Green Tape or Green Light? Brazilian Permitting Between Transparency and Political Pressure*

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Abstract

This research examines environmental permitting processes in Brazil, in the context of public policies, focusing on high-impact projects seeking permits between 2011 and 2014, following a significant reform of environmental legislation and preceding the dam collapses of Mariana and Brumadinho. The study investigates the influence of governance structures, transparency, and political factors on permit approval times using survival analysis, employing machine learning approaches for robustness checks. It is found that enhanced transparency and independence within permitting agencies are associated with shorter processing times. Political affiliations also seem to influence processing time. Our results show that a higher share of votes for conservative and populist parties in Brazilian states, especially Bolsonaro, appears to be correlated with shorter permitting processes and adverse environmental impacts, an effect observed also for moderate, non-populist right leaning parties. The study underscores the importance of policymakers taking into account governance frameworks and environmental assessments to strike a balance between economic development and environmental protection.

Keywords: Environmental Permitting Process, Environmental Regulation, Survival Analysis, Machine Learning

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1 Introduction

Environmental permitting balances economic growth with environmental protection. The development of economic activities demands the approval of local and national governments for the construction of infrastructure (roads, power plants, etc.), the waste and handling of hazardous rejects, and every step in those ventures. Even investments in sustainable projects, such as clean energy, are not immune to this control, as they also have a considerable environmental impact (Jaber, 2014).

In fact, the exploration of economic activities requires concessions from governments, such as in oil drilling and mining projects, with interested companies bidding for permissions while committing themselves to regulatory policies, including environmental permitting requirements. Specifically, regarding environmental permitting processes, there is a debate still in place on their effectiveness, questioning if this is the best way to ensure protection for the natural environment. In this sense, an important strand of the literature deals with the so called 'Harrington Paradox', observing that, despite the low penalties and reduced chances of being caught, companies comply with environmental regulations, deeming permitting processes unnecessary (Harrington, 1988).

Beyond effectiveness, concerns about costs persist, mainly about opportunity costs that arise from delays in granting permits (Ulibarri et al., 2017). Although it is undeniable that the analysis of such complex projects demands time, unnecessary delays could jeopardize socially desirable projects. Streamlining permit processes without endangering environmental protection should be a goal that any government should pursue. Healthy measures to expedite permits would include circumventing informational asymmetries by enhancing transparency, and solving collective action problems by fostering participation and amplifying the variety of stakeholders involved.

The risk lies in an unbalanced policy, one that promotes simplifications of regulation without sufficient consideration of environmental risks. The rise of conservative and populist leaders throughout the world exacerbates this problem, raising concerns about unsustainable environmental policies. In Poland, the government implemented policies to accelerate the permitting process, mainly for coal and other energy projects, as part of a broader strategy to reduce dependence on external energy sources. The Trump administration's rollback of environmental regulations in the US and the Bolsonaro administration's policies toward deforestation in Brazil illustrate how governments can both accelerate environmental permitting processes and undermine existing protections.

However, this dynamic is not restricted to populistic leadership. In Australia, the Environment Protection and Biodiversity Conservation Act (EPBC) has undergone such reforms, aimed at streamlining environmental approvals and addressing inefficiencies. By emphasizing speed, it could reduce scrutiny and lower environmental standards, harm public participation, and privilege special interest groups, potentially starting a "race to the bottom." (Mostafavi et al., 2022; Radford, 2020; Slevin and Tait, 2020).

We take advantage of the data available in an early report (Ribeiro, 2015) on the determinants of the time required to issue environmental permits for high-impact projects to examine these questions. We update this report with additional data on political economy variables (votes for conservative parties and candidates concerned about the environment), data on environmental degradation, and others. We employ various survival analysis methods and machine learning robustness checks to examine the determinants of the time length of permit approval and to link a more or less expedited procedure to environmental results. Overall, we could divide a good and a bad shortening of time to grant a permit. Transparency, responsiveness, and openness to society seem to abbreviate the process, with no sign of environmental degradation. However, the kind of reduction in permitting time promoted by populist, conservative governments, on the other hand, seems to be connected with worse results.

This article is organized in five sections, in addition to this Introduction. The next section presents the related literature and highlights the main contributions of the paper. Section 3 presents an outlook of Brazilian permitting process, Section 4 discusses the methods, detailing the scope of the 2015 report, with emphasis on data collection, the construction of variables and additional data search undertook today, and the jurimetric models and machine learning methods, Section 5 brings results and discussions, and section 6 concludes.

