Inaccessibility and Compliance: Geography, Institutions, and Agency in Foreign Aid*

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Abstract

Existing scholarship highlights that bureaucratic capacity is crucial to overcoming international development challenges. We argue that bureaucrats' impacts are often more conditional on geographic structures, such as physical inaccessibility. Underpinning our argument is a rational inattention mechanism: cost- and information-constrained bureaucrats focus their finite time on more seemingly solvable problems. By the same token, higher-quality bureaucrats retain some ability to mitigate structural constraints. We test our pre-registered hypotheses using data on project-level compliance with World Bank safeguard policies on resettlement, indigenous peoples, and the environment. We find that longer travel times for bureaucrats to monitor projects negatively affect safeguard compliance. Higher densities of projects within neighboring areas less consistently affect compliance, as density does not account for road infrastructure and state presence. Interaction analyses also confirm that the highest-quality bureaucrats only have *some* agency to overcome geographic structures. Given that our models address numerous inferential threats, including spatial autocorrelation, our results shed light on geography, agency, and institutions in development. It is not only one factor or the other, but their interplay, that yields diverging outcomes.

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Does geographic structure shape international development outcomes? The question has attracted high-profile answers from Acemoglu and Robinson (2012), Collier (2007), Diamond (1999), and Sachs (2005), among others. Politics, being landlocked, natural resources, disease, and other salient factors that these scholars underscore in making their arguments remain subjects of inquiry and debate. Nevertheless, the literature has coalesced around the idea that institutions are more crucial than geography in shaping development outcomes (e.g., Robinson, 2002; Rodrik, Subramanian and Trebbi, 2004).

In this paper, we contribute to a better understanding of the interplay between geography and institutions in international development by studying foreign aid implementation. Specifically, we examine whether bureaucrats have agency to overcome the structural constraints posed by projects that are difficult to access and monitor, where the state's institutional reach is low.

Drawing from work in monetary policy (Sims, 2003), we argue that bureaucrats are rationally inattentive to development problems that geographic structures make more seemingly intractable. Bureaucrats are time- and cost-constrained, so they strategically limit information acquisition, tuning out the highest-cost signals first. However, the highest-quality bureaucrats can separate signal from noise and at least partly address structural problems, as appropriate. The framework paper of this special issue refers such situations as ones of "conforming alignment" between structural challenges and agents' reactions to them (Weaver, Morrison and Heinzel, 2026).

We examine the relevance of our argument in project-level compliance with the World Bank's social and environmental safeguard policies on resettlement, indigenous peoples, and the environment (Denly, 2025). When there is noncompliance with these risk management policies, the resulting negative externalities can even involve the loss of life (Weaver, 2008, 22-23), undermining the value of undertaking a foreign aid project in the first place. That is why all major aid donors nowadays have social and environmental safeguard policies—even if compliance with them is uneven (Greenstein, 2022).

To measure the constraints posed by geographic structures, we use data on (log) driving times from Open Street Maps to capture which aid projects are most difficult to access and monitor. Our measure combines the driving times from (1) the closest airport to each project's most accessible location; and (2) that project's location to the nearest location of another project, which differs on a yearly basis as new projects start and close. We incorporate the airport time to mimic a supervision mission from abroad, and we use the nearest neighbor project travel time to capture how structural pressures change over time. As an alternative measure of geographic structure, we perform spatial grid-cell analysis to map the density of nearby projects operating within the same area, as well as first- and second-order neighboring areas.[1]

To complement the above analyses that focus on the structural constraints to development, we undertake more agency-centric analyses as well. Using Denly's (2025) data on World Bank Task Team Leaders (TTL) quality, we interact the latter with the log total travel time. The interaction provides a measure of whether having higher-quality agents can mitigate structural development challenges.

Consistent with our pre-analysis plan,[2] we find statistical support for the proposition that larger (log) driving times yield lower levels of safeguard policy compliance. Analyses of nearby projects indicate that higher project density increases compliance directionally but not consistently, suggesting that roads and state presence drive compliance rather than density itself. The interaction analyses also indicate that higher-quality TTLs can mitigate structural development challenges, though not always. Even at the highest observed levels of TTL quality, geographic inaccessibility constrains compliance efforts that aim to protect individuals and the environment from the negative externalities of development.

Our paper make three larger contributions. First, it speak to debates about the role of geography in international development. While institutions remain arguably the most

[1]Technically, first- and second-order neighboring areas refer to first- and second-order spatial lags, which we describe later in the paper.
[2]See: https://osf.io/ru9dp/?view_only=e7458ea391bd4a90b7ffae2b5baba451

central determinants of cross-country differences (e.g., Acemoglu and Robinson, 2012), geography remains consequential within countries, especially where institutional reach is low. Our results show that inaccessible project locations amplifying monitoring, enforcement, and implementation costs, resulting in significant development losses in the form of lower safeguard compliance. These patterns persist even after accounting for local-level population measures, underscoring the interplay of geography and institutions, not more contested accounts of population density (e.g., Acemoglu, Johnson and Robinson, 2002; Herbst, 2000).

Second, our paper reconciles both more incentive-based and sociological accounts about bureaucrats in development. Both principal-agent and public choice approaches emphasize that bureaucrats are often self-interested (e.g., Frey, 1984; Williamson, 1985), whereas constructivist and Weberian accounts stress how rules and professional norms shape behavior (e.g., Barnett and Finnemore, 2004; Dahlström and Lapuente, 2017).[3] Our results are consistent with all approaches. Geographic inaccessibility raises the costs of monitoring and enforcement, generating patterns consistent with rational inattention: even capable agents cannot allocate sustained effort to prevent all negative externalities in the hardest-to-monitor settings. At the same time, higher-quality Task Team Leaders partially mitigate these structural constraints, highlighting a meaningful—though limited—–margin of bureaucratic agency (Heinzel and Liese, 2021; Limodio, 2021; Fenizia, 2022). The broader implication is that mission motivation and professional norms shape what bureaucrats aim to achieve, and in many cases they are successful (Honig, 2024; Khan, 2025). Nevertheless, incentives, information, and monitoring constraints also shape what bureaucrats can reliably accomplish (Khan, Khwaja and Olken, 2016, 2019; Dhaliwal and Hanna, 2017; Williams, 2017; Bertrand et al., 2020; Dasgupta and Kapur, 2020; Bandiera et al., 2021).

Third, the results add nuance to the literature on whether "good countries" or "good projects" are more important for fostering aid effectiveness outcomes. Denizer, Kaufmann and Kraay (2013) and Bulman, Kolkma and Kraay (2017) provide the headline findings.

[3]To be clear, constructivist approaches also underscore that bureaucratic norms can be all-encompassing lead to poor results (e.g., Weaver, 2008)

They highlight that 75-90% of the variation in project-level aid effectiveness outcomes pertain to within-country features.[4] These headline findings are consistent with the present paper's focus on within-country phenomena, but the larger take-away is different. In the debate on "good countries" versus "good projects", the latter generally refer to country-specific design and implementation choices for which aid providers have agency. However, aid providers usually engage in complicated negotiations with recipients (Swedlund, 2017; Bennon and Fukuyama, 2022), and providers generally do not have full control over which locations within a country receive aid (Hodler and Raschky, 2014; Briggs, 2017; Dreher et al., 2019; Song, Brazys and Vadlamannati, 2021; Bommer, Dreher and Perez-Alvarez, 2022). Consequently, within-country structural problems still underpin much of the foreign aid literature that tackles bureaucratic autonomy (e.g., Honig, 2018; Denly, 2021), suggesting a further role for them—and how bureaucrats address them—in explaining compliance outcomes.

1. Rational Inattention and Compliance

In this paper, we derive insights from all of the canonical theories of compliance (see Table 1) to construct an account focusing on rational inattention. It stems from bounded rationality explanations of macroeconomics (Sims, 2003), and we echo Maćkowiak, Matějka and Wiederholt (2023) in emphasizing that rational inattention can deliver valuable insights well beyond macroeonomics.

Our rational inattention theory of compliance to explain patterns in foreign aid, international organizations, and development begins with a simple recognition: both macro-structural and more microfoundational explanations focusing on individuals shape compliance behavior.[5] Consistent with Coleman's (1986) boat that guides much research in sociology, we argue that the interplay between macro-structural and microfounded behavior explains compliance patterns.

[4]See also Briggs (2020) and Ashton et al. (2023).
[5]Our definition of microfoundations derives from Kertzer (2017, 83).

Table 1: Canonical Theories of Compliance in International Relations and Organizations

Theory	Core Predictions	Key References
Enforcement	Monitoring and credible sanctions increase compliance; weak punishment yields delay or violation.	Keohane and Nye (1977), Downs, Rocke and Barsoom (1996), Tallberg (2002)
Management	Noncompliance often reflects limited capacity, so providing assistance improves compliance.	Chayes and Chayes (1993)
Domestic Politics	Compliance rises when domestic coalitions and institutions favor it and can punish violations.	Dai (2005)
Rationalism	States choose precision and flexibility to manage uncertainty.	Koremenos, Lipson and Snidal (2001), Koremenos (2005)
Principal-Agent	Compliance depends on agent incentives and principals' ability and willingness to monitor.	Nielson and Tierney (2003), Stone (2011)
Constructivism	Compliance increases as norms are internalized and violations become stigmatized via socialization and shaming.	Finnemore and Sikkink (1998), Barnett and Finnemore (2004)
Public Choice	Bureaucrats respond to career, budget, and ideology incentives, and compliance rises with principal-bureaucrat alignment.	Frey (1984), Vaubel (1986)

1.1. Macro-Structural Factors

Before delving into bureaucrats' microfounded behaviors, it is necessary to understand macro-structural constraints related to institutions and domestic politics that bureaucrats cannot alter in the short term. For example, states relying on natural resources revenues can resist outside pressure and shirk more,[6] but states relying on foreign direct investment must be more attentive to outside signals and are more compliant (Girod and Tobin, 2016). In another more structural account, Carcelli (2024) shows that states with more fragmented bureaucracies have differing principal-agent relationships that make universal state-level compliance outcomes more difficult.

Consistent with geography being a more structural factor (Gerring and Christenson,

[6]See, for example, Morrison (2009), McGuirk (2013), Ross (2015) on the relationship between natural resources and accountability pressures.

2017, Chapter 5), we posit that geography can drive compliance in a similar way as states' revenue streams and bureaucratic make-up. To be clear, geography is not fully deterministic, as excellent climates and natural resource access frequently do not lead to optimal development outcomes over time (e.g., Acemoglu, Johnson and Robinson, 2002; Dell, 2010). Specifically, our contention is that geography can drive compliance in areas *within countries* where the state's reach is limited. In this sense, our contention is related to Mann's (1984) theory of infrastructural power. Incidentally, our rationale for focusing on geography relates to its ability constrain the state's ability to provide infrastructure and, in turn, foster economic growth and development (Donaldson, 2018; Rogowski et al., 2022).

Significant empirical state capacity research supports the pattern that geographically difficult-to-reach areas produce more development challenges. Müller-Crepon (2023), for example, shows that longer distances to the capital cities in Africa predict lower levels of educational attainment, higher infant mortality, and lower electricity provision. Provenzano (2024) documents a link between these patterns and accountability in Africa, and Campante and Do (2014) showcase their external validity given that they focus on the United States. In the conflict space, Fearon and Laitin (2003) famously argue that rugged terrain fuels civil wars.

All of these empirical patterns related to geography and development support our argument that the interplay of geography and lack of state presence makes compliance more difficult. In this way, our argument follows the enforcement, management, and domestic politics schools of compliance (e.g., Chayes and Chayes, 1993; Downs, Rocke and Barsoom, 1996; Dai, 2005).

1.2. Microfounded Bureaucratic Incentives

Compliance with development-oriented mandates does not only depend geographically-related structural constraints. In particular, individual-level incentives and biases from bureaucrats and leaders also affect outcomes (Poulsen and Aisbett, 2013; Bayram, 2017;

Hafner-Burton et al., 2017; Fjelstul and Carrubba, 2018).

Principal-agent and public choice theories offer helpful starting points for understanding individual-level factors. They highlight that bureaucrats are self-interested and frequently take into account career, ideology, and pecuniary considerations (e.g., Frey, 1984; Williamson, 1985). Chwieroth (2013, 2015), Nelson (2014), and Lang, Wellner and Kentikelenis (2025) demonstrate empirical support for bureaucrat-related biases at the International Monetary Fund (IMF), and similar phenomena take place at the World Bank (Smets, Knack and Molenaers, 2013; Clark and Dolan, 2021).

The literature also provides specific evidence about bureaucrat calculus on safeguard compliance. Humphrey (2015) argues that along with loan-processing time and procurement rules, safeguard compliance is one of the main "hassle factors" of multilateral aid. Among the three institutions that Humphrey (2015) analyzes, he finds that the World Bank has the most stringent safeguard requirements, followed by the Inter-American Development Bank (IDB) and the Development Bank of Latin America and the Caribbean (CAF).[7] Buntaine (2016) demonstrates the consequences of the hassles that safeguards create at the World Bank, African Development Bank, Asian Development Bank, and Inter-American Development. Buntaine (2016) finds that safeguard failures generally hurt staff careers, and borrowing countries with safeguard failures receive lower aid allocations in future periods. Consistent with principal-agent dynamics (Nielson and Tierney, 2003), underpinning these patterns are the very significant donor attention that safeguard failures receive, often due to NGOs and interest group pressure (Greenstein, 2022).

It is thus clear that bureaucrats pay attention to aid compliance issues, particularly those involving safeguards, but how exactly? We argue that compliance patterns follow rational inattention patterns. The *rational* part comes from bureaucrats not having the career flexibility to completely ignore problems that donor principals monitor, at least selectively. The *inattention* part derives from bureaucrats having competing demands on their time

[7] The CAF mainly uses its Spanish acronym, which stands for *Corporación Andino de Fomento*.

and limited resources, which ultimately translate to information constraints and shortcuts (Maćkowiak, Matějka and Wiederholt, 2023).

