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Wedded to prosperity? Spousal favoritism in foreign aid and regional development

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Wedded to Prosperity? Spousal Favoritism in Foreign Aid and Regional Development

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Abstract

This paper examines the influence of political leaders' spouses on resource allocation and regional development. We construct two new global datasets: one tracking leaders' and spouses' characteristics and one that geocodes aid projects, including new data from the United States and 18 European donors. For 1990–2020, we find that Western bilateral donors direct significantly more aid to spouses' birth regions during their partners' tenure, while leader birth regions do not experience comparable favoritism, consistent with donors' efforts to avoid the appearance of political bias. Spousal favoritism is best explained by recipient-driven informal influence, particularly around elections, rather than systematic spouse selection, career preparation, settlement motives, or strategic donor behavior. Aid inflows to spouses' birth regions are less effective, turning favoritism into a liability for local development. Our findings suggest that even in closely monitored areas, such as foreign aid, political favoritism takes less visible channels, raising questions about accountability and effectiveness.

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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 of his association with the president’s wife was Herminio Disini, who was married to Imelda Marcos’s cousin. Disini obtained a virtual monopoly in his cigarette-filter business by taking advantage of a presidential decree that raised import tariffs for foreign competitors to 100 percent (Branigin 1984). Imelda Marcos held no elected office—yet, it seems she could exercise substantial influence over the allocation of resources.

Anecdotal evidence illustrating the influence of powerful politicians’ unelected spouses on the allocation of resources outside formal institutional channels abounds.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 study addresses this gap by analyzing the spouses of political leaders in a maximum of 123 countries over the 1990–2020 period. We focus on spousal birth regions to capture areas in which we expect spouses to take a particular interest. Specifically, we examine whether subnational regions that are the birthplaces of leaders’ spouses receive more foreign aid than they do at other times and how these regions develop after receiving such aid.

Western donors—those organized in the OECD’s Development Assistance Committee (DAC) and multilateral institutions with U.S.-dominated governance structures—exercise substantial efforts to avoid the misappropriation of their funds for reasons of recipient country politics. Western donors demonstrate greater interest in preventing the use of their aid for within-country political purposes than China (Blair et al. 2022). For example, World Bank Task Team Leaders seem to be aware that recipient governments seek to direct aid to presidential hometowns and actively try to prevent such allocation (Briggs 2021). In turn, while political leaders’ birth regions receive more aid from China, they do

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 the 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 Houssein 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).

not receive more aid from the World Bank (Dreher et al. 2019, Dolan and McDade 2020).² While Western donors seem to avoid the most blatant abuse of their aid for recipients’ domestic politics to some extent, it seems unlikely that they can entirely prevent such allocation (Bjørnskov 2010). To the extent that they successfully prevent aid from being targeted to the leaders’ birth regions, we expect part of the aid to target other places of direct interest to the leader, potentially as effective for domestic political purposes but less easily detectable by donors. Such targets may include the birth regions of other members of the governing elite (Francois et al. 2015) or other places of interest to them. We suggest that the birth region of leaders’ spouses is one such place. Leaders and their spouses can benefit from the aid allocated to these regions. Simultaneously, donors are less attuned to the influence of the spouses of political leaders. Unlike leaders, spouses do not typically hold formal office, and their influence on aid allocation may not be scrutinized. This reduced visibility could result in aid flowing to these regions, as donors may overlook such favoritism or deem it less politically sensitive.³

To the extent that political motives undermine the effectiveness of aid, rather than being put into 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 occur when donors carefully scrutinize their projects in regions with obvious political connections but apply less scrutiny when connections are harder to identify.

The importance of unelected spouses in policy outcomes and the lack of solid evidence have long been recognized. After leaving the White House, the 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) highlights, the influence of leaders’ spouses is even more difficult to measure than that of elected officials. However, ignoring such indirect influences excludes “what may well prove to be a highly significant” factor in answering the question of who governs (Dahl 1961, cited in O’Connor et al. 1996, 836). According to O’Connor et al. (1996, 849), “[t]he 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 through various channels. They are important advisors to their partner. For example, President Truman consulted his wife on whether to use the atomic bomb, fight in Korea, or the European Recovery Program after World War II (O’Connor et al. 1996). Observers often attribute more power to spouses than

²Dreher 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 (2025) 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.

³Spousal influence may even be advantageous for donors, as it allows them to interfere with the politics of recipient countries without attracting attention and opposition.

to elected vice presidents.⁴ They derive status from their marriage, have influence over their partner, and often control access to them (Van Wyk et al. 2018). This may make it difficult to decline requests.⁵ Often, spouses develop their own political agendas and patronage networks, allowing them to deliver spoils in exchange for support.⁶ Thus, it seems that the spouses of national leaders have the means to favor their birth regions.⁷

We expect the home regions of national leaders' spouses to attract additional resources for several reasons. First, spouses could cultivate political support for their partners, especially during election periods.⁸ To maximize voter turnout in their strongholds, political leaders strategically allocate resources to their birth regions (Hodler and Raschky 2014, 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 both instrumental and expressive reasons, highlighting how marriage serves as a signal of the likelihood of resource allocation to a particular region or as an end in itself. Their findings show that people who share their spouse's ethnicity express substantially greater support for the leader. Second, spouses might use their role to prepare for their future political campaigns (Gonnella-Platts and Fritz 2017). Well-known examples include Cristina Fernández de Kirchner (Argentina), Sonia Gandhi (India), and Hillary Clinton (United States). Again, to the extent that political support from birth regions is particularly strong, focusing resources there to maximize turnout at election time can be a successful 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

⁴As 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).

⁵As 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).

⁶As 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.

⁷Anecdotes 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, the Ntungamo District is Janet Museveni's birthplace. See <https://www.independent.co.ug/janet-thanks-museveni-for-building-roads-in-ntungamo/>, last accessed July 13, 2023.

⁸Following Mrs. Museveni's praise for her husband cited in footnote 7, she assured him of solid support from the region's voters in the upcoming elections.

(Dreher et al. 2019). Taken together, spouses have motive and opportunity.

Our panel data at the level of the second administrative (ADM2) divisions within a country enable us to test whether the home regions of leaders' spouses receive more aid during their partners' tenures than during other periods. We capture this with a binary variable that is equal to one when a region is the birthplace of the effective leader's spouse. The data allow us to control for ADM2 region and ADM1 region-year fixed effects. We also compare aid flows in years when a region attains *Spouseregion* status with the years immediately before, thereby disentangling shifts driven by time-varying factors that jointly influence aid and political relevance from the effect of *Spouseregion*. This approach builds on previous event studies in the aid allocation and effectiveness literatures (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. By additionally controlling for leader birth and ethnic regions, our design isolates the role of spouses, enabling us to test the effect of spousal influence on resource allocation and the conditions under which it arises.

Our findings demonstrate that regions containing the birthplaces of political leaders' spouses receive significantly more aid from the United States and European donors. We find no increase in aid to leaders' birth regions, and regions with populations that share the leader's ethnicity receive—if anything—less rather than more aid. These results suggest that Western donors attempt to avoid channeling their aid to regions where political motives are overt. 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 targeting as less politically motivated than Chinese aid allocation (Dreher et al. 2019), our findings challenge this view, highlighting that political considerations are simply more obscured rather than absent.

We examine five potential mechanisms: formal versus informal influence, preparation for a future political career, strategic marriage, electoral mobilization, and retirement plans. We also explore the importance of donor-related strategies. Tests of spousal characteristics show that formal political roles—before, during, or after tenure—do not systematically strengthen the spouse-region effect, while key positions in NGOs before or after leaders' tenure affect the extent of favoritism. This suggests that informal rather than formal spousal influence is key. This also suggests that spouses' (successful) preparation for their own future political careers is not the main driver of our findings. The data also suggest that strategic spouse selection is unlikely to drive our results. In contrast, electoral dynamics matter: aid to spouse regions increases before competitive elections, while aid to leader regions does not, consistent with leaders using the former as a less scrutinized channel for voter mobilization. We find no evidence that the effect is more pronounced in environments where the future settlement of the first couple in

the spouse's birth region is more likely. Finally, regarding donor-driven strategies, we find that countries that are more politically aligned with their donors channel more aid to leaders' birth regions prior to elections and when elections are more competitive, suggesting that donors provide friendly governments with more leeway or extend outright support. We further find that Western donors provide more aid to leaders' birth regions when they also receive substantial aid from China. We find no similar results for the birth regions of spouses, in line with our expectation that donors or their constituents do not recognize the political significance of such regions. Overall, the evidence suggests that allocation to spouse regions is driven more by recipient discretion—operating within the constraints set by donors—than by direct strategic behavior on the part of donors.

We test whether the observed politicization of aid has implications for regional development, as measured by nighttime light emissions. Our results show that regions tied to leaders or their spouses develop faster when politically salient, but these gains are undermined once aid flows in. Politically motivated aid is significantly less effective than other types of aid, and at high volumes, it can even reverse development gains, turning politically motivated allocations into liabilities for local development.

This paper contributes to three main strands of literature. The first investigates the influence of politicians' familial ties on political decision-making and outcomes. For example, studying the 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 studies on the role of elected leaders' spouses in the allocation of resources or developmental outcomes. While this question has received some attention, previous studies have been qualitative and selective in nature. 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 the wives of the ten longest-serving African presidents. These works point to the substantial influence of some of the first ladies they investigate, but, due to their qualitative nature, they remain 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. Owing to the growing availability of data at the subnational level, scholars have assessed the extent to which national 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 find 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 2025).

Several recent papers have focused on foreign aid as a specific form of favoritism. They find that the 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). However, spouses differ fundamentally from leaders, ministers, and other political appointees. Unlike these actors, they typically hold no formal office, and their influence over government resources is opaque and under-examined. Contrary to the existing literature, we shift the focus from formal political power to examine how unelected spouses leverage their influence to redirect resources. What is more, due to data availability, previous studies have 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, in 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). Previous studies have primarily focused 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 the influence of donors.

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 various 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 177 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 dataset of subnational 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 DAC 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 these 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 class of algorithms employs deep learning models to identify specific categories within a text, including geographic entities. We successfully geocode 217,440 projects, for which we identify 276,226 unique project-location pairs. The extracted entities undergo a series of data cleaning and cross-checking.⁹ 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 \(2024\)](#).¹⁰

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.¹¹ Our final sample provides granular information on 234,411 aid projects for 21 donors and 181 recipient countries. Importantly, we provide data on Western bilateral aid flows, which amount to almost US\$200 billion (in constant 2014 dollars) over the 1990–2020 period, which includes a wealth of details regarding lending arrangements and modalities.¹²

⁹Appendix B explains the evaluation of the NER model accuracy on our dataset, data cleaning, and how we deal with false positives and negatives.

¹⁰Appendix B.2.4 explains in detail how we integrated these data.

¹¹Raw data on Chinese aid projects are available from Custer et al. (2021) and Dreher et al. (2022a) for the period 2000–2021, for which Goodman et al. (2024) provide geocodes. We clean these raw data and merge them with our administrative regions. AidData (2017) provides geocoded data for a subset 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 1997–2020. We thank Christopher Kilby for sharing code that helps perform this task. Data on World Bank disbursements are from Kersting and Kilby (2021).

¹²The CRS provides data from 1973 onward. However, the share of missing information is substantially

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 spousal influence on the subnational allocation of funds. [Section 4](#) shows our main results for OECD DAC donors and compares them with the World Bank and China. This section also investigates the underlying mechanisms, the robustness of our findings, 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 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.¹³ 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 ([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 follow Archigos to identify political leaders until 2015 and complement their database for subsequent years by consulting online libraries and databases, such as the CIA World Factbook, Munzinger, Encyclopaedia Britannica, and Ethnicity of Celebs, as well as reports from popular news services. We describe the data collection process in detail in [Appendix A](#). Altogether, our database covers 1,088 political leaders with 1,240 terms in office from 177 countries over the 1989–2020 period.¹⁵

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

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.

¹³We were also considering coding where the leaders’ spouses have lived the longest or where they have the greatest number of acquaintances. However, collecting such detailed residential and network data for a substantial share of spouses in our sample proved prohibitively difficult, if not impossible.

¹⁴We make these data available to the public through our project website at <https://www.plad.me>. We currently include information on leaders only, covering the period 1989–2023, but will add spouse characteristics upon publication of this paper. We plan to update these data annually. A future version of PLAD will also include geocoded information on birth regions of cabinet members ([Asatryan et al. 2023](#)).

¹⁵Although we have collected data on political leaders up to 2023, we restrict our analysis to the 1989–2020 period, as we have only collected data on leaders’ spouses up to 2020 so far.

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.¹⁶ For polygamous marriages, we identified whether the spouse held the official or informal title of ‘first lady’ or ‘first gentleman’ or fulfilled representative functions.¹⁷ Table A.1 in Appendix A.2 lists all variables with their definitions and sources.

Our estimation sample contains information on spouses for 94% of the leaders in our database, totaling 575 spouses. Of these, 383 served as the spouse of a leader at some point during the leader’s tenure. On average, a spouse is ‘in power’ for 6.4 years. The median spouse holds at least a bachelor’s degree (or equivalent) and has three children with the 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.¹⁸ We aggregate the birth region information for administrative regions at the first (ADM1) and second (ADM2) subnational levels.¹⁹ Specifically, we geocoded the birth regions of 266 ‘spouses in office’ (69%) to the respective ADM1 regions. Figure 1 shows a world map of the ADM1 birth regions of political leaders and their spouses, highlighting significant spatial variation.²⁰ 222 spouses (58%) were geocodable to the more fine-grained ADM2 region level, leading to 1,025 ADM2 region-year observations that indicate their birthplaces.

We observe some overlap between the birth regions of leaders and their spouses. For 23.4% of the ADM2 region-year observations that contain the spouse birth regions, the leader also originates from that same ADM2 region. The raw correlation between the

¹⁶Leaders in our dataset have on average 1.1 spouses. The only monogamous leaders in our dataset that had more than four spouses are Michael Manley of Jamaica and Gerhard Schröder of Germany, both of whom had five spouses.

¹⁷For example, during Laurent Gbagbo’s presidency, Simone Ehivet officially held the title of First Lady of the Ivory Coast, whereas his second wife, Nady Bamba, whom he married while still officially married to Simone, did not. We therefore code Simone as the relevant spouse. By contrast, Jigme Singye Wangchuck’s four wives were all officially Queens of Bhutan and are therefore coded equally. When no spouse could be identified as holding an official title, we likewise treated all spouses equally. Results are unchanged when including all spouses from polygamous marriages, regardless of title, given the small number of such cases.

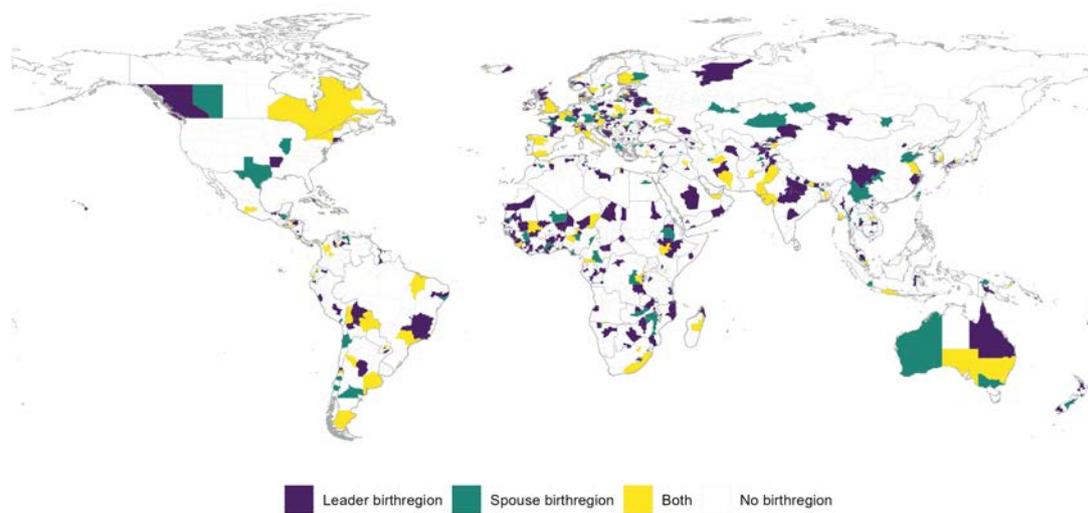
¹⁸See <http://www.geonames.org>. As a secondary source, we rely on Google Maps.

¹⁹Depending 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 districts. The Database of Global Administrative Areas (GADM) provides shapefiles with information on subnational administrative regions and their boundaries (Hijmans et al. 2018).

²⁰Figure D.1 in Appendix D 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 time. In Latin America, a comparatively small number of regions are coded as (exclusive) spousal birth regions, as many spouses are born in the same regions as leaders.

two variables is 0.15.²¹ Out of the 1,025 spousal-year observations in our sample, 240 are leader-year observations as well. Of the 106 distinct ADM2 regions that switch to being a spouse birth region at least once in our sample, 28% of the new spousal regions are the birth region of both the leader and their spouse, while their predecessors were born in two different regions. 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.

Figure 1 – Birth Regions of Political Leaders and Their Spouses, ADM1, 1990–2020



Notes: 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. On average (in the 1989–2020 period), an ADM2 region is coded as a spousal region in 0.16%—or 0.05 years. There is notable variation across continents: in Africa, an ADM2 region is coded as a spousal region in about 0.3% of all years, compared to 0.1% in the Americas. In our estimation sample, 133 ADM2 regions experience changes in their status as spousal birth regions, with some regions undergoing multiple changes. In total, there are 232 status switches. This is the variation we use in most of the empirical analyses below. The number of switches is lowest in Europe, with only 25 changes, and largest in Africa, with 76 changes.

²¹Similarly, 36.3% of ADM1 region-year observations are cases in which the spouse and the leader originate from the same ADM1 region, and the raw correlation is 0.2.

2.2 Geocoded Official Development Assistance Dataset (GODAD)

To analyze the subnational allocation of aid for a large set of donors, we build the *Geocoded Official Development Assistance Dataset (GODAD)*.²² It contains geographic information on Official Development Assistance (ODA) projects of 19 bilateral donors from the OECD’s Creditor Reporting System (CRS): 18 European member countries of the OECD’s DAC and the United States.²³ 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 match geocoded data on French aid projects provided by the *Agence Française de Développement (2024)*.²⁴ 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. 2021a, Goodman et al. 2024) for the 2000–2021 period and World Bank projects for the years 1995–2020 from AidData and IATI.²⁵ The resulting database allows researchers to address a broader set of questions, moving beyond a literature on subnational aid allocation and effectiveness that has so far been either limited to single-country analyses or to the few donors for which geocoded data were available—mainly China and the World Bank.

To geocode projects for European donors and the United States, we leverage the project titles and descriptions to identify geographic entities within the recipient country. This builds on an emerging empirical approach that uses text-as-data methods to extract economic information from administrative records. For example, Clayton et al. (2025) use language models on large text corpus to measure “gocioeconomic pressure,” identifying which governments apply pressure to which foreign targets with which instruments, firms, and products. Similarly, Juhász et al. (2025) show how off-the-shelf supervised machine learning tools can be used to categorize government industrial policies at scale. Previous work has also relied on the CRS’s project descriptions for georeferencing aid projects, but only for a small set of countries (Findley et al. 2011). To the best of our knowledge, we are the first to provide a systematic geocoding of the OECD project-level aid data. The OECD’s CRS data provide project-level information on OECD donors beginning in 1973. Given the time coverage of PLAD and other geocoded data, our empirical analysis uses

²²We make these data available to the public through our project website at <https://www.godad.me>.

²³The 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.

²⁴See Section B.2.4 in Appendix B for details.

²⁵We take data until 2014 from AidData (2017) and merge project-level data from IATI, available since 1997. Our publicly available dataset also includes geocoded data on Indian aid from Asmus-Bluhm et al. (2025). However, since the data are restricted to the 2007–2014 period, we exclude them from the empirical analysis below.

aid data for the 1990–2020 period only. Unless otherwise noted, all descriptive statistics reported below refer to this shorter sample period.

The raw CRS data contain financial information on commitments and disbursements (in US\$), classified either as ODA or OOF, 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 the ADM2 level, allowing us to study the subnational allocation and effects of aid. As described in detail in [Section B.2 of Appendix B](#), we apply the following procedure for the extraction 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 costs), general budget support, administrative costs, and debt relief. We then use CRS project titles and descriptions to extract candidate geographical entities. These are matched to known cities, regions, or administrative units within the recipient country. We run each project through a NER algorithm based on a (pre-trained) RoBERTa base transformer model for entity identification. This class of algorithms uses deep learning models to identify specific categories within a text, including geographic entities. Finally, we pass these extracted entities through the Google Maps geocoder API. Our geocoding pipeline returns subnational locational information for 217,440 projects.²⁶ From these, we identify 276,226 project-location pairs, as some projects are destined for more than one location.

In [Section B.5 of Appendix B](#), we investigate whether these geocoded projects are a representative sample of all aid projects. 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 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.²⁷

In [Section B.3.3 of Appendix B](#), 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

²⁶This corresponds to roughly 16% of the initial sample of CRS projects. Note that this does not mean that the model misses 84% of the geographical 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 geocoding.

²⁷In our empirical analysis below, we control for ADM2 region and ADM1 region-year fixed effects, which should mitigate compositional concerns. We also run separate regressions for individual donors that account for differences in the likelihood of projects being geocoded across countries.

geocoding). Missed information is limited, as the entity extraction model responsible for identifying candidate geographical locations has an accuracy of almost 90%.²⁸ Among erroneously 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.²⁹ In other cases, the location may be referring to a wider geographical area (“the Sahara Desert”), which provides no proper subnational information on the aid project.

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. First, the number of aid projects after geocoding is only a fraction of the raw CRS data. To a large extent, this is explained by the fact that most of the OECD DAC-reported aid is not earmarked for specific, *subnational* purposes. In terms of project size, very large loans and grants are typically large multi-regional or sector-wide approaches, which would not indicate a specific location of implementation. Hence, these cases drive many of the changes in the distribution of project sizes before and after geocoding. However, as shown in Figure B.3 in Appendix B, the sectoral distribution of commitments remains overall stable before and after geocoding.

A skeptical reader might note that the share of CRS-reported projects we could geocode appears rather low. This, however, reflects not only potential limitations of our geocoding approach but also the inherent difficulty of determining the set of projects that can be geocoded in the first place. We perform two benchmarking exercises. First, Section B.4 in Appendix B compares total disbursements by donor in our geocoded dataset with country-level ODA disbursement data reported by the OECD. Our geocoded data accounts for up to 20% of country-level disbursements in recent years, highlighting the subnational nature of our aid projects with respect to the numerous other aid activities in the CRS. Second, we benchmark GODAD against other existing geocoded aid data. Section B.6 in Appendix B compares our data to one of the most widely used aid datasets on a single country (Uganda), showing that the number of reported projects in GODAD compares favorably to those reported in the AIMS Geocoded Research Release (*AidData 2016*).³⁰ Specifically, AIMS covers 224 projects by the donors we consider in our sample, while GODAD includes 4,929 projects. Notably, AIMS reports no World Bank projects in Uganda, whereas we include 61 projects from the World Bank. Aside from the specific case of Uganda, GODAD has better subnational coverage of aid projects across all other 11 AIMS datasets we compare to (Table B.7). In sum, our dataset 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

²⁸See Section B.3.2 in Appendix B.

²⁹For example, the NGO “Moving to Freedom” can appear to the model as a locality named Freedom.

³⁰Examples for publications that use the Uganda data include Briggs (2018), Civelli et al. (2018), and Pickbourn et al. (2022).

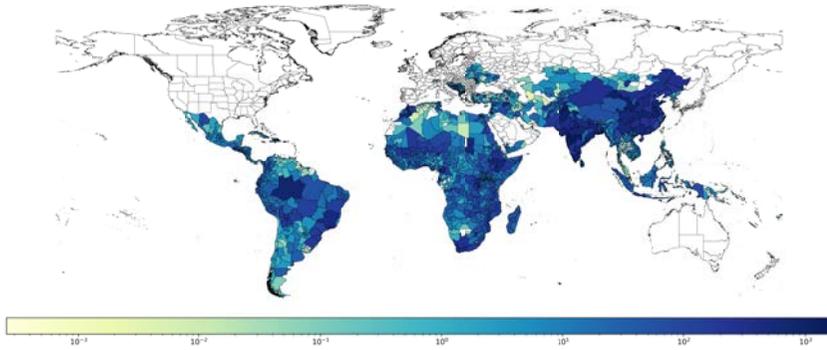
are available at all (see [Section B.6](#) for details).

As a final step, we merge our new data with the existing datasets described above. As shown in [Table B.2](#), to the 217,440 geocoded projects already included (180,780 from European bilateral donors and 36,660 from the United States), we add 5,695 projects from the World Bank and 7,724 from China. We then aggregate all projects to the first and second administrative regions of each aid recipient country, resulting in a panel with up to 97,569 (1,446,339) region-year observations at the ADM1 (ADM2) level. We include information on both commitments and disbursements of ODA- and OOF-classified projects. For better comparability across donors in our baseline analysis, we focus on ODA flows. [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.