2 Related Literature

Various studies have examined the factors that influence the duration of environmental permitting processes. (Ribeiro, 2015; Ulibarri, 2018; Ulibarri et al., 2017) The literature highlights the influence of variables such as government structures, transparency, political affiliations, economic conditions, and even the presence of environmental champions. (Innes and Mitra, 2015; McCubbins and Schwartz, 1984) Researchers have employed various methods, including survival analysis, to assess the impact of these factors. (Ulibarri et al., 2017; Ulibarri, 2018) However, more research is needed to fully understand the complexities of the permitting process and develop more effective strategies to balance economic development with environmental protection.

The literature highlights the importance of social participation and transparency in shaping effective environmental permitting processes. (Ansell and Gash, 2008; Mostafavi et al., 2022) Research suggests that greater public participation and oversight can lead to more rigorous environmental assessments, potentially mitigating the risks of delayed permit decisions. (McCubbins and Schwartz, 1984; Mostafavi et al., 2022) Transparency, through the availability of information about the permitting process and the criteria used to make decisions, can reduce information asymmetry, leading to more equitable and predictable outcomes. (Stiglitz, 1985; Arrow, 1985) However, the relationship between agency independence and permitting outcomes is complex. Although independence can facilitate faster decision making, it can also lead to regulatory capture, where agencies are influenced by special interest groups. (Hart, 2009) This highlights the importance of balancing agency autonomy with mechanisms to ensure transparency and accountability.

A growing body of research explores the relationship between conservative policies and environmental outcomes, often finding a complex link between expedited permitting processes and detrimental environmental consequences. (Decker, 2003; Mostafavi et al., 2022; Woods, 2021) Studies suggest that conservative governments, often driven by partisan views and a focus sorely on economic growth, may be more likely to prioritize speed over environmental safeguards in permitting decisions (Jessop, 2016; Neumayer, 2017). This can lead to a "race to the bottom" scenario, where states compete to attract investment by offering less stringent environmental regulations (Neumayer, 2017). Furthermore, conservative governments may be more susceptible to lobbying pressure from industries seeking expedited approvals, potentially resulting in regulatory capture and a weakening of environmental protections (Barrett et al., 2006; Gunningham et al., 2004)[1].

3 Institutional Setting

The underpinnings of environment protection in Brazil are constituted by the country's National Environmental Policy (*Política Nacional de Meio Ambiente – PNMA*), created by Federal Law 6938 of 1981, and Title VIII, Chapter VI of the Constitution of 1988. The Constitution has other provisions related to environmental matters, including those dividing responsibility for environmental protection among municipalities, states, and the Union, both on the authority to enact law and rules (the legal, or formal, competence, established at article 24 of the constitution) and to manage personal, budgetary, and other resources (the administrative, or material, competence, established at the article 23).

On the management of the environmental policy, there is a provision in article 23 which determines that the cooperation among the three levels of administration would be detailed in a National Law. This law was enacted only in December 2011, establishing responsibilities for each body, including those relative to environmental permitting process. It defines responsibilities, attributing specific roles and shared responsibilities, establishes forms of coordination, such as intergovernmental agreements, and the sharing of information. It also sets guidelines for joint planning and implementation. Lastly, it establishes the allocation of financial resources and enhances fiscal responsibility. All these provisions have a decisive impact on environmental permitting. In our study, we expect this 2011 legislation piece to have impact on the time for granting environmental permits, as an exogenous shock, which determined our choice of the period for data collection.

The uniqueness of Brazilian permitting process, the ongoing construction of the collaboration among the three government levels, and the somehow vague language of some pieces of legislation leaves room for an endless debate on the discretionary of permitting bodies, the need for social participation and control, and some other formal aspects of the law and regulations. For example, legal scholars in the country are divvy up among those who believe the permitting process follows a shall-issue criteria, those who believe a may-issue standard applies, and those who describe the permitting process as a *sui generis* legal provision.[2]

The permitting process in the country is an instrument for anticipated control of economic activities with the potential for environmental harm and has some unique aspects. Environmental permitting in Brazil encompasses three types of authorizations, a previous permit, a permit for installation of the activity, and a permit for the ongoing operation. Permits refer not only to environmental aspects but also to social and economic impacts for specific groups. In line with the idea of a one-stop permitting process,

[1] This section is still under a detailed review.