Ethnographic analyses of safeguard compliance confirm the difficulty of bureaucrats' information constraints. Tello (2015) provides case studies for development projects in Latin America, discussing problems such as indigenous peoples lacking of property titles for their land; settlers burning down indigenous property; and corruption in the allocation of property titles. Without time and resources, bureaucrats do not have sufficient information to solve these challenging problems and prevent people from the negative externalities of aid. Randeria and Grunder's (2011) analysis of resettlement of an urban slum in the context of the World Bank's Mumbai Urban Transport Project provides another relevant example. In this instance, World Bank bureaucrats could not gather sufficient information and support the 120,000 people affected by resettlement. That even happened under poor living conditions, the government ignoring citizens' legally-defensible grievances, and numerous other problems that brought real harm to citizens. In some sense, the compliance problems that both Randeria and Grunder (2011) and Tello (2015) expose are even more "unimplementable by design" than the ones Reinsberg, Stubbs and Kentikelenis (2022) highlight at the IMF.

Under the above types of circumstances, even the most mission-driven bureaucrats must make difficult decisions under time, resource, and information constraints, so allowing a structural constraint like geography drive decisions is consistent with rational inattention. Monitoring areas with limited state presence is not just logistically challenging, but it is also difficult to justify from career and administrative perspectives.

From a career perspective, it is well-known that international development organizations have approval cultures, rewarding bureaucrats who work on more projects (Weaver, 2008; Buntaine, 2016). Bureaucrats must thus be selective about which problems to avoid, because entangling themselves in "wicked" problems without clear solutions may hurt career prospects (Rittel and Webber, 1973).

From an administrative perspective, visiting one geographically remote area may, for example, result in the loss of sufficient resources to visit three more accessible areas. That is significant from bureaucrats' perspectives, because visiting more areas affords more them protection in case something goes wrong and principals take punitive action. Building on Heinzel, Weaver and Jorgensen (2025), visiting more accessible areas is not only the more "shallow" or "box-ticking" compliance activity, but it is also the safer one. Scott's (1998) path-breaking work on legibility helps describe why: metrics such as numbers of visits and consultations are more legible to principals, and the packaging of information matters (Lee and Zhang, 2017, 118).

By the same token, the highest-quality bureaucrats are better able to distinguish signal from noise and address structural problems, as appropriate. Indeed, Denly (2025) shows a strong positive and direct association between TTL quality and safeguard compliance. More broadly, Denizer, Kaufmann and Kraay (2013), Bulman, Kolkma and Kraay (2017), and Heinzel and Liese (2021) all show that higher-quality TTLs generate improved aid effectiveness and borrower performance outcomes. In short, high-quality bureaucrats have some agency to address structural problems, as appropriate.

2. Research Design

2.1. Pre-Analysis Plan

Our anonymous pre-registration prior to running any analysis is available at OSF.[8] The only deviation from the pre-analysis plan is our exclusion of the highly-correlated spatial variables from the HYDE dataset, which we explain in Section 2.6.2.

2.2. Setting

We test the relevance of our argument using data from the world's largest and most influential international development organization, the World Bank. According to AidData

[8]See: https://osf.io/ru9dp/?view_only=e7458ea391bd4a90b7ffae2b5baba451.

(Tierney et al., 2011), from 1947-2013 the World Bank financed 42% of multilateral foreign aid commitments, roughly accounting for $US2013 1.66 trillion (Denly, 2021). The World Bank offers numerous services, including loans, credits, guarantees, data, and technical assistance.

We examine projects financed by both the World Bank's concessional lending arm, the International Development Association (IDA), and the institution's market-based lending arm, the International Bank for Reconstruction and Development (IBRD). Specifically, we focus on investment project financing (IPF),[9] which provides input-based financing for specific investments, such as in infrastructure, health, governance, etc. We do not consider structural adjustment/development policy loans, because they disburse on the basis of completing prior actions, not monitorable inputs (World Bank, 2012). We also exclude Program-for-Results (PforR) loans, as they only focus on recipient governments' existing programs and require different monitoring requirements than a typical development project.

The World Bank executive board formally approves and oversees all projects and operational initiatives, but Task Team Leaders (TTLs) are responsible for project management. Although there are several layers of directors and managers above TTLs, daily TTL work includes conceiving the projects in line with Country Partnership Frameworks, shepherding projects through executive board approval, and supervising project implementation (Heinzel and Liese, 2021, 628-629). Aside from site visits and consulting with recipient country stakeholders and bureaucrats, a lot of TTLs' daily work includes overseeing other staff members working on the three hassle factors: loan processing, procurement, and safeguards (Humphrey, 2015).

The empirical analysis in this paper focuses on the third hassle factor, environmental and social safeguard compliance. While TTLs are formally responsible for monitoring all aspects of the projects that they lead, including safeguards, implementation is formally the responsibility of the aid-receiving country. That is especially the case following the 2005

[9]Previously, IPF was called Investment Lending.

Paris Declaration on Aid Effectiveness (OECD, 2005). TTLs thus cannot compel compliance, particularly because the World Bank almost never cancels a project that is already under implementation.

2.3. Dependent Variable

The primary outcome variable is whether each respective World Bank project complies with the institution's social and environmental safeguard policies. They concern Environmental Assessment; Resettlement; Physical Cultural Resources; Indigenous Peoples; Natural Habitats; Pest Management; Forests; International Waterways; Dams; Disputed Areas; and Environmental Action Plans. We take the variable from Denly (2025), whose coding covers non-supplementary investment lending projects that are subject to safeguard policies for the years 2007-2015.[10] Denly (2025) chooses this time period to capture the years in which World Bank safeguard-related guidance are subject to official policies, not mere directives, prior to the 2016 change in safeguard policies (see Greenstein, 2022). Similar to Buntaine (2016), Denly (2025) codes safeguard compliance on a 1-4 scale, in which 4 represents full compliance; 3 represents moderate compliance; 2 represents moderate non-compliance; and 1 represents full non-compliance. Overall, the data correspond to the safeguard policy compliance outcomes for 1,309 projects approved from 2007-2015. Figure 1 presents relevant summary statistics. They show that around half of the projects are in full compliance; 37% of projects enjoy moderate compliance; and 17% projects exhibit some form of moderate or full non-compliance.

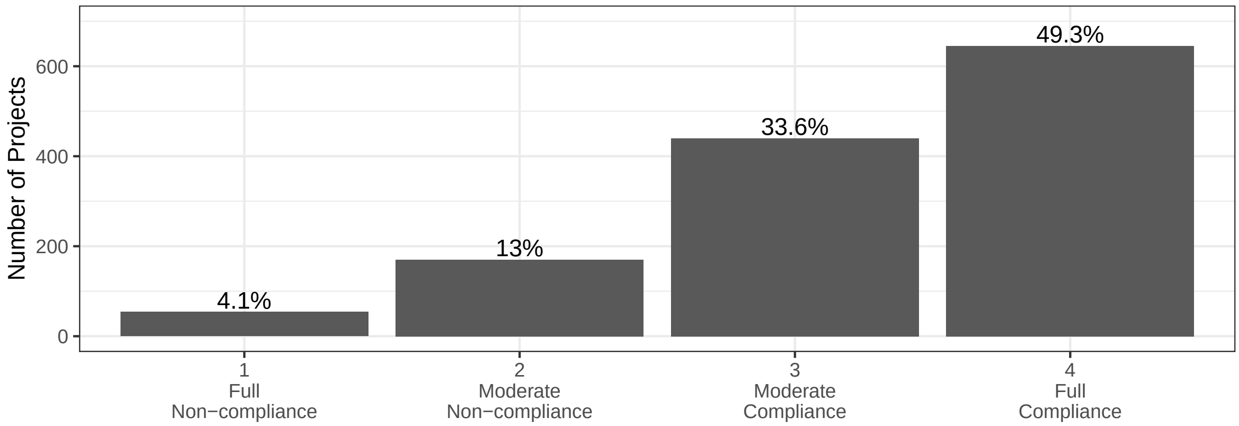
2.4. Treatments

2.4.1. Travel Time

Our main treatment variable to capture the effect of geography and state presence is the natural log of travel times to access World Bank project locations. We draw our

[10] Supplementary/additional financing projects are not subject to safeguard policy review, which is why Denly (2025) excludes them.

Figure 1: Summary Statistics of World Bank Safeguard Policy Compliance (2007-2015)



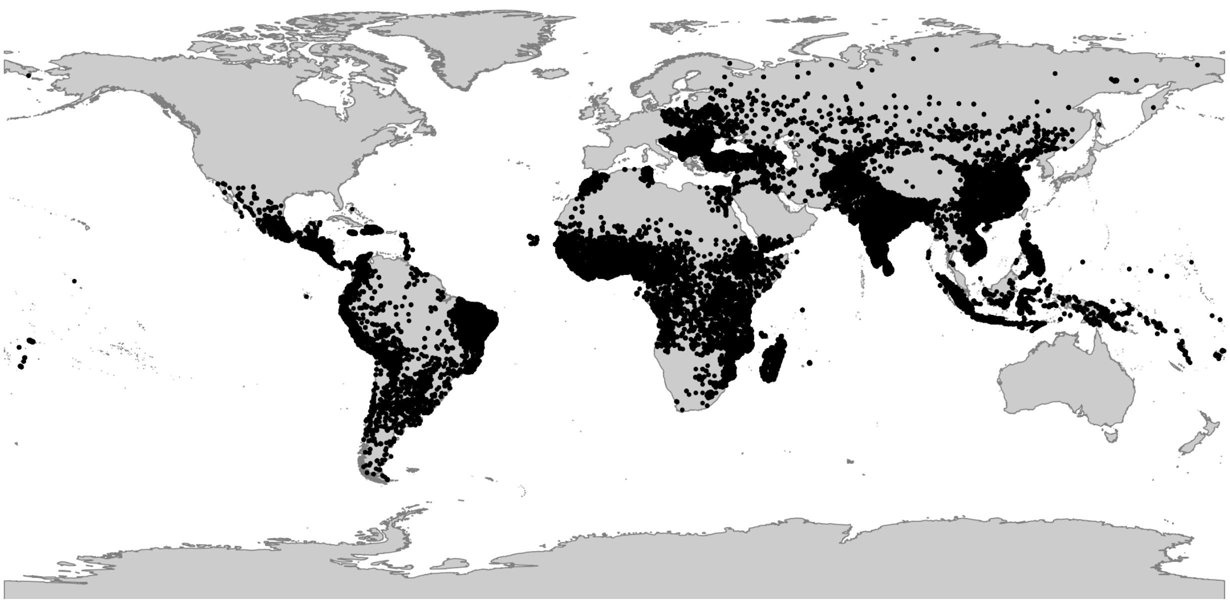
Source: Denly (2025)

baseline spatial World Bank project data from Bomprezzi et al.'s (2025) Geocoded Official Development Assistance Dataset (GODAD). In cases where GODAD does not include the respective latitudes and longitudes of each project, we take them from the World Bank's external website as well as a freedom of information request. In total, we are able to obtain location data for all but 21 of the 1,309 projects in Denly's (2025) dataset, corresponding to missingness rate of 1.6%. Figure 2 provides a map of all projects in the dataset.

For the travel time calculations, we partition the Open-Source Routing Machine into regional servers using the OpenStreetMap Foundation's (2025) maps in line with Appendix G. Our calculations account for the actual shapes of the roads, stops, speed limits, and traffic. Three algorithmic steps that we detail in Appendix F, Figure 3, and below underpin our calculations.

In Step 1, we use geolocated data from Megginson (2025) on 48,000 worldwide airports to measure the closest airport in minutes to each project's most accessible location. In doing so, we direct the algorithm to search within each country of the project and prioritize large airports over medium-sized ones and medium-sized airports over small-sized ones. The rationale behind the prioritization is that TTLs usually fly into to a larger airport, assuming one exists.

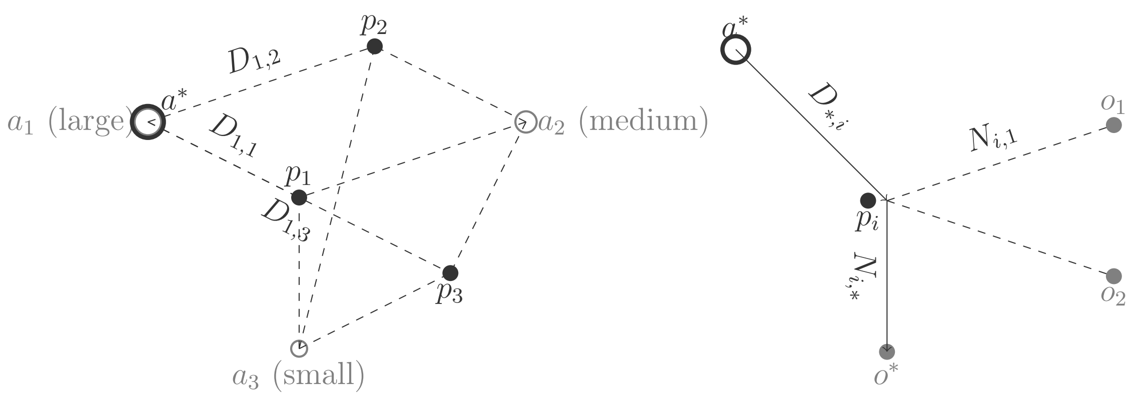
Figure 2: Locations of World Bank Projects



Sources: Bomprezzi et al. (2025) and the World Bank.