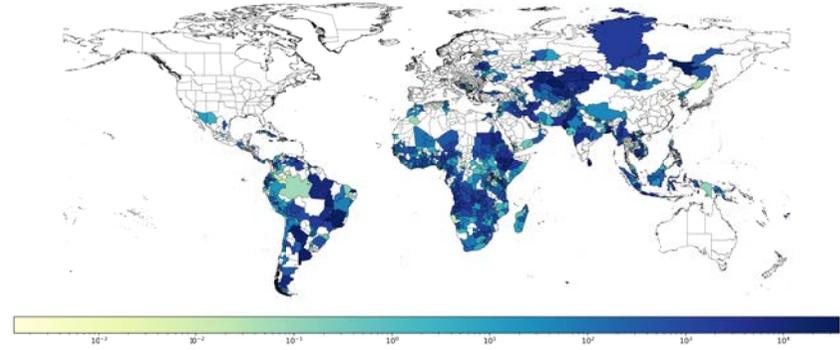
To illustrate the co-location of aid and birthplaces, we display four administrative maps of the DRC in [Figure 3](#), where each panel represents one of our four donor (groups) as indicated in the column header. The darker the region, the more aid it has received from the respective donor. The red markers 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 conforms to birth-region favoritism with respect to both the leader and spouse. Of course, the example presented here is purely suggestive and implies no causality. We next turn to the econometric analysis to analyze systematic patterns.

Figure 2 – Aid by ADM1 Region, 1990–2020

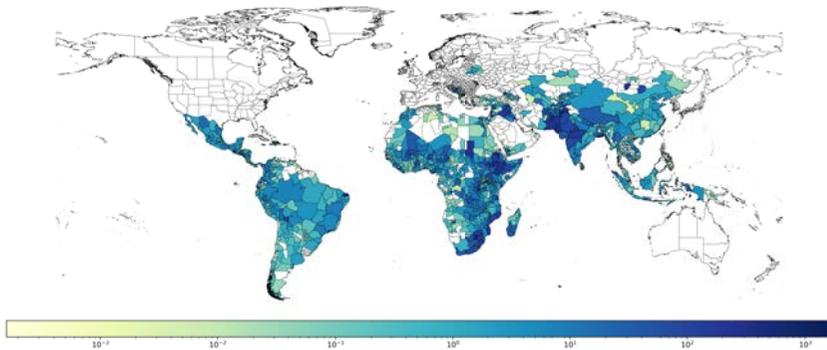
Panel A: European OECD DAC Bilateral Donors



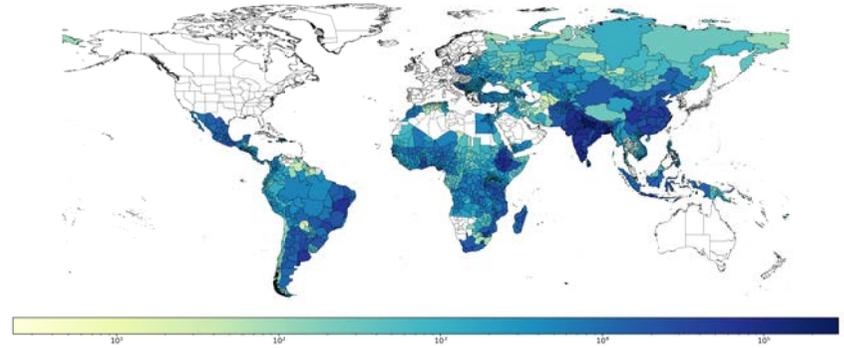
Panel C: China



Panel B: United States



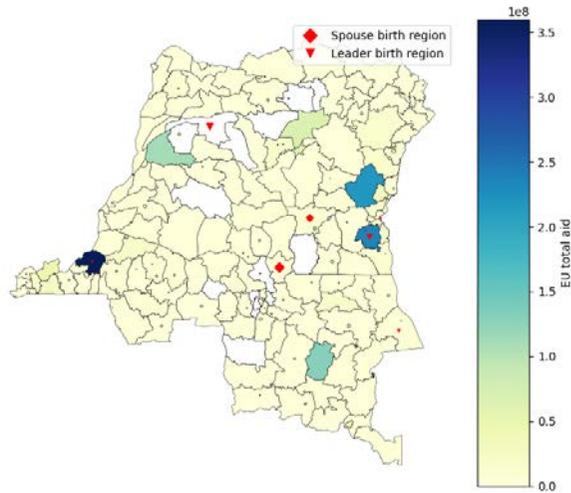
Panel D: World Bank



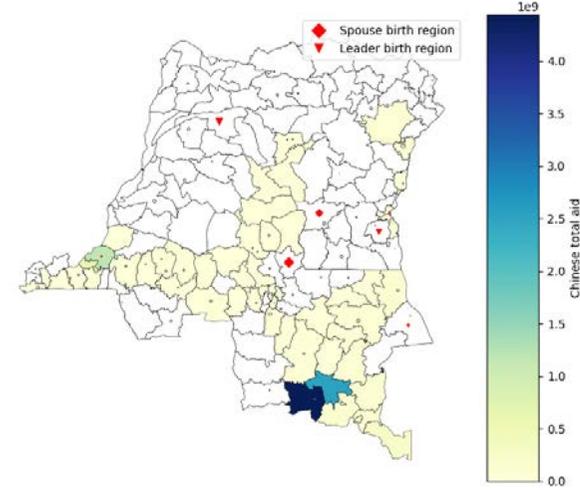
Notes: The world map displays for each ADM1 region the (log) amount of commitments in 2014 US\$ it has received over the 1990–2020 period on a color scale, with darker colors indicating larger aid receipts. The panel header indicates the donor (group). Note that data for China (the World Bank) are available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

Figure 3 – Aid by ADM2 Region, 1990–2020

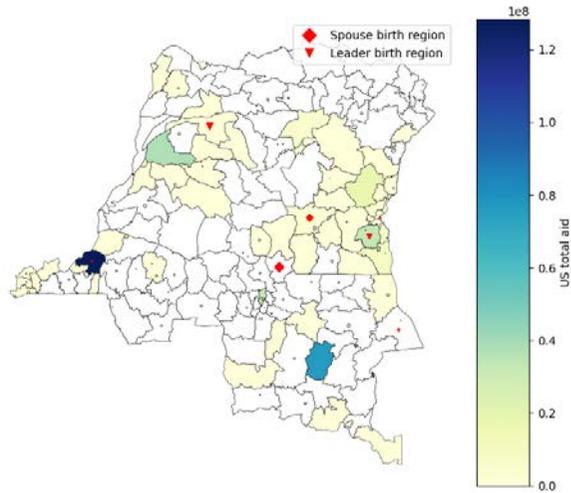
Panel A: European OECD DAC Bilateral Donors



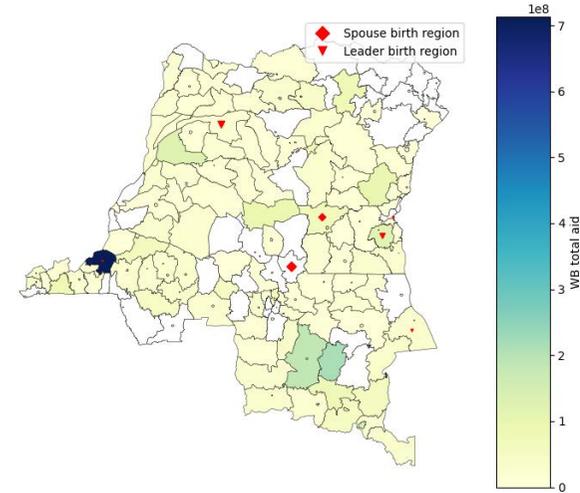
Panel C: China



Panel B: United States



Panel D: World Bank



Notes: The map illustrates the total amount of aid in each ADM2 region of the Democratic Republic of Congo (DRC) over the 1990–2020 period, measured in 2014 US\$ and represented on a color scale, with darker shades indicating higher aid amounts (disbursements for Western donors, commitments for China). 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 spousal influence on resource allocation, 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 received aid at least once during the sample period. Following standard practice in the literature (Hodler and Raschky 2014), we run our regressions at the level of ADM2 regions.³¹ We estimate the following equation with ordinary least squares:

$$Aid_{c,r,i,t} = \beta_1 Spouse_{region_{c,r,i,t-1}} + \beta_2 Leader_{region_{c,r,i,t-1}} + \beta_3 Leader_{region_{c,r,i,t-1}}^{ethnic} + \beta_4 Pop_{c,r,i,t} + \sigma_i + \tau_{r,t} + \varepsilon_{c,r,i,t}. \quad (1)$$

Our main dependent variable is $Aid_{c,r,i,t}$, which captures the logarithm of aid in constant 2014 US\$ given to ADM2 region i within ADM1 region r of country c in year t .³² We apply OECD definitions and thus analyze aid that qualifies as ODA, which is government aid aimed at promoting economic development and welfare in developing countries and provided on concessional terms. The main analysis focuses on gross aid disbursements from 18 European bilateral OECD DAC donors and the United States over the 1990–2020 period. We focus on disbursements rather than commitments as substantial parts of committed aid are never disbursed, and exerting political influence often consists in lobbying for the disbursement of committed funds or for existing projects to receive more funds than initially committed (Kilby 2013a).³³ We also show results for the World Bank and China for comparison. Data for the Bank’s International Development Association (IDA) and International Bank for Reconstruction and Development (IBRD) are available for the 1995–2020 period; data for China’s ODA and Other Official Flows (OOF) are available for the years 2000–2020.³⁴

We measure spousal influence at the subnational level using a binary variable $Spouse_{region_{c,r,i,t-1}}$ —referred to as $Spouse_{region}$ in the text and tables below—that

³¹The most appropriate level of geographic disaggregation is ultimately an empirical question. We therefore also present results at the ADM1 level in a robustness check. ADM3 shapefiles are unavailable for many countries, precluding consistent analysis at that level. What is more, our geocoding is insufficiently precise for analyses at the level of grid cells.

³²We 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 0. 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 the disbursement amounts to A and one third to B. In the case of China, the data provide outlines of project infrastructure instead of precise project locations. We therefore split the amounts across those regions that receive parts of the project.

³³We below test whether our results depend on this choice.

³⁴Note that data on Chinese aid *disbursements* are not available; therefore, we rely on commitment data throughout the analysis.

equals 1 if the spouse of the effective political leader of country c in year $t - 1$ is born in ADM2 region i within ADM1 region r . By lagging the *Spouseregion* indicator by one year, we ensure that leadership changes precede aid disbursements.³⁵ If 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 number of regions for which birth region information is available only in a limited number of years. 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.³⁶

Mirroring our definition of spouse birth regions, we code a binary variable $Leaderregion_{c,r,i,t-1}$ that takes a value of 1 if the effective political leader of country c in year $t - 1$ is born in ADM2 region i within ADM1 region r .³⁷ Given that leaders and their spouses are often born in the same region, this variable allows us to isolate the two effects.³⁸ To the extent that leaders and their spouses are born in the same place, this approach ensures that the influence we attribute to spouse regions is not instead capturing the effect of leader regions.

Finally, in some regressions, we further control for regions where the dominant ethnicity is the same as the ethnicity of the leader in power. We construct this variable using data from GeoEPR (Vogt et al. 2015) combined with the leader ethnicity data that we introduce in this paper, defining it as the ethnicity that has the largest geographical coverage in ADM2 region i at time t . Given the well-documented importance of leaders' ethnicity for the allocation of resources (Franck and Rainer 2012, De Luca et al. 2018), this is a potentially important control variable. If leaders and their spouses share the same ethnicity, failing to control for leader ethnicity may cause the *Spouseregion* coefficient to (partly) reflect the effect of co-ethnicity with the leader. Ideally, we would also want to examine whether aid allocation is influenced by the ethnicity of the spouse. However, we were unable to trace spouses' ethnicity for a substantial number of spouses in our dataset. Importantly, this limitation does not undermine our identification strategy: what we capture are effects related to spouses rather than leaders, even if part of the birth-region effect might instead be the effect of the spouses' ethnicity.

Our regressions control for the logarithm of a region i 's population size in year t

³⁵We acknowledge that parts of the funds disbursed likely result from commitments received by previous governments. To address this, we examine the timing between a region's political salience and aid disbursements in the robustness checks presented below.

³⁶For 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.

³⁷In 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.

³⁸To be precise, 10.5% of leaders in the sample are born in the same region as their spouse during tenure.

(CIESIN 2018, $Pop_{c,r,i,t}$).³⁹ They also 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 ADM1-year fixed effects to account for factors that affect aid given to the larger ADM1 region (including an ADM2 region of interest) in a given year.⁴⁰ Examples include national or regional economic crises, policy changes, or shifts in diplomatic relations that affect aid flows uniformly across all ADM2 regions within an ADM1, or even across the entire country. We cluster standard errors at the country level, which allows for arbitrary spatial and temporal correlation among all regions within a country.⁴¹

Although ADM2 region fixed effects rule out bias from time-invariant characteristics that both increase aid and make a region more likely to be a spouse’s birthplace, our estimates may still fall short of causal interpretation. Time-varying factors at the subnational level could simultaneously influence aid flows to a region and the likelihood that a region obtains spouse status. To address this concern, we also show a regression that includes 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. Rather than estimating one coefficient for the years a region is the birth region of the leader’s spouse, we include separate binary variables, $Spouseregion_{c,r,i,t}^{y=1}, \dots, Spouseregion_{c,r,i,t}^{y=5}$ for each of the first five years a region is classified as a spousal birth region, along with an additional binary variable $Spouseregion_{c,r,i,t}^{y \geq 6}$ that captures all additional years when the spouse’s “tenure”

³⁹We 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.

⁴⁰De 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 E, none of the Average Treatment Effects of the Treated receive a negative weight in our baseline regression. This finding aligns with results from Widmer and Zurlinden (2022) and Bluhm et al. (2025) in similar settings. In line with these studies, we thus mainly report results from traditional two-way fixed effects estimators. Appendix E shows that our results are not affected by this choice. Also note that ADM1-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 or replace them with fixed effects for country-years.

⁴¹Our results hold when we cluster standard errors in a number of different ways, as we show in Table D.1 in Appendix D below.

extends beyond five years. We obtain the following event-time specification:

$$\begin{aligned}
Aid_{c,r,i,t} = & \sum_{j=-2}^0 \alpha_{1,j} PreSpouseregion_{c,r,i,t-j} + \beta_1^1 Spouseregion_{c,r,i,t}^{y=1} + \beta_1^2 Spouseregion_{c,r,i,t}^{y=2} \\
& + \beta_1^3 Spouseregion_{c,r,i,t}^{y=3} + \beta_1^4 Spouseregion_{c,r,i,t}^{y=4} + \beta_1^5 Spouseregion_{c,r,i,t}^{y=5} \\
& + \beta_1^6 Spouseregion_{c,r,i,t}^{y \geq 6} + \sum_{k=1}^2 \gamma_{1,k} PostSpouseregion_{c,r,i,t-k} + \beta_2 Leaderregion_{c,r,i,t-1} \\
& + \beta_3 Leaderregion_{c,r,i,t-1}^{ethnic} + \beta_4 Pop_{c,r,i,t} + \sigma_i + \tau_{r,t} + \varepsilon_{c,r,i,t}.
\end{aligned} \tag{2}$$

Note that these additional variables are not simple leads and lags of the birth region indicators. $PreSpouseregion_{c,r,i,t-j}$ with $j = -2, -1, 0$ indicates 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 birth region in just part of this year). The year in which a region loses its status as a spouse region is covered by the lagged $Spouseregion_{c,r,i,t-1}$ indicator. We then estimate two additional coefficients for the first two full years: $PostSpouseregion_{c,r,i,t-1}$ and $PostSpouseregion_{c,r,i,t-2}$ indicate that one and two years ago, respectively, the region lost its spouse-region status.

Our final set of regressions again captures all years in which a region is the birth region of a leader's spouse in the (lagged) variable $Spouseregion_{c,r,i,t-1}$. Just like Equation (2), this specification however also includes the indicators for the years before a region gains political status, which again allows us to test for pre-trends. We obtain the following equation:

$$\begin{aligned}
Aid_{c,r,i,t} = & \sum_{j=-2}^0 \alpha_{1,j} PreSpouseregion_{c,r,i,t-j} + \beta_1 Spouseregion_{c,r,i,t-1} + \\
& \beta_2 Leaderregion_{c,r,i,t-1} + \beta_3 Leaderregion_{c,r,i,t-1}^{ethnic} + \beta_4 Pop_{c,r,i,t} + \sigma_i + \tau_{rt} + \varepsilon_{c,r,i,t}.
\end{aligned} \tag{3}$$

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 spousal influence might still be visible. Aid committed earlier might be disbursed with a lag, 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.

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 and ethnic regions of the leaders themselves, this within-region comparison allows us to isolate the spousal influence 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 during politically important periods. 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 [Section B.5](#) in [Appendix B](#). If heightened scrutiny led to more detailed reporting, we would expect to find more small projects in spouse regions, while large ones would likely be included regardless. 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

Based on [Equation \(1\)](#), columns 1 and 2 of [Table 1](#) present results for Western bilateral aid, first without and then with the indicator for regions that share the leader’s ethnicity.⁴² As can be seen in column 1, regions receive 103 percent more aid during periods when a leader is in power whose spouse was born there, compared to other periods. Put differently, an ADM2 region receives slightly more than twice its usual amount of aid—approximately an additional US\$ 100,000 on average—when it is the birthplace of the leader’s spouse, compared to what this region receives at other times. Including the indicator for regions where the dominant group shares the leader’s ethnicity (column 2) does not materially affect the point estimate of the *Spouseregion* variable.⁴³ The significant effect for *Spouseregion* does thus not reflect omitted joint ethnicity between leaders and their spouses.⁴⁴

⁴²Recall that we control for (log) population as well as fixed effects for ADM2 regions and ADM1-years. We do not show their coefficients to reduce clutter.

⁴³While the coefficient in column 2 is slightly larger than in column 1, this difference is entirely due to the reduction in sample size from including the ethnicity indicator. When we replicate the specification from column 2, assigning zero to missing values for dominant ethnic regions, the coefficient becomes identical to the coefficient in column 1 (results not shown).

⁴⁴A related concern is that the estimated effect could partly capture spillovers from the leader’s region of birth if the spouse was born in a neighboring region. However, this only applies to 8.5% of the spouses

Table 1 – Birth Regions and Aid, ADM2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	DAC	DAC	DAC	DAC	IDA	IBRD	China ODA	China OOF
PreSpouseregion ($t + 2$)			-0.40 (1.00)	-0.43 (1.11)	0.31 (0.80)	0.34 (1.04)	0.39 (1.21)	0.44 (1.18)
PreSpouseregion ($t + 1$)			-0.74* (1.66)	-0.78* (1.81)	0.34 (0.88)	0.43 (0.94)	-0.09 (0.45)	0.18 (0.54)
PreSpouseregion (t)			0.07 (0.15)	0.002 (0.00)	0.48 (1.35)	0.07 (0.15)	0.03 (0.09)	-0.08 (0.32)
Spouseregion	0.71** (2.38)	0.79** (2.25)		0.74* (1.95)	0.33 (0.90)	0.85* (1.74)	-0.25 (1.59)	-0.08 (0.62)
Spouseregion (year 1)			0.81 (1.64)					
Spouseregion (year 2)			0.75 (1.51)					
Spouseregion (year 3)			1.32*** (2.67)					
Spouseregion (year 4)			1.73*** (3.14)					
Spouseregion (year 5)			1.65** (2.53)					
Spouseregion (year ≥ 6)			0.22 (0.41)					
PostSpouseregion (t)			1.03** (2.08)					
PostSpouseregion ($t - 1$)			0.55 (1.05)					
PostSpouseregion ($t - 2$)			0.58 (1.45)					
Leaderregion	0.17 (1.07)	0.20 (1.11)	0.22 (1.23)	0.23 (1.25)	0.18 (0.59)	-0.28 (1.60)	-0.00 (0.03)	-0.09 (0.89)
Leaderregion ^{ethnic}		-0.18* (1.97)	-0.18** (2.04)	-0.18** (2.00)	-0.25** (2.32)	0.02 (0.40)	-0.02 (0.53)	0.05* (1.84)
ADM2 fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
ADM1-year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
First year	1990	1990	1990	1990	1995	1995	2000	2000
Last year	2020	2020	2020	2020	2020	2020	2020	2020
Number of countries	110	104	104	104	104	104	104	104
Number of regions	29362	27464	27464	27464	27422	27422	27422	27422
Number of observations	855102	754929	747363	745179	628178	628178	509553	509553
Prob > F Spouse				0.00	0.49	0.19	0.23	0.23

Notes: 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 from 18 European donors and the United States (columns 1–4), the World Bank’s IDA (column 5) and IBRD (column 6), as well as ODA and OOF commitments from China (columns 7–8). *Spouseregion* and *Leaderregion* are lagged by one year. *Prob > F Spouse* tests whether the coefficient of *Spouseregion* is larger than that of *PreSpouseregion* _{$t+1$} . All regressions include the logarithm of a region’s population size. *Leaderregion*^{ethnic} is a binary variable that takes a value of one if a region’s dominant ethnicity is the same as the ethnicity of the leader in power. Standard errors are clustered at the country level.

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

Our results further show that there is no comparable effect for regions where the leader of a country is born or for regions with populations that share the leader’s ethnicity. While the coefficient for leader birth regions is positive, its coefficient is small and imprecisely estimated. The coefficient of the leader’s ethnic regions is estimated more precisely, but with a negative coefficient. These results are in line with the subtle aspects of political connections that we highlight above: Donors may be less willing to publicly support regions of obvious political salience. They support our hypothesis that donors are more cautious about directing aid to regions where domestic political motives are more obvious (i.e., leader birth and ethnic regions), and, as a result, more aid flows to regions where such influences are less visible, such as the birth regions of the leaders’ spouses.

Column 3 of [Table 1](#) shows the event-time specification of [Equation \(2\)](#) that includes separate binary variables for each of the first five years a region is classified as a spousal birth region, along with an additional binary variable that captures all additional years when the spouse’s ‘tenure’ extends beyond five years. We further include indicators for the one and two years before a region’s status as *Spouseregion* changes and one for the year of change itself (i.e., years with a change in leader, marriage, divorce, or a spouse’s death). In analogy, we include two indicator variables for the two years after a region loses its status as a spouse region. As can be seen, regions receive *less* aid, on average, before they gain status as *Spouseregion*. This indicates the potential of negative trends in aid in such regions (to which we return below). The negative coefficient reverses sign in the year a region switches its status but is estimated imprecisely. The coefficients on all individual *Spouseregion* variables are then positive and reach statistical significance at conventional levels in years 3–5 of a region’s “tenure” as spousal region. The effect on aid is also significantly positive during the transition year, as indicated by the coefficient of *PostSpouseregion_{c,r,i,t}*. Beyond this point, the effects become small and insignificant, indicating that aid disbursements decrease to their average levels one and two years after the spouse of a leader originated from a region. This rapid dissipation suggests that these political dynamics do not have a permanent influence on the allocation of aid. It seems that spouses need time to build significant influence to affect foreign aid decisions, and such influence is quickly reversed.

To check how sensitive our results are to possible violations of the parallel trends assumption, we apply the Honest Difference-in-Differences (DiD) method developed by [Rambachan and Roth \(2023\)](#). This approach allows us to test how deviations from the parallel trends assumption would affect our estimates. The size of these deviations is calibrated using the variation observed in the pre-treatment period, and the method then constructs confidence intervals that remain valid even if such deviations exist. We use the event-study specification from column 3 of [Table 1](#) and focus on the treatment effect

in our sample. Excluding the affected region-year observations (fewer than 3% of our data) leaves the results unchanged; see [Table D.2](#) in [Appendix D](#).

in year 4. This is the year where the estimated effect is strongest under the conventional parallel trends assumption. It also serves as a useful benchmark for sensitivity analysis, since we can ask at what point the effect becomes statistically indistinguishable from zero.

Figure D.6 shows the estimated effect in year 4 under different relaxations of the parallel trends assumption. Panel A uses the magnitude restriction (M), where M indicates how large post-treatment deviations are allowed to be compared to the largest deviation seen in the pre-treatment period. We find a breakdown value of about $M \approx 1$, meaning that if post-treatment deviations were as large as the largest deviations observed before treatment, the positive effect of spouse regions would no longer be significant. Panel B applies the smoothness restriction, which allows the post-treatment trend to bend away from the pre-treatment linear trend. Even under relatively flexible assumptions—for example, permitting slope changes of up to 0.05 log-points—the effect of spouse regions on aid from Western bilateral donors remains statistically significant.⁴⁵ This suggests that our main finding is fairly robust to moderate violations of the parallel trends assumption.

We next examine the specification of Equation (3), where we again subsume all *Spouseregion* indicators in one dummy, and omit the *PostSpouseregion* indicators.⁴⁶ The results in column 4 show that spousal regions experience an increase in aid of 110 percent, significant at the ten-percent level. The two *PreSpouseregion* coefficients—representing a region’s future spousal status in one or two years—are again negative, making it unlikely that the positive effect we find for spouses’ birth regions reflects a positive trend in such regions. What is more, the coefficient on *Spouseregion* is significantly larger than the 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).

The remaining columns of Table 1 replicate the regression of column 4, but replace Western bilateral aid with the World Bank’s International Development Association (IDA) and its International Bank for Reconstruction and Development (IBRD) in columns 5 and 6 and China—distinguishing between ODA and OOF commitments—in columns 7 and 8. We find that IBRD (but not IDA) aid increases significantly in regions that are the birthplace of a leader’s spouse, with a coefficient similar in size to that observed for Western bilateral donors. IBRD resources are largely raised in capital markets and backed by shareholder guarantees, which makes the institution more directly accountable to its shareholders—particularly the major contributors. Arguably, this institutional arrangement could subject IBRD to greater scrutiny than IDA, thereby aligning it more closely with Western bilateral donors. By contrast, neither Chinese ODA nor Chinese

⁴⁵The linear trend over the three pre-treatment periods is -0.30 . Allowing $M = 0.05$ means deviations of up to $\pm 16.7\%$ from that trend per year.