[2] In the "shall-issue" model permits are granted automatically if the applicant meets the requirements; in the "may-issue" model the permitting agency has discretion to approve or deny permits based on a broader range of factors; and in the "sui generis" perspective, legal scholars argues that the Brazilian permitting process is unique and cannot be easily categorized as either "shall-issue" or "may-issue."

these permits are meant to enclose all needed preventive measures for environmental and social protection in one single document, renewable from time to time.

The permitting process can demand the production of in-depth studies (Environmental Impact Study), or more cursory and simplified procedures. Regulation enacted by the National Environmental Council (CONAMA) determines which activities would require this higher standard for evidence production on environmental risks and planned mitigation measures. CONAMA Resolution 237 determines, for activities that are regarded as having high impact on environment and, hence, having to produce those studies, to have such obligation made public by announcements in official gazettes with specific language. As we will see in the next sections, this law requirement was important for the localization of high environmental impact projects.

All these variables allow for a variation amongst Brazilian states on local regulations, attributions, and structure of permitting bodies, exposure to different levels of social, economic, and legal constraints and a number of factors. The tests proposed in this article attempt to capture the effects of such diverse scenario in each state on the time to have environmental permits issued.

4 Methods

4.1 The Data

The collection of data for the period would be a difficult task. Most local governments were in the very beginning of the process of migrating information to the Internet, and even at the federal level, information from that time was not easily available until today. Official gazettes still exist just in paper form, or as non-searchable digitized documents, among other limitations.

Transparency was not a strong commitment of local governments. We had the enactment of a law for public access to information (Law 12.527, from November 2011) and the further regulation of the law in a Presidential Decree (7.724, in May 2021), but as far as five years after the passing of the law, its implementation was precarious at best (Michener et al., 2018).

Fortunately, we could profit from a huge effort in data collection for an analysis of the determinants of delay in the permitting process that was carried out in another study (Ribeiro, 2015). Two researchers' teams dealt with two different tasks in data collection, on what they called the 'institutional' and 'quantitative' fronts. The first group looked, state by state and for the federal government, for each piece of local and national legislation regulating permitting processes and the organization of the bodies in charge of such processes. This led to information on the nature of these bodies (if they were part of direct administration or whether they were some sort of indirect administration body such as a foundation or a more autonomous structure), the existence and composition of auxiliary councils, the regulation of permits on high impact projects, and so on. They also examined the structure of these bodies, as specified in local executive decrees and other pieces of information. Finally, they undertook a thoughtful examination of websites, registering each aspect of information and tools available to those looking for a permit granting.

The second front was in charge of mapping all applications for environmental permits in projects with high environmental impact (that means, those that are determined to produce an Environmental Impact Study and/or to release an Environmental Impact Report), state by state and for the federal government for the entire year of 2011, and to gather information on these applications for the following-up period starting with the file of the request up to December 2013. For this task, the research team looked at each website and search engines for official gazettes in each state. When search engines were not available, digital versions of official gazettes were downloaded for each day, both in the initial sampling and the follow-up period, and searched as a PDF document. Still in some cases, where the issues of official gazettes were in the form of non-searchable documents, they were read one by one, with the research team looking for the information of interest.

The result was that for some states we were able to search for information in the entire period in the research design, but in some cases (e.g., those states where official gazettes did not have a website with search engines and whose individual issues were digitized as non-searchable images), we reduced the search for the formation of the sample to just a quarter or, in some few cases, a shorter period. The amount of personnel, time, and financial resources to do otherwise forced researchers to follow these sampling strategies, trying at the same time not to introduce any sort of bias.

It could be that the Brazilian states where data collection has been shown to be harder could have worse conditions to have a streamlined environmental permitting process. To reduce the chance of bias, we had the assistance of local law firms in some of the problematic Brazilian states, so we are still having some observation for those states. We also looked for covariates that could express different social and economic conditions. The details of the data collection process and the description of all covariates are in the Electronic Appendix, but some institutional variables deserve some considerations.

In line with Decker (2003), who proposed that states in the US with greater support for the Republican Party could have a shorter period for the granting of environmental permits, we tried to control for political influence. We collect data on the proportion of votes to the Liberal Party presidential candidate (and winner) in 2018, Jair Messias Bolsonaro. Bolsonaro's presidency has been marked by policies and statements that resonate with conservative and right-wing ideologies, affecting various sectors, including environmental regulation and conservation efforts. We also collected data on the voting for the social democratic runners in 2010 and 2014, respectively, José Serra and Aécio Neves from PSDB political party, and the voting of Marina Silva, a 2014 runner for presidential election with a strong environmental program.