Figure 3: Airport Selection and Travel Time Algorithms

(a) Airport-to-Project Travel Time (b) Project-to-Neighbor Travel Time



Note: The above figure provides a graphical illustration of the combined optimal travel time calculations. As we detail in Appendix F.2, we first use an airport selection algorithm. It evaluates project locations p_1, p_2, p_3 (filled circles) against airports a_1 (large), a_2 (medium), and a_3 (small). Then, the algorithm sums the travel times, $D_{j,i}$, to obtain the total travel time for each airport, S_j. Finally, the algorithm selects a^* if $S_j > 0$ and is the lowest. Then, per Appendix F.3, we calculate the nearest neighbor project location, o^*, by minimizing the project-to-project travel time in seconds, $N_{i,*}$, from the closest other project in the same country, o, among all of its locations o_1, o_2, o_3. The total travel time, $D_{*,i} + N_{i,*}$, for which we take the log to minimize the influence of outliers. Although we present the above figure using straight lines for readability purposes, our actual routes follow the actual shapes of the roads and take into account stops, speed limits, and traffic patterns. Appendix F provides the full mathematical presentation of the calculations.

In Step 2, we calculate the driving time in minutes to the nearest location of another project. It differs on a yearly basis as new projects start and close, which allows for the data to be time-varying. As with the airport-to-project calculations, the project-to-neighboring project calculations are country-specific. In other words, these calculations do not allow for the crossing of country boundaries, even if the route is faster. We adopt such a strategy because TTLs rarely supervise projects from different countries in *one supervision mission* without taking a different flight. It is also generally also not straightforward to cross international borders in the low- and middle-income countries that receive World Bank projects.

In Step 3, we sum the minute-based driving times from Step 1 and Step 2. Then, we take the natural log to normalize the effect of outliers and allow for the independent variable to represent a semi-elasticity.

Table 2 provides relevant summary statistics. We supplement the overall statistics with country-level ones for Bangladesh, Ethiopia, and Kazakhstan to provide face validity to the intricate travel time calculations. Ostensibly, Bangladesh is a much smaller country than Kazakhstan, so it is intuitive that average driving times are shorter in Bangladesh. Similarly, the size of Ethiopia is somewhere between the sizes of Bangladesh and Kazakhstan, making it logical that Ethiopia's summary statistics fall in the middle. With respect to large maximum values for the overall panel, they pertain to projects in the Brazilian Amazon, where the road network is extremely sparse. In any event, we are not concerned by these large values. Even if TTL supervision missions to such places normally involve taking a small plane or helicopter to an airport that is outside of Megginson's (2025) airport data, it remains that such a location is very difficult or costly to access and supervise. Furthermore, because our final travel time variables incorporates a natural logarithm, we minimize the influence of outliers in very remote locations and enable proportional, non-linear interpretation. Again, we pre-registered this specification.

Table 2: Raw Driving Time Summary Statistics

Variable	N	Mean	SD	Min	Max
Panel A: Overall					
Airport to Location	368,385	410.81	568.55	0.00	18754.20
Location to Nearest Neighbor	379,462	71.77	280.55	0.00	16961.20
Total Travel Time	366,990	481.98	758.43	0.00	35715.40
Airport to Location (Log)	368,385	5.44	1.16	0.00	9.84
Location to Nearest Neighbor (Log)	379,462	3.51	1.23	0.00	9.74
Total Travel Time (Log)	366,990	5.65	1.08	0.00	10.48
Panel B: Bangladesh					
Airport to Location	17,152	167.59	84.62	12.10	627.80
Location to Nearest Neighbor	17,152	18.37	23.93	0.00	464.90
Total Travel Time	17,152	185.96	95.98	16.70	1092.70
Airport to Location (Log)	17,152	4.97	0.62	2.57	6.44
Location to Nearest Neighbor (Log)	17,152	2.61	0.90	0.00	6.14
Total Travel Time (Log)	17,152	5.09	0.57	2.87	7.00
Panel C: Ethiopia					
Airport to Location	7,204	414.84	233.46	1.80	1486.10
Location to Nearest Neighbor	7,204	67.37	65.25	0.00	741.20
Total Travel Time	7,204	482.21	265.33	9.60	2227.30
Airport to Location (Log)	7,204	5.73	1.00	1.03	7.30
Location to Nearest Neighbor (Log)	7,204	3.76	1.13	0.00	6.61
Total Travel Time (Log)	7,204	5.91	0.95	2.36	7.71
Panel D: Kazakhstan					
Airport to Location	1,750	823.05	616.59	1.20	2907.00
Location to Nearest Neighbor	1,750	158.50	174.21	0.00	2069.00
Total Travel Time	1,750	981.55	705.30	29.60	4976.00
Airport to Location (Log)	1,750	6.25	1.19	0.79	7.98
Location to Nearest Neighbor (Log)	1,750	4.37	1.58	0.00	7.64
Total Travel Time (Log)	1,750	6.50	1.09	3.42	8.51

Note: The unit of analysis for these summary statistics is driving times are in minutes. See Appendix F for the full mathematical details behind our algorithmically-derived calculations.

2.4.2. TTL-Specific Travel Time

Consistent with our pre-analysis plan, we also calculate TTL-specific travel times that distinguish by the name of the project Task Team Leader (TTL) in each country-year, using data from Denly (2025). The data come from the name of the TTLs at each World Bank project's Implementation Status Reports (ISRs). In the rare cases where TTLs switch within a given calendar year, we take the first chronological TTL in the list.[11]

Despite our efforts to avoid missingness, it is impossible to avoid it for these TTL-specific variables. The reason is simple: TTLs do not always supervise more than one project in a respective country at the same time. In total, we are only able to capture 17% of the 180,000 country-location-years with the TTL-specific variables. Given this low share, we use both standardized mean differences (SMDs) and p-values to analyze the balance of all pre-treatment covariates in Table A.3. We observe that none of the covariates are balanced, as p-values are all < 0.001 and SMDs all exceed $\pm$ 0.5. Against this backdrop, it is clear that the TTL-specific data are not a random sample of all projects and likely pose selection problems that make inference tenuous. Consequently, while we still conduct the relevant analyses to be consistent with our pre-analysis plan, we only report these analyses in Appendix E.

2.4.3. Spatial Density

As our primary alternative to the overall travel time treatment, we calculate the density of projects operating within the same areas as well as neighboring ones. To operationalize the same versus neighboring areas, we use the PRIO GRID to aggregate the project locations data into roughly 55 $\times$ 55 kilometers grid cells, corresponding to 0.5 degrees longitude by 0.5 degrees latitude (Tollefsen, Strand and Buhaug, 2012). Specifically, we calculate the number of unique projects operating within:

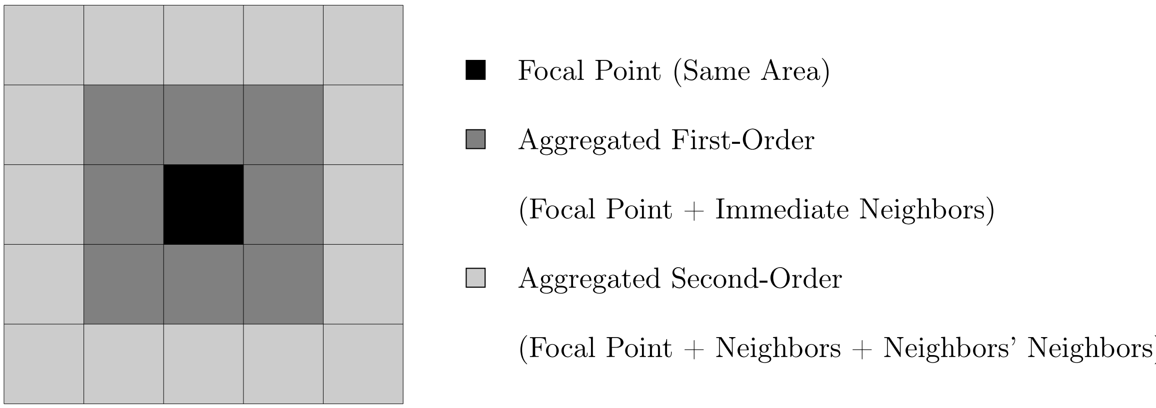
1. the same grid cell (focal point);
2. all immediately neighboring grid cells (first-order spatial lag);
3. all of the neighbors' neighboring grid cells (second-order spatial lag).

Given our focus on how project density increases with area, we aggregate the above quantities using the Queen Contiguity method (Darmofal, 2015, 15-17), which we graphically

[11] Given that Denly's (2025) data only extend through 2021, we fill down the names of the TTL for projects that are still running in 2022 and 2023. Such instances are also rare: Denly's (2025) safeguard compliance data refer to projects approved from 2007 to 2015, and there are very few projects still running in 2022 or 2023, as World Bank projects take around 5 years to complete.

illustrate in Figure 4. In turn, the aggregated first-order spatial lag category also includes the number of projects in the focal point. Similarly, the aggregated second-order spatial lag includes the number of projects in both the focal point grid cell and first-order neighbors.

Figure 4: Aggregated Spatial Lag Diagram (Queen Contiguity Method)



2.5. Moderating Variable for the Interactions

For all of the interactions to capture whether bureaucratic agency can moderate geographic pressures, we use Denly's (2025) measure of TTL quality. Denly's (2025) measure attempts to mimic earlier coding from Denizer, Kaufmann and Kraay (2013), Bulman, Kolkma and Kraay (2017), and Ashton et al. (2023) using publicly-available data. Specifically, Denly (2025) codes (i) the TTL name at each project's bi-annual Implementation Status Report (ISR); (ii) computes each TTL's daily average project Independent Evaluation Group (IEG) outcome score for his/her completed projects, excluding the current and future ones to prevent circularity; (iii) merges the daily average IEG scores back into each ISR for each project; and (iv) averages across all ISRs for each respective project to obtain a weighted, project-specific TTL quality score.

2.6. Control Variables

2.6.1. Project-Level Variables

Given that larger projects may require more attention from TTLs, we control for the commitment amount (i.e., project loan/credit size). These commitment amounts involve millions and sometimes billions of US dollars, so we deflate the data to constant dollars and take the natural log. Additionally, we control for the safeguard category, which the captures the pre-project-approval safeguard risk. It makes sense to control for it that given that projects with higher risks may prompt TTLs to dedicate more time to their supervision. We do not control for supervision or project costs because doing so would invoke post-treatment bias—or what Angrist and Pischke (2008) call a "bad control".

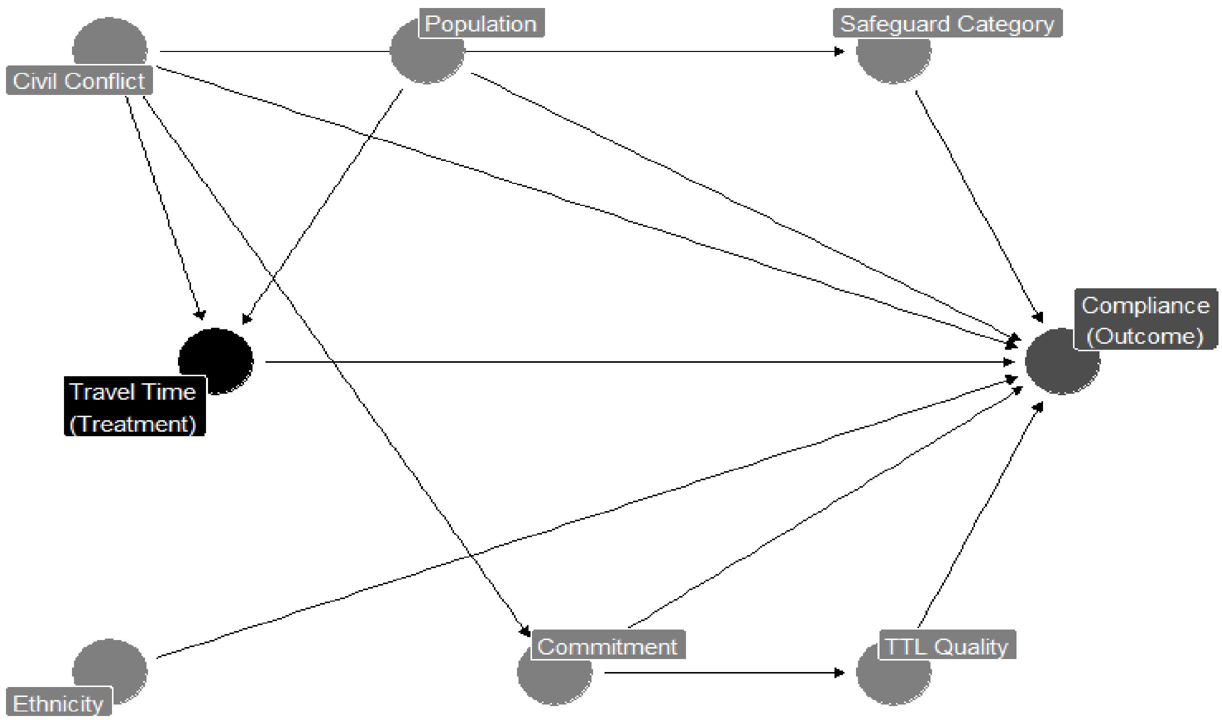
2.6.2. Spatial Control Variables

A particularly essential control variable is the spatial measure of log population counts per square kilometer from the HYDE project (Klein Goldewijk, Beusen and Janssen, 2010; Goldewijk et al., 2017).[12] The measure is essential because failing to control for it would make it difficult to discern whether population or geography/lack of state presence from travel times or density is responsible for producing the relevant effects. By controlling for the variable, we explicitly avoid difficult-to-adjudicate debates on the role of population (e.g., Herbst, 2000; Robinson, 2002). We can be confident about that conclusion because, unlike other social science studies using HYDE data aggregated by the PRIO GRID (e.g., Briggs, 2018, 2021), we do not use five-year intervals and linear interpolation to fill in missing values. Instead, we rasterize the original HYDE data to obtain full panels of yearly values.