⁴⁶If we continue to include them, results are qualitatively unchanged.

OOF shows any systematic association with spousal regions. Turning to leader-related indicators, the IDA allocates significantly less aid to regions dominated by the leader’s ethnicity, while non-significant effects arise for IBRD aid. For China, we find no effect of leader or spousal birth regions on ODA, but OOF commitments increase significantly to regions when a co-ethnic leader is in power. These results reinforce the interpretation that Chinese aid flows, especially OOF, are more closely tied to cultivating strategic elite alliances, whereas Western and World Bank aid tends to accommodate less visible forms of favoritism, such as privileging leaders’ spousal regions.⁴⁷

Figure 4 visualizes allocation patterns over time, focusing on differences between our (groups of) donors.⁴⁸ The specifications mirror those of columns 4–8 in Table 1 but add binary indicators for the first and second year after a region ends to be the birth region of a leader’s spouse and investigate aid from the group of European donors and the United States separately rather than jointly. The figures show significant increases in aid to birth regions of leaders’ spouses for aid from European donors, the United States, and the IBRD, but no significant effects for Chinese ODA or OOF, as well as IDA aid.⁴⁹ If at all, Chinese ODA decreases at times when a region is the birth region of a leader’s spouse, potentially because aid is fungible and less of it is needed given the increases of Western aid. The figures also indicate the absence of any obvious trends in aid to birth regions of spouses over time, with the exception of Chinese OOF, which seems to trend downwards with time.

In summary, our results demonstrate that birth regions of leaders’ spouses benefit from increased aid inflows of Western donors but not of Chinese aid. Regions with populations that share the leaders’ ethnicity receive less aid from Western bilateral donors and the IDA, but more OOF from China. This is in line with the expectation that Western donors 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.

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.⁵⁰ However, our results reveal that, rather than being directed toward more

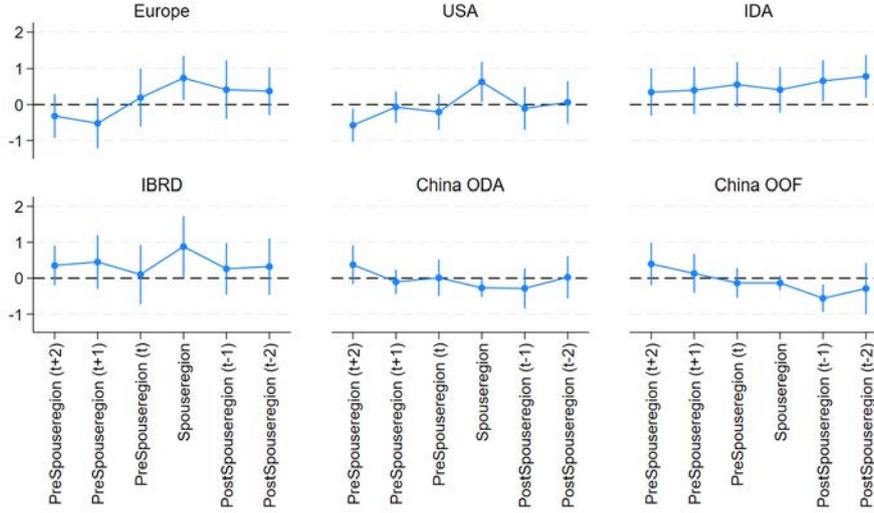
⁴⁷We have tested whether the use of disbursements vs. commitments drives the differences in results. While data on Chinese aid disbursements are unavailable, Table D.3 in Appendix D replicates the analysis for commitment amounts for all (groups of) donors, as well as using a binary variable indicating that a project has been committed in a year. Results are overall similar.

⁴⁸Table D.4 in Appendix D shows the regressions corresponding to these plots.

⁴⁹The slight increase in IDA flows during the post-tenure years—after the spouse’s region loses its privileged status—potentially reflects compensation for the reduction of resources from other donors.

⁵⁰For example, while Kersting and Kilby (2014) emphasize donors’ preferences for promoting

Figure 4 – Effects of Spouse Birth Regions on Aid, ADM2



Notes: The figure displays the coefficients and 90% confidence intervals for *Spouseregion*, along with all *PreSpouseregion* and *PostSpouseregion* variables. The results are based on [Table D.4](#).

productive uses, Western aid is also diverted for political purposes, though it tends to flow to regions where such motives are less apparent.

4.2 Mechanisms

While our findings could, in principle, be driven by either donor interests or recipient strategies, the distinct patterns between Western and Chinese donors suggest that donor-side factors play a significant role. These differences imply that donor decisions matter—and that Western donors may have stronger incentives than China to conceal political favoritism. At the same time, recipients may adapt their requests based on each donor’s specific approach. In seeking to reward their in-group while remaining responsive to Western concerns about favoritism, recipients may strategically propose directing aid to spouses’ birth regions rather than to those of the leader.

To better understand *why* the birth regions of leaders’ spouses receive more Western foreign aid, we examine potential mechanisms behind our baseline findings. These include: (i) *formal influence* through political office, (ii) spouses leveraging their personal networks to channel aid in *preparation of a future political career*; (iii) *strategic marriage*, where leaders deliberately choose spouses from politically important regions; (iv) the use of spouse regions as a *political tool to mobilize electoral support* for the leader while avoiding donor scrutiny; and (v) *future settlement motives*, where aid flows reflect personal attachment to home communities. We also shed light on the role of *donor-driven strategies*

democratic governance, our findings suggest that less overt domestic political interests of recipient governments also play a significant role in shaping the allocation of aid from Western donors.

rather than recipient-led influence. While these mechanisms are not mutually exclusive, we assess their plausibility using a series of interaction tests and descriptive patterns.

Informal vs. Formal Influence Under the informal influence interpretation, spouses leverage personal networks and relationships to channel aid to their birth regions. We examine whether such influence is amplified when a spouse also holds, has held, or will hold formal positions of authority. Specifically, we compare aid flows to the birth regions of spouses with formal influence to those without, distinguishing three periods: prior to the partner’s tenure as the country’s effective leader, during that tenure, and after it has ended. For example, Asif Ali Zardari, the husband of the late Pakistani Prime Minister Benazir Bhutto, exemplifies formal influence in 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 pre-tenure period in column 1 of [Table 2](#), we test whether 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. To this end, we extend our baseline specification from column 1 of [Table 1](#), interacting 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).⁵¹ All three interaction coefficients are positive, as expected, and the one for prior NGO leadership is statistically significant at conventional levels. This pattern is consistent with the idea that spouses draw on preexisting networks once their partner is in office, supporting an interpretation of informal influence.

Next, we test whether the *Spouseregion* effect can be explained by spouses’ *formal* influence. To do so, column 2 tests whether regions associated with spouses holding concurrent positions of power do not exhibit a stronger *Spouseregion* effect compared to regions with spouses without a 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

⁵¹This specification excludes pre-trends and the indicator for coethnic regions used in later columns of [Table 1](#). Dropping pre-trends increases efficiency, and, although the coethnic region indicator is significant in previous models, it does not materially affect the results for our variables of interest. Its inclusion however substantially decreases the sample size. Note that the levels of the binary indicators that form the interactions with *Spouseregion* do not vary within countries in a year and are thus absorbed by the region-year fixed effects.

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 data, 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. None of the interaction terms is statistically significant at conventional levels. This suggests that spouses’ formal influence does not drive our main finding.

Preparation of a Future Political Career In column 3 of [Table 2](#), we assess whether a spouse’s ambition 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 realized post-tenure positions. In other words, we examine 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, birth regions of spouses who hold important positions in NGOs later in life receive significantly more aid, while the interactions with positions of elected and non-elected power are estimated imprecisely. This is suggestive evidence that increased aid to spouse regions is not driven by (successful) efforts to support a spouse’s future political career.

Strategic Marriage To assess the explanatory power of the *strategic marriage* interpretation, we examine the spousal data in greater detail. While ministers and political appointees are typically selected with strategic or institutional considerations in mind (e.g., [Francois et al. 2015](#)), spousal ties typically emerge from personal, familial, or cultural contexts and mostly predate a leader’s rise to power. In our dataset, 91% of marriages occurred before the leader assumed national office, with only 12% taking place shortly before (within five years of) or during the year the leader came to power. Fewer than 9% happened during the leader’s tenure. While this does not entirely rule out politically motivated marriages, such cases are too few to drive our results. What is more, if strategic spouse selection were the main explanation, our within-region identification strategy would not yield significant increases in aid to spouse regions *only* during periods of tenure. Consistent with this interpretation, birth regions of spouses—especially those married shortly before or during tenure—do not display pre-tenure characteristics one would expect to be associated with regions a leader would target for political reasons. They are not different from other regions in terms of foreign aid they receive, corruption, leader ethnicity, or geographic distance to the soon-to-be leader’s birth region (see [Appendix A.3.8](#) for details). Taken together, these patterns are more consistent with aid effects being driven primarily by spousal influence exercised during the leader’s tenure than by widespread strategic spouse selection.

Table 2 – Birth Region Interactions and Aid I, ADM2, 1990–2020

	(1)	(2)	(3)
	before	during	after
Spouseregion	0.41 (1.21)	0.85** (2.32)	0.66* (1.97)
Leaderregion	0.17 (1.08)	0.16 (1.05)	0.18 (1.13)
Spouseregion × elected power	1.23 (0.99)	0.62 (0.59)	0.15 (0.12)
Spouseregion × non-elected power	1.19 (0.92)	-0.42 (0.44)	-1.21 (0.91)
Spouseregion × NGO	2.02* (1.77)	-0.51 (0.89)	2.26*** (3.05)
ADM2 fixed effects	✓	✓	✓
ADM1-year fixed effects	✓	✓	✓
Number of countries	110	110	110
Number of regions	29362	29362	29362
Number of observations	855102	855102	855102

Notes: The dependent variable is *Aid*, i.e., the logarithm of ODA disbursements from 18 European donors and the United States (plus 1) given to region i of country c in year t . *Spouseregion* and *Leaderregion* are lagged by one year. We 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). All specifications control for the logarithm of a region’s population size. Standard errors are clustered at the country level. t-statistics are reported in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Cultivate Political Support To assess the explanatory power of the “cultivating political support for the leader interpretation,” we examine whether electoral dynamics amplify aid flows to spouse regions. Leaders may attempt to channel aid to their own or their spouse’s birth region in anticipation of elections, especially where electoral support is strongest and turnout most consequential (Dreher et al. 2019, Jablonski 2023). However, donors might be particularly wary during election periods in recipient countries to ensure that aid is not misused to advance the electoral interests of incumbent leaders.

To test these expectations, we again build on our baseline specification from column 1 of Table 1 and interact the *Spouseregion* and *Leaderregion* indicators with a binary variable that is one when executive elections are scheduled within the next one or two years, and which is zero otherwise. Column 1 of Table 3 presents the results. The estimated *Spouseregion* effect more than doubles in magnitude in the lead-up to elections, whereas the corresponding *Leaderregion* effect declines slightly. Only the interaction term for *Spouseregion* is statistically significant at conventional levels, and the difference between the two interaction coefficients is itself significant ($p = 0.02$). On one hand, these findings 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 no evidence that donors are more effective at preventing aid from being redirected to leaders’ birth regions during these times of heightened scrutiny.

Column 2 examines the influence of electoral competitiveness by incorporating an interaction term 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. A similar pattern emerges: When electoral competitiveness is high, the positive interaction coefficient for *Spouseregion* differs significantly from the negative (and insignificant) coefficient for *Leaderregion* (p -value: 0.04). These findings are again consistent with leaders using spouse regions to mobilize electoral support during periods of heightened donor scrutiny. They are also in line with our expectation that Western donors prevent the use of their aid for obvious political reasons, contrary to results previously reported for Chinese aid in Dreher et al. (2019).

Future Settlement Motives One explanation for increased aid to a spouse’s birth region is parochial altruism—the tendency to favor one’s home community out of personal attachment rather than political strategy. These motives are likely to be stronger if the first couple expects to return to the spouse’s region after holding office. While direct evidence of leaders’ post-tenure migration is unavailable, cultural norms offer indirect evidence. Cultural traditions, such as patrilocality, can shape return migration: in strongly patrilocal societies, couples settle near the husband’s family (Landmann et al. 2018, Reynolds et al. 2023), implying that leaders are more likely to retire in their own birth region. This reduces incentives to channel resources to the spouse’s region, since

Table 3 – Birth Region Interactions and Aid II, ADM2

	(1)	(2)
Spouseregion	0.55*	-1.40
	(1.69)	(1.39)
Leaderregion	0.22	0.40
	(1.23)	(0.70)
Spouseregion × election	0.67**	
	(2.57)	
Leaderregion × election	-0.08	
	(0.45)	
Spouseregion × competitiveness		0.35**
		(2.22)
Leaderregion × competitiveness		-0.04
		(0.45)
ADM2 fixed effects	✓	✓
ADM1-year fixed effects	✓	✓
First year	1990	1990
Last year	2019	2020
Number of countries	109	109
Number of regions	29201	29201
Number of observations	825029	850107
Prob > F (Spouse = Leader)	0.02	0.04

Notes: The dependent variable is *Aid*, i.e., the logarithm of ODA disbursements from 18 European donors and the United States (plus 1) given to region i of country c in year t . *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 instead uses electoral competitiveness as part of the interactions. All regressions include the logarithm of a region's population size. Standard errors are clustered at the country level. t-statistics are reported in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

the couple would not benefit from long-term project benefits.

To test this mechanism, we draw on WomanStats (Caprioli et al. 2009). We use two indicators. The first is the Patrilocal Marriage Scale, which measures expectations that couples reside with the husband’s family (coded 0–2). The second is the Women’s Property Rights Scale, which captures legal and practical restrictions on women’s property rights. For comparability, we rescale the index to range from 0–2, with higher values reflecting greater discrimination of women.

Table 4 – Birth Region Interactions and Aid III, ADM2, 1990–2020

	(1)	(2)
Spouseregion	1.24*** (2.68)	1.10** (2.57)
Leaderregion	0.43* (1.85)	0.17 (0.82)
Leaderregion × patrilocal	-0.21 (1.23)	
Spouseregion × patrilocal	-0.45 (1.36)	
Leaderregion × women’s property rights		-0.006 (0.04)
Spouseregion × women’s property rights		-0.40 (1.16)
ADM2 fixed effects	✓	✓
ADM1-year fixed effects	✓	✓
Number of countries	110	109
Number of regions	29362	29178
Number of observations	855102	852526

Notes: The dependent variable is the logarithm of Western bilateral aid (plus 1) given to region i in year t : ODA disbursements from 18 European donors and the United States. Patrilocal is a categorical variable coded as 0 for no patrilocality, 1 for partial/soft patrilocality, and 2 for strong patrilocality. Women’s Property Rights captures property rights for women both in practice and under the law. The scale ranges from 0 to 2, with higher values reflecting more severe legal and practical restrictions on women’s rights. All regressions include the logarithm of a region’s population size. Standard errors are clustered at the country level. t-statistics are reported in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4 presents the results, again following the specification reported in column 1 of Table 1. As a proxy for future settlement motives, column 1 includes interactions of the spouse’s and leader’s birth regions with the patrilocal marriage indicator. We find no evidence that the spouse effect is moderated by patrilocality. This result holds when we instead interact birth regions with women’s property rights (in column 2). Overall, we find no evidence supporting a future settlement motive when allocating aid.

Donor-driven Strategies Finally, we examine whether the spouse-region effect reflects donor strategies rather than (only) recipient-driven demands on the allocation of aid. Western donors may actively support allies or give them more discretion over the use of aid. Aid would then be more likely to end up in important regions, especially during election periods and when competition is high. Western donors might also be more willing to give aid to important regions in response to competition with China (Hernandez 2017, Zeitz 2020). In addition to being of interest in their own right, these tests allow us to infer whether donors consider spousal birth regions to be of strategic interest in the same way they are aware of birth regions of leaders themselves, by allowing aid to flow more or less freely there at times of political salience.

First, we test whether birth region effects differ in countries that are more closely aligned in how they vote with the United States on important votes in the United Nations General Assembly (UNGA), which the literature suggests as a proxy for alliances with the U.S. and Western countries more broadly.⁵² Column 1 of Table 5 shows that UNGA voting does not mediate the birth region effects, on average. Column 2 tests whether this changes at times when elections approach. We find that the coefficient of the triple interaction between UNGA voting alignment, election, and the leaders' birth regions is positive and significant: countries with closer UNGA alignment channel more aid to leaders' birth regions in the period preceding elections. Consistent with Faye and Niehaus (2012), this result suggests that donors to countries with closer UNGA voting alignment may be more lenient or trusting, giving recipients greater discretion and enabling them to channel aid more easily for political reasons ahead of elections, or even actively support governments of allied countries.⁵³ We do not find similar results for birth regions of leaders' spouses, in line with the expectations that these regions are insufficiently salient for donors to take note. These patterns find further support in column 3, where we replace proximity to elections with electoral competitiveness as part of the interactions. Again, U.S. allies receive more aid in the birth regions of leaders—but not their spouses—at times when political favors are potentially more valuable (i.e., when elections are more competitive).⁵⁴

⁵²Important votes are classified by the U.S. Department of State, which submits a yearly report to Congress detailing how countries vote in the UNGA. Congress tracks UNGA voting alongside U.S. aid, and in some years reports even include tables comparing assistance with voting alignment. For some years, aid to countries that consistently opposed the U.S. position was even restricted by law; see Dreher et al. (2022b) for details. The indicator is coded on a 0–1 scale, with 1 indicating recipient countries that vote in line with the U.S. on all votes, and which is zero for those that never do.

⁵³Faye and Niehaus (2012) find that only politically aligned recipient countries receive more aid during election years.

⁵⁴A modified specification where we interact the birth region variables with indicators for upcoming elections in *donor* countries also allows us to test whether donor politics affects the magnitude of the birth region effect. If audience costs are higher during periods of heightened political scrutiny, we would expect donors to exercise greater caution in politically sensitive allocations. Consistent with this, we find that Finland, Germany, Greece, Italy, and Switzerland give less aid to leader birth regions in election years at home compared to other years. Only Germany does the same in the less politically salient

Finally, we examine the interplay between Chinese and Western aid flows by interacting Chinese aid committed to an ADM2 region with the birth region indicators. The results in column 4 of [Table 5](#) show that Western aid to leaders’ birth regions increases with Chinese aid committed in the same region, suggesting potential strategic complementarity or competition. We find no evidence that Western aid allocation to spouses’ birth regions is equally shaped by Chinese aid, which is further evidence in line with our expectation that spousal birth regions “fly below the radar.”

In summary, while donor policies seem to shape aid flows to leaders’ birth regions, the evidence suggests that aid to spouse regions is instead mainly driven by recipient discretion.

4.3 Heterogeneity and Robustness Tests

We extend our main analysis and subject the *Spouseregion* effect to a series of robustness checks and heterogeneity tests. We investigate whether institutional quality constrains or amplifies spousal influence, whether features of the marital relationship condition the magnitude of the effect, and whether our findings hold across placebo specifications, geographic and donor subsamples, aid sectors, and subnational characteristics.

Institutions We assess whether governance quality moderates or amplifies spousal favoritism. Stronger governance is expected to limit the ability of both political leaders and their spouses to influence the allocation of aid for personal or political purposes. At the same time, stronger governance may curtail leaders’ overt political influence more than their spouses’ informal influence, potentially resulting in a net increase in aid to spouses’ birth regions under better governance. The balance between these effects likely depends on the specific dimension of governance under study.

In column 1 of [Table D.5](#) in [Appendix D](#), we interact birth regions with the law and order index from [PRS Group \(2023\)](#) for each recipient country and year, ranging from 0–6. Column 2 uses an indicator measuring the perceived absence of corruption, taken from the same source, and measured on a 0–100 scale. As corruption varies within countries, column 3 instead uses subnational corruption data from [Crombach and Smits \(2024\)](#), which offers regional-level corruption measures on the same 0–100 scale with higher values again indicating less corruption. We focus on corruption defined as “the abuse of entrusted power for private gain,” which [Crombach and Smits \(2024\)](#) extract from a number of sources.⁵⁵

The results show that the positive spouse region effect on aid is less pronounced in countries with strong law and order and low corruption, although the coefficient on

spouse regions as well. Detailed results are available upon request.

⁵⁵Given that their measure varies between regions, it is not captured by fixed effects and we therefore control for the level of corruption in the regression in column 3.

Table 5 – Birth Region Interactions and Aid IV, ADM2, 1990–2020

	(1)	(2)	(3)	(4)
Spouseregion	0.82 (1.39)	0.42 (0.68)	0.20 (0.09)	0.47* (1.69)
Leaderregion	0.66 (1.53)	0.91* (1.87)	3.55*** (3.03)	-0.04 (0.22)
Spouseregion × UNGA	-0.18 (0.12)	0.39 (0.27)	-3.95 (0.95)	
Leaderregion × UNGA	-1.14 (1.35)	-1.60* (1.69)	-7.70*** (3.15)	
Spouseregion × election		1.28 (1.55)		
Leaderregion × election		-0.82* (1.73)		
Spouseregion × UNGA × election		-1.51 (0.89)		
Leaderregion × UNGA × election		1.75* (1.71)		
Spouseregion × competitiveness			0.12 (0.33)	
Leaderregion × competitiveness			-0.51*** (2.71)	
Spouseregion × UNGA × competitiveness			0.57 (0.78)	
Leaderregion × UNGA × competitiveness			1.14*** (2.84)	
Chinese ODA				0.002 (0.32)
Leaderregion × Chinese ODA				0.06** (2.15)
Spouseregion × Chinese ODA				-0.05 (0.98)
ADM2 fixed effects	✓	✓	✓	✓
ADM1-year fixed effects	✓	✓	✓	✓
Number of countries	110	109	109	110
Number of regions	29362	29201	29201	29362
Number of observations	850288	820215	846421	855102

Notes: The dependent variable is the logarithm of Western bilateral aid (plus 1) given to region i in year t : ODA disbursements from 18 European donors and the United States. Column 1 interacts with coincidence in UNGA voting with the United States on important votes. Column 2 in addition interacts with an indicator for whether an executive election will be held within one or two years; column 3 uses electoral competitiveness as part of the interactions. Column 4 interacts with (logged) Chinese ODA commitments in a region and year. All regressions include the logarithm of a region’s population size. Standard errors are clustered at the country level. t-statistics are reported in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

corruption is estimated imprecisely. We find the same qualitative result for *regions* with low corruption, significant at the one percent level. Turning to leaders' birth regions, we also find that in less corrupt countries, the aid premium associated with leader region status is significantly smaller than in more corrupt environments.⁵⁶

Column 4 examines the role of “grand” corruption, defined as the abuse of high-level power, also drawing from [Crombach and Smits \(2024\)](#), with higher values again indicating less corruption. Although data are available for a much smaller sample, the results indicate that spousal birth regions receive significantly more aid in countries with higher levels of grand corruption, in line with the results for overall corruption. Taken together, these results suggest that when corruption is higher and institutional checks are weaker, aid allocation is more susceptible to informal spousal influence or direct favoritism toward leaders' own regions.

Finally, in column 5, we examine whether democratic quality influences aid targeting to birth regions. Using data from [Bjørnskov and Rode \(2020\)](#), we find no evidence that more democratic regimes allocate more or less aid to leader or spousal birth regions. One possible explanation is that democracy pulls in two opposite directions: on the one hand, electoral competition may strengthen incentives to target politically important regions, including those linked to leaders' spouses; on the other hand, democracies tend to have stronger institutions and greater scrutiny, which may curb the scope for such favoritism. The net effect appears to balance out, resulting in no systematic difference between democracies and autocracies in this respect.

Features of the Marital Relationship Columns 1 and 2 of [Table D.6](#) in [Appendix D](#) investigate whether features of the first couple's marital relationship influence the birth-region effect. A larger family could imply that multiple informal networks compete for influence. We expect the effect of a region's spouse-region status to weaken when it is shared with more individuals, either due to a higher number of spouses or children. To test this, we interact the *Spouseregion* and *Leaderregion* indicators with the number of spouses a leader has concurrently (column 1) and the number of children the first couple has (column 2). The results show that the aid premium for the birth region of the first spouse decreases significantly when leaders have multiple spouses. However, we find no comparable effect associated with the number of children. We also assessed whether higher education gives spouses more leverage and shapes the allocation of aid differently. As can be seen in column 3, and using data from our PLAD dataset, we find no systematic relationship between spouses' education—measured on an eight-point scale with 8 indicating a PhD—and the likelihood of aid flowing to their birth regions.

⁵⁶This pattern is also consistent with recipient-driven informal influence: if donors were driving allocation, we would expect them to favor the leader's region under lower corruption and avoid it under higher corruption.

In column 4, we investigate whether aid is especially likely to flow to regions that are the shared birthplace of both the leader and their spouse. We test for a multiplicative effect by including an interaction term between the two birth region indicators. The results show no statistically significant interaction, suggesting that aid targeting is not amplified when political and familial ties coincide geographically.

Placebo Regression Column 5 of Table D.6 runs a placebo regression, where we include an indicator for regions that are the birthplace of a future or past spouse of the country’s leader, but where the current leader’s spouse was born elsewhere. The results show no significant effect.⁵⁷ This is reassuring as it suggests that the observed effects of *Spouseregion* on aid patterns are likely not driven by omitted variables correlated with spousal origin but are consistent with genuine patterns of spousal influence.