We use a series of indexes as controls, most of them from the Brazilian Statistical Agency (IBGE), described in the Electronic Annex. For corruption, judiciary quality, and environmental results, we employed indicators proposed by other researchers. The state-level corruption index was computed by Boll (2010), using as a departure point the Registry of Irregular Accounts of Public Administrators of the National Auditing Authority (TCU). The state-level indicators for the quality of the courts are those of the National Council of Justice (CNJ), or those developed by Ribeiro (2008). The latter tries to capture how unlikely state courts are to uphold a contract between private parties.

Ex post environmental results were added to the models to control for unobserved characteristics. These variables, showing environmental deterioration after the permitting process, could not explain the time length for the permitting process that occurs before, but they are likely to relate to unobserved characteristics that affect both the duration of the permit process and the future environmental results. Pinto et al. (2016) consider biological, economic, and demographic aspects of environmental degradation in each state and proposes an index trying to capture environmental degradation. A second index for environmental results was produced by Brazilian NGO Map Biomas, who collect denounces of deforestation of six different biomes, namely the Amazon, Caatinga, Cerrado, Mata Atlantica, Pampa and Pantanal.

Besides the description of the data, we provide in the Electronic Appendix the data set, the log files of the estimation both in R and Stata, and the data collection research diary in the form of a detailed data collection report.

4.2 Survival Analysis Models

The pattern of the data to assess the determinants of time duration for obtaining an environmental permit for a large impact project would recommend the use of survival analysis. In addition to the issue of the presence of censorship, which we will address below, the problem of using linear regression with survival analysis applications is that we cannot assume normality. The time distribution for an event tends to be nonsymmetrical and bimodal (Cleves, 2010).

At any time, we have a portion of the sample waiting to be analyzed. How should we deal with these observations? If we arbitrarily establish a study end time, there would be a downward bias for the average permitting process time because of unfinished observations. It also affects the influence of covariates, the economic, social, regulatory, and governance determinants of the time span to obtain a permit. Excluding these unfinished observations would introduce bias and would be a bad strategy. Observations *censored on the right* are those about which we do not have a decision on the granting of the permit in the last analysis period of the study or those that we no longer have information during the analysis period. The excluded observations could be of interest in explaining the inefficiency of the permitting process.

Pushing back the sampling start period still does not solve the problem. We would not have a guarantee that the problematic observations would have been examined. This type of data is called left-censored because we do not observe when the process started. Moreover, as we will see more in the following, the assumption that covariates do not change over time could be violated. We are particularly interested in the period between 2011, when we have new legislation (Complementary Law 140/2011, on the cooperation between the three levels of government, country, state, and city levels) and the time before the collapses of the Mariana and Brumadinho dams.

We follow the literature that deals with the duration of environmental permitting processes and hazard functions (Decker, 2003; Ulibarri, 2018; Ulibarri and Tao, 2019). The set of approaches includes nonparametric, semiparametric, and parametric models. The time to have a permit granted can be estimated non-parametrically from the observed granting time of permit applications, both censored and uncensored. In this model, t_j is the time elapsed since the permit application process started, and $S(t_j)$ is the probability that you will not have a final decision on a permit application at the time t_j. We can calculate $S(t_j)$ from the probability $S(t_{j-1})$ of not having a final decision in period t_{j-1}. We assume that the decision in each period is an independent event, so the probabilities can be multiplied together to give us a cumulative probability of the decision. The probability of not having a final decision about the permit application at the time t_j would be:

$$S\left(t_j\right) = S\left(t_{j-1}\right)\left(1 - \frac{d_j}{n_j}\right) \tag{1}$$

where d_j is the number of permit applications that had a final decision on t_j (granted, denied, or truncated), and n_j is the total number of applications under analysis at time t_j. More generally, the Kaplan-Meier estimate of the survivor function $S\left(t_j\right)$ (the probability that the final decision is longer than t) is given by:

$$\hat{S}\left(t\right) = \prod_{j|t_j \leq t}\left(1 - \frac{d_j}{n_j}\right) \tag{2}$$

where $\prod$ is the product operator. The plot in a graph of the various estimates for each time period looks like a series of declining horizontal steps. This allows us to assess the assumptions on the parameters of the distribution of the hazard, the proportionality of hazard function for various different groups in the population and other relevant parameters.