To account for ethnicity, we use the measure of excluded ethnic groups from Vogt et al. (2015). Accounting for ethnicity is essential in the context of safeguard compliance: indigenous peoples must frequently resettle and lose of culturally-relevant property as a result

[12] The pre-analysis plan also specified that we would control for the (log) population counts per square kilometer; (log) population density per square kilometer; (log) urban population counts; (log) rural population counts; and (log) built-up area. In reality, all of these variables are extremely highly correlated. Additionally, most of social science uses the HYDE population count variable, so that is what we use here.

Figure 5: A DAG for Determining the Adjustment Sets



Note: See Appendix B for a full verbal description of all paths.

of World Bank projects.

We considered using Denly et al.'s (2022) natural resource measure. Unfortunately, it contained too much missingness to include.

Finally, we use UCDP's spatial conflict data from Pettersson, Högbladh and Öberg (2019). It accounts for the effect that conflict may have on ability to travel to an area.

2.7. Identification and Determining the Adjustment Sets

To ensure that we actually estimate our target average treatment effect, we draw a Directed Acyclic Graph (DAG) to determine our final adjustment sets. Figure 5 depicts the DAG, which suggests that there are no mediators, colliders, or descendants that alter the target estimand.

For the models focusing on the effect of travel time (or density) on compliance, civil conflict and population variables comprise the minimal adjustment set: they are the only two variables that directly affect both the treatment and the outcome (see Pearl, 2009). The rest of the independent variables enter in a precision-oriented controls in our specifications using canonical adjustment sets (see Perković et al., 2018).

The models focusing on the interactive effect of TTL quality follow a similar logic. The only variable that directly affects both TTL quality and compliance is the commitment amount, so it constitutes the minimal adjustment set. The other independent variables take the form of precision-oriented controls for the canonical adjustment set estimates.

Appendix B elucidates that most of the non-outcome relationships that the DAG showcases are straightforward, but it is worth further probing the relationship TTL quality and the safeguard risk category. The World Bank may wish to protect its reputation by assigning better TTLs to riskier projects, suggesting possible endogeneity concerns, but the data do not reflect such patterns. Figure A.1 indicates that the pairwise correlation between TTL quality and the safeguard risk category is merely 0.12. To further ensure that endogeneity is not a risk, Figure A.1 also considers the overall Independent Evaluation Group (IEG) project outcome scores and find that they correlate with the safeguard risk categories at 0.11. In short, the data and DAG suggest that endogeneity represents a very low risk for these models.

2.8. Final Unit of Analysis and Estimand

As the previous sections demonstrate, estimating the effect of travel time or density on safeguard compliance outcomes involves variables at different units of analysis. Consistent with our pre-analysis plan, we tackle the unit of analysis challenge in what we believe is the most principled possible way. Given that travel time and project density treatments differ on a yearly basis as new projects open and others close, we need a unit of analysis and estimand that can best capture these dynamics.

With the above goal in mind, aggregating the data to the project level to match the dependent variable is not ideal. Not only would doing so yield a static estimand, thereby eliminating the dynamics, but it also would invoke an arbitrary aggregation rule (e.g., mean or maximum). The resulting estimand would thus be non-systematically different and contain measurement error, producing estimates with attenuation bias (see King, Keohane and Verba, 1994, 163-164).

To obviate such issues while still respecting that the fact that dependent variable is at the project level, we create a spatially balanced dataset and weight the regression by the number of times that each project appears in the unit of analysis (see Section 2.9). Our dataset is spatially balanced because it contains separate rows for each year in which each project location is active, starting with the project approval year and ending with the project closing year. Then, after making location-specific travel time calculations (see Section 2.4.1), we use the PRIO GRID to aggregate the project locations data into roughly 55×55 kilometers grid cells, corresponding to 0.5 degrees latitude by 0.5 degrees longitude (Tollefsen, Strand and Buhaug, 2012). After aggregating, there are 105,689 project-cell-years in the data.

The resulting project-cell-year dataset offers numerous benefits. First, using grid cells enables us to capture projects located in similar areas with a consistent aggregator. Second, the project-cell-year dataset enable us to capture within-project variation in local conditions. Third, it allow us to merge in numerous spatially-relevant control variables that are not available at the spatial point level but are available at the raster level (see Section 2.6.2).

2.9. Statistical Models

Consistent with Berman et al. (2017) and Denly et al. (2022), we use a spatial heteroskedastic and autocorrelation consistent (HAC) linear regression model:

$$\text{compliance}_{(k,i,t)} = \beta_{\text{log travel time/ density}_{(k,i,t)}} + \beta_{\text{controls}_{(k,i,t)}} + FE + \epsilon_{(k,i,t)} \tag{1}$$

The interaction models also follow a similar structure:

$$\begin{aligned}\text{compliance}_{(k,i,t)} = &\beta_{\text{log travel time /density}_{(k,i,t)}} + \beta_{\text{TTL Quality}_{(k,i,t)}} + \\ &\beta_{\text{log travel time/density} \times \text{ TTL Quality}_{(k,i,t)}} + \beta_{\text{controls}_{(k,i,t)}} + FE + \epsilon_{(k,i,t)}\end{aligned} \quad (2)$$

where subscript k refers to the respective grid cell, i corresponds to the project, t denotes the time/year, ϵ is an error term, and FE corresponds to fixed effects. With respect to the latter, we consider fixed effects at the country and year levels. Within-grid cells effects are irrelevant for the question and estimand of interest, so we do not include grid cell fixed effects. Fundamentally, the study concerns whether distances away from projects yield lower compliance levels. Because grid cell fixed effects would pull interpretation back within the same grid cell, the resulting estimand would become difficult to interpret and irrelevant for the research question. On the subject of the research question and estimand, we also weight both the main and interactive regressions by the number of projects in each grid cell-year per Section 2.8.

Given our focus on spatial driving time and densities, the most appropriate standard error specification entails the use of Conley (1999) standard errors. To account for spatial dependence, we specify distance cutoffs for potential spatial correlation of 150 kilometers, thereby capturing grid cells within the second to third order spatial lag of each other (see Figure 4). As a robustness measure, we also consider spatial cutoffs of 75 kilometers not only because it is half the 150 threshold, but also because the mean project-to-neighbor distance is 82 kilometers. Using such a structure with Conley standard errors has three key benefits. First, Conley standard errors capture the spatial nature of our estimations, which would entail to autocorrelated residuals without an appropriate spatial specification. Second, given that locations from the same project tend to be located within the same area, Conley standard errors allow for addressing project-specific serial correlation—i.e, similar to clustering the standard errors at the project level. Third, using Conley standard errors avoids ambiguous decisions concerning whether to cluster at the level(s) of the grid cell, project, country, year, or the 24 combinations thereof.[13]

3. Results

3.1. Travel Time Results

Columns (1)-(4) of Table 3 present the main results for the travel time treatment, using a spatial cutoff of 150 kilometers. Results with both country fixed effects as well as country and year fixed effects are nearly identical in terms of magnitude, explained variance, and statistical significance. We also find very similar results when we switch the spatial cutoff to 75 kilometers in Table C.1. Because travel time enters the regression in natural log form, we use the summary statistics in Table A.4 to translate the canonical adjustment set estimates in Columns (3)-(4) of Table 3 into changes over the observed distribution of travel times.

Starting with inter-quartile range (IQR), the estimates suggest that moving from the 25th percentile (194 minutes) to the 75th percentile (688 minutes) of travel time decreases compliance by 0.045 points on the 1–4 scale.[14] That corresponds to a 1.5% decrease in the scale range.[15] These effects in the middle of the distribution are rather modest in size.

[13] $4 \times 3 \times 2 \times 1 = 24$

[14] $\Delta y = -0.036 \times 1.26 = -0.045$. Note that $6.53 - 5.27 = 1.26$, which represents the difference between 25th and 75th percentile values on the log scale according to Table A.4.

[15] The scale range decrease is calculated as $0.045/3 = 0.015$, given that compliance outcomes are on a 1-4 scale.

Table 3: Travel Time and the Interactive Effect of TTL Quality on Compliance (150 KM Spatial Cutoff)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total Travel Time (Log)	−0.032**	−0.032**	−0.036**	−0.036**	−0.208***	−0.208***	−0.171**	−0.172**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.080)	(0.080)	(0.086)	(0.086)
Travel Time × TTL (Log)					0.044**	0.044**	0.033	0.033
					(0.019)	(0.019)	(0.021)	(0.021)
TTL					0.015	0.015	0.051	0.049
					(0.117)	(0.117)	(0.124)	(0.124)
Commitment (Log)			−0.105***	−0.108***	−0.158***	−0.158***	−0.163***	−0.162***
			(0.021)	(0.021)	(0.023)	(0.023)	(0.023)	(0.023)
Safeguard Category			0.103***	0.102***			0.101***	0.101***
			(0.023)	(0.023)			(0.024)	(0.024)
Conflict Count	0.023	0.022	0.010	0.009			−0.004	−0.002
	(0.020)	(0.020)	(0.022)	(0.021)			(0.024)	(0.024)
Ethnic Groups			−0.010	−0.010			−0.007	−0.007
			(0.011)	(0.011)			(0.011)	(0.011)
Population (Log)	−0.009	−0.009	−0.011	−0.011			−0.013	−0.013
	(0.009)	(0.009)	(0.009)	(0.009)			(0.010)	(0.010)
Observations	101 264	101 264	92 855	92 855	89 276	89 276	82 530	82 530
R^2	0.190	0.191	0.205	0.206	0.241	0.243	0.248	0.248
Adj. R^2	0.189	0.190	0.204	0.205	0.240	0.241	0.247	0.247
Country FE	X		X		X		X	
Country + Year FE		X		X		X		X

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; spatial cutoff at 150 kilometers; minimal adjustment sets in (1), (2), (5), and (6); canonical adjustment sets in (3), (4), (7), and (8)

Where the effects are less modest is in the upper-right tail, as the distribution is highly skewed and changes in geographic accessibility are multiplicative. For example, moving from the median (375 minutes) to the 95th percentile (1619 minutes) results in a decrease in 0.0526 compliance points, corresponding to 1.8% decrease in the scale range.[16] The jump from 75th percentile (687 minutes) to the 95th percentile (1619 minutes) exhibits similarly multiplicative patterns. In this instance, compliance decreases by 0.032 points,[17] reflecting a 1.0% scale decrease.[18] Finally, the shift from the 90th percentile (1219 minutes) to the 99th percentile (3022 minutes) results in a decrease of 0.032 compliance points,[19] corresponding to a 1.1% scale decrease.[20]

Overall, the above patterns show that geographic structures in the form of travel times have modestly negative impacts on safeguard compliance in the middle of the distribution and larger impacts toward upper tail. These patterns fit rational inattention theory: when bureaucrats have cost, time, and information constraints, geographic structures provide an informative but coarse cue, as clear signals primarily come from the tail of the distribution.

3.2. Travel Time Interaction's with TTL Quality

Columns (5)-(8) of Table 3 present the main results for the travel time treatment, again using a spatial cutoff of 150 kilometers. As with the travel time main effect estimates, results with both country fixed effects as well as country and year fixed effects are essentially identical in terms of magnitude and variance explained. The results with 75 kilometer cutoffs in Table C.1 also suggest very similar results. The minimal adjustment set estimates in Columns (5)-(6) of Table 3 are highly statistically significant and suggest that higher

[16] $\Delta y = -0.036 \times 1.46 = -0.053$. Note that $7.39 - 5.93 = 1.46$, which represents the difference between the log values at the 50th and 95th percentiles according to Table A.4. The scale range decrease is calculated as $0.053/3 = 0.018$

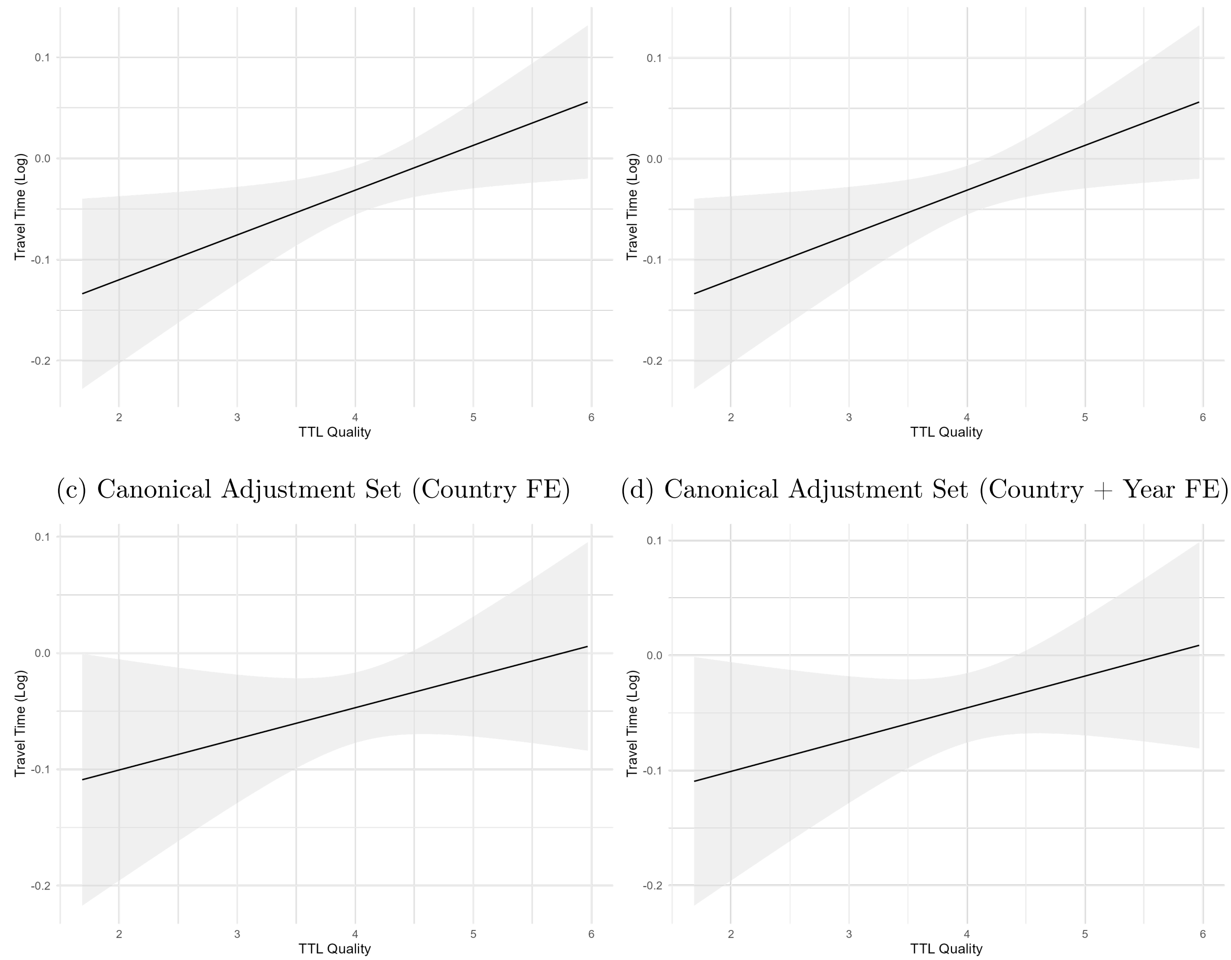
[17] $\Delta y = -0.036 \times 0.86 = -0.032$. Note that $7.39 - 6.53 = 0.86$, which represents the difference between the log values at the 50th and 95th percentiles according to Table A.4.