Subsamples In Table D.7, we explore variation across world regions. The effect is largest for the Americas, followed by Asia. However, none of the interactions between world-region dummies and *Spouseregion* are statistically significant, indicating that the effect is not geographically specific.

Although all our specifications control for whether a region is the leader’s birthplace, we further address potential concerns about disentangling spousal from leader-region effects by re-estimating our baseline model on a restricted subsample limited to country-years in which the leader and spouse were born in different regions. The results in Table D.8 show that the coefficient on *Spouseregion* remains positive and statistically significant at conventional levels, confirming that the observed pattern cannot be attributed solely to countries with a geographic overlap between leader and spousal birthplaces.

Heterogeneity by Donor Table D.9 examines individual European donors. We find that 17 of 18 European donors display positive coefficients on *Spouseregion*, indicating a broadly consistent pattern of spousal influence. Although the smaller number of non-zero aid observations reduces statistical precision in many cases, we observe statistically significant increases in aid to spouse birth regions for Germany, Ireland, Luxembourg, and Spain. The effect is largest for Germany: German aid increases by 49% when a region is the birth region of a country’s first spouse, followed by Spain (47%) and Italy (30%). These findings suggest that the spouse-region effect is not driven by a few outliers but reflects a broader pattern across European donors.

⁵⁷Note however that the number of future and past birth regions is small—just 40 region-year observations with 10 unique region-spouse observations.

Heterogeneity by Aid Sector We also test whether the spouse effect varies across types of aid. We find that the effect is most pronounced for aid directed toward social infrastructure and services, with increases of 125 percent (see [Table D.10 of Appendix D](#)).⁵⁸ By comparison, the estimates for the economic infrastructure and production sectors are a more modest (and less precisely estimated), with increases in aid of 38 and 19 percent, respectively. This pattern likely reflects the more immediate visibility of social infrastructure projects like hospitals and schools, which voters can more easily attribute to political leadership in their region. These differential findings align with the conclusions in [Dolan and McDade \(2020\)](#) and the idea that “geographic features make roads, railways and other types of economic infrastructure less vulnerable to political capture” ([Dreher et al. 2019](#), p. 54).

Subnational Regional Heterogeneity We also examine whether subnational regional heterogeneity affects the magnitude of the birth region effects. To minimize the risk of endogeneity, we interact birth regions with variables measured at the start of the sample period (or the earliest available year). These characteristics include a region’s road density, (log) nighttime light, population size, land area, presence of ports, oil and gas availability, mining activity, and whether the region is a national capital. [Table D.11](#) shows that there is little evidence that these variables mediate the magnitude of the birth region effects. However, two exceptions emerge: Leader regions benefit more when they host a port, and the spouse-region effect is stronger in regions with larger populations and active mines.

4.4 Consequences of Spousal Favoritism

Having established the presence and patterns of spousal influence in aid allocation, we now turn to examining their potential consequences. 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 rather than diverted, its benefits in spouse regions must still be weighed against potential alternative uses of these funds in the donor country. Instead of addressing these broader opportunity costs, we focus here on the *direct* consequences of aid in the birth regions of leaders’ spouses. Regardless of the motives for providing aid, donors may ensure that the

⁵⁸We follow the OECD’s DAC guidelines 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. Production Sectors include Agriculture, Forestry, Fishing, Industry, Mining, Construction, Trade Policies & Regulations, and Tourism.

aid is utilized effectively, particularly when directed toward politically sensitive regions or during periods of heightened donor scrutiny. However, it is 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.

Columns 1 and 2 of [Table 6](#) examine how aid conditions the relationship between a region’s status as the birthplace of a leader’s spouse and economic development. Our 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 .⁵⁹ 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 the 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.⁶⁰

To investigate the potential role of aid in how birth regions affect development, we sum the amount of aid received over the last three years and interact this variable with each of the two birth region indicators. Focusing on the immediate consequences of aid rather than its effects on long-run development is common in the aid effectiveness literature, given the lack of long time series and the difficulties of attributing longer-run changes in outcomes to aid disbursed at specific points in time ([Nunn and Qian 2014](#), [Dreher et al. 2021a](#), and [Dreher et al. 2021b](#)). We follow this literature here and leave an analysis of medium- and long-run effects for future research.

If donors are aware of the politically sensitive nature of a leader’s birth region, they might subject aid projects in these regions to heightened scrutiny. This type of donor accountability could help ensure that aid to leader regions is implemented more effectively, despite the potential for political favoritism. In contrast, spouse regions—less visible and politically salient—may attract less scrutiny, allowing recipient governments to exercise greater discretion. As a result, we would expect aid to be less effective in spouse regions during periods when they hold that status. By comparison, aid to leader regions could be less effective, equally effective, or even be more effective compared to aid allocated to these regions at other times, depending on how donors and recipients interact to balance political incentives with implementation standards.

⁵⁹We add 0.01 before taking logs in order to not lose zero observations.

⁶⁰As [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 ADM2 region fixed effects for regions is likely to make this choice inconsequential.

Table 6 – Birth Regions and Economic Development, ADM2

	(1)	(2)	(3)	(4)
	OLS	CFA	OLS	CFA
	Light	Light	Control	Control
Aid	-0.003*** (3.78)	-0.055*** (5.14)	0.001 (0.84)	-0.000 (0.04)
Spouseregion	0.131** (2.36)	0.168*** (2.93)	-0.008 (0.05)	-0.007 (0.04)
Spouseregion × Aid	-0.013*** (3.53)	-0.012*** (3.55)	-0.013* (1.94)	-0.013* (1.94)
Leaderregion	0.183*** (4.82)	0.202*** (5.17)	0.318*** (2.78)	0.321*** (2.78)
Leaderregion × Aid	-0.010*** (4.06)	-0.009*** (3.81)	-0.009* (1.71)	-0.009* (1.70)
ADM2 fixed effects	✓	✓	✓	✓
Country-year fixed effects	✓	✓	✓	✓
First year	1993	1993	1995	1995
Last year	2020	2020	2020	2020
Number of countries	124	124	104	104
Number of regions	29728	29728	28851	28851
Number of observations	784241	781809	709624	709488
Kleibergen-Paap F-stat		50.96		63.18
Prob SR × Aid = LR × Aid	0.53	0.43	0.60	0.61

Notes: The dependent variable in columns 1–2 is the log of mean nightlight emissions in region i of country c in year t (+0.01). The dependent variable in columns 3–4 is control 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 ODA disbursements from 18 European donors and the United States (plus 1). We sum aid over three years and lag it by one year. *Spouseregion* and *Leaderregion* are lagged by one year. The row “Prob SR × Aid = LR × Aid” shows p-values for a test of equality between the two interactions. All regressions include the logarithm of a region’s population size. Standard errors are clustered at the country level. t-statistics are reported in parentheses; * p<0.10, ** p<0.05, *** p<0.01.

We show results for two sets of regressions. First, we use OLS. Given that aid is likely endogenous due to reverse causality and omitted variable bias, we do not interpret the coefficient of aid as a causal effect. However, to the extent the bias of our estimate of the effect of aid is constant at times the leader or their spouse is born in a region, we can interpret the difference in the effect of aid on development at times when a region is politically salient as causal.⁶¹

We complement this regression with a Control Function Approach (CFA) that more directly addresses the potential endogeneity of aid, using an instrumental variable suggested elsewhere (Ahmed 2016, Dreher and Langlotz 2020, Dreher et al. 2025). Our instrument for aid is the interaction of donor government fractionalization with the share of years a recipient region has received aid over the sample period. As these previous works explain in considerable detail (also see Appendix F), larger fractionalization of donors' politics increases demands on the government, ultimately leading to larger budgets. This increase in the overall budget translates into larger development budgets as well, which has been shown to disproportionately benefit more frequent recipients of aid. As Dreher and Langlotz (2020) explain, the exclusion restriction can be illustrated in the context of a difference-in-differences approach, leveraging variations in donor government fractionalization to estimate differential impacts of aid on regions with high versus low probabilities of receiving aid. Our identification thus hinges on the assumption that year-to-year changes in development outcomes do not systematically vary across regions based on their probability of receiving aid, apart from through changes in aid flows. While we explain this approach in more detail in Appendix F, space constraints prevent us from presenting the full battery of tests typically required to support the exclusion restriction; we therefore refer readers to the articles introducing the instrument, which provide such tests in detail.

We explain development with aid and the interaction of aid with leader and spousal birth region status, controlling for (log) population and fixed effects for ADM2 regions.⁶² Rather than controlling for fixed effects that capture ADM1 regions in a year, as in the aid allocation regressions shown above, we include less conservative fixed effects for country-years. To the extent that the effects of aid projects extend to areas larger than the ADM2 region that receives them, including ADM1 region-year fixed effects biases against finding significant coefficients. As we show in Appendix F, results are overall highly similar between these choices, though as expected coefficients are estimated less precisely in the more conservative specification.⁶³

⁶¹See Dreher et al. (2018) for a similar argument and formal demonstration.

⁶²We acknowledge that including population as a control may introduce bias if aid influences migration patterns and thereby affects population size (Fuchs et al. 2024). While our results remain robust when excluding population as a control (available upon request), we retain it in our main specifications to account for differences in economic potential across regions over time, which is standard in the literature.

⁶³Standard errors are again clustered at the level of countries.

Given that our regressions include interactions between aid and birth regions, we estimate them using a CFA, which is more efficient than the standard 2SLS approach of interacting the instrument with the interacted variable to form a second instrument (Wooldridge 2015). Thus, we address potential endogeneity by including the first-stage residual (excluding the interactions between aid and the birth regions) in all regressions.⁶⁴

Columns 1 and 2 display the results of the OLS and CFA regressions. The first-stage F-statistic for the instrumental variable used in the CFA—indicated at the bottom of the table—exceeds 50 and is thus substantially larger than the rule-of-thumb value of 10, indicating a strong instrument. We find that nightlight emissions increase in the birth regions of spouses and leaders compared to how these regions develop at other times, conditional on the interaction with aid being zero (i.e., when no aid is received). Specifically, the coefficients suggest that nightlight emissions increase by 14–18 percent when a region holds spouse-region status. This effect is somewhat smaller but of a similar magnitude to the effect observed for leader birth regions, where the coefficients imply an increase in nightlight emissions of 20–22 percent in the absence of aid. Furthermore, we also find that nightlight emissions are lower in regions that receive more aid, even at times when a region is not politically salient (i.e., when *Spouseregion* and *Leaderregion* are zero).

Turning to our main variables of interest, the coefficients on the interactions between aid and the indicators for spousal and leader birth regions are negative and highly significant. Notably, they are not statistically different from each other. This finding aligns with two potential interpretations. First, aid allocated for political reasons may be sufficiently less effective than aid allocated for other reasons (e.g., developmental needs), resulting in a lower overall impact of aid on regional growth when a region is politically salient—i.e., when it is the birthplace of the leader or their spouse—compared to periods when it is not (Dreher et al. 2021b). Second, even the aid a region would have received regardless of its political salience may become less effective at times a leader or leader spouse is born there. This could occur if project implementation is less carefully vetted or if oversight and supervision become lax or more politicized.

To illustrate the magnitude of the estimated coefficients, Figure 5 plots the marginal effects of *Spouseregion* and *Leaderregion* over the range of aid these regions receive (based on the regression of column 1). The figure shows that regions where the country’s current leader or their spouse was born develop better—measured by nightlight emissions—when they receive no aid, compared to how they develop at other times. However, as the amount of aid increases, the positive effect of being a birth region diminishes. The marginal effect of *Spouseregion* (*Leaderregion*) on lights turns significantly negative once (log) aid exceeds 11.4 (19.8). This pattern suggests that

⁶⁴When we use the interactions of our instrumental variable and birth regions as additional instruments in a 2SLS, the first stage is weak.

the additional aid a *Spouseregion* receives as a consequence of its political status harms these regions’ development outcomes. In fact, when aid volumes are high, the detrimental effects are large enough to fully offset—and even reverse—the initial development gains associated with birth region status.

Columns 3 and 4 of [Table 6](#) replicate the analysis focusing on corruption as an alternative 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. However, we again find significant interactions between birth region status and aid, indicating that corruption in (leader and spousal) birth regions increases once they receive large inflows of aid.

[Table F.1](#) in [Appendix F](#) shows additional results for how birth region status and aid affect nighttime light. We separately show results for European donors and the United States and provide results for IDA and IBRD aid as well as Chinese ODA and OOF for comparison. We estimate CFAs with shift-share instrumental variables that follow the same intuition as our instrument for Western bilateral aid. More precisely, we substitute the shift variables in our interacted instrument with the respective donor government fractionalization for European donors and the United States, respectively, use yearly outputs of Chinese production materials for China (as discussed in [Bluhm et al. 2025](#)), and resource availability for the IBRD and IDA (as discussed in [Dreher et al. 2021a](#)).⁶⁵ As can be seen, birth regions develop less strongly when they receive more Western bilateral aid. Results are similar for IDA aid to spousal birth regions and IBRD funds to birth regions of leaders. The same holds for IBRD and Chinese aid to birth regions of spouses and Chinese ODA and OOF given to leader regions, though coefficients are estimated less precisely there.⁶⁶

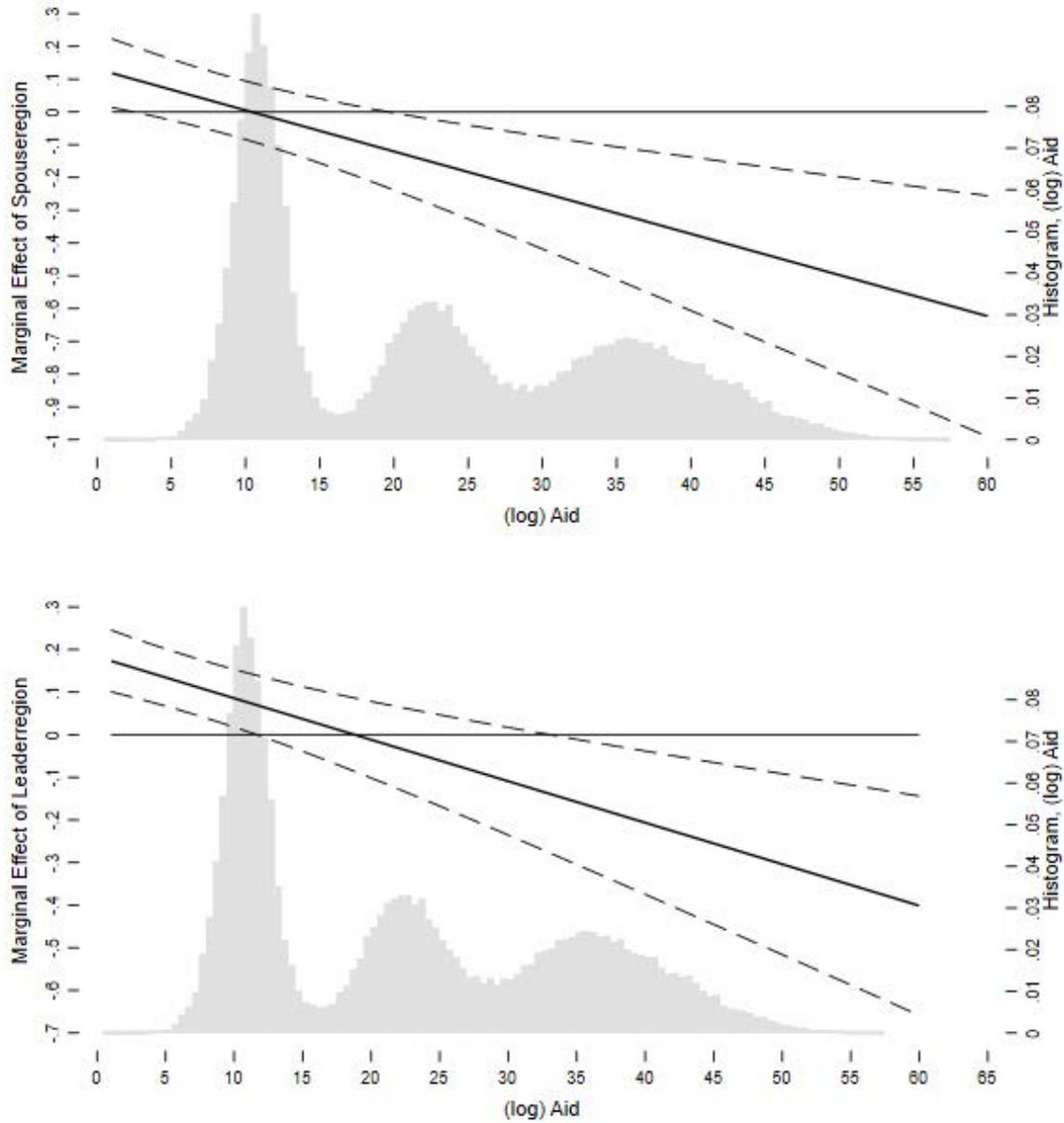
5 Conclusions

This study presents the first systematic global analysis of how political leaders’ spouses shape regional development flows and outcomes. We provide novel evidence that the birth region of a leader’s spouse receives significantly more foreign aid from the United States and European donors during the leader’s tenure, demonstrating a distinct form of regional favoritism that largely operates outside formal governance structures. This poses 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 impact on development. Thus, aid that appears free from obvious political

⁶⁵[Appendix F](#) provides details on these instrumental variables.

⁶⁶We again include fixed effects for country-years. [Table F.2](#) instead includes fixed effects for ADM1 region-years, with similar but somewhat less precisely estimated coefficients.

Figure 5 – Effects of Birth Regions on Light Conditional on Aid, ADM2



Notes: The figure plots the marginal effects and 95% confidence intervals of *Spouse region* and *Leader region* conditional on the value of (log) Western bilateral aid, corresponding to column 1 of Table 6. 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.

interference may still produce similarly ineffective outcomes, as political motivations manifest in more nuanced and subtle ways.

Drawing on the rich heterogeneity of our newly geocoded aid data, we show that the observed patterns of regional favoritism vary by donor. Our main findings show that although Western donors succeed in avoiding overt political targeting in aid allocation, they instead channel resources through subtler political connections, whether inadvertently or intentionally. They direct disproportionately more aid to spousal birth regions during the tenure of their partner. Notably, regions associated only with the leaders themselves do not receive such preferential treatment from the same Western donors. We argue that this reflects Western donors' efforts to avoid the appearance of political bias—or recipient governments' strategic tendency to propose fewer overtly political projects to donors with (supposedly) strong safeguards. While the political significance of a leader's birth region is obvious, their spouse's birthplace presents a less conspicuous channel for political influence. The pattern for China differs, showing an increase in aid flows to the ethnic regions of leaders, indicating no attempt to avoid politically visible targeting. By contrast, Western donors' accountability to their electorates may compel them to exploit less visible political connections. In line with previous work for Africa (Dreher et al. 2019), we find that the World Bank's IDA aid does *not* increase when a region is politically influential. On the other hand, we find that IBRD aid increases significantly in regions that are the birthplace of a leader's spouse. Its institutional arrangement appears to subject the IBRD to greater scrutiny than the IDA, making it resemble Western bilateral donors more closely.

To probe why the birth regions of leaders' spouses receive more Western aid, we examine five potential mechanisms: formal as compared to informal influence, preparation of a future political career, strategic marriage, electoral mobilization, and retirement plans. We also explore the importance of donor-related strategies. The data suggest that strategic spouse selection can not explain our results—over 90% of marriages predate the leader's rise to power—and spouse regions lack the pre-tenure traits typically linked to political favoritism. By contrast, electoral dynamics matter: aid to spouse regions increases before competitive elections in recipient countries, while aid to leader regions does not, consistent with leaders using the former as a less scrutinized channel for voter mobilization. Tests of spousal characteristics show that formal political roles—before, during, or after tenure—do not systematically amplify the spouse-region effect. By contrast, leadership positions in NGOs, either before or after a spouse holds office, strengthen the birth-region effect. This points to informal rather than formal influence as the key driver of favoritism. This also suggests that spouses (successfully) preparing for their own future career in politics is not a main driver of our findings. We find no evidence of future settlement motives, whether using cultural variables on patrilocal versus matrilineal societies or measures of discrimination against women in property rights.

We find that countries politically aligned with their donors channel more aid to leaders' birth regions before elections and when elections are more competitive, suggesting that donors provide friendly governments more leeway or extend outright support. We further find that Western donors give more aid to leaders' birth regions that also receive more aid from China. We find no similar results for birth regions of spouses, in line with our expectation that donors or their constituents do not recognize the political salience of such regions. Overall, the evidence suggests that allocation to spouse regions is driven more by recipient discretion—operating within the constraints set by donors—than by direct strategic behavior on the part of donors.

We also tested whether the observed politicization of aid has implications for regional development, as measured by nighttime light emissions. Our results show that regions tied to leaders or their spouses develop faster when politically salient, but these gains are undermined once aid flows in abundance. Politically motivated aid proves significantly less effective than other aid, and at high volumes can even reverse development gains, turning politically motivated allocations into a liability for local development. 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 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. In concert, these datasets create opportunities for addressing fundamental questions about political influence, family networks, and development outcomes.

Despite the strengths of our approach and the novelty of the data, several limitations remain. Chief among them is the absence of comprehensive information on the ethnicity of political leaders' spouses, which could not be systematically collected for a sufficiently large number of spouses.⁶⁷ This prevents us from fully disentangling whether the observed increase in aid to spousal birth regions reflects favoritism toward those regions specifically or toward co-ethnic regions more generally. However, since we control for the co-ethnic

⁶⁷In a pilot coding for African countries—where ethnicity is arguably particularly salient—we were able to identify the ethnicity of only about 10% of spouses.

regions of the political leaders themselves, we isolate the influence of spousal connections as the driver of the observed patterns. A further limitation is that, while we argue that the lack of increased aid to leaders' own regions reflects Western donors' efforts to avoid the appearance of political bias, we cannot rule out an alternative explanation: that recipient governments strategically propose fewer overtly political projects to donors perceived to have strong safeguards against political targeting. Our data do not allow us to distinguish between these two interpretations.

Above the research and data contribution, our findings bear important policy implications. One interpretation of our findings is 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 IDA 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.⁶⁸

Another interpretation of our results suggests that preventing favoritism in the allocation of aid is complicated by 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.

⁶⁸For 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, 2013b, 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 177 countries around the world in the 1989–2023 period. The dataset is at the political leader level and reports information on 1,161 effective leaders who served 1,345 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.⁶⁹ We provide the same information for the birth regions of leaders’ spouses over the 1989–2020 period, covering 288 spouses “in power” (29.2% of the leaders 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 Dataset Description

The following table describes the variables included in the dataset:

Table A.1 – Description of PLAD Variables

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

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⁶⁹We link leaders’ ethnicity to the definitions of the GeoEPR database (Vogt et al. 2015).

Table A.1 – continued from previous page

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/during}_spouse*	Spouse’s level of political power before, during, or after the 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 partner) [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

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Table A.1 – continued from previous page

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 is 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 birthplace 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

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Table A.1 – continued from previous page

Variable	Description
geoname	Search term used in Geonames to geolocate birthplace ⁷⁰
geo_precision	Precision of birthplace information on a scale of 1–6 (see Section A.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_geopr1	First ethnic group corresponding to the names of groups in the GeoEPR dataset
ethnicity_geopr2	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 a scale of 1–4 (see Section A.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) ⁷¹
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)

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⁷⁰When 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.

⁷¹Object 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.

Table A.1 – continued from previous page

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

* 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 Wikipedia⁷² 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*.⁷³ The variables *longitude* and *latitude* contain the coordinates of the leaders' birthplace. As the quality of information, i.e., the accuracy of 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.⁷⁴
- 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).

⁷²While we prefer non-editable sources, Wikipedia offers comprehensive and well-structured information on leader characteristics.

⁷³Oftentimes, 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.

⁷⁴Sometimes 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.⁷⁵ 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

⁷⁵Due 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

We take data on leaders' education level from [Yu and Jong-A-Pin \(2020\)](#) for the period up to 2012 and update them 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 categorize 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 are available.

We find a large heterogeneity in the types of positions held by spouses that reflect political power. Among these, we identify several qualitative accounts that indicate influence over the allocation of foreign aid. As hypothesized, some of this influence is exercised through non-elected roles, including leadership in NGOs. For instance, Margarita Penón Gongora was the first President of the Arias Foundation for Peace

and Human Progress, which received funding from a range of donors, including the governments of Belgium, Canada, Finland, Germany, Japan, the Netherlands, and Switzerland, as well as the European Union (IANSA 2025). We also find qualitative evidence of formalized political influence. For example, Uganda’s First Lady Janet Museveni served as Minister for Education and Sports, overseeing the allocation of development projects (Van Wyk et al. 2018). Beyond individual cases, first ladies engage collectively with donors through institutionalized platforms. For instance, the Coalition of First Ladies and Women Leaders of Latin America facilitates dialogue with donors and has supported health initiatives. Similarly, the Organization of African First Ladies for Development has been involved in channeling aid; one example includes a donation in support of Kenyan First Lady Margaret Kenyatta’s Beyond Zero initiative to aid mothers and children during the COVID-19 pandemic (AidData 2025).

A.3.7 Descriptive Statistics

Tables A.2 and A.3 show summary statistics.⁷⁶ On average, during the 1989-2020 period, a region-year (ADM2) observation is coded as a spousal region in about 0.16% of cases. This is equivalent to 0.05 years—a little less than a month—across all regions. Conditional on being a spousal region, the average (uninterrupted) duration of a spousal region is 6.3 years. There is some variation across continents: an ADM2 region is coded on average as a spousal region in about 0.3% of all years in Africa and 0.1% in the Americas. An average spousal region spell lasts 8 years in Africa and 4 years in Oceania.