As noted, our interest goes beyond the estimation of an average hazard ratio. We are interested in estimating the effects of various factors on the time to have a permit application decided, such as the ideological inclination of the party ruling federal and local administrations, the impact of specific regulations and governance arrangements, and so on. The exercise would be to establish which ones influenced expectations about the time to have the environmental permit.

As time to have a decision only takes up on positive values, a normal distribution would not fit well, so OLS regressions are not an appropriate empirical strategy. Compounding the inappropriateness of OLS, we still must consider the right-censored nature of permit application data. As seen, the hazard models accommodate censored data by adjusting the number of cases under analysis in each period. Proportional hazard models, such as the Cox model, associate an estimated baseline hazard with mean-centered explanatory variables and can be estimated as follows:

$$S\left(t_j \left| X_i \right.\right) = S_0\left(t_j\right) e^{\left(X_i - \bar{X}\right)\beta + \varepsilon} \tag{3}$$

Where $S_0\left(t_j\right)$ stands for the baseline hazard or, in our study, the risk that a permit application would be granted after t periods when all covariates are set to zero. X is the matrix of explanatory variables, such as local environmental regulations, composition of the board for environmental permits, and others, β is a vector of parameters to be estimated, and ε is an error term.

It was proposed by (Decker, 2003) that the hazard function for the permitting processes exhibits a positive duration dependence, meaning that "*the longer the permit applications remain outstanding, the greater the probability that the permit will be issued soon*". After visual inspection, the author realizes that the hazard function appears to be monotonically increasing, compatible with a Weibull distribution with positive duration dependence. In this study, we use a hazard function for the Weibull distribution as a robustness check, reported in the electronic appendix.

Finally, since we are looking for different characteristics among Brazilian states (so the covariates are computed at state and federal level), one might wonder if variance is different within each state. We calculated robust clustered error by state (informed in the electronic Appendix), and results do not change significantly.

4.3 The Proportional Hazard Assumption

The proportional hazards assumption, an important basis for Cox models, proposes that the hazard ratios for different groups remain constant over time. This assumption allows the interpretation of the model's coefficients as representing the relative risk of an event occurring between groups. However, this assumption can be violated, leading to biased estimates and potentially misleading conclusions. The Schoenfeld residuals test provides a tool for assessing the validity of the proportional hazards assumption.

The test based on Schoenfeld residuals looks for a linear association between scaled covariate-specific residuals and a smooth function of time (Grambsch and Therneau, 1994; Schoenfeld, 1982; Therneau and Grambsch, 2000). The Schoenfeld residual for the covariate $x_u, u = 1, ..., p$, and for observation j, can be computed as:

$$r_{uj} = x_{uj} - \frac{\sum_{i \in R_j} x_{ui} \exp\left(x_i \hat{\beta}_x\right)}{\sum_{i \in R_j} \exp\left(x_i \hat{\beta}_x\right)} \tag{4}$$

So, the residual is the difference between the covariate value for the failed observation[3] and the average of the covariate values for all permit applications pending approval in time j, weighted according to the estimated relative hazard.

As said, these residuals are regressed against some transformation of the time scale, a procedure to circumvent the effects of outliers. Standard time transformations in statistical packages include natural logarithm time-scaling function, Kaplan-Meier product-limit estimate, rank of analysis time or a monotone transformation. It has been argued that such tests would be sensitive to the presence of outliers and influential observations, or high levels of censoring in the data, in addition to the functional forms of the predictor variables (Park and Hendry, 2015; Xue and Schifano, 2017), strands that we are still pursuing in research.

4.4 Machine Learning Robustness Check

With the increasing popularity and feasibility of adjusting more sophisticated machine learning models, new techniques such as gradient boosting regression trees (GBRT) have been applied to capture complex patterns in survival data (Gerds and Schumacher, 2006; Molnar, 2020). In this robustness analysis, we adjust and evaluate survival models with GBRTs, performing the selection of the best models using cross-validation. The main concepts in this approach are:

- **Decision Trees:** Decision trees are a type of supervised learning algorithm that recursively partitions data into smaller subsets based on the values of predictor

[3]Failed observation, in our case, would be the permit application that, at certain time, is granted and, as a consequence, leave the pool of following up observations.

variables. Each split in the tree represents a decision based on the value of a specific predictor, and the tree grows until it reaches a stopping criterion, such as a minimum number of observations in a terminal node or a maximum depth.