[18] The scale range decrease is calculated as $0.031/3 = 0.010$.

[19] $\Delta y = -0.036 \times 0.90 = 0.031$. Note that $8.01 - 7.11 = 0.90$, which represents the difference between the log values at the 90th and 99th percentiles.

[20] The scale range decrease is calculated as $0.032/3 = 0.011$

Figure 6: Marginal Effects for the Travel Time × TTL Interactions (150 KM Spatial Cutoff)



(a) Minimal Adjustment Set (Country FE)

(b) Minimal Adjustment Set (Country + Year FE)

(c) Canonical Adjustment Set (Country FE)

(d) Canonical Adjustment Set (Country + Year FE)

Note: The above estimates reflect 95% confidence intervals.

quality TTLs can partially mitigate the structural constraints imposed by travel times. The canonical adjustment set estimates in Columns (7)-(8) are also positive but not statistically significant. By extension, these estimates are less suggestive that higher-quality TTLs can overcome the structural constraints imposed by travel times.

The marginal effect plots in Figure 6 help with better understanding the effect sizes. Consistent with Table 3, the point estimates increase quite meaningfully across the different levels of TTL quality. The most telling part for TTLs' lack of ability to actually overcome the structural constraints from travel time comes from investigating TTLs averaging a perfect rating of 6/6. Even at this level, lower confidence intervals never eclipse zero for the minimal adjustment sets. The canonical adjustment set estimates for these high-performing TTLs barely even cross zero, too.

Overall, agents' abilities to overcome structural impediments to compliance from longer travel times is positive but inconsistent. Like the results from the travel time treatments, these interaction results are broadly consistent with rational inattention: geography provides an informative but imperfect cue, and higher-quality bureaucrats are not powerless but exhibit limited agency.

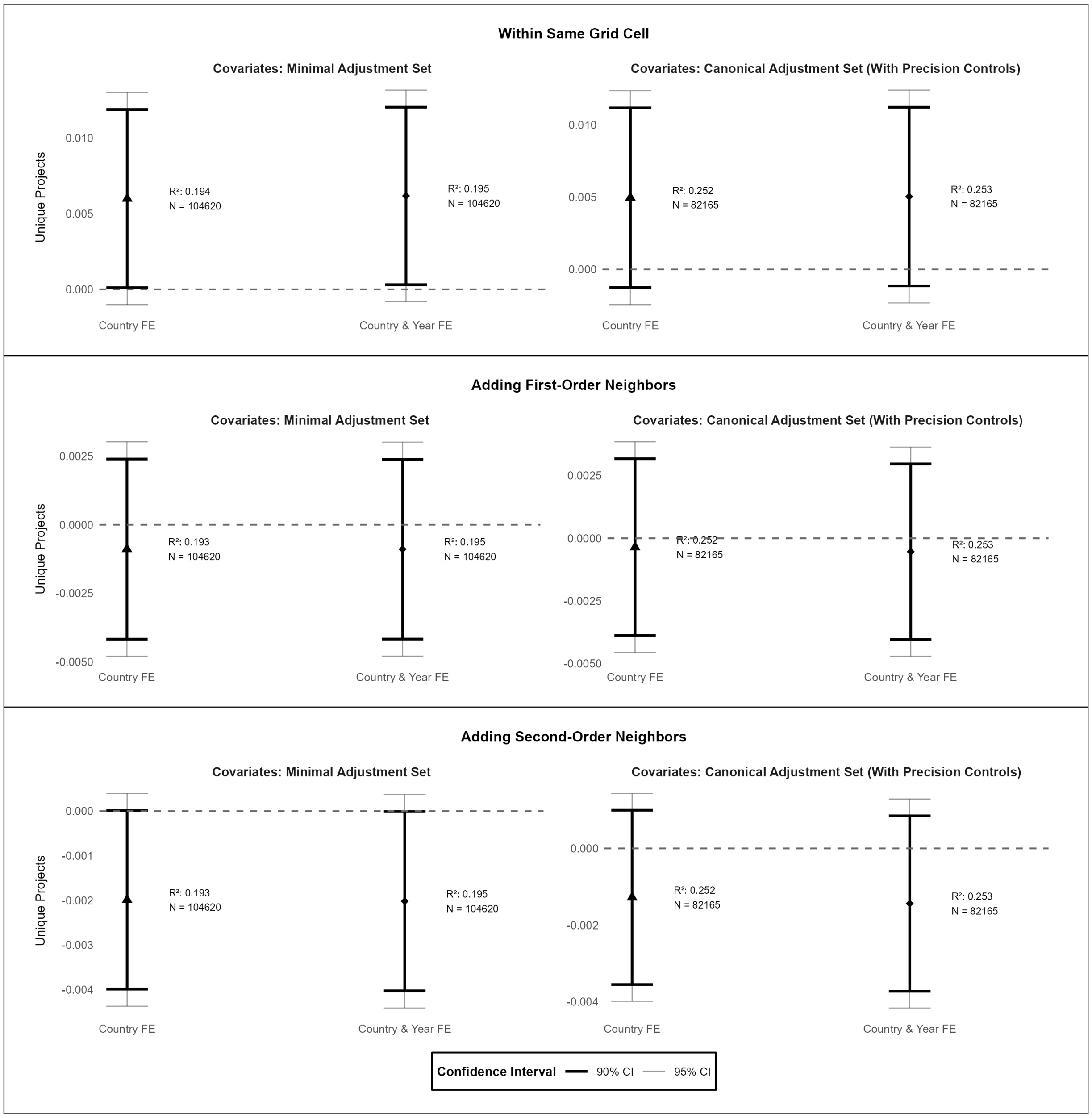
3.3. Density Results

Figure 7 presents the main results of our spatial density analysis, using a 150 kilometer spatial cutoff. The results from Figure D.1 using a 75 kilometer cutoff are also similar. Directionally, the results for the focal point are consistent with the idea that compliance increases as more projects are operating within the same area. The rationale is that more projects in the same area increase legibility and make for more efficient supervision missions—that is, ones in which bureaucrats can monitor multiple projects.

The focal point results for the minimal adjustment sets are statistically significant at the 10% level but not at the 5% level. The canonical adjustment set results have even higher p-values, suggesting even further caution. Considering that compliance follows a 1-4 scale, the effect sizes are also rather small in size, hovering around 0.005 compliance points.

The results are after adding first- and second-order neighboring grid cells consistent with a Queen continguity approch move the sign toward the other direction. The very small effect sizes close to zero suggest two possible conclusions. First, there is saturation point at which is becomes useful for bureaucrats to have "projects in the area". Second, project density cannot substitute for the interplay of geography and state presence. In other words, project density is not helpful for bureaucrats unless those projects can really be monitored. Our interpretation is that explanation two is the more convincing one.

Figure 7: Project Density Results: 150 Kilometer Spatial Cutoff



4. Conclusion

In this paper, we probe the interplay of geographic structures, institutions, and bureaucratic agency in international development by studying foreign aid implementation. Specifically, we examine compliance with the World Bank's environmental and social safeguard policies, which aim to protect people and the environment from the negative externalities of development. Consistent with our pre-analysis plan and theory focusing on rational inattention, we find that longer driving times to reach projects for monitoring purposes generally decreases compliance. We also find some more limited support for our hypothesis that higher-quality bureaucrats have agency to overcome structural problems.

From a theoretical perspective, statistical support for the rational inattention mechanism yields two insights. First, it elucidates that although theories of compliance tend draw sharp lines, the integration of a macro-structural and behavioral lens clarifies that the integration is often yields more insights (see also Tallberg, 2002). Second, and related to the first point, distinctions between geography versus institutions, structure versus agency, and other phenomena that tend to provoke bifurcated arguments are often are not so clear-cut. Indeed, further study of their interplay likely will yield many valuable lessons. Along these lines, we fully agree with the framework paper of this special issue's focus on alignment patterns between agency and structure (Weaver, Morrison and Heinzel, 2026).

From a policy perspective, the results suggests that the most inaccessible locations regularly produce negative externalities that are not simple to consistently address. On the one hand, inaccessible locations are the places that need development programs the most. On the other hand, inaccessible areas are also the ones that perhaps should not receive development programs, particularly if they cause undue and significant harm to people and the environment. Addressing these types of fundamental tensions is, however, precisely the work of foreign aid and development.

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Appendices

A. Summary Statistics

Figure A.1: Correlation Plot

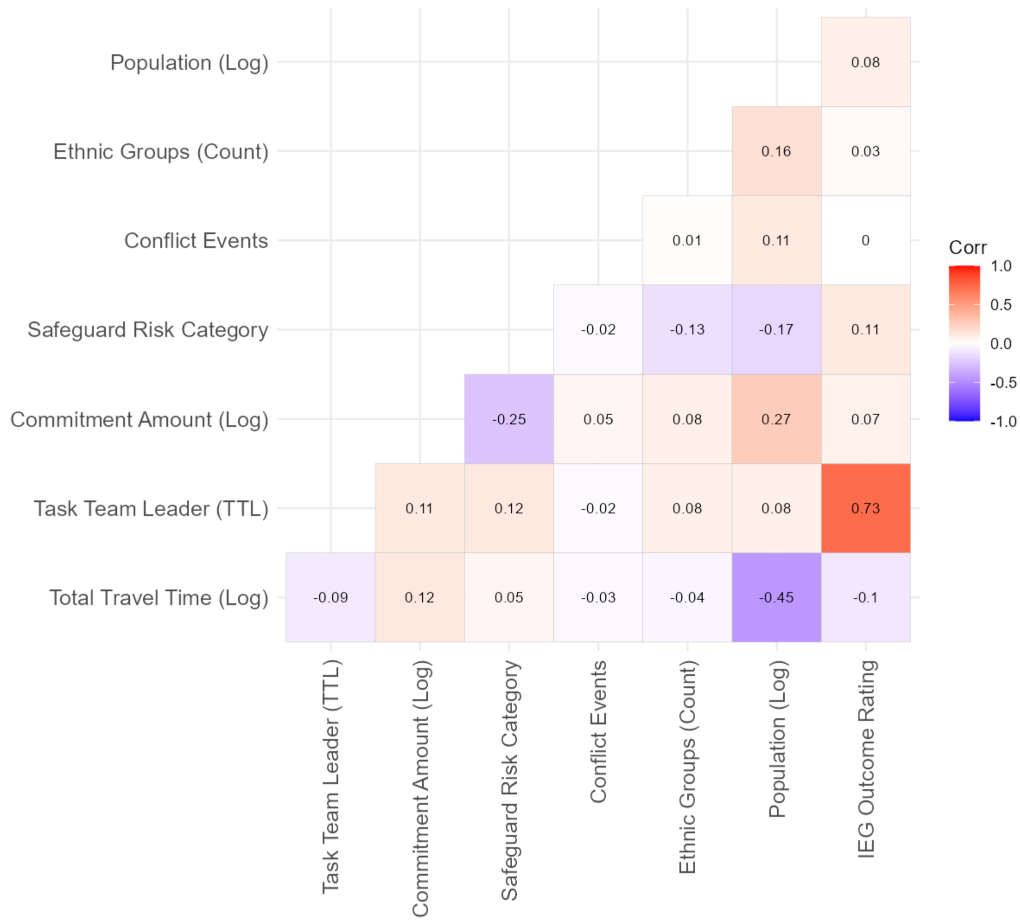


Table A.1: 150 Balance Table: Full vs TTL Sample

Variable	Mean.Full	Mean.TTL	Std.Diff	Var.Ratio	P.Value
Commitment (Log)	18.390	18.607	-0.138	1.108	0
Safeguard Category	2.030	1.938	0.083	0.881	0
Conflict Count	0.168	0.111	0.077	1.719	0
Ethnic Groups	2.078	2.139	-0.033	0.983	0
Population (Log)	8.858	8.969	-0.041	1.031	0