We record 285 distinct ADM2 regions that change their status as spousal birth region at least once, and a total of 566 changes. This value is lowest in Oceania, with only 17 changes, and highest in Europe with 184 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 0.173. Out of the 2,292 spouse-year observations in our sample, 581 are leader-year observations as well. Of the 285 distinct ADM2 regions that change their status as spousal birth region at least once, 4.2% 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.

⁷⁶Note that we provide statistics for the entire database here, rather than the estimation sample used in the main part of the paper.

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

	Mean	Std.Dev.
<hr/>		
<i>Spouse</i>		
Spouse birthregion dummy	0.16	4.02
Change spouse birthregion	0.04	2.00
<i>Leader</i>		
Leader birthregion dummy	0.35	5.92
Change leader birthregion	0.09	3.03
<i>Both</i>		
Spouse and leader birthregion dummy	0.04	2.04
Change of spouse and leader birthregions	0.01	1.06

Notes: 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).

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

	<i>Spouses</i>			<i>Leaders</i>			<i>Both</i>		
	Mean	Std.Dev.	Obs	Mean	Std.Dev.	Obs	Mean	Std.Dev.	Obs
<i>Africa</i>									
Birthregion dummies	0.2989	5.4593	194696	0.7553	8.6579	196480	0.0426	2.0643	194696
<i>Americas</i>									
Birthregion dummies	0.0962	3.0996	494983	0.1786	4.2218	485004	0.0369	1.9212	484772
<i>Asia</i>									
Birthregion dummies	0.1833	4.2779	343083	0.3742	6.1060	349512	0.0515	2.2693	341593
<i>Europe</i>									
Birthregion dummies	0.1645	4.0525	344081	0.3077	5.5389	361017	0.0416	2.0396	343598
<i>Oceania</i>									
Birthregion dummies	0.1451	3.8065	26878	0.4410	6.6266	28342	0.0000	0.0000	26878

Notes: 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).

A.3.8 Characteristics of Marriages and Spouse Regions

In our sample, we observe marriage dates of 366 spouses whose partner served as political leader. The large majority of these marriages (334) took place before the leader assumed office (91.3%), whereof only 45 marriages occurred shortly before (within five years of) or during the year the leader came to power. 32 (8.7%) marriages occurred during the leader’s tenure.⁷⁷

One potential concern is that political leaders may marry strategically—choosing spouses in ways that improve their electoral prospects or increase their chances of attaining office. If spouses were selected based on the importance of their birth region just before the leader’s tenure, observed increases in aid would not be caused by birth-region status. However, given the small share of marriages occurring just before tenure, this does not threaten identification in our setting.

To further examine whether the birth regions of spouses—particularly those from spouses who married shortly before or during the year of assuming office—differ systematically from other regions, we compare the characteristics of these regions to all other regions in a country (excluding the soon-to-be birth region of the leader in the year prior to assuming office). Columns 1 to 4 of [Table A.4](#) present results for all spouse birth regions, while columns 5 to 8 focus specifically on birth regions of spouses whose marriages occurred within five years before or during the leader’s tenure. We begin by examining core regional characteristics such as natural resource presence, infrastructure, and socioeconomic development in columns 1 and 5. Columns 2 and 6 add leader-specific variables, and columns 3 and 7 introduce aid-related indicators. Lastly, columns 4 and 8 incorporate subnational corruption indices—though this specification comes with a smaller sample size due to data limitations.

Starting with column 1, we find that soon-to-be birth regions of spouses, on average, have higher population density and greater economic development, as proxied by nighttime lights, compared to other regions in the country. We find no statistically significant differences with respect to natural resource extraction or regarding road and port infrastructure. What is more, these regions are not systematically more likely to share the leader’s ethnicity or be geographically closer to the soon-to-be leader’s birth region (see columns 2 and 5). Once we control for leader characteristics, however, we observe a lower likelihood of port presence in spouse regions. We also find no evidence that spouse regions receive higher aid inflows or have higher levels of corruption, suggesting these regions do not display characteristics typically associated with political favoritism before tenure.⁷⁸

⁷⁷15 marriages occurred in the year the leader came to power. Since we do not have information on the exact dates, we cannot determine whether the marriage or the start of the tenure happened first. We count these as recent marriages rather than as marriages occurring during tenure.

⁷⁸While the distance to the leader’s region becomes statistically significant in column 4, attributable to the large decrease in sample size, the coefficient is literally zero in our main sample (columns 2–3).

In summary, while spouse birth regions do differ from other regions in some observable ways—particularly in population and economic development—these differences are not systematically linked to political favoritism. Most marriages occur well before political ascension. Reassuringly, these differences disappear once we restrict spouse regions to the birthplaces of spouses whose marriages occurred within five years before or during the leader’s tenure. This supports our broader claim that the effects we observe are causal effects reflecting the influence of leaders’ spouses rather than correlations arising from strategic spouse selection.

Table A.4 – Characteristics of Spouse Regions in the Year Before Starting Tenure

	All spouses				Spouses wt recent marriages			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
No. of ports	-0.01 (1.31)	-0.01** (2.40)	-0.01** (2.39)	-0.05 (1.52)	-0.00* (1.69)	-0.01 (1.66)	-0.01 (1.66)	-0.01 (0.63)
No. of active mines	0.00 (0.60)	0.00 (1.02)	0.00 (1.01)	0.02 (1.09)	0.00 (0.93)	0.00 (0.94)	0.00 (0.93)	0.02 (0.91)
No. of petroleum fields	0.01 (0.74)	0.01 (1.14)	0.01 (1.14)	0.05 (0.81)	0.01 (1.47)	0.01 (1.44)	0.01 (1.44)	0.00 (0.70)
Road density	-0.01 (1.33)	-0.00 (0.33)	-0.00 (0.35)	-0.02 (1.16)	-0.00 (0.92)	-0.00 (0.58)	-0.00 (0.62)	-0.00 (0.63)
Area (km ²)	0.00 (0.69)	0.00 (0.82)	0.00 (0.81)	0.00 (0.31)	-0.00 (0.15)	-0.00 (0.16)	-0.00 (0.18)	-0.00 (0.21)
No. of ethnic groups	-0.00 (0.57)	-0.00 (0.38)	-0.00 (0.38)	-0.03 (0.84)	-0.00 (1.49)	-0.00 (1.42)	-0.00 (1.44)	-0.01 (0.87)
Population	0.01** (2.47)	0.01* (1.85)	0.01* (1.82)	0.02 (1.14)	0.00 (1.41)	0.01 (1.41)	0.00 (1.46)	0.00 (0.50)
Light	0.00* (1.90)	0.01* (1.95)	0.01* (1.96)	0.01 (1.25)	0.00 (1.05)	0.00 (0.99)	0.00 (0.98)	0.00 (0.95)
Leader ethnicity		0.00 (0.27)	0.00 (0.27)	0.13 (1.64)		0.01 (0.47)	0.01 (0.47)	0.03 (0.98)
Distance leader region		-0.00 (0.68)	-0.00 (0.68)	-0.66* (1.73)		-0.00 (0.62)	-0.00 (0.61)	-0.26 (1.00)
Aid			0.00 (0.10)	-0.01 (1.37)			0.00 (0.21)	-0.00 (0.95)
Subnat. corruption index				0.00 (0.33)				-0.00 (1.00)
Subnat. corruption perception index				-0.00 (0.05)				0.00 (1.00)
Country fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Number of observations	155127	95017	95017	16568	155118	95010	95010	16564

Notes: The table shows results from ordinary least squares (OLS) regressions of a binary variable indicating the soon-to-be birth region of the spouse (one year before tenure) on several regional characteristics. The dependent variable was multiplied by 100 given the small number of spouse regions with information on marriage date, allowing to better read the coefficients. Countries for which we do not have any information on the marriage date of leaders were dropped from the sample. *No. of ports* gives the number of ports within an ADM2 region, derived from the World Port Index provided by the National Geospatial-Intelligence Agency (NGA). *No. of active mines* is the number of currently producing mines taken from Lujala (2009). *no. of petroleum fields* gives the number of petroleum fields taken from the PETRODATA, Lujala et al. (2007). *Road density* measures the road length per area based on the global road open access data from CIESIN, SEDAC. *Area* captures the size of the ADM2 region in km². *No. of ethnic groups* gives the number of ethnic groups that reside in this region based on GeoEPR data. *Population* is the log of the region’s population (CIESIN 2018). *Light* refers to log of nighttime light (plus 0.01, Li et al. 2020). *Leader ethnicity* identifies if the ethnicity of the soon-to-be leader is the dominant one in the region, based on GeoEPR. *Distance leader region* gives the geodesic distance to the soon-to-be leader region. *aid* captures the logarithm of aid disbursements (plus 1) given to that region. The last two variables are indicators for corruption at the subnational level taken from Crombach and Smits (2024). All regressions include country and 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.

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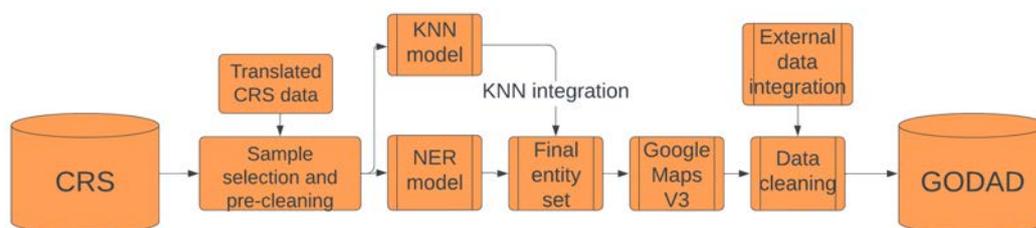
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B Constructing GODAD

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 the matched locations and coordinates.

Figure B.1 – Entity Extraction and Geotagging Pipeline



Notes: 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.5, we compare the final geocoded sample to the original CRS data to assess its representativeness. Second, in Section B.6, we compare our data to an existing source for geocoded aid data, the Aid Information Management System (AIMS) data for Uganda.

B.2 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), a classification as either ODA or OOF, aid sectors and sub-sectors, and the corresponding 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. To construct the dataset, we utilize all the information contained in the CRS, including classification of aid flows as ODA or OOF. In our regression analysis, we utilize ODA flows as the baseline in order to facilitate comparisons between donors and with other aid datasets. [Table B.1](#) provides some examples of these raw data.

Table B.1 – CRS Raw Data Example

DonorName	RecipientName	ProjectTitle
Germany	Afghanistan	Building a skateboarding facility in Kabul 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 Mbas-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

The CRS vintage we use contains information on aid activities from the 19 donors combined, covering the period from 1973 to 2020.⁷⁹ We focus on bilateral projects and thus exclude cases where the recipient is marked either as 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 from which we start consists of 1,605,748 bilateral aid projects spanning the entire period. As a first step, we filter out elements that are not geocodable ex ante. We exclude flows that are by definition not attributable to a subnational location, such as general budget support, debt relief, donors’ administrative costs, and expenditures incurred in the donor country, such as those for refugee hosting. In addition, we exclude projects where both titles and descriptions are missing, as there is no candidate text

⁷⁹At the time of extraction (January 2023), data for 2021 were only partially complete and thus not included in this version of the data.

for the NER model to process. Furthermore, we identify reported entries that represent thematic or regional grouping of smaller, individual activities and therefore cannot be geocoded. Examples include “Technical Cooperation Aggregated Activities” and “Chiesa Cattolica 8xMille.” These steps reduce the number of aid projects available for geocoding to 1,328,163 for the 1990–2020 period.⁸⁰

B.2.2 Entity Extraction

To extract geographic entities from the data, the first step consists in utilizing the natural language processing tools within the (pre-trained) Spacy core English transformer pipeline with the Named Entity Recognition (NER) model. These models are typically used to identify pieces of information within text such as names, actions, or geographical entities. The underlying model is the RoBERTa-base 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.⁸¹ In the first part of this approach, we split the text 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 geographic entity to be passed to the geocoder only when the precision is sufficiently high and the NER output did not return 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 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.

⁸⁰We additionally translate non-English project information using Google Translate API and use the English text as additional input for the entity extraction model. These translated projects are predominantly Spanish (69,908), French (81,631), and Belgian (16,706).

⁸¹Specifically, we use a Term Frequency–Inverse Document Frequency (TF–IDF) algorithm with k-Nearest Neighbor (KNN) matching.

Figure B.2 – NER Model Geotagged Example

Project title:
Skateboarding hall **Kabul GPE**
Project description:
Build a skateboarding facility in **Kabul GPE** to engage youth throughout **Afghanistan GPE**, building technical skills, confidence and life opportunities

Notes: Figure shows stylized example of NER model output.

B.2.3 Geocoding

We geocode the extracted entities with the GoogleV3 geocoding API. The choice of geocoder is relevant when obtaining geocodes for a large number of cross-country locations. While the performance of Google Maps may vary by country, it overall provides results of consistent quality across the sample. Unlike other popular (free) geolocating services, which essentially match locations to multiple geodatabases of locations, the Google Maps API can leverage more sophisticated ranking algorithms in combination with an immense amount of lower-level GPS, WIFI, network, and other data. This ranking algorithm for matching locations results in substantially fewer errors with respect to geocoders that rely on matching algorithms. The geocoder is then restricted to return matches only within the CRS-reported aid recipient country. The process returns 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 geocoding, we standardize the level of subnational precision. First, we remove project locations with only country-level information as these provide insufficient spatial detail.⁸² We then correct errors in subnational classification, such as points that fall just offshore or near borders by snapping them to the nearest ADM2 unit within the correct recipient country.

Next, we verify ADM2 precision by cross-validating geocoded locations against both the project narrative and the recipient’s GADM polygons. For example, consider a project geocoded with the location Lashkargah and described as “...school rehabilitation in Lashkargah and Kabul...” The narrative confirms that Lashkargah is a valid location, indicating that the geocode was not spuriously assigned elsewhere within Afghanistan. Additionally, Lashkargah maps uniquely to a GADM ADM2 location, further validating our administrative classification. Similarly, we treat over-precise street-level geocodes as unreliable unless they are clearly supported by the narrative and align with the GADM administrative hierarchy. In such cases, we collapse the location to the corresponding

⁸²The geocoding API returns a country centroid when no finer match is available.

ADM2, otherwise we exclude them.

When multiple locations remain for a project, we distinguish nested from distinct entities and keep only the most specific unit to avoid double counting. Following on the previous example, if the text mentions both *Lashkargah, Helmand, Afghanistan* and *Helmand, Afghanistan*, we keep only Lashkargah. If it mentions *Lashkargah, Helmand province* and *Kabul province*, we keep both Lashkargah and Kabul province.

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 match our data with 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. When 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 217,440 geocoded projects, and 276,226 project-location combinations, of European and U.S. aid projects between 1990 and 2020.⁸³

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.

The final geocoded sample consists of 217,440 unique projects (and 276,226 project-location combinations). This corresponds to about 16% of the original 1,328,163 bilateral projects considered. It is important to note that this does not indicate a failure to geocode the majority of projects. The pre-geocoded set includes projects that contain geographic entities and are, ultimately, successfully geocoded—for example, a 2008 grant of US\$1.29 million from the Spanish Ministry of Foreign Affairs and Cooperation to provide health

⁸³AIMS (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.”

services in Afar and Amhara, Ethiopia. However, it also includes projects that reference subnational geographic entities in their description, but are not successfully geocoded. Additionally, it includes 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. 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. These include large loans for sector-wide support (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).

Table B.2 provides an overview of the final data by showing the main descriptive statistics both before and after geocoding. Geocoded projects have an average commitment of around US\$600,000, 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. Figure B.3 shows the average commitments by aid sectors for the pre- and post-geocoded sample. For most sectors, the average project size remains consistent before and after geocoding. One exception is infrastructure, where projects are more likely to be geocoded due to their inherently spatial nature, resulting in somewhat larger average commitments in the geocoded sample.

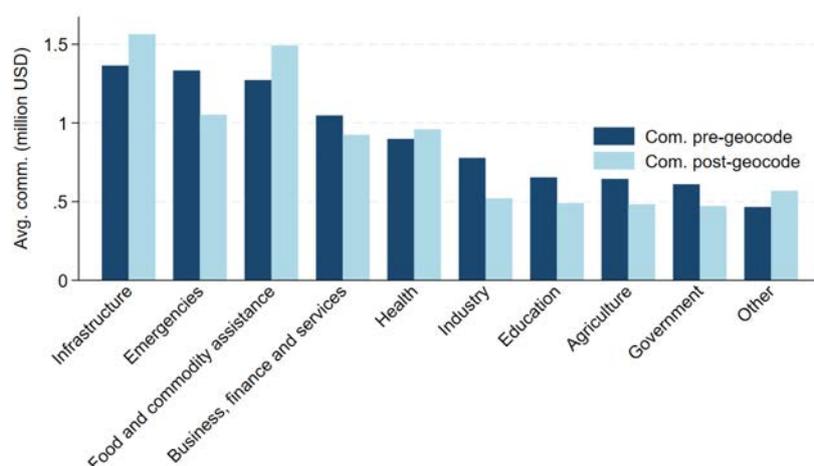
Table B.2 – GODAD EU and U.S. Sample Description

	Pre-geocode			Post-geocode		
	N	Mean	S.D	N	Mean	S.D
Number of projects	1,328,163			217,440		
Commitments	1,328,163	0.9	7.8	217,440	0.6	5.8
Disbursements	1,328,163	0.6	5.1	217,440	0.4	3.2

Notes: Table shows the distribution of projects from the raw CRS data and the distribution for the final sample after geocoding the years 1990–2020. Values are in millions of 2014 US dollars.

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

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



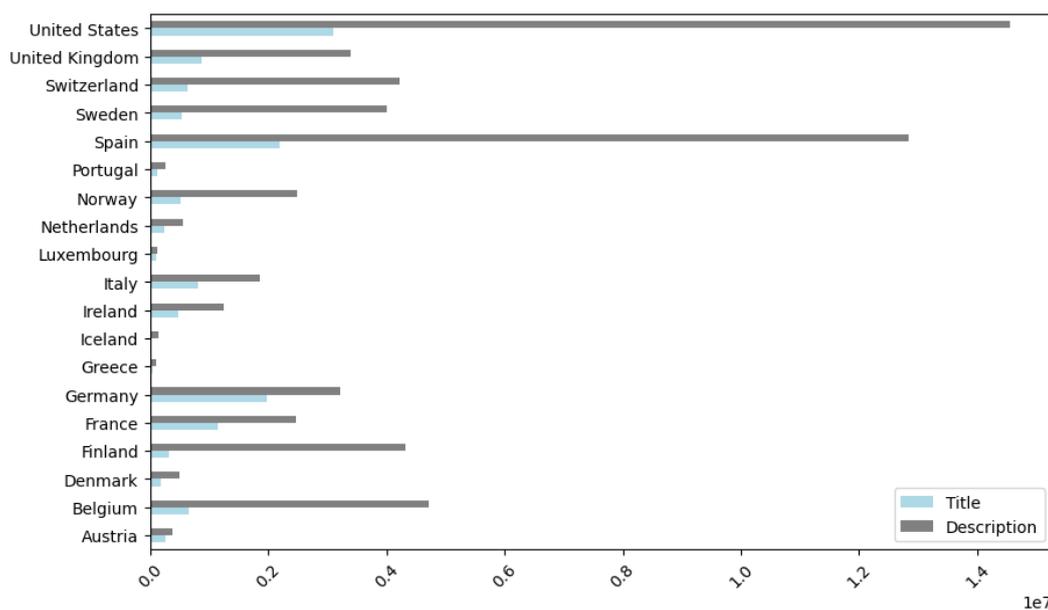
Notes: Figure shows the average size of project commitments (in 2014 US\$) pre and post geocoding across the main aid sectors: economic infrastructure, emergency aid, food and commodity assistance, business and financial services, health, industry, education, agriculture, government, and other.

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



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

B.3.2 Evaluating 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:

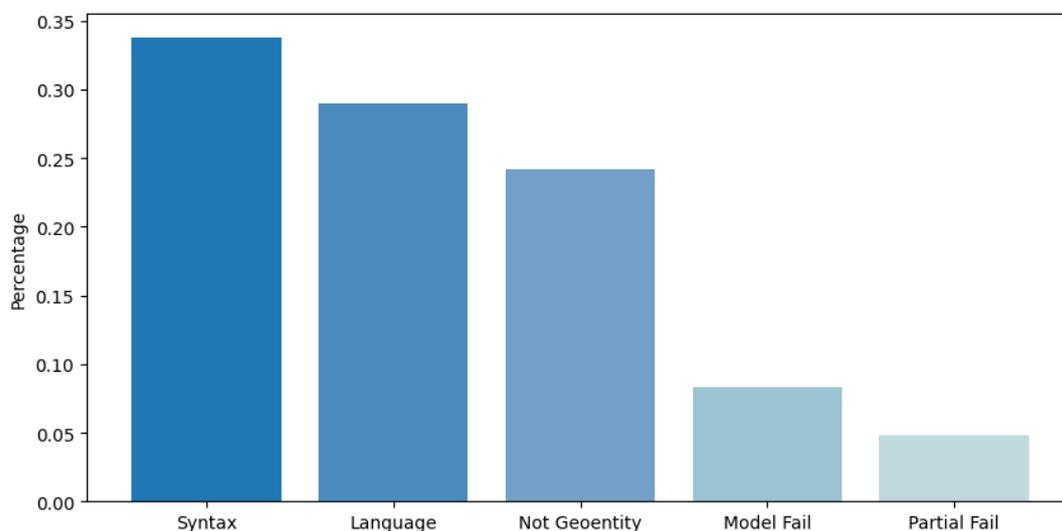
$$Accuracy = \frac{|Y_i \cap Z_i|}{|Y_i \cup Z_i|}, \quad (B.1)$$

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 political 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).

Figure B.5 – Distribution of NER Errors



Notes: Figure shows the distribution of the NER 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.

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. Most project descriptions include locations that allow us to reliably geocode at the ADM2 level, usually referencing large cities or municipalities.

Second, the geocoding pipeline identifies explicitly mentioned geographical entities, but not 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 using a random sample of 10,000 projects. Specifically, we randomly select projects 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). Within each region, the sampling is representative of the donor’s regional footprint: if, for example, Spain accounts for 30% of projects in South America, then 30% of this random sample will consist of Spanish projects. To ensure coverage, we impose a minimum of 100 projects per donor in each region and at least 1,000 projects overall per region. Sampling is performed at the project level rather than the location level, since a single project may contain multiple sites with different geocoding outcomes. All sampled projects then undergo the same cleaning procedures as the rest of the dataset.

Table B.3 presents a classification of the main errors considered. We classify errors as false positives (locations incorrectly assigned) or false negatives (locations missed). These arise primarily from three sources: common place names, geocoder limitations, and entity extraction errors. To illustrate how these errors can manifest in the final data, we provide representative examples, which should be understood as illustrative cases and not as an exhaustive catalog.

“Common names”, or ambiguity in place names, can lead to misclassification. For example, when a Spanish project mentions a partner agency in Córdoba (Spain) in

connection to a Colombian project, the pipeline may incorrectly geocode the project to Córdoba, Colombia. Similar problems arise with common names such as “San José,” “Victoria,” or “La Paz,” which exist in multiple countries. In these cases, the geolocated entity does not correspond to the intended project site, but to a different place with the same name.

Errors also occur when the geocoder receives the correct string but cannot return the intended location. This happens with ethnic territories, informal settlements, or historical place names. Humanitarian projects for the Sahrawi refugee camps, for example, are almost always reported under Morocco in CRS data, but the project descriptions reference camps on the Algerian side of the border. Because the geocoder is calibrated to search within Morocco, it fails to return a match. Other cases involve historical or local naming conventions, such as “Moskitia Coast” in Honduras, which may not be recognized unless spelled as “Mosquito Coast.” These errors illustrate that even when the pipeline extracts the correct text, the geocoder’s coverage and nomenclature rules can lead to both missed matches (false negatives) and mis-assigned ones (false positives).

Finally, as previously outlined in [Section B.3.2](#), errors can originate during entity extraction. When the NER model fails to identify a candidate geographical entity due to syntax, language variation, or unusual formatting, the geocoder receives no input, leading to false negatives. Conversely, the model can falsely tag words that resemble locations but are not geographic entities (e.g. acronyms, institutional names, or person names).

