_{t+2}$, $PreLeaderregion_{t+1}$, $PreLeaderregion_{t+2}$, $PreLeaderregion_{t+1}$, $PostLeaderregion_{t+2}$, and $PostLeaderregion_{t-2}$, all other regressions control for $PreLeaderregion_{t+2}$, $PreLeaderregion_{t+1}$, $PostLeaderregion_{t+2}$, $PostLeaderregion_{t-1}$, and $PostLeaderregion_{t-2}$, all other regressions control for $PreLeaderregion_{t+2}$, $PreLeaderregion_{t+1}$, $PostLeaderregion_{t+2}$, $PostLeaderregion_{t-1}$. Each specification includes Pop, i.e., the logarithm of a region's population size, ADM2 fixed effects, and country-year fixed effects. Standard errors are clustered at the country level.

D Dynamic Treatment Effects

A skeptical reader might be concerned that our fixed effects estimations rely on posttreatment information, potentially resulting in a biased estimate of our coefficient of interest. Recall however that our identification strategy does not require the inclusion of fixed effects for country-years and we have shown that their exclusion does not affect our results. Moreover, our strategy for identifying causal effects in part consists in comparing aid received while being the birth region of a spouse to the years just before, which should not be biased by the inclusion of regions treated at different points in time. Also note that our setting is unlike those typically discussed in the recent heterogeneous treatment effects literature.⁷⁶ Contrary to this literature, we do not estimate two-way fixed effects models with fixed effects for cross-sectional units and time, but rather include fixed effects for country-year in addition to those for ADM2 regions. Our treatment—birth region in most cases reverses over time, and our prior is that the effect of birth regions on aid quickly fades out once a region loses its status as spousal birth region (an expectation that finds support in our event-time specifications shown above). A number of regions are treated in the first year of our sample, so we have no prior information to compare with. What is more, regions might or might not have been treated before they are included in our sample, so "never treated" or "not yet treated" regions do not comprise adequate control groups. Most of the recently developed estimators such as those of Callaway and Sant'Anna (2021) or Wooldridge (2021) thus cannot directly be applied to our setting. What is more, when we estimate the weights attached to the two-way fixed effects regressions studied in De Chaisemartin and d'Haultfoeuille (2020), we find that the share of negative weights is low. Using De Chaisemartin et al.'s (2019) estimator we find that just 3 percent of the Average Treatment Effects on the Treated receive negative weights, and are thus unlikely to affect our results.

We nevertheless twist our model to better fit the assumptions of the recent two-way fixed effects literature. We drop those regions that are the birth region of a spouse in the first year of our estimation sample and estimate the modified model using Wooldridge's (2021) Extended Two-Way Fixed Effects Estimator, allowing for heterogeneous treatment effects in any year.⁷⁷ As before, we include the (lagged) binary leader birth region indicator and logged population as control variables for the outcome model but use fixed effects for years rather than country-years to estimate heterogeneous effects by time. We do not allow for treatment reversal, implying that all regions change their status once a spouse first originates from the region.

Figure D.1 shows the dynamic treatment effects of being a (lagged) spouse region

⁷⁶While the literature on heterogeneous treatment effects is voluminous and rapidly expanding, recent replication work has also shown that results of conventional two-way fixed effects estimators are rarely affected by accounting for potentially heterogeneous treatment (Chiu et al. 2023).

⁷⁷The estimator does this by including interactions between treatment-year cohorts and years.

Figure D.1 – Spouse Birth Regions and Total Aid, Extended Two-Way Fixed Effects



Note: The figure plots the Average Treatment Effect on the Treated (ATET) of (lagged) *Spouseregion* on total aid, using Wooldridge's (2021) Extended Two-Way Fixed Effects Estimator at the ADM2-level in the 1995–2020 period. We drop regions that are the birth region of a spouse in the year 1995 and estimate the modified model allowing for heterogeneous treatment effects in any year. The (lagged) binary leader birth region indicator and the logarithm of population size are included as control variables in concert with fixed effects for years and ADM2 regions. Not yet treated regions represent the control group.

on logged total aid disbursements, compared to regions that have not yet been treated. All coefficients are positive and considerably larger than that corresponding to the base estimate. One reason for this is the exclusion of country-year fixed effects, which leads to higher effect sizes (see columns 1 and 2 of Table 1). In addition, it seems that the omission of regions we exclude here to fit the model's requirements bias the coefficients upwards.

Figure D.2 shows results using the doubly robust augmented inverse probabilityweighted (AIPW) estimator. The AIPW estimator is robust to misspecification of the treatment or outcome models. While the ATET parameters of Figure D.1 are shown for each cohort at the time of treatment exposure and the years thereafter, they are not calculated for the years prior to treatment.⁷⁸ To the contrary, Figure D.2 shows treatment effects for the entire sample range, from 24 years before to 24 years after treatment. As can be seen, there are no significant effects prior to the treatment. Effects turn larger and significant at the one-percent level in t=3 and t=4, which are the fourth and fifths years after a region's status changed to *Spouseregion* (recall that we lag the *Spouseregion* indicator by one year). Coefficients then stay positive—but are estimated less precisely—except for lags exceeding t=21 which turn negative, but are estimated based on comparably few regions treated early in the sample period.

 $^{^{78}{\}rm This}$ is because parameters are identified based on the parallel-trends assumption (see Wooldridge 2021).

Figure D.2 – Spouse Birth Regions and Total Aid, Augmented Inverse Probability-weighted



Note: The figure plots the Average Treatment Effect on the Treated (ATET) of (lagged) *Spouseregion* on total aid, using the doubly robust augmented inverse probability-weighted (AIPW) estimator at the ADM2-level in the 1995–2020 period. We drop regions that are the birth region of a spouse in the year 1995 and estimate the modified model allowing for heterogeneous treatment effects in any year. The (lagged) binary leader birth region indicator and the logarithm of population size are included as control variables in the treatment and outcome models, in concert with fixed effects for years and ADM2 regions. Not yet treated regions represent the control group.

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