Table A.2: 75 Balance Table: Full vs TTL Sample

Variable	Mean.Full	Mean.TTL	Std.Diff	Var.Ratio	P.Value
Commitment (Log)	18.390	18.607	-0.138	1.108	0
Safeguard Category	2.030	1.938	0.083	0.881	0
Conflict Count	0.168	0.111	0.077	1.719	0
Ethnic Groups	2.078	2.139	-0.033	0.983	0
Population (Log)	8.858	8.969	-0.041	1.031	0

Table A.3: Balance Table Describing the Full Sample vs. TTL-Specific Sample

Variable	Full Mean	Full SD	TTL Mean	TTL SD	p-value	SMD
TTL	4.082	0.592	4.201	0.538	<0.001	-0.210
Safeguard Category	2.056	0.723	1.924	0.846	<0.001	0.168
Commitment (Log)	18.323	1.146	18.659	1.088	<0.001	-0.300
Ethnic Groups	2.110	1.335	2.181	1.377	<0.001	-0.053
Conflict Count	0.149	0.532	0.103	0.418	<0.001	0.096
Population (Log)	8.871	1.930	9.367	1.769	<0.001	-0.268

Table A.4: Summary Statistics for Table 3

Variable	mean	sd	min	p1	p5	p10	p25	median	p75	p90	p95	p99	max
Compliance (Spatial)	3.26	0.84	1.00	1.00	2.00	2.00	3.00	3.00	4.00	4.00	4.00	4.00	4.00
Travel Time (Log)	5.85	1.06	0.00	2.85	3.93	4.58	5.27	5.93	6.53	7.11	7.39	8.01	10.48
Travel Time (Minutes)	568.44	870.26	0.00	16.25	49.85	96.70	194.10	375.40	687.70	1218.79	1619.40	3021.61	35 715.40
Travel Time × TTL (Log)	23.98	5.22	0.00	10.49	15.33	17.65	20.81	24.03	27.34	30.53	32.45	35.65	51.89
TTL	4.11	0.58	1.69	2.45	3.11	3.35	3.77	4.10	4.53	4.82	5.00	5.21	5.97
Commitment (Log)	18.39	1.14	13.74	15.53	16.56	16.91	17.63	18.45	19.22	19.74	20.12	21.21	22.13
Safeguard Category	1.91	0.47	1.00	1.00	1.00	1.00	2.00	2.00	2.00	2.00	3.00	3.00	3.00
Conflict Count	0.17	0.58	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00	3.00	13.00
Ethnic Groups	2.08	1.29	1.00	1.00	1.00	1.00	1.00	2.00	3.00	4.00	5.00	7.00	11.00
Population (Log)	8.86	1.92	0.00	3.02	5.41	6.52	7.80	9.02	10.18	11.14	11.54	12.53	13.61

B. DAG Paths

In this section, we describe the paths underpinning all of the coding decisions in the DAG (see Figure 5):

- **Travel time/density**:
  - *Civil conflict* affects travel time (or project density) because conflicts make travel more difficult. Beyond increasing security risks, civil conflicts can result in the destruction of road infrastructure that makes travel slower.
  - *Population* affects travel time (or project density) because cities generally have greater access to airports, which facilitate travel for bureaucrats conducting supervision missions from abroad.
- **Population**:
  - *Civil conflict* affects population because citizens wish to reside in areas without conflict for security reasons.
- **Safeguard category**:
  - *Population* affects the safeguard risk category because population affects the ability of projects to receive goods, services, and other measures that may reduce risks World Bank (2013, 2022).
  - *Civil conflict* affects safeguard risk category because civil conflict makes assistance and other services more difficult to furnish in the case of a safeguard dispute.
- **TTL quality**:
  - *Commitments* affect TTL quality because the World Bank generally will not assign an inexperienced or lower-quality TTL to projects involving larger commitment amounts. The relationsship flows from commitments to TTL, not the other way around, because the World Bank determines commitment amounts according to country-level criteria (Denly, 2021).

C. Additional Travel Time Results

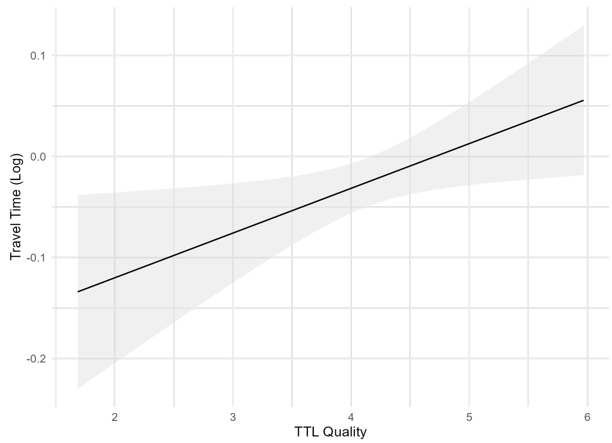
Table C.1: Travel Time and the Interactive Effect of TTL Quality on Compliance (75 KM Spatial Cutoff)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total Travel Time (Log)	−0.032**	−0.032**	−0.036**	−0.036**	−0.208**	−0.208**	−0.171**	−0.172**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.081)	(0.081)	(0.087)	(0.087)
Travel Time × TTL (Log)					0.044**	0.044**	0.033	0.033
					(0.019)	(0.019)	(0.021)	(0.021)
TTL					0.015	0.015	0.051	0.049
					(0.117)	(0.117)	(0.123)	(0.124)
Commitment (Log)			−0.105***	−0.108***	−0.158***	−0.158***	−0.163***	−0.162***
			(0.019)	(0.019)	(0.021)	(0.021)	(0.021)	(0.021)
Safeguard Category			0.103***	0.102***			0.101***	0.101***
			(0.019)	(0.019)			(0.020)	(0.020)
Conflict Count	0.023	0.022	0.010	0.009			−0.004	−0.002
	(0.019)	(0.019)	(0.020)	(0.020)			(0.022)	(0.021)
Ethnic Groups			−0.010	−0.010			−0.007	−0.007
			(0.011)	(0.011)			(0.011)	(0.011)
Population (Log)	−0.009	−0.009	−0.011	−0.011			−0.013	−0.013
	(0.009)	(0.009)	(0.009)	(0.009)			(0.010)	(0.010)
Observations	101 264	101 264	92 855	92 855	89 276	89 276	82 530	82 530
R^2	0.190	0.191	0.205	0.206	0.241	0.243	0.248	0.248
Adj. R^2	0.189	0.190	0.204	0.205	0.240	0.241	0.247	0.247
Country FE	X		X		X		X	
Country + Year FE		X		X		X		X

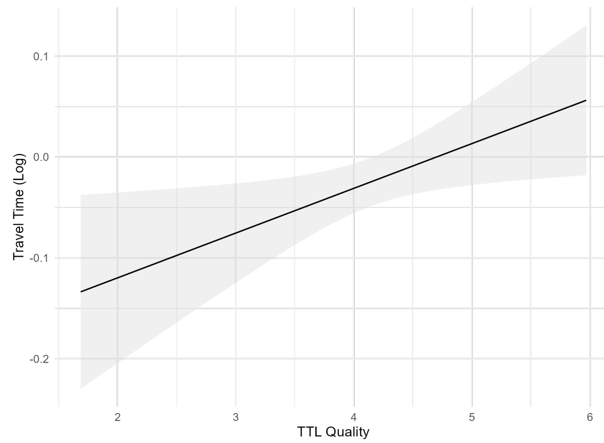
Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; spatial cutoff at 75 kilometers; minimal adjustment sets in (1), (2), (5), and (6); canonical adjustment sets in (3), (4), (7), and (8).

Figure C.1: Marginal Effects for Interactions (75 Kilometer Spatial Cutoff)

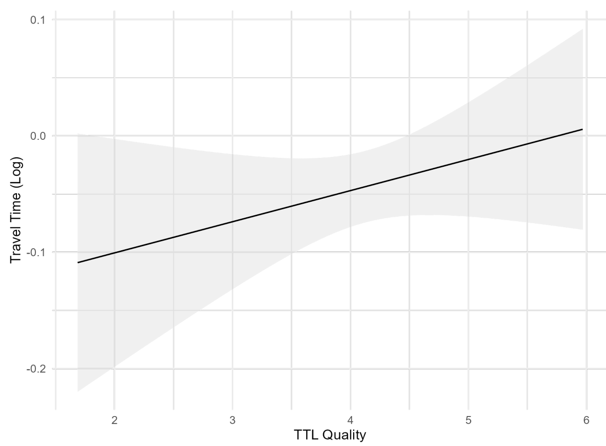
(a) Minimal Adjustment Set (Country FE)



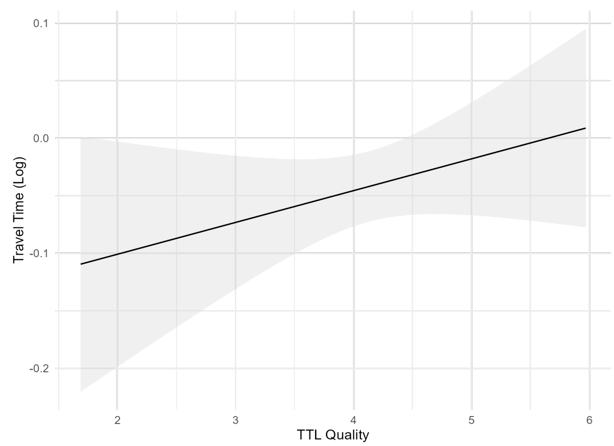
(b) Minimal Adjustment Set (Country + Year FE)



(c) Canonical Adjustment Set (Country FE)



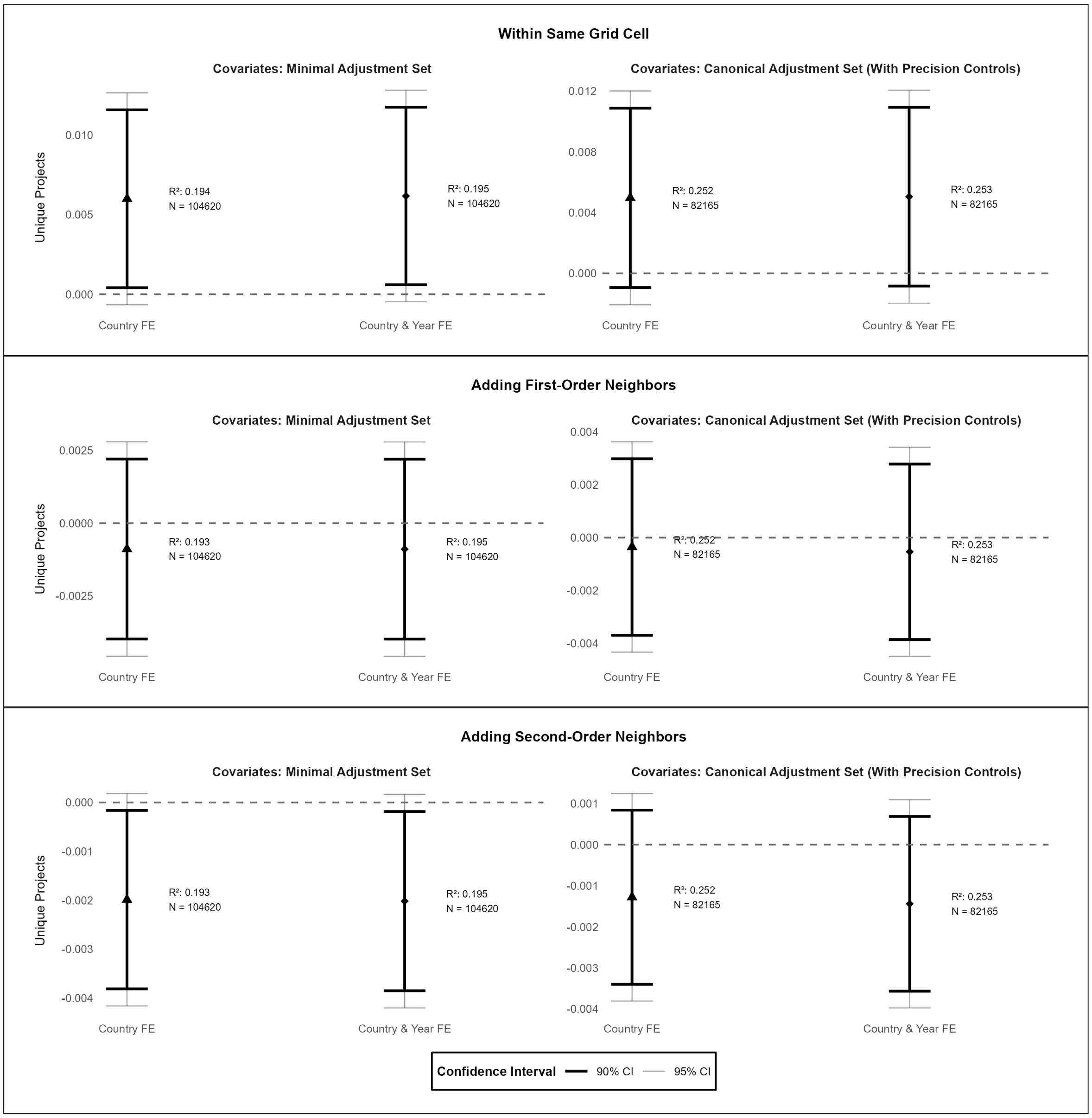
(d) Canonical Adjustment Set (Country + Year FE)



Note: the above estimates reflect 95% confidence intervals.

D. Additional Density Results

Figure D.1: Density Plot: 75 Kilometer Cutoff



E. TTL-Specific Analyses

As we specified in Section 2.4.2, only 17% of the project-cell-year observations include TTLs supervising multiple projects within the same country. These observations are also not a random sample of the full sample (see Table A.3), suggesting series selection-related problems that are likely worthy of a whole new paper. We only report the results here to be consistent with our pre-analysis plan.