Table B.3 – Geocoding Pipeline Errors

	False positives	False negatives
Common names	Similar names in donor and recipient	
	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	Not geo entity	Syntax
		Language
		NER model failure

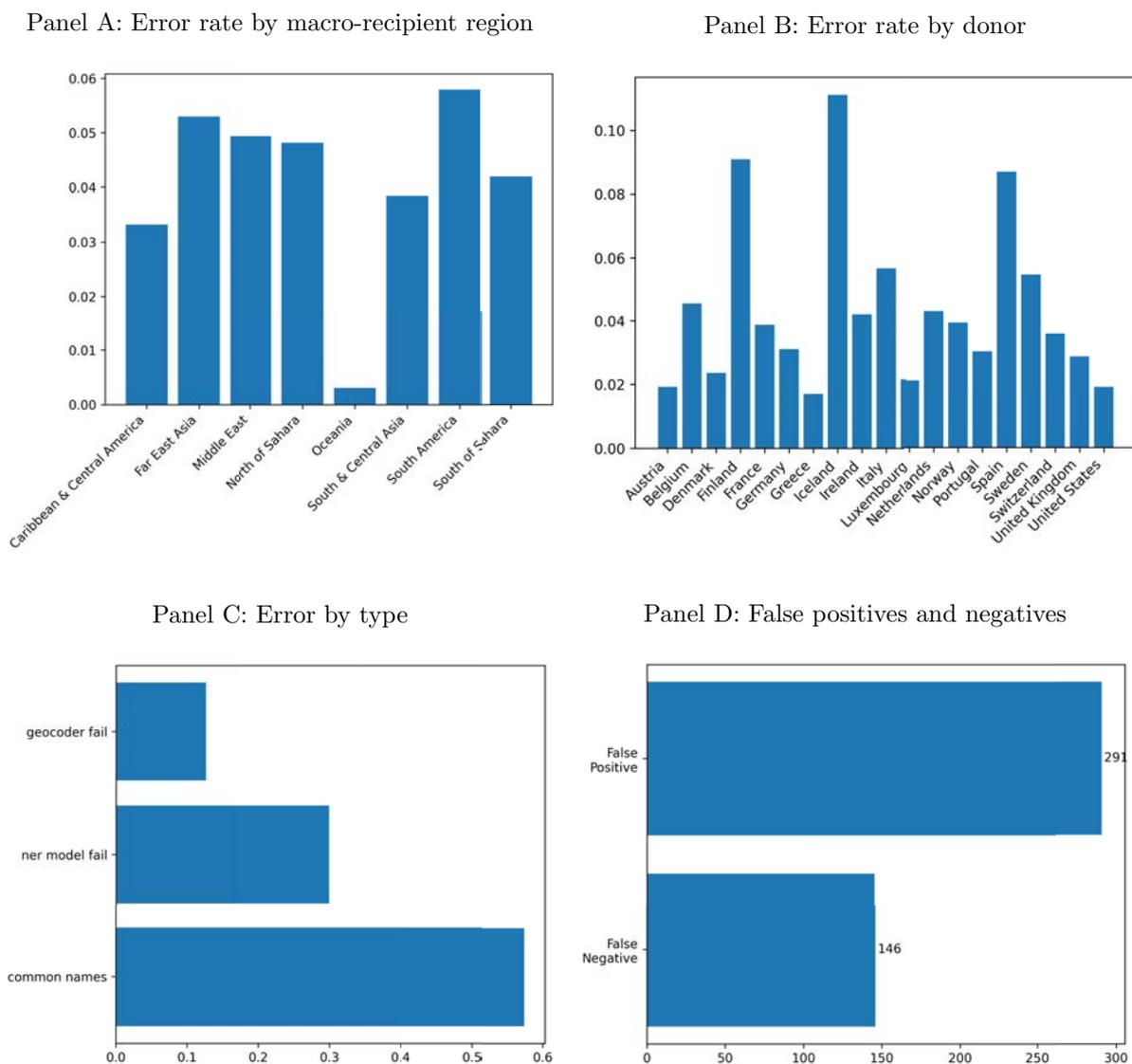
Notes: Table shows examples of different error categories occurring in the geocoding pipeline.

[Figure B.6](#) shows the error rates across different categories. In the random sample of over 10,000 projects, about 4% (437) of the projects exhibited an error described as in [Table B.3](#). Breaking down the errors by type, 291 are false positives, while 146 are false negatives. Among all errors, 57% (251) 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 12% (55) and 30% (131) respectively).

When examining individual donors rather than aggregates, the error rate is below 10% for most countries. The exception is Iceland, which represents a very small share of total aid in the sample. Disaggregating by recipient region rather than donor, we find similarly low error rates—averaging around 5%—with no region standing out. The only exception is Oceania, where the error rate is close to 0.

Figure B.6 – Decomposition of Pipeline Errors

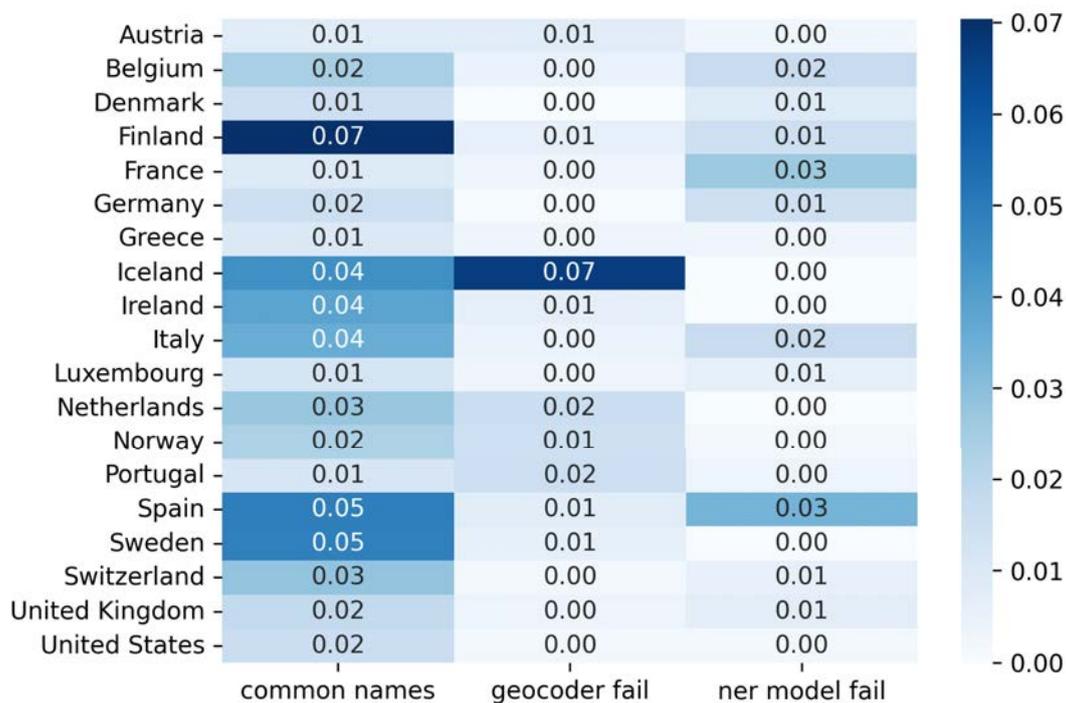


Notes: The figure shows a decomposition of the pipeline errors in different classifications: by recipient macro region, by donor, by type, and by type and category. We calculate the error rate for projects as the share of projects with at least one error in the geocoding output, based on a random sample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

Figure B.7 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 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 11%, compared with the mean of 4%. 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 some countries like Ireland, Iceland, or the Netherlands having none of these errors in the random sample.

Figure B.7 – Donor-Error Heatmap



Notes: 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 Representativeness of GODAD

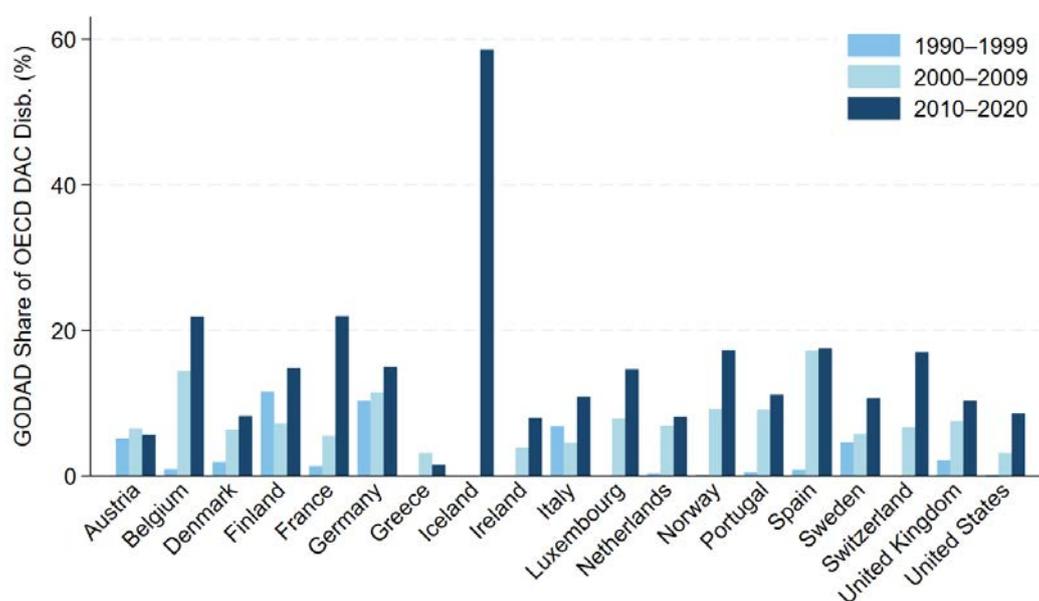
An important step for using GODAD is to understand its representativeness and scope. A simplistic approach would be to compare the total volume of aid in GODAD to commonly used country-level statistics. We argue that such a comparison is uninformative and potentially misleading for several reasons. First, these aggregate statistics encompass a wide variety of flows that are fundamentally different in scope from the subnational project aid captured in GODAD. These include general budget support, debt relief, and administrative costs, which are not location-specific and were intentionally filtered from

our initial sample. Second, they often include bilateral contributions that are channeled to multilateral organizations or projects carried out within the donor countries.

Nevertheless, to provide a quantitative benchmark, we compare against country-level data from the OECD’s Table DAC2A.⁸⁴ To create the most reasonable “apples-to-apples” comparison, we filter the DAC data to exclude all contributions for multilateral organizations and debt relief. However, the final value will still include aid activities which are non-geocodable by design such as government-to-government transfers or in-donor refugee costs.

Figure B.8 shows total aid commitments for each donor, aggregated into ten-year intervals for the 1990–2020 sample period. We find that on average our subnational, project-level dataset covers around 10% of total reported DAC disbursements, with coverage increasing to 20% in later years, as expected due to improving CRS quality over time. While this exercise provides a useful point of reference, we caution against over-interpreting this figure. The comparison underscores a fundamental point: GODAD is not a dataset of all foreign aid but of subnationally driven project aid. Much of what is reported in aggregate DAC tables, even after filtering, does not consist of geographically targeted projects that can be assigned to a specific region within a country.

Figure B.8 – Comparison of GODAD to OECD DAC Country Data



Notes: Figure shows the share of total disbursements, in 2014 US\$, of GODAD data with respect to the OECD DAC2A bilateral disbursement data for the 3 decades between 1990 and 2020. The DAC2A data include total ODA net of debt relief for the same set of aid recipient countries covered in GODAD.

⁸⁴The data can be accessed via the [OECD Data Explorer](#).

In the following [Section B.5](#) we provide an internal comparison which offers a more informative assessment of GODAD’s representativeness. That analysis compares the characteristics of our final geocoded projects to the full set of potentially geocodable projects we initially identified in the CRS, confirming that GODAD represents the underlying data well with respect to key features.

B.5 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 at the location level. 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 four project characteristics: the year of reporting, the project size (measured as total commitments), donor country, project sector, and type of financial flow. 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 show in column 1 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 measured by commitments.

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 13 European countries (Austria, Belgium, Finland, France, Germany, Iceland, Italy, Luxembourg, Netherlands, Norway, Portugal, Sweden, and Switzerland) are significantly more likely to be geocoded. Conversely, projects from Greece are significantly less likely to be geocoded compared to the United States. Relative to projects in the government sector (our baseline category), projects in the health, infrastructure, and agriculture sectors, as well as emergency aid and others, are more likely to be geocoded. Conversely, projects in business, finance, and services, and food and commodity assistance 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 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 shows a statistically significant difference between ODA loans and ODA grants. Additionally, there is no longer a statistically significant difference for Austria, Germany, and the Netherlands relative to the United States. However, for the United Kingdom the coefficient becomes 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, projects from the Netherlands, Switzerland, and Sweden are equally 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 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.

Table B.4 – Factors Correlated with Geocoded Projects

	Geo-coded project					
	(1)	(2)	(3)	(4)	(5)	(6)
Year	0.006*** (13.048)					
Commitment in USD, ln	0.000 (0.080)	0.003 (0.771)	0.002 (0.698)	0.005 (1.391)	0.003 (0.804)	-0.001 (-0.432)
Austria	0.126*** (7.015)	0.112*** (6.596)	0.112*** (6.594)	-0.017 (-0.680)	-0.023 (-0.900)	-0.006 (-0.256)
Belgium	0.137*** (9.969)	0.093*** (6.576)	0.093*** (6.637)	0.052** (2.496)	0.047** (2.213)	0.088*** (4.173)
Denmark	0.020 (1.590)	0.013 (1.022)	0.014 (1.071)	-0.014 (-0.416)	-0.019 (-0.579)	-0.012 (-0.370)
Finland	0.249*** (15.996)	0.236*** (15.596)	0.238*** (15.767)	0.276*** (10.103)	0.279*** (9.984)	0.280*** (10.316)
France	0.025** (2.173)	0.011 (0.955)	0.011 (0.936)	-0.089*** (-4.528)	-0.107*** (-5.583)	-0.084*** (-4.380)
Germany	0.110*** (9.251)	0.100*** (8.771)	0.099*** (8.676)	-0.022 (-0.987)	-0.027 (-1.242)	-0.016 (-0.719)
Greece	-0.049*** (-3.252)	-0.007 (-0.527)	-0.010 (-0.678)	-0.081*** (-3.033)	-0.087*** (-3.285)	-0.104*** (-4.011)
Iceland	0.481*** (6.928)	0.465*** (6.848)	0.463*** (6.776)	0.514*** (9.966)	0.512*** (9.880)	0.519*** (10.117)
Ireland	0.043 (1.109)	0.013 (0.452)	0.012 (0.443)	-0.050** (-2.233)	-0.055** (-2.408)	-0.039* (-1.723)
Italy	0.204*** (14.057)	0.192*** (13.754)	0.192*** (13.867)	0.106*** (4.812)	0.100*** (4.474)	0.107*** (4.791)
Luxembourg	0.071*** (4.699)	0.011 (0.747)	0.012 (0.831)	-0.039 (-1.473)	-0.045* (-1.675)	0.016 (0.553)
Netherlands	0.042*** (3.959)	0.027*** (2.633)	0.029*** (2.776)	0.019 (0.755)	0.014 (0.537)	0.016 (0.635)
Norway	0.083*** (6.230)	0.077*** (6.012)	0.077*** (6.069)	0.068*** (2.652)	0.063** (2.440)	0.066** (2.545)
Portugal	0.083*** (4.015)	0.081*** (3.785)	0.081*** (3.838)	-0.039 (-1.467)	-0.045* (-1.699)	-0.047* (-1.750)
Sweden	0.037*** (3.385)	-0.005 (-0.478)	-0.006 (-0.567)	-0.046** (-2.042)	-0.051** (-2.262)	-0.029 (-1.245)
Switzerland	0.070*** (5.151)	0.031** (2.284)	0.032** (2.328)	-0.056** (-1.997)	-0.063** (-2.248)	-0.017 (-0.590)
United Kingdom	0.020 (1.313)	0.029* (1.961)	0.029* (1.954)	-0.064* (-1.846)	-0.068* (-1.956)	-0.085** (-2.463)
Education	-0.008 (-1.106)	-0.014* (-1.882)				
Health	0.095*** (12.450)	0.091*** (11.646)				
Infrastructure	0.057*** (7.854)	0.052*** (7.334)				
Business, finance and services	-0.038*** (-4.826)	-0.036*** (-4.517)				
Agriculture	0.129*** (15.953)	0.121*** (15.280)				
Industry	0.002 (0.255)	0.001 (0.140)				
Food and commodity assistance	-0.019* (-1.896)	-0.008 (-0.770)				
Emergencies	0.028*** (2.684)	0.031*** (3.175)				
Other	0.033*** (4.043)	0.021*** (2.614)				
Equity Investment	-0.134*** (-4.908)	-0.144*** (-4.808)	-0.144*** (-4.868)	-0.130*** (-4.323)	-0.102*** (-4.905)	-0.062*** (-3.105)
ODA Loans	0.009 (0.727)	-0.028* (-1.934)	-0.026* (-1.804)	-0.035** (-2.349)	-0.150*** (-7.411)	-0.085*** (-4.608)
Other Official Flows (non Export Credit)	-0.140*** (-5.212)	-0.199*** (-6.600)	-0.182*** (-6.016)	-0.185*** (-6.248)	-0.130*** (-2.757)	-0.118** (-2.488)
All columns filled-in	0.146*** (16.093)					0.153*** (19.493)
Recipient FE	✓					
Recipient-Year FE		✓				
Sector-year FE			✓			
Donor-sector Interactions				✓		
Donor-flow interaction					✓	
Observations	1458476	1458380	1458380	1458380	1458380	1458380

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

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 (significantly) lower, rather than higher, in the year when the tenure of leaders or their spouses begins. 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

	Legislative election	Executive election	Leader taking office	Spouse taking office
	(1)	(2)	(3)	(4)
5 years before	0.005 (1.032)	-0.000 (-0.051)	-0.002 (-0.364)	0.004 (0.920)
4 years before	0.006 (0.790)	-0.000 (-0.026)	-0.002 (-0.491)	-0.001 (-0.187)
3 years before	0.006 (0.689)	0.004 (0.404)	-0.009 (-1.354)	-0.009 (-1.435)
2 years before	-0.001 (-0.132)	0.001 (0.043)	-0.006 (-1.093)	-0.005 (-0.848)
1 year before	-0.010 (-1.038)	-0.002 (-0.151)	-0.009 (-1.541)	-0.012** (-2.194)
Year of election/office start	-0.013 (-1.591)	-0.005 (-0.417)	-0.012** (-2.357)	-0.014*** (-2.703)
1 year after	-0.018** (-2.284)	-0.006 (-0.474)	-0.008 (-1.317)	-0.007 (-1.314)
2 years after	-0.019*** (-2.721)	-0.013 (-1.249)	-0.009 (-1.511)	-0.012*** (-2.642)
3 years after	-0.015** (-2.427)	-0.013 (-1.553)	-0.007 (-1.382)	-0.009** (-2.300)
4 years after	-0.009* (-1.719)	-0.013* (-1.906)	-0.003 (-0.649)	-0.006 (-1.253)
5 years after	-0.006 (-1.403)	-0.009* (-1.801)	0.001 (0.131)	-0.003 (-0.588)
Country FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Continent time trend	✓	✓	✓	✓
Observations	2382	2382	2411	2411

Notes: 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 are reported in parentheses; * p<0.10, ** p<0.05, *** p<0.01.

B.6 Benchmarking GODAD

GODAD represents a significant milestone as the first comprehensive cross-country compilation of geocoded aid data, spanning across 181 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.⁸⁵ Among the geocoded projects, 120 pertain to budget support and are not included in the following statistics.⁸⁶ 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.⁸⁷ In total, for the Western bilateral donors in the CRS sample, AIMS includes 197 projects, 144 of which are also included in the CRS.⁸⁸

Column 4 shows data from GODAD. As can be seen, when compared to AIMS, GODAD contains a substantially larger number of aid projects in Uganda (4,929 in total). When we restrict the sample period to those years that are covered in AIMS (in column 5), GODAD still includes 3,017 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, GODAD thus improves substantially on previously available data, even for the few recipient countries where such data exist at all.

While data included in the Uganda AIMS Geocoded Research Release provides a useful case study, we find that in general this pattern holds up across the remaining 11 different geocoded AIMS datasets we analyze. These include Burundi, the Democratic Republic of Congo, Colombia, Honduras, Iraq, Nigeria, Nepal, Senegal, Sierra Leone, Somalia, and Timor-Leste. Table B.7 gives information on the number of projects from the two respective sources. As can be seen, in almost all cases we are able to have more extensive coverage in the number of projects, years, and number of geocoded locations.

⁸⁵We 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.

⁸⁶AIMS 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.

⁸⁷The 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.

⁸⁸AIMS 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.

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

	(1) AIMS Uganda	(2) Merged projects	(3) CRS	(4) GODAD	(5) GODAD (1978-2014)	(6) CRS (1978-2014)
Total	224	144	30716	4929	3017	21262
Austria	35	25	1400	436	286	927
Belgium	4	3	1079	223	95	786
Denmark	31	18	1105	120	95	890
Finland	-	-	469	156	87	262
France	-	-	625	110	26	376
Germany	5	3	2404	666	355	1629
Greece	-	-	40	1	1	34
Iceland	1	-	71	50	15	23
Ireland	17	14	3877	556	413	3051
Italy	-	-	1254	509	361	966
Luxembourg	-	-	85	2	2	31
Netherlands	-	-	1028	113	106	971
Norway	60	45	2399	349	303	1917
Portugal	-	-	2	-	-	-
Spain	1	-	381	151	104	267
Sweden	11	9	2323	255	144	1741
Switzerland	-	-	417	33	11	180
United Kingdom	12	10	1881	240	149	1188
United States	20	17	9876	820	334	6023
World Bank	-	-	-	61	46	-
China	27	-	-	78	41	-

Table B.7 – Comparison AIMS vs. GODAD

	AIMS Data				GODAD Data				Difference
	Projects	Locations	Min Year	Max Year	Projects	Locations	Min Year	Max Year	
BDI	930	7562	1988	2016	1804	4813	1990	2023	874
COD	256	1750	1999	2014	7963	12560	1989	2023	7707
COL	665	2981	1994	2013	5621	8694	1989	2023	4956
HND	379	5028	1013	2016	2074	3866	1989	2023	1695
IRQ	1324	3624	2002	2014	5023	7433	1992	2023	3699
NGA	365	1408	1988	2014	2612	4892	1991	2023	2247
NPL	475	20952	1997	2013	2387	6910	1989	2023	1912
SEN	406	1124	1994	2013	3906	5349	1989	2023	3500
SLE	856	2314	1992	2014	963	1924	1989	2023	107
SOM	1210	3130	2000	2014	2224	3600	1989	2023	1014
TLS	499	3506	1998	2013	501	1047	1999	2023	2

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C Other Data Sources

Table C.1 – Description of Variables from Other Data Sources

Variable	Description
Population	Logarithm of regional population size taken from CIESIN (2018)
Election	Binary variable indicating whether an executive election is scheduled within the next one or two years (derived from Scartascini et al. 2021)
Competitiveness	0–7 index of executive election competitiveness (derived from Scartascini et al. 2021)
Patrilocal	Marriage Scale, derived from the variables MARRIAGE PRACTICE 7 (derived from Caprioli et al. 2009)
Women’s property rights	Women’s Property Rights Scale (LO-SCALE-3), introduced in 2012, which captures women’s property rights both in practice and under the law (derived from Caprioli et al. 2009)
UNGA voting coincidence	United Nations General Assembly voting coincidence (0–1) on important votes with the U.S., based on raw data from Fjelstul et al. (2025)
Light	Logarithm of average nightlight emissions (plus 0.01) in an ADM2 region, measured as the sum of emissions of all pixels in a region weighted by the fraction of each cell that falls within a specific polygon (Li et al. 2020)
Law & order	0–6 index of law and order (derived from PRS Group 2023)
Control of corruption	0-100 index on perceived absence of corruption (derived from PRS Group 2023)
Subnational corruption	A scale of 0–100, with higher values indicating less corruption (derived from Crombach and Smits 2024)
Grand corruption	0-100 index on absence of grand corruption, taken from Crombach and Smits (2024) , defined as the “abuse of high-level power,” with higher values measuring less corruption.
Democracy	Binary indicator for democracies, taken from Bjørnskov and Rode (2020)

References

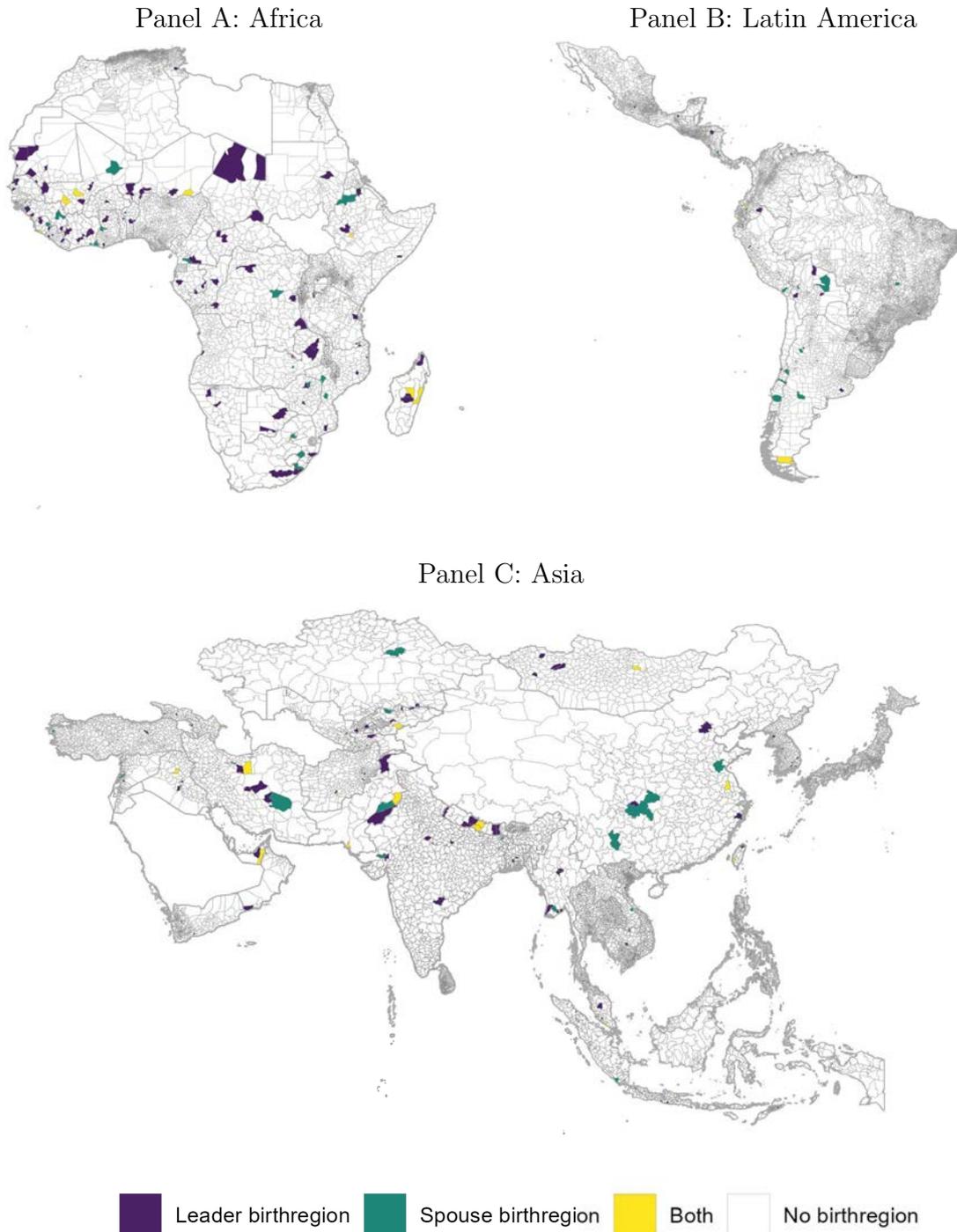
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D Additional Figures and Tables