Table E.1: TTL-Specific Travel Time and the Interactive Effect of TTL Quality on Compliance (150 KM Spatial Cutoff)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total Travel Time (Log)	−0.018	−0.019	−0.032	−0.035	−0.002	−0.004	0.043	0.043
	(0.022)	(0.022)	(0.022)	(0.022)	(0.141)	(0.141)	(0.150)	(0.149)
TTL × Travel Time (Log)					−0.009	−0.008	−0.018	−0.018
					(0.034)	(0.034)	(0.035)	(0.035)
TTL					0.328	0.324	0.370	0.368
					(0.228)	(0.227)	(0.238)	(0.237)
Commitment (Log)			−0.142***	−0.145***	−0.160***	−0.161***	−0.150***	−0.151***
			(0.034)	(0.033)	(0.033)	(0.033)	(0.034)	(0.034)
Safeguard Category			0.073*	0.072*			0.065*	0.064*
			(0.038)	(0.038)			(0.036)	(0.036)
Conflict Count	0.048	0.043	0.028	0.023			0.030	0.025
	(0.049)	(0.049)	(0.052)	(0.051)			(0.048)	(0.048)
Ethnic Groups			−0.001	−0.002			−0.002	−0.003
			(0.019)	(0.019)			(0.019)	(0.019)
Population (Log)	0.020	0.020	0.005	0.005			0.006	0.006
	(0.013)	(0.013)	(0.013)	(0.013)			(0.013)	(0.013)
Observations	27 018	27 018	25 618	25 618	27 150	27 150	25 618	25 618
R^2	0.303	0.305	0.316	0.318	0.334	0.336	0.333	0.335
Adj. R^2	0.300	0.302	0.313	0.316	0.332	0.334	0.330	0.332
Country FE	X		X		X		X	
Country + Year FE		X		X		X		X

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; spatial cutoff at 150 kilometers; minimal adjustment sets in (1), (2), (5), and (6); canonical adjustment sets in (3), (4), (7), and (8).

Table E.2: TTL-Specific Travel Time and the Interactive Effect of TTL Quality on Compliance (75 KM Spatial Cutoff)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total Travel Time (Log)	−0.018	−0.019	−0.032	−0.035*	−0.002	−0.004	0.043	0.043
	(0.020)	(0.020)	(0.021)	(0.021)	(0.131)	(0.131)	(0.138)	(0.139)
TTL × Travel Time (Log)					−0.009	−0.008	−0.018	−0.018
					(0.031)	(0.031)	(0.032)	(0.032)
TTL					0.328	0.324	0.370*	0.368*
					(0.206)	(0.206)	(0.216)	(0.216)
Commitment (Log)			−0.142***	−0.145***	−0.160***	−0.161***	−0.150***	−0.151***
			(0.031)	(0.031)	(0.030)	(0.030)	(0.032)	(0.031)
Safeguard Category			0.073**	0.072**			0.065**	0.064**
			(0.032)	(0.031)			(0.030)	(0.029)
Conflict Count	0.048	0.043	0.028	0.023			0.030	0.025
	(0.046)	(0.046)	(0.048)	(0.047)			(0.045)	(0.044)
Ethnic Groups			−0.001	−0.002			−0.002	−0.003
			(0.016)	(0.016)			(0.016)	(0.016)
Population (Log)	0.020	0.020	0.005	0.005			0.006	0.006
	(0.012)	(0.012)	(0.013)	(0.013)			(0.013)	(0.013)
Observations	27 018	27 018	25 618	25 618	27 150	27 150	25 618	25 618
R^2	0.303	0.305	0.316	0.318	0.334	0.336	0.333	0.335
Adj. R^2	0.300	0.302	0.313	0.316	0.332	0.334	0.330	0.332
Country FE	X		X		X		X	
Country + Year FE		X		X		X		X

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; spatial cutoff at 75 kilometers; minimal adjustment sets in (1), (2), (5), and (6); canonical adjustment sets in (3), (4), (7), and (8).

Figure E.1: Density Plot: 150 km Cutoff (TTL-Specific)

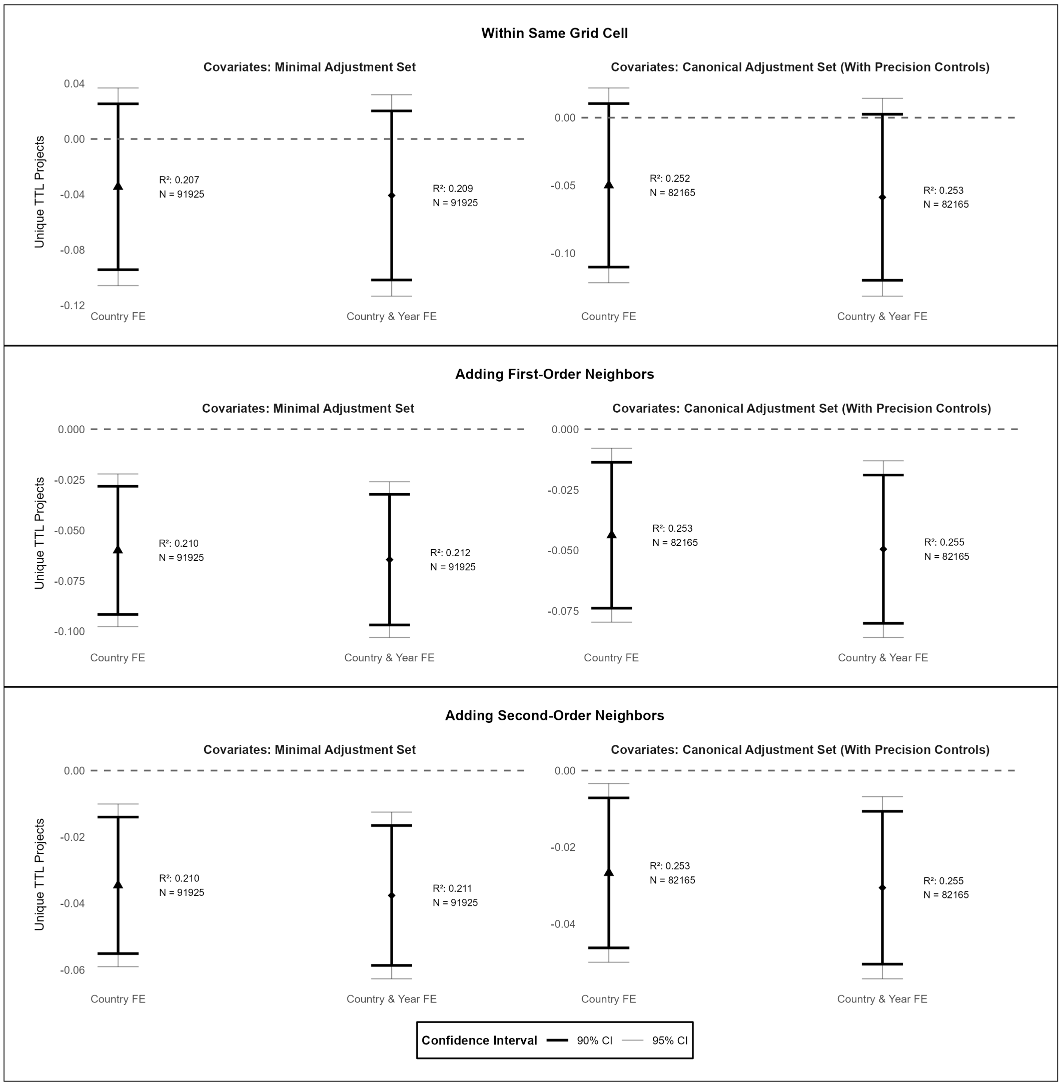
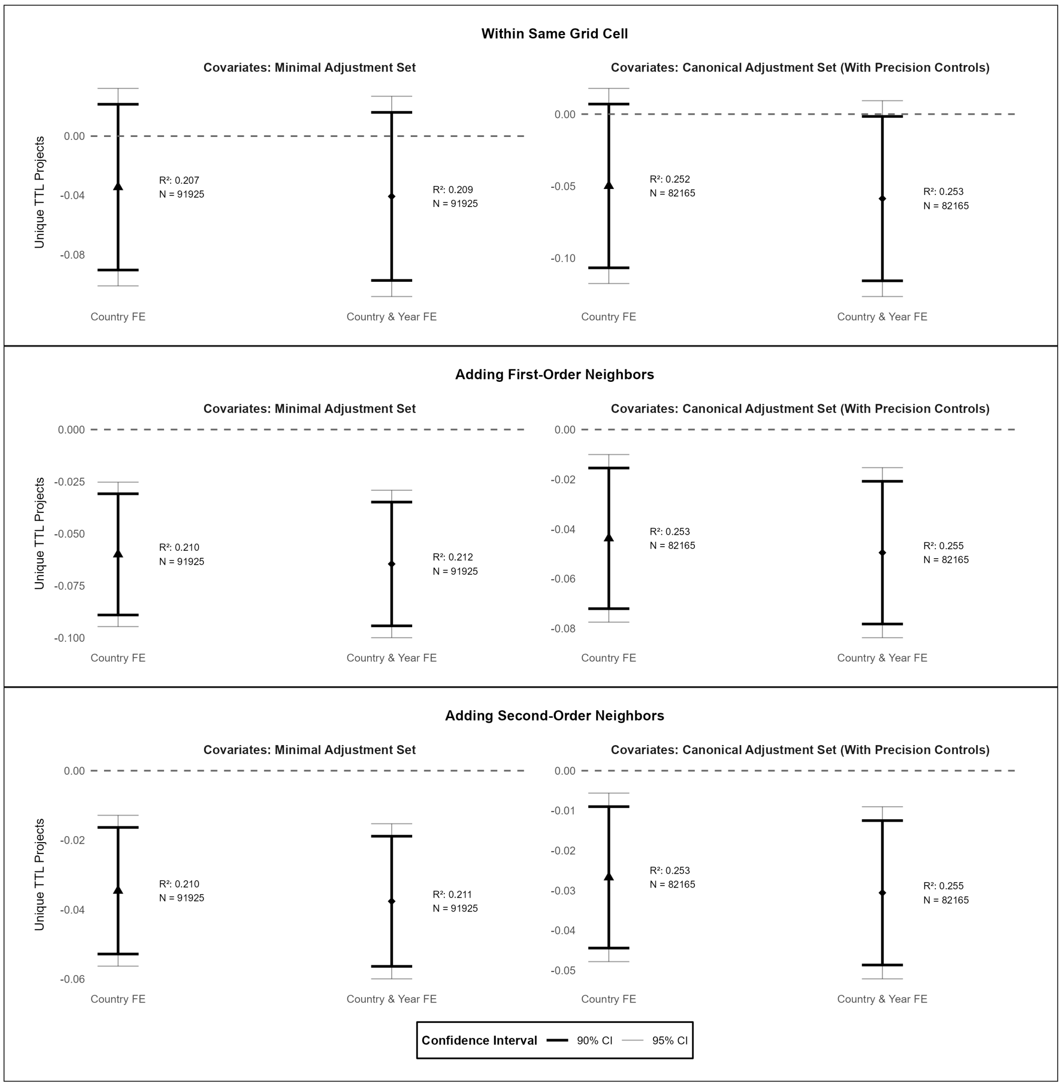


Figure E.2: Density Plot: 75 km Cutoff (TTL-Specific)



F. Mathematical Framework

F.1. Input Data

Let:

- $P = \{p_1, p_2, \ldots, p_n\}$ be the set of project locations for a given project, where each p_i refers to the latitude and longitude coordinates of each project's location.
- $A = \{a_1, a_2, \ldots, a_m\}$ be the set of airports in the same country, where each a_j uses data from Megginson (2025) to denote each airport's latitude and longitude coordinates as well as its size in terms of whether it is `large`, `medium`, or `small`.
- $O = \{o_1, o_2, \ldots, o_k\}$ be the set of other project locations in the same country and year, excluding the current project, where o_i refers to the latitude and longitude coordinates of each other project's location.

F.2. Nearest Airport Selection

For each project, the algorithm selects one airport $a^* \in A$ that minimizes the total travel time to all project locations P while ensuring at least one non-zero travel time. The algorithm evaluates airports in the following priority order: `large`, then `medium`, and finally `small`.

We define the travel time matrix D from OSRM as:

$$D_{j,i} = \text{travel time (seconds) from } a_j \text{ to } p_i$$

We compute the total travel time for airport a_j by

$$S_j = \sum_{i=1}^{n} D_{j,i}$$

Then, we select the airport a^* as:

$$a^* = \arg\min_{a_j \in A_{\text{size}}} S_j \quad \text{such that} \quad S_j > 0$$

where A_{size} represents the subset of airports for the current size being evaluated. The minimization first considers `large` airports, then `medium`, and finally `small` until a valid a^* is found. If no a^* with $S_j > 0$ exists, the related fields are set to missing. For each location p_i, if a^* is selected, we compute:

$$\text{travel time in minutes}_i = \frac{D_{*,i}}{60}$$

where $*$ denotes the index of a^*, respectively. If $D_{*,i} = 0$ or if no a^* is found, we assign it as missing.

F.3. Neighbor Calculations

For each location p_i, we identify the nearest neighbor project $o^* \in O$ within the same country. We define the neighbor travel time N from OSRM as:

$$N_{i,l} = \text{travel time (seconds) from } p_i \text{ to } o_l$$

We next determine the nearest general neighbor, o^*, by

$$o^* = \arg\min_{o_l \in O} N_{i,l}$$

Then, we calculate the neighbor time as follows:

$$\text{neighbor time} = \frac{N_{i,*}}{60}$$

Next, we compute the total travel time in minutes as follows:

$$\text{total time minutes}_i = \text{travel time in minutes}_i + \text{neighbor time}$$

G. Local Server Setup and Data Processing Steps

G.1. Overview

The Open Source Routing Machine (OSRM) is a high-performance routing engine that computes shortest or fastest paths across large-scale road networks using OpenStreetMap (OSM) data. It employs the Multi-Level Dijkstra (MLD) algorithm to enable efficient routing queries, making it suitable for applications requiring rapid pathfinding on continental-scale datasets. This appendix provides a comprehensive, step-by-step guide to installing prerequisites, preparing OSM data, building routing graphs, and launching a local OSRM server on a Windows system using Windows Subsystem for Linux 2 (WSL2) and Docker.