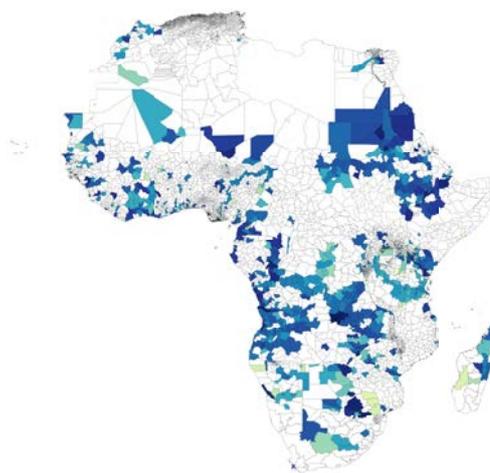
Figure D.1 – Leader and Spouse Birth Region, ADM2, 1990–2020



Notes: 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 D.2 – Chinese Aid by Macro Region, ADM2, 1990–2020

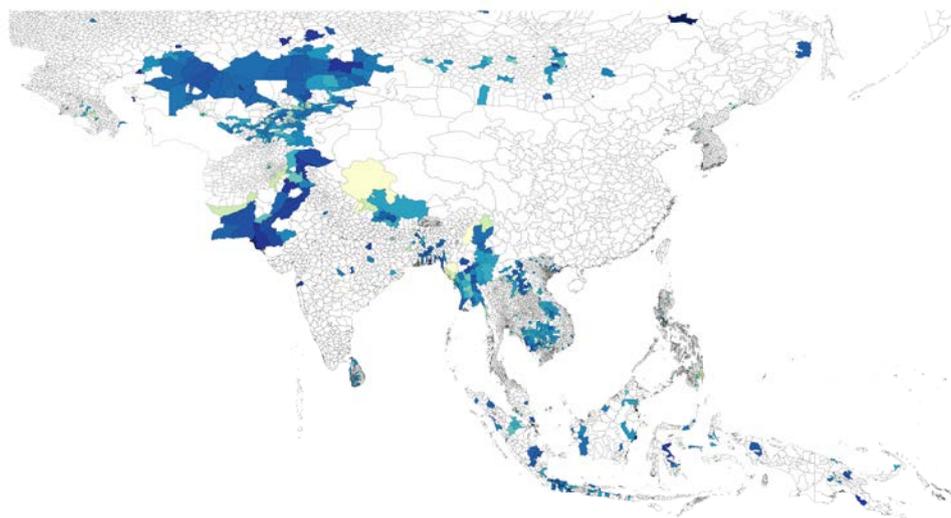
Panel A: Africa



Panel B: Latin America



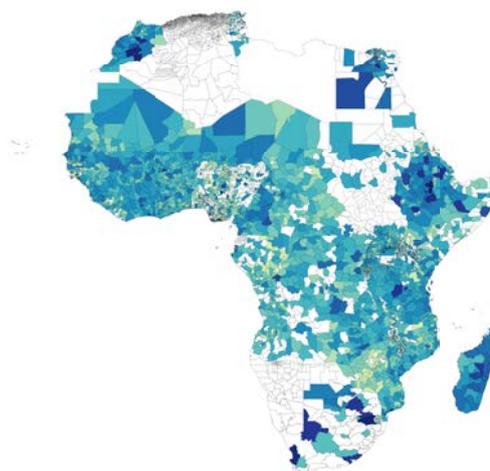
Panel C: Asia



Notes: The maps indicate the amount of log Chinese aid commitments per ADM2 region over the 1990–2020 period.

Figure D.3 – World Bank Aid by Macro Region, ADM2, 1990–2020

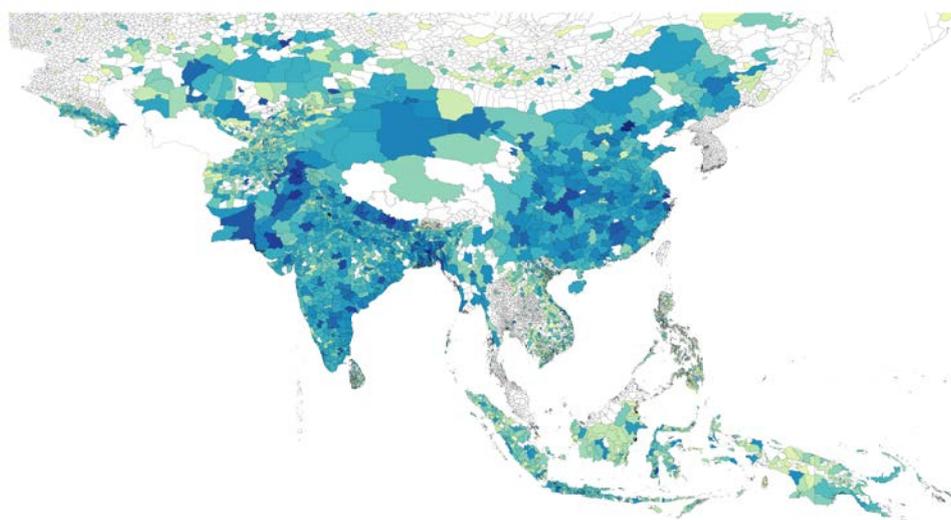
Panel A: Africa



Panel B: Latin America



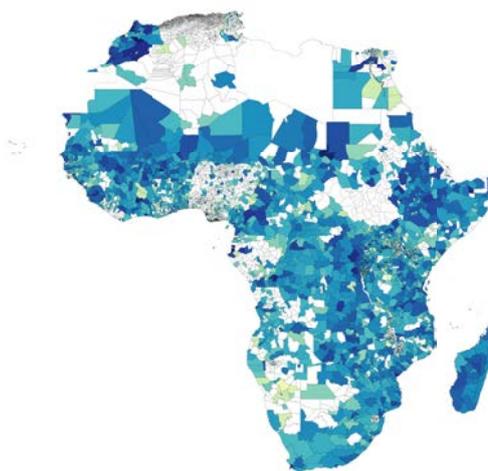
Panel C: Asia



Notes: The maps indicate the amount of log World Bank aid commitments per ADM2 region over the 1990–2020 period.

Figure D.4 – EU Aid by Macro Region, ADM2, 1990–2020

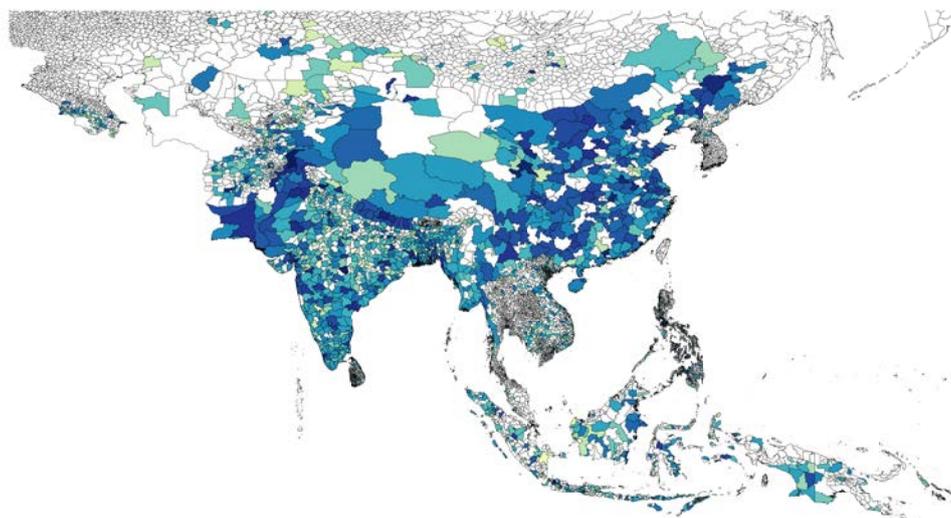
Panel A: Africa



Panel B: Latin America



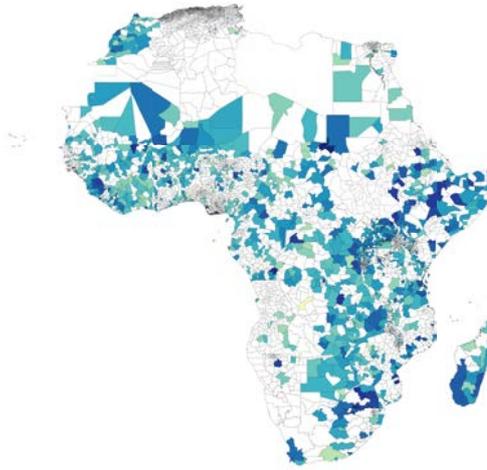
Panel C: Asia



Notes: The maps indicate the amount of log aid commitments from 18 European donors per ADM2 region over the 1990–2020 period.

Figure D.5 – U.S. Aid by Macro Region, ADM2, 1990–2020

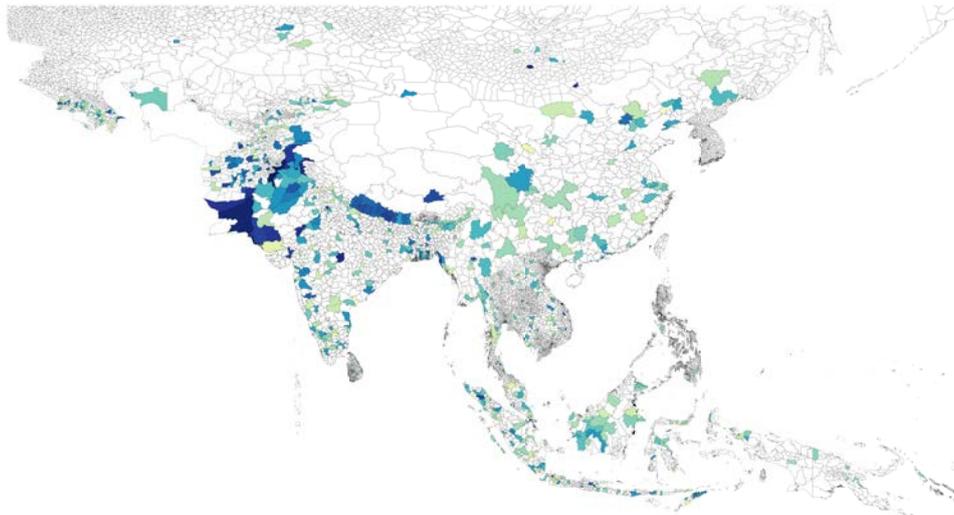
Panel A: Africa



Panel B: Latin America

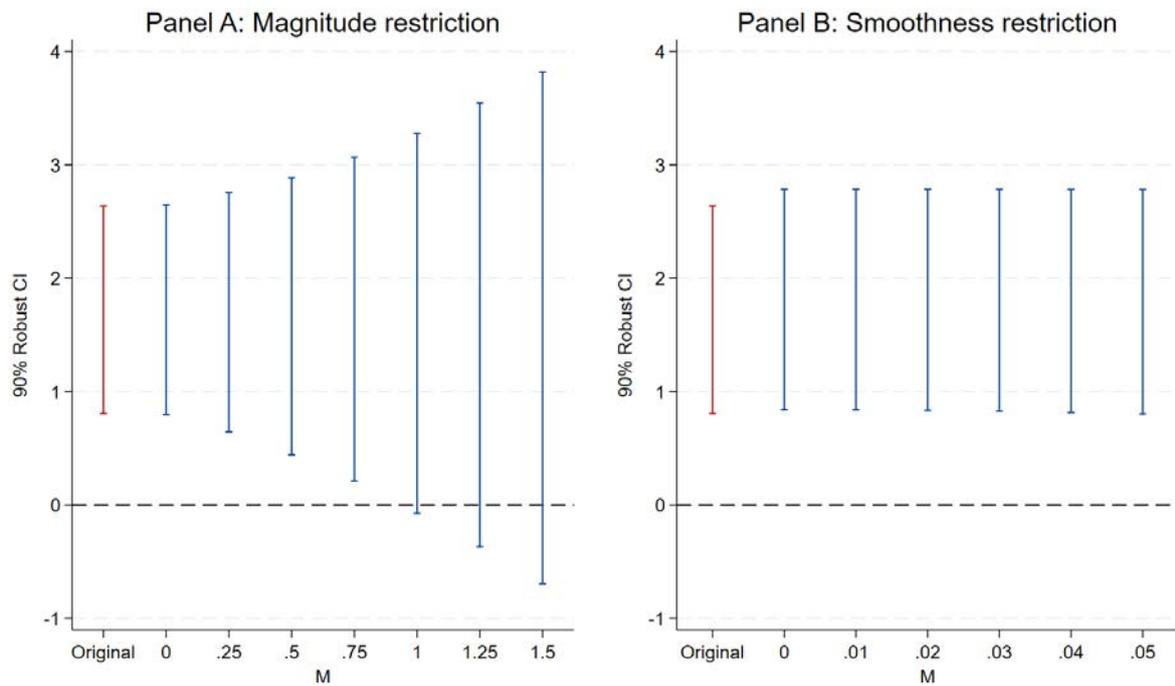


Panel C: Asia



Notes: The maps indicate the amount of log U.S. aid commitments per ADM2 region over the 1990–2020 period.

Figure D.6 – Sensitivity Analysis of Parallel Trend Assumption



Notes: The figure displays the coefficient and 90% confidence intervals for *Spouseregion* under varying assumptions of parallel trend violations. In Panel A, we consider violations of the parallel trend in the post-treatment periods as defined by *M*, the maximum violation in the pre-treatment periods, whereas in Panel B we allow for changes in the linear extrapolation as defined by a change in the slope of the pre-trend by no more than *M*. In both panels, we estimate Column 3 of Table 1 with one additional pre-treatment period (three pretreatment periods) and plot the coefficient of *Spouseregion* in year 4, where we find the strongest effect.

Table D.1 – Birth Regions and Aid with Different Clustering, 1995–2020

	(1)	(2)	(3)	(4)
	ADM2	c-y	HAC	DK
Spouseregion	0.71**	0.71***	0.71***	0.71***
	(2.45)	(4.44)	(3.67)	(3.71)
Leaderregion	0.17	0.17*	0.17	0.17
	(0.94)	(1.69)	(1.37)	(0.99)
Number of countries	110	110	110	110
Number of regions	29362	29362	29362	29362
Number of observations	855102	855102	855102	855102

Notes: The dependent variable is *Aid*, i.e., the logarithm of European and United States aid disbursements (plus 1) given to region i of country c in year t . *Spouseregion* and *Leaderregion* are lagged by one year. All regressions include the logarithm of a region’s population size, ADM2 fixed effects and ADM1-year fixed effects. Standard errors are clustered as indicated in the column header: at the ADM2 level, at the country-year level, heteroskedasticity-consistent (HAC), and employing Driscoll-Kraay (DK) corrections.

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

Table D.2 – Birth Regions and Aid, Excluding Neighboring Birth Regions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	DAC	DAC	DAC	DAC	IDA	IBRD	China ODA	China OOF
PreSpouseregion ($t + 2$)			-0.42 (1.06)	-0.45 (1.16)	0.28 (0.70)	0.34 (1.03)	0.39 (1.21)	0.44 (1.17)
PreSpouseregion ($t + 1$)			-0.75 (1.65)	-0.80* (1.80)	0.29 (0.73)	0.43 (0.92)	-0.10 (0.50)	0.17 (0.52)
PreSpouseregion (t)			-0.09 (0.19)	-0.16 (0.32)	0.46 (1.24)	0.26 (0.50)	-0.05 (0.15)	-0.06 (0.20)
Spouseregion	0.72** (2.17)	0.81** (2.06)		0.74* (1.75)	0.39 (1.06)	1.03** (2.02)	-0.28 (1.65)	-0.08 (0.63)
Spouseregion (year 1)			0.73 (1.34)					
Spouseregion (year 2)			0.61 (1.09)					
Spouseregion (year 3)			1.17** (2.14)					
Spouseregion (year 4)			1.74*** (2.99)					
Spouseregion (year 5)			1.77** (2.58)					
Spouseregion (year ≥ 6)			0.29 (0.46)					
PostSpouseregion (t)			1.00* (1.94)					
PostSpouseregion ($t - 1$)			0.52 (0.99)					
PostSpouseregion ($t - 2$)			0.66 (1.65)					
Leaderregion	0.18 (1.23)	0.23 (1.36)	0.26 (1.53)	0.26 (1.51)	0.14 (0.45)	-0.34* (1.81)	-0.00 (0.01)	-0.12 (1.14)
Leaderregion ^{ethnic}		-0.17* (1.87)	-0.18* (1.94)	-0.18* (1.90)	-0.23* (1.91)	0.02 (0.34)	-0.02 (0.56)	0.06** (2.02)
First year	1990	1990	1990	1990	1995	1995	2000	2000
Last year	2020	2020	2020	2020	2020	2020	2020	2020
Number of countries	109	103	103	103	103	103	102	102
Number of regions	29208	27324	27324	27324	27282	27282	27105	27105
Number of observations	831863	733088	725522	723338	610159	610159	493820	493820
Prob > F Spouse				0.00	0.40	0.11	0.22	0.24

Notes: This table is a replication of [Table 1](#), excluding region-year observations in which the leader's spouse originates from a region neighboring the leader's birth region. 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 from 18 European donors and the United States (columns 1–4), the World Bank's IDA (column 5) and IBRD (column 6), as well as ODA and OOF commitments from China (columns 7–8). *Spouseregion* and *Leaderregion* are lagged by one year. *Prob > F Spouse* tests whether the coefficient of *Spouseregion* is larger than that of *PreSpouseregion* _{$t+1$} . All regressions include the logarithm of a region's population size. Columns 2–8 control for *Leaderregion*^{ethnic}, which is a binary variable that takes a value of one if a region's dominant ethnicity is the same as the ethnicity of the leader in power. Standard errors are clustered at the country level.

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

Table D.3 – Birth Regions and Aid, ADM2, Alternative Definitions of Aid

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	West, bil.		Europe		USA		IDA		IBRD		China, ODA		China, OOF	
	Com	Dum	Com	Dum	Com	Dum	Com	Dum	Com	Dum	Com	Dum	Com	Dum
Spouseregion	0.418*	0.040*	0.327	0.034*	0.392*	0.046**	0.267	0.011	0.339	0.058**	-0.213	-0.024*	-0.064	0.001
	(1.76)	(1.91)	(1.55)	(1.69)	(1.74)	(2.21)	(1.26)	(0.57)	(1.53)	(2.38)	(1.65)	(1.95)	(0.67)	(0.07)
Leaderregion	0.188	0.009	0.186	0.007	-0.074	-0.006	0.130	0.007	-0.173*	-0.020*	0.021	0.007	-0.050	-0.003
	(1.39)	(0.67)	(1.36)	(0.47)	(0.50)	(0.46)	(0.99)	(0.41)	(1.74)	(1.90)	(0.24)	(0.90)	(0.61)	(0.60)
First year	1990	1990	1990	1990	1990	1990	1995	1995	1995	1995	2000	2000	2000	2000
Last year	2020	2020	2020	2020	2020	2020	2020	2020	2020	2020	2020	2020	2020	2020
Number of countries	110	110	110	110	110	110	110	110	110	110	110	110	110	110
Number of regions	29362	29362	29362	29362	29362	29362	29362	29362	29362	29362	29362	29362	29362	29359
Number of observations	855102	855102	855102	855102	855102	855102	720001	720001	720001	720001	585202	585202	585202	585173

Notes: The dependent variable is *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, from 18 European donors and the United States (columns 1–2), 18 European donors (columns 3–4), the United States (columns 5–6), the World Bank’s IDA (columns 7–8), the World Bank’s IBRD (columns 9–10), China’s ODA (columns 11–12), and China’s OOF (columns 13–14). *Spouseregion* and *Leaderregion* are lagged by one year. All regressions include the logarithm of a region’s population size, ADM2 fixed effects, and ADM1-year fixed effects. Standard errors are clustered at the country level.

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

Table D.4 – Birth Regions and Aid Over Time, ADM2

	(1)	(2)	(3)	(4)	(5)	(6)
	Europe	USA	IDA	IBRD	China, ODA	China, OOF
PreSpouseregion ($t + 2$)	-0.32 (0.86)	-0.57** (2.06)	0.35 (0.88)	0.35 (1.06)	0.37 (1.14)	0.40 (1.11)
PreSpouseregion ($t + 1$)	-0.52 (1.23)	-0.07 (0.26)	0.40 (1.01)	0.45 (1.00)	-0.10 (0.51)	0.13 (0.40)
PreSpouseregion (t)	0.19 (0.40)	-0.21 (0.70)	0.56 (1.48)	0.10 (0.21)	0.01 (0.03)	-0.13 (0.53)
Spouseregion	0.74** (2.00)	0.63* (1.87)	0.41 (1.08)	0.88* (1.72)	-0.27* (1.75)	-0.13 (1.08)
PostSpouseregion ($t - 1$)	0.41 (0.84)	-0.11 (0.30)	0.66* (1.90)	0.26 (0.60)	-0.28 (0.85)	-0.56** (2.44)
PostSpouseregion ($t - 2$)	0.37 (0.93)	0.06 (0.18)	0.78** (2.19)	0.32 (0.68)	0.03 (0.08)	-0.29 (0.67)
Leaderregion	0.26 (1.43)	-0.10 (0.51)	0.18 (0.59)	-0.27 (1.59)	-0.00 (0.03)	-0.09 (0.88)
Leaderregion ^{ethnic}	-0.17* (1.84)	-0.05 (1.53)	-0.25** (2.31)	0.02 (0.41)	-0.02 (0.53)	0.05* (1.84)
First year	1990	1990	1995	1995	2000	2000
Last year	2020	2020	2020	2020	2020	2020
Number of countries	104	104	104	104	104	104
Number of regions	27464	27464	27422	27422	27422	27422
Number of observations	745179	745179	628178	628178	509553	509553
Prob > F Spouse	0.00	0.03	0.49	0.19	0.23	0.22

Notes: 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 from 18 European donors (column 1), the United States (column 2), the World Bank's IDA (column 3) and IBRD (column 4), as well as ODA and OOF commitments from China (columns 5–6). *Spouseregion* and *Leaderregion* are lagged by one year. *Prob > F Spouse* tests whether the coefficient of *Spouseregion* is larger than that of *PreSpouseregion* _{$t+1$} . All regressions include the logarithm of a region's population size. Standard errors are clustered at the country level.

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

Table D.5 – Birth Region Interactions and Aid—Additional Interactions I

	(1)	(2)	(3)	(4)	(5)
	law	control	control subn.	grand	democ
Spouseregion	1.96** (2.63)	1.31* (1.78)	5.01*** (3.61)	1.21* (1.92)	0.64* (1.94)
Leaderregion	-0.02 (0.03)	1.07** (2.26)	1.31 (1.60)	0.14 (0.53)	0.14 (0.83)
Spouseregion × INTER	-0.44** (2.04)	-0.29 (1.15)	-0.08*** (3.44)	-0.12*** (3.10)	0.85 (1.51)
Leaderregion × INTER	0.08 (0.51)	-0.37** (2.09)	-0.02 (1.53)	-0.02 (0.75)	0.42 (1.05)
First year	1990	1990	1995	1990	1990
Last year	2020	2020	2020	2020	2020
Number of countries	88	88	104	110	110
Number of regions	27377	27377	28851	29362	29362
Number of observations	791962	791962	709896	855102	855102
Prob > F (Spouse = Leader)	0.02	0.77	0.02	0.02	0.02

Notes: The dependent variable is *Aid*, i.e., the logarithm of ODA disbursements from 18 European donors and the United States (plus 1) given to region i of country c in year t . *Spouseregion* and *Leaderregion* are lagged by one year. Column 1 incorporates the law and order index (*law*), column 2 the control of corruption index (*control*, both taken from the ICRG and ranging from 0–6 and 0–100, respectively), and column 3 subnational corruption from [Crombach and Smits \(2024\)](#) on a scale of 0–100 (*control subn.*). *Grand* measures subnational grand corruption, taken from [Crombach and Smits \(2024\)](#), and defined as the “abuse of high-level power,” on a scale of 0–100. Higher values across these governance measures indicate better governance and less corruption. *Democ* is a binary indicator for democracies, taken from [Bjørnskov and Rode \(2020\)](#). All regressions include the logarithm of a region’s population size. Columns 3 and 4 control for the regional levels of corruption. Standard errors are clustered at the country level. t-statistics are reported in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.6 – Birth Region Interactions and Aid—Additional Interactions II, ADM2, 1990–2020

	(1)	(2)	(3)	(4)	(5)
	#spouses	#children	educ	leaderregion	placebo
Spouseregion	1.53*** (2.66)	0.65 (1.22)	-1.13 (1.12)	0.64* (1.94)	0.73** (2.44)
Leaderregion	0.33 (1.24)	0.14 (0.67)	0.12 (0.10)	0.14 (0.83)	0.17 (1.06)
Spouseregion × number spouses	-0.54** (2.02)				
Leaderregion × number spouses	-0.13 (0.77)				
Spouseregion × number children		0.02 (0.14)			
Leaderregion × number children		0.01 (0.20)			
Spouseregion × education			0.21 (1.19)		
Leaderregion × education			-0.01 (0.05)		
Spouseregion × Leaderregion				0.32 (0.49)	
Past/future spouseregion					0.54 (1.05)
Number of countries	110	110	110	110	110
Number of regions	29362	29362	29362	29362	29362
Number of observations	855102	855102	855102	855102	855102

Notes: The dependent variable is *Aid*, i.e., the logarithm of ODA disbursements from 18 European donors and the United States (plus 1) given to region i of country c in year t . *Spouseregion* and *Leaderregion* are lagged by one year. Column 1 interacts with the number of spouses a leader has, column 2 with the number of children. *Educ* is an indicator for spouses' higher education, with eight categories (see [Appendix A](#) for details). *Leaderregion* is a binary indicator for leader birth regions. Column 5 presents a placebo regression using a (lagged) indicator for regions where a future or past spouse of the country's leader is born. All specifications control for the logarithm of a region's population size. Standard errors are clustered at the country level. t-statistics are reported in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.7 – Birth Regions and Aid, Regional Interactions, 1995–2020

	(1)
Spouseregion	1.21* (1.92)
Leaderregion	0.14 (0.53)
Spouseregion × Africa	-1.02 (1.26)
Spouseregion × Asia	-0.16 (0.22)
Spouseregion × Europe	-1.23 (0.78)
Spouseregion × Oceania	-0.83 (1.26)
Number of countries	110
Number of regions	29362
Number of observations	855102

Notes: The dependent variable is *Aid*, i.e., the logarithm of aid disbursements from Europe and the United States (plus 1) given to region i of country c in year t . *Spouseregion* and *Leaderregion* are lagged by one year. All regressions control for the logarithm of a region’s population size. The omitted category is the Americas; note that we also interact *Leaderregion* with the same continents. All regressions include ADM2 fixed effects, ADM1-year fixed effects, and the logarithm of a region’s population size. Standard errors are clustered at the country level.

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

Table D.8 – Distinct Spouse and Leader Birth Regions and Aid, ADM2, 1990–2020

	(1)
Spouseregion	0.62* (1.72)
Leaderregion	0.12 (0.73)
Number of countries	108
Number of regions	28976
Number of observations	775611

Notes: 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 from 18 European donors and the United States. *Spouseregion* and *Leaderregion* are lagged by one year. The regression includes the logarithm of a region's population size. The sample is restricted to country-year observations in which leader and spouse were born in different regions. Standard errors are clustered at the country level.

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

Table D.9 – Birth Regions and Aid by European Donor Country, ADM2, 1990–2020

	(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
Spouseregion	0.151 (1.22)	0.080 (0.52)	0.101 (1.12)	0.112 (0.92)	0.017 (0.11)	0.402* (1.75)	0.005 (0.45)	0.006 (0.61)	0.110* (1.84)	0.263 (1.24)	0.196* (1.73)	0.134 (1.35)	0.089 (0.58)	0.029 (0.75)	0.384** (2.09)	-0.035 (0.47)	0.186 (1.45)	0.076 (0.48)
Leaderregion	0.000 (0.00)	0.155 (1.65)	0.028 (0.38)	-0.033 (0.37)	-0.124 (1.16)	0.033 (0.20)	0.023 (1.22)	-0.014 (1.05)	0.089** (2.36)	0.042 (0.32)	-0.113** (2.19)	0.072 (0.91)	0.189 (1.57)	-0.009 (0.39)	-0.013 (0.13)	0.183** (2.43)	-0.052 (0.52)	0.030 (0.28)
Number of countries	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110
Number of regions	29362	29362	29362	29362	29362	29362	29362	29362	29362	29362	29362	29362	29362	29362	29362	29362	29362	29362
Number of observations	855102	855102	855102	855102	855102	855102	855102	855102	855102	855102	855102	855102	855102	855102	855102	855102	855102	855102

Notes: The dependent variable is the logarithm of ODA disbursements from one from 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. All regressions include the logarithm of a region’s population size, ADM2 fixed effects, and ADM1-year fixed effects. Standard errors are clustered at the country level.

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

Table D.10 – Birth Regions and Aid by Sector, 1990–2020

	(1)	(2)	(3)
	Econ	Social	Prod
Spouseregion	0.32 (1.25)	0.81*** (2.85)	0.17 (1.21)
Leaderregion	-0.12 (0.74)	0.20 (1.31)	0.11 (1.29)
Number of countries	110	110	110
Number of regions	29362	29362	29362
Number of observations	855102	855102	855102

Notes: 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 from 18 European donors and the United States. 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. All regressions include the logarithm of a region’s population size. All regressions include ADM2 fixed effects and ADM1-year fixed effects. Standard errors are clustered at the country level. t-statistics are reported in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.11 – Birth Regions and Aid with Control Variables, ADM2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	DAC	DAC	DAC	DAC	DAC	DAC	DAC	DAC
Spouseregion	-3.31** (2.53)	0.39 (1.31)	0.36 (1.19)	0.74** (2.34)	1.30 (1.41)	0.75** (2.45)	0.71* (1.75)	0.45 (0.74)
Leaderregion	0.06 (0.06)	0.19 (1.12)	0.29* (1.68)	0.16 (0.96)	0.12 (0.19)	0.03 (0.18)	-0.02 (0.09)	0.29 (1.38)
Spouseregion × population	0.33*** (2.94)							
Spouseregion × capital		0.74 (0.93)						
Spouseregion × active mine			1.75** (2.15)					
Spouseregion × oil/gas				-0.21 (0.27)				
Spouseregion × area size					-0.09 (0.63)			
Spouseregion × port						-0.24 (0.25)		
Spouseregion × road density							0.00 (0.01)	
Spouseregion × nightlight								0.03 (0.38)
Leaderregion × population	0.01 (0.12)							
Leaderregion × capital		-0.26 (0.32)						
Leaderregion × active mine			-0.75 (1.37)					
Leaderregion × oil/gas				0.13 (0.26)				
Leaderregion × area size					0.01 (0.08)			
Leaderregion × port						1.12* (1.70)		
Leaderregion × road density							0.69 (1.20)	
Leaderregion × nightlight								-0.02 (0.58)
First year	1990	1995	1990	1990	1990	1990	1990	1992
Last year	2020	2020	2020	2020	2020	2020	2020	2020
Number of countries	103	107	110	110	110	110	110	106
Number of regions	28766	29256	29362	29362	29362	29362	29362	29016
Number of observations	842811	717427	855102	855102	855102	855102	855102	798542

Notes: The table shows results for subnational regional heterogeneity. 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 from 18 European donors and the United States. *Spouseregion* and *Leaderregion* are lagged by one year. All regressions include the logarithm of a region's population size (*population*). *capital* is a dummy which equals one if the capital city falls within the region. *active mines* is the number of currently producing mines taken from Lujala (2009); *oil/gas* gives the number of petroleum fields taken from the PETRODATA, Lujala et al. (2007) and *area* captures the size of the ADM2 region in km². *ports* gives the number of ports within an ADM2 region, derived from the World Port Index provided by the National Geospatial-Intelligence Agency (NGA); *road density* measures the road length per area based on the global road open access data from CIESIN, SEDAC and *nightlight* refers to log of nighttime light (plus 0.01, Li et al. 2020). All regressions include the constituent terms of the interacted variables as well as country and year fixed effects. t-statistics are reported in parentheses; * p<0.10, ** p<0.05, *** p<0.01.

E Dynamic Treatment Effects

A skeptical reader might be concerned that our fixed effects estimations rely on post-treatment 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 ADM1-years (and their exclusion does not affect our results). Moreover, our conclusions hold when we compare 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.⁸⁹ 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 ADM1-years 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 \(2025\)](#) 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 none of the 965 Average Treatment Effects on the Treated receive a negative weight, using [De Chaisemartin et al.’s \(2019\)](#) estimator.

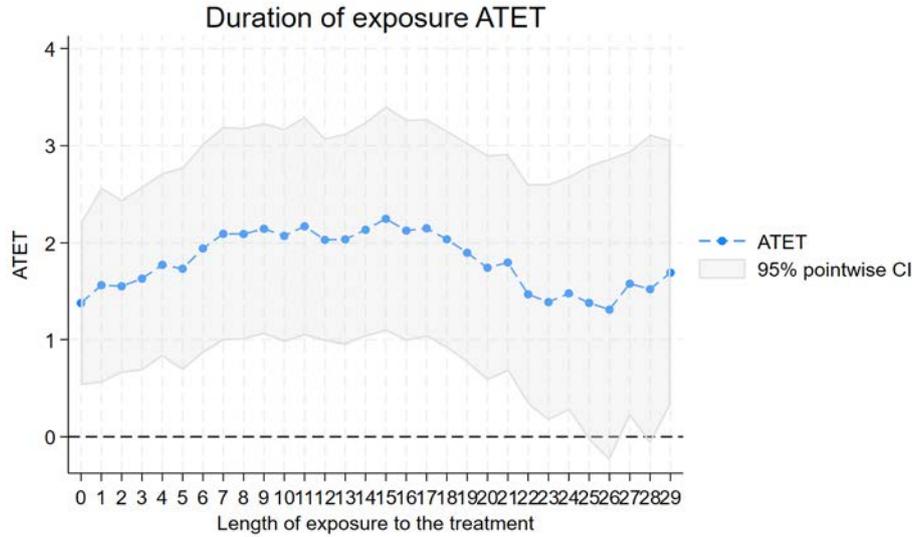
We nevertheless twist our model to better fit the assumptions of the recent two-way fixed effects literature. We drop those regions that are the birth region of a spouse in the first year of our estimation sample and estimate the modified model using [Wooldridge’s \(2025\)](#) Extended Two-Way Fixed Effects Estimator, allowing for heterogeneous treatment effects in any year.⁹⁰ 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 ADM1-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 E.1](#) shows the dynamic treatment effects of being a (lagged) spouse region 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

⁸⁹While 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. 2025](#)).

⁹⁰The estimator does this by including interactions between treatment-year cohorts and years.

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



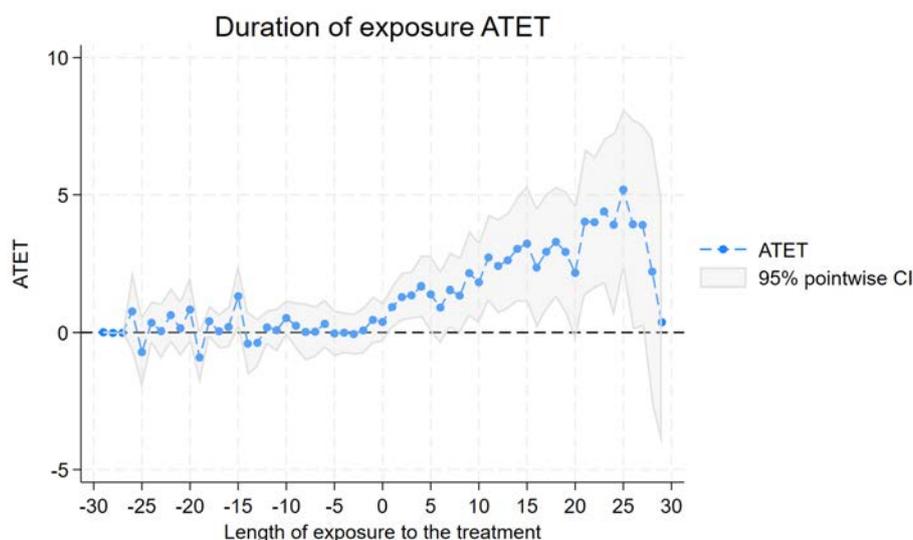
Notes: The figure plots the Average Treatment Effect on the Treated (ATET) of (lagged) *Spouse*region on Western bilateral aid, using Wooldridge’s (2025) Extended Two-Way Fixed Effects Estimator at the ADM2-level in the 1990–2020 period. We drop regions that are the birth region of a spouse in the year 1990 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.

estimate. One reason for this is the exclusion of ADM1-year fixed effects, which leads to higher effect sizes, also when estimated with OLS (not reported here). In addition, it seems that the omission of ADM2 regions we exclude here to fit the model’s requirements bias the coefficients upwards.

Figure E.2 shows the results obtained using the doubly robust augmented inverse probability-weighted (AIPW) estimator. The AIPW estimator is robust to misspecification of the treatment or outcome models. While the ATET parameters of Figure E.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.⁹¹ To the contrary, Figure E.2 shows treatment effects for the entire sample range, from 29 years before to 29 years after treatment. As can be seen, there are no obvious trends prior to the treatment. Effects turn larger and significant at the one-percent level in the first full year a region is the birth region of the leader’s spouse ($t=1$, recall that we lag the *Spouse*region indicator by one year). They fall substantially in the last years of treatment, which are however estimated based on comparably few regions treated early in the sample period.

⁹¹This is because parameters are identified based on the parallel-trends assumption (see Wooldridge 2025).

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



Notes: The figure plots the Average Treatment Effect on the Treated (ATET) of (lagged) *Spouse* region on Western bilateral aid, using the doubly robust augmented inverse probability-weighted (AIPW) estimator at the ADM2-level in the 1990–2020 period. We drop regions that are the birth region of a spouse in the year 1990 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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F Instrumental Variables Approach

Table 6 in the main text shows that development outcomes are weaker in regions that received more Western bilateral aid at the time they were a *Spouseregion* compared to outcomes in the same regions at other times. This appendix explains the instrumental variables approach in more detail and shows additional regressions for individual (groups of) donors rather than just for Western bilateral aid in aggregate. Our instrumental variables closely mirror previous work.⁹² Specifically, we employ the instrument proposed by Ahmed (2016) and Dreher and Langlotz (2020) for bilateral Western aid. Their instrument exploits temporal variation in donor-country government fractionalization, which they interact with a time-invariant measure of the likelihood of receiving aid from a specific donor at the donor-recipient level. Intuitively, greater government fractionalization increases demands on the budget, as coalition partners push for additional spending. This, in turn, tends to expand the overall budget, which includes allocations to foreign aid.⁹³ The increase in the overall budget translates to larger development budgets as well (Fuchs et al. 2014). Dreher and Langlotz (2020) then show that more frequent recipients of aid receive larger chunks of this aid, on average.⁹⁴

Following the strategy of Nunn and Qian (2014) and Ahmed (2016), Dreher and Langlotz (2020) introduce variation at the recipient country level by interacting donor government fractionalization with the share of years over the sample period during which a country received aid from specific donors. We adapt this strategy to the subnational context and use the probability of a subnational region to receive aid p_{ji} ⁹⁵ to construct the instrumental variable.

We use donor government fractionalization in combination with regional likelihoods of receiving Western bilateral aid to instrument for aid disbursements at the subnational level.⁹⁶ As Dreher and Langlotz (2020) explain, the exclusion restriction can be illustrated in the context of a difference-in-differences approach, leveraging variations in donor government fractionalization to estimate differential impacts of aid on regions with high versus low probabilities of receiving aid. Our identification thus hinges on the assumption

⁹²Our description of the instrumental variables borrows from Dreher et al. (2025).

⁹³As substantial literature establishes the link between political fragmentation and government expenditures (e.g., Roubini and Sachs 1989, Volkerink and De Haan 2001).

⁹⁴Whether additional resources are given to traditional recipients or to new ones is an empirical question. Bilateral donors tend to give them to established clientele, while multilateral donors extend aid to less regular recipients (Lang 2021, Dreher et al. 2021a).

⁹⁵Specifically, a region's probability to receive aid from a particular donor j is $\bar{p}_{ji} = \frac{1}{31} \sum_{t=1990}^{2020} p_{jit}$, with p_{jit} indicating whether recipient region i received positive amounts of aid from donor j in year t . As Dreher and Langlotz (2020) explain, this approach is equivalent to using a "zero stage procedure" that runs a zero stage regression at the donor-recipient-year level where bilateral aid from all donors j to all recipient regions i is predicted with the instrumental variable $FRAC_{jt} * p_{ji}$.

⁹⁶Constructed instruments yield IV standard errors that are consistently estimated as long as the second-stage error term is not correlated with our donor-recipient-specific instrument ($FRAC_{jt} * p_{ij}$) from the zero-stage regression (Wooldridge 2010).

that year-to-year changes in development outcomes do not systematically vary across regions based on their probability of receiving aid, apart from through changes in aid flows themselves.

The choice between using government or legislature fractionalization as part of the instrument is not immediately clear. As noted by [Ahmed \(2016\)](#) in the context of the United States, the “funding and allocation of bilateral economic aid involves both the executive branch and Congress” (p. 184), and this observation is applicable to other donor countries in our dataset. Since budget proposals are initiated by the government rather than the legislature, we measure donor fractionalization by the likelihood that two randomly selected members from the governing coalition belong to different parties (taken from [Beck et al. 2001](#)). However, this approach has a limitation: There is no variation in government fractionalization for the United States during the period under study. To address this, we substitute government fractionalization with legislature fractionalization there.⁹⁷

Donor government fractionalization is zero for China and is undefined for the World Bank. We predict year-to-year changes in the supply of Chinese aid using the first principal component of (detrended) production volumes of five construction materials that China produces in abundance, following [Dreher et al. \(2021b\)](#), [Bluhm et al. \(2025\)](#), and [Dreher et al. \(2021a\)](#). These previous works show that China provides more aid in years when such input materials into aid projects are available in abundance, and derive instrumental variables for Chinese ODA and OOF by interacting the supply shock with the share of years a recipient region received ODA or OOF, respectively. For the World Bank, we build on [Lang \(2021\)](#), who suggests the IMF’s liquidity ratio, interacted with the likelihood of a country being under an IMF program, as an instrument for IMF loans. Adopting a similar approach, [Dreher et al. \(2021a\)](#) use resource-based proxies to assess the World Bank’s lending capacity. We follow this previous paper by using the IBRD’s equity-to-loans ratio, consistently reported since 1994, to measure the availability of IBRD resources. This ratio reflects the IBRD’s ability to issue loans without using its callable capital. For IDA resources, we rely on the World Bank’s measure of the IDA’s funding position, defined as the extent to which the IDA can commit to new loans, grants, and guarantees given its current financial position and ability to meet undisbursed commitments. Since the IDA’s funding position has only been reported annually since 2008, [Dreher et al. \(2021a\)](#) reconstruct the time series for earlier years applying the World Bank’s method. This involves summing the Bank’s net investment portfolio and its non-negotiable, non-interest-bearing demand obligations (from members’ subscriptions and

⁹⁷It is not surprising that government fractionalization remains constant in the United States. While most DAC donor countries have parliamentary systems with proportional representation, the United States has presidential elections. The United Kingdom and France also differ from other donors due to their lack of proportional representation. However, government fractionalization in both countries varies over time.

contributions) and dividing this by the total undisbursed commitments of development credits and grants.

Table F.1 shows our results for Western bilateral donors—DAC—which displays the results provided above for comparison, European aid, the United States, IDA, IBRD, as well as Chinese ODA and OOF in concert with the Kleibergen-Paap first-stage F-statistic. As can be seen, with the exception of U.S. aid the first stages are strong. Our results for European donors and the U.S. closely mirror those reported in the main text. With two exceptions the coefficients of the interactions between aid and birth regions are estimated imprecisely, though most of them point in the same direction and there are no significant differences in the effects of the interaction with birth regions of spouses and leaders in most regressions.

Table F.2 shows the same set of regressions but includes the more conservative ADM1-year fixed effects instead of fixed effects for country-years. The results are overall similar, though most coefficients are estimated less precisely. Overall, we conclude that there is no differential effect in how aid given to birth regions of spouses affects development compared to aid given to birth regions of leaders, and the effects of birth regions on development turn negative if aid is given in abundance.

Table F.1 – Birth Regions and Light, Control Function Approach, ADM2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	DAC	Europe	USA	IDA	IBRD	China, ODA	China, OOF
Spouseregion	0.131** (2.36)	0.157*** (2.79)	0.056 (0.83)	0.050 (0.92)	0.000 (0.00)	-0.033 (0.48)	-0.053 (0.76)
Leaderregion	0.183*** (4.82)	0.194*** (4.92)	0.122*** (3.26)	0.043 (1.06)	0.098** (2.13)	0.126** (2.58)	0.121** (2.49)
Aid	-0.003*** (3.78)	-0.054*** (5.13)	0.004 (0.16)	-0.025*** (4.97)	-0.000 (0.16)	-0.120*** (3.90)	-0.172*** (8.14)
Spouseregion*Aid	-0.013*** (3.53)	-0.013*** (3.46)	-0.021*** (4.21)	-0.007** (2.27)	-0.003 (1.43)	-0.010 (1.59)	0.003 (0.39)
Leaderregion*Aid	-0.010*** (4.06)	-0.009*** (3.46)	-0.015*** (3.15)	0.001 (0.24)	-0.006*** (3.32)	-0.006 (1.33)	-0.013 (1.55)
ADM2 fixed effects	✓	✓	✓	✓	✓	✓	✓
Country-year fixed effects	✓	✓	✓	✓	✓	✓	✓
Kleibergen-Paap F-stat	50.96	54.86	3.96	31.94	50.84	9.94	16.11
First year	1993	1993	1993	1998	1998	2003	2003
Last year	2020	2020	2020	2020	2020	2020	2020
Number of countries	124	124	124	124	124	124	124
Number of regions	29728	29728	29728	29728	29728	29728	29728
Number of observations	784241	781809	781809	646331	646331	506043	506043
Prob > F (Spouse = Leader)	0.53	0.42	0.39	0.04	0.34	0.68	0.24

Notes: The table reports results from a Control Function Approach, where we control for the residual of the first-stage regression. The dependent variable is $\log(\text{lights})$, defined as the log of mean nightlight emissions in region i of country c in year t (+0.01). *Aid* is the logarithm of aid (plus 1): ODA disbursements from 18 European donors and the United States (column 1), 18 European donors (column 2), the United States (column 3), the World Bank's IDA (column 4), the World Bank's IBRD (column 5), China's ODA commitments (column 6), and China's OOF commitments (column 7). The variables *Spouseregion* and *Leaderregion* are lagged by one year. Prob SR*Aid = LR*Aid shows p-values for a test of equality between the two interactions. All regressions include 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 are reported in parentheses; * p<0.10, ** p<0.05, *** p<0.01.

Table F.2 – Birth Regions and Light, Control Function Approach, ADM2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	DAC	Europe	USA	IDA	IBRD	China, ODA	China, OOF
Spouseregion	0.022 (0.43)	0.067 (1.31)	0.035 (0.55)	0.029 (0.51)	0.009 (0.14)	-0.020 (0.30)	0.001 (0.01)
Leaderregion	0.143*** (3.78)	0.140*** (3.73)	0.096*** (2.86)	0.058 (1.29)	0.089* (1.93)	0.112** (2.02)	0.097* (1.81)
Aid	-0.003*** (4.72)	-0.044*** (5.46)	-0.010 (0.42)	-0.017*** (4.89)	0.002 (1.47)	-0.140*** (3.17)	-0.111*** (4.89)
Spouseregion*Aid	-0.004 (1.33)	-0.004 (1.26)	-0.010** (2.42)	-0.003 (0.96)	-0.001 (0.63)	-0.004 (0.70)	-0.007 (1.19)
Leaderregion*Aid	-0.006*** (3.39)	-0.005*** (2.78)	-0.006* (1.92)	0.001 (0.34)	-0.004** (2.42)	-0.007 (1.54)	-0.005 (1.05)
ADM2 fixed effects	✓	✓	✓	✓	✓	✓	✓
ADM1-year fixed effects	✓	✓	✓	✓	✓	✓	✓
Kleibergen-Paap F-stat	53.69	58.79	3.10	42.41	68.91	3.74	24.98
First year	1993	1993	1993	1998	1998	2003	2003
Last year	2020	2020	2020	2020	2020	2020	2020
Number of countries	110	110	110	110	110	110	110
Number of regions	29362	29362	29362	29362	29362	29362	29362
Number of observations	775027	772655	772655	638477	638477	499815	499815
Prob > F (Spouse = Leader)	0.57	0.72	0.47	0.28	0.44	0.75	0.76

Notes: The table reports results from a Control Function Approach, where we control for the residual of the first-stage regression. The dependent variable is $\log(\text{lights})$, defined as the log of mean nightlight emissions in region i of country c in year t (+0.01). *Aid* is the logarithm of aid (plus 1): ODA disbursements from 18 European donors and the United States (column 1), 18 European donors (column 2), the United States (column 3), the World Bank's IDA (column 4), the World Bank's IBRD (column 5), China's ODA commitments (column 6), and China's OOF commitments (column 7). *Spouseregion* and *Leaderregion* are lagged by one year. Prob SR*Aid = LR*Aid shows p-values for a test of equality between the two interactions. All regressions include the logarithm of a region's population size, ADM2 fixed effects, and ADM1-year fixed effects. Standard errors are clustered at the country level. t-statistics are reported in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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