We assume that regional `.osm.pbf` files, which are Protocol Buffer Format files containing OSM data, have been downloaded from Geofabrik (OpenStreetMap Foundation, 2025), a service providing pre-processed OSM extracts by continent or country, and are stored locally. This guide is tailored for Windows users and prioritizes reproducibility: all variables are explicitly declared, commands are formatted for direct copy-pasting into PowerShell, and detailed explanations clarify each step's purpose and potential challenges. Troubleshooting tips and resource considerations are included to address common issues, particularly for memory-intensive tasks like preprocessing large datasets.

G.2. System Requirements

Processing large OSM files (e.g., continent-scale datasets exceeding 10 GB) requires substantial computational resources. The following are recommended:

- Windows 10 (version 2004 or later) or Windows 11 with administrator privileges to enable system features like WSL2.
- A solid-state drive (SSD) with at least 500 GB of free space, as preprocessing generates temporary files that can be 5–10 times the size of the input `.osm.pbf` file.
- At least 32 GB of RAM (64 GB or more preferred) to handle memory-intensive graph partitioning and customization steps.
- A multi-core CPU (at least 8 cores, 12 or more preferred) for parallel processing during graph construction.
- WSL2 enabled for Linux compatibility and Docker Desktop installed for containerized execution of OSRM tools.

If your system does not meet these specifications, consider using smaller regional datasets (e.g., individual countries) or cloud-based alternatives like AWS EC2 instances with sufficient resources.

G.3. Step 1: Enable WSL2

Windows Subsystem for Linux 2 (WSL2) provides a lightweight Linux kernel within Windows, offering superior performance and compatibility for tools like Docker compared to WSL1. To enable WSL2:

Open **PowerShell as Administrator** (right-click the PowerShell icon and select "Run as administrator"):

```
wsl --install
```

This command installs WSL2 and the default Linux distribution (Ubuntu recommended for its stability and package ecosystem). After execution, Windows will prompt for a system reboot. Following the reboot, complete the Ubuntu setup by setting a username and password when prompted.

Verify that WSL2 is correctly installed:

```
wsl --version
# Expected output: "WSL version: 2" along with kernel and distribution details.
```

If the output indicates WSL1, convert the Ubuntu distribution to WSL2:

```
wsl --set-version Ubuntu 2
```

Troubleshooting: If `wsl -install` fails, ensure virtualization is enabled in your system's BIOS/UEFI settings (look for "Virtualization," "VT-x," or "AMD-V" in your motherboard manual). In Windows, verify that the "Virtual Machine Platform" and "Windows

Subsystem for Linux" features are enabled via *Control Panel* → *Programs* → *Turn Windows features on or off*. If issues persist, update Windows to the latest version.

G.4. Step 2: Install Docker Desktop

Docker Desktop provides a user-friendly interface for managing containers on Windows and integrates seamlessly with WSL2 to run Linux-based images like OSRM.

1. Download the Docker Desktop installer from `https://www.docker.com/products/docker-desktop` and run it with administrator privileges. Follow the on-screen instructions to complete the installation.

2. After installation, open Docker Desktop and configure the following settings for optimal performance:

   - In *Settings* → *General*, ensure **Use the WSL 2 based engine** is checked. This leverages WSL2 for better resource isolation and performance.
   - Under *Resources* → *WSL Integration*, enable integration with your Ubuntu distribution to allow Docker commands to run within WSL2.
   - Under *Resources* → *Advanced*, allocate at least 32 GB of RAM and 12 CPU threads to Docker. This prevents out-of-memory errors during OSRM preprocessing. Adjust based on your hardware, but leave sufficient resources for Windows to avoid system instability.
   - Under *Resources* → *File Sharing*, add your working directory (e.g., `D:\OSRM`) to allow Docker to mount it as a volume for data access.

3. Restart Docker Desktop after applying changes to ensure they take effect.

Verify Docker installation by running a test container:

```
docker run hello-world
# Expected output: A welcome message indicating Docker is functioning correctly.
```

Troubleshooting: If the `hello-world` container fails to run, ensure Docker Desktop is running and WSL2 integration is enabled. Check that your WSL2 distribution is listed under *WSL Integration*. If errors persist, restart Docker Desktop or reinstall it, ensuring all prerequisites (e.g., WSL2) are met.

G.5. Step 3: Configure Swap Space for WSL2

Preprocessing large `.osm.pbf` files (e.g., continent-scale datasets) can exceed physical RAM, leading to crashes. Configuring a swap file provides virtual memory to prevent out-of-memory errors.

Create a dedicated directory for the swap file:

```
mkdir C:\wsl_swp
```

Edit the WSL2 configuration file to allocate swap space. Open `%UserProfile%\.wslconfig` (typically `C:\Users\YourUsername\.wslconfig`) in a text editor (e.g., Notepad). If the file does not exist, create it. Add the following configuration:

```
[wsl2]
memory=32GB
processors=12
swap=200GB
swapFile=C:\\wsl_swp\\wsl.swap
localhostForwarding=true
```

This configuration allocates 32 GB of RAM, 12 CPU threads, and a 200 GB swap file. Adjust `memory` and `processors` based on your hardware, and set `swap` to at least 2–3 times the size of the input `.osm.pbf` file for large datasets.

Apply the changes by shutting down WSL2:

```
wsl --shutdown
```

Restart Docker Desktop to ensure the new configuration is applied. Verify the swap file by running a Linux command within WSL2:

```
wsl free -h
# Expected output: Displays total, used, and free swap space (e.g., 200G total).
```

Troubleshooting: If the swap file is not recognized, ensure the `swapFile` path uses double backslashes (`\\`) and that the directory `C:\wsl_swp` exists. Avoid placing the swap file on a mechanical hard drive, as it significantly slows down preprocessing.

G.6. Step 4: Prepare Working Directory and Data

Choose a persistent working directory on an SSD to store OSM data and processed files. SSDs are critical for performance due to the high I/O demands of preprocessing.

Set up the directory in PowerShell:

```
$OSRM_DATA = "D:\OSRM"
mkdir $OSRM_DATA
```

Download `.osm.pbf` files from Geofabrik (https://download.geofabrik.de/) and place them in the working directory. For example:

D:\OSRM\africa-latest.osm.pbf
D:\OSRM\asia-latest.osm.pbf

Ensure the directory path has no spaces or special characters, as these can cause issues with Docker volume mounting. If you encounter permission errors, verify that your user account has full read/write access to the directory.

G.7. Step 5: Preprocess Map Data

Preprocessing transforms the raw `.osm.pbf` file into a routing graph optimized for the MLD algorithm. This involves three stages: extraction, partitioning, and customization. Each stage is executed within the OSRM Docker container to ensure a consistent environment.

Define variables for the dataset to process:

```
$OSRM_DATA = "D:\OSRM"
$PbfFile   = "africa-latest.osm.pbf"
$BaseName  = "africa-latest"
```

These variables specify the working directory, input file, and base name for output files. Ensure `$PbfFile` matches the exact filename of your downloaded `.osm.pbf` file.

Run the preprocessing stages:

1) Extract road network with profile: The extraction step filters the `.osm.pbf` file to extract road network data using a Lua profile (`car.lua`) that defines routing rules (e.g., speed limits, road types).

```
docker run --rm -t -v "|$OSRM_DATA|:/data" osrm/osrm-backend `
  osrm-extract -p /opt/car.lua "/data/|$PbfFile|"
```

The `-rm` flag ensures the container is removed after execution to save disk space, `-t` allocates a terminal for output, and `-v "${OSRM_DATA}:/data"` mounts the working directory to `/data` in the container. This step generates an `.osrm` file (e.g., `africa-latest.osrm`).

2) Partition graph for MLD algorithm: The partitioning step divides the road network into hierarchical levels to optimize query performance for the MLD algorithm.

```
docker run --rm -t -v "${OSRM_DATA}:/data" osrm/osrm-backend `
  osrm-partition "/data/$BaseName.osrm"
```

This step creates additional files, such as `.osrm.partition` and `.osrm.cells`, which store the hierarchical graph structure.

3) Customize weights (speed limits, turn costs): The customization step applies weights (e.g., travel times, turn penalties) to the partitioned graph, enabling fast routing queries.

```
docker run --rm -t -v "${OSRM_DATA}:/data" osrm/osrm-backend `
  osrm-customize "/data/$BaseName.osrm"
```

This step generates files like `.osrm.mldgr`, completing the preprocessing pipeline.

Upon completion, the `D:\OSRM` directory will contain derived files, including:

- `africa-latest.osrm`
- `africa-latest.osrm.nodes`
- `africa-latest.osrm.edges`
- `africa-latest.osrm.mldgr`
- `africa-latest.osrm.partition`
- `africa-latest.osrm.cells`

Troubleshooting: Preprocessing can fail due to insufficient memory or disk space. Monitor resource usage with tools like Task Manager or `htop` in WSL2. If errors occur, verify that the swap file is active and the working directory is accessible. For very large datasets, consider increasing the swap size or using a smaller region. If Docker commands fail, ensure Docker Desktop is running and the volume mount path is correct.

G.8. Step 6: Launch Routing Server

Start the OSRM server to handle routing queries using the preprocessed data. First, remove any existing container to avoid conflicts:

```
docker rm -f osrm 2>$null
```

The `-f` flag forces removal, and `2>$null` suppresses error messages if no container exists. Then, launch the server:

```
docker run -d --name osrm -p 5000:5000 -v "${OSRM_DATA}:/data" osrm/osrm-backend `
  osrm-routed --algorithm mld "/data/$BaseName.osrm"
```

The `-d` flag runs the container in detached mode (background), `–name osrm` names the container, `-p 5000:5000` maps port 5000 on the host to 5000 in the container, and `–algorithm mld` specifies the MLD algorithm for routing.

G.9. Step 7: Verify Server Health

Confirm that the server is running correctly by checking its health endpoint:

```
Invoke-RestMethod "http://localhost:5000/health"
# Expected response: OK
```

Test the server with a sample routing query, such as finding the shortest driving path between two coordinates (e.g., Houston, TX at -95.3698, 29.7604 and Dallas, TX at -96.7969, 32.7767):

```
Invoke-RestMethod "http://localhost:5000/route/v1/driving/-95.3698,29.7604;-96.7969,32.7767
    "
```

This returns a JSON object containing the lat and longitude of said project,airport,and nearest location ass well as the distance, and estimated travel time. For example, the response includes a `polyline` field encoding the route path and a `duration` field in seconds.

This workflow converts OSRM's returned `duration` (seconds) to `travel_time_minutes` (minutes) by dividing by 60, and converts `distance` (meters) to `travel_distance_km` (kilometers) by dividing by 1000; these converted values are what get written to the final CSV.

Troubleshooting: If the health endpoint returns an error or no response, verify that the container is running (`docker ps`) and that port 5000 is not blocked by a firewall. If the routing query fails, ensure the coordinates are within the preprocessed region's bounds and that preprocessing completed successfully.

G.10. Step 8: Switching Regions

To switch to a different preprocessed region (e.g., from Africa to Asia), use a PowerShell script to automate stopping the current OSRM server, removing its container, and launching a new server with the desired dataset. The script `Switch-OSRMRegion.ps1` simplifies this process by taking the dataset's base name (e.g., `asia-latest`) as a parameter.

Prepare the Script: Save the following PowerShell script as `Switch-OSRMRegion.ps1` in your working directory (e.g., `D:\OSRM`):

```
# Switch-OSRMRegion.ps1
# Switches the OSRM server to a new preprocessed region dataset

param (
    [Parameter(Mandatory=$true)]
    [string]$BaseName
)

# Define working directory
$OSRM_DATA = "D:\OSRM"
```

```
# Stop and remove existing OSRM container
docker stop osrm 2>|$\|null
docker rm osrm 2>|$\|null

# Launch new OSRM server with specified dataset
docker run -d --name osrm -p 5000:5000 -v "|$OSRM_DATA|:/data" osrm/osrm-backend `
    osrm-routed --algorithm mld "/data/|$BaseName|.osrm"

Write-Output "OSRM server switched to $BaseName dataset."
```

Ensure the dataset for the new region (e.g., `asia-latest.osrm`) has been preprocessed as described in Section G (Step 5).

Run the Script: Execute the script in PowerShell, specifying the base name of the preprocessed dataset:

```
Put script name here
```

This command stops any running OSRM container, removes it, and starts a new server using the `asia-latest.osrm` dataset. The script assumes the working directory is `D:\OSRM`; adjust the `${OSRM_DATA}` variable in the script if your directory differs.

Troubleshooting: If the script fails, verify that Docker Desktop is running and the specified `.osrm` file exists in the working directory. Ensure the dataset has been fully preprocessed (including extraction, partitioning, and customization). If the port 5000 is in use, check for conflicting processes with `netstat -a -n -o | find "5000"` and terminate them if necessary.

Ensure the new `$BaseName` matches the preprocessed dataset's base filename. Preprocessing must be completed for the new region beforehand, following the steps in Section G (Step 5).

G.11. Summary

This appendix provides a fully reproducible pipeline for setting up and running a local OSRM routing server on Windows using WSL2 and Docker. By explicitly declaring variables and file paths, and including detailed instructions and troubleshooting tips, this guide enables readers to replicate the computational environment with their own Geofabrik datasets. The pipeline supports large-scale routing applications and can be adapted to different regions or extended with custom Lua profiles for specialized routing scenarios.