- **Boosting Algorithm:** The boosting algorithm builds upon a sequence of weak learners, typically decision trees. Each tree focuses on minimizing the prediction errors made by the previous trees, leading to a gradual improvement in the model's performance. This iterative process allows for greater accuracy and improved handling of complex relationships in the data.

In a nutshell, GBRT models combine multiple simple decision trees to form a more robust model. It works by successively adjusting new trees to the residuals, iteratively minimizing the loss function. These models also adapt to censored data, functioning as an alternative to traditional models such as the Cox model (Li et al., 2024). The general framework for gradient boosting can be summarized as follows:

1. **Initialization:** An initial model (often a simple model like a constant or the average of the response variable) is constructed.
2. **Iteration:** The boosting algorithm iteratively adds new trees to the model. At each iteration, the model focuses on correcting the prediction errors of the previous trees.
3. **Loss Function:** A loss function is used to measure the model's error. The boosting algorithm aims to minimize the loss function at each iteration. For survival analysis, common loss functions include the Cox proportional hazards loss function, the choice for this article, or the negative log-likelihood function.
4. **Weighted Average:** The final model is a weighted average of all the individual trees, where the weights are determined based on the performance of each tree in minimizing the loss function.

4.4.1 Mathematical Underpinnings

While the complete mathematical formulation of gradient boosting can be quite complex, a simplified representation of the algorithm can be presented. Let:

- y_i represent the observed survival time for observation i.
- x_i be the vector of predictor variables for observation i.
- $f(x_i)$ be the initial model's prediction for observation i.
- L be the loss function.
- $h_m(x_i)$ be the prediction of the m-th decision tree for observation i.
- α_m be the weight assigned to the m-th decision tree.

The gradient boosting algorithm aims to find a set of trees $h_1(x_i), ..., h_M(x_i)$ and weights $\alpha_1, ..., \alpha_M$ that minimize the loss function:

$$\sum_{i=1}^{N} L(y_i, \sum_{m=1}^{M} \alpha_m h_m(x_i)) \tag{5}$$

The algorithm iteratively updates the model by adding new trees, where each tree is trained to minimize the negative gradient of the loss function with respect to the previous model's predictions. This process can be expressed as:

$$h_{M+1}(x_i) = argmin_{h_m} \sum_{i=1}^{N} \nabla L(y_i, \sum_{m=1}^{M} \alpha_m h_m(x_i)) h_m(x_i) \tag{6}$$

The weights, α_m, are updated to minimize the loss function at each iteration. The final model's prediction is then the weighted average of all the individual trees.

4.4.2 Hyperparameter Tuning and Robustness Checks

To fit the models, we use a data split into training sets (80%) and testing sets (20%). Five-fold cross-validation was employed in the training set to test various possible configurations of the hyperparameters. The adjusted hyperparameters include:

(i) the number of predictor variables to be considered at each node, which determines how many variables the model should consider when seeking the best split point at each node of the tree;

(ii) the number of trees in the model, which defines how many decision trees will be built in the boosting model; more trees can improve performance but also increase training time and the risk of overfitting;

(iii) the minimum number of observations in a terminal node, which establishes the minimum number of data that a node must contain to be considered a terminal node; smaller values allow for more complex trees, while larger values result in simpler trees;

(iv) the maximum depth of the trees, which controls the complexity of individual trees in the boosting model, limiting the number of splits that each tree can have.

The hyperparameter tuning was performed through a grid search with Latin hypercube sampling Yang et al. (2020). Grid search systematically tests every combination of hyperparameter values within a defined range. To efficiently explore the hyperparameter space, Latin hypercube sampling is employed. This approach aims at balancing predictive accuracy and generalization capacity (Greenwell et al., 2018). The hyperparameter space can be defined as follows:

Let $\mathcal{X} = \{x_1, x_2, ..., x_p\}$ be the set of hyperparameters, where p is the number of hyperparameters. Each hyperparameter x_i has a range, denoted as $[l_i, u_i]$, where l_i is the lower bound and u_i is the upper bound.

The grid search approach divides each range $[l_i, u_i]$ into k_i equally spaced intervals. The grid search then evaluates all possible combinations of hyperparameter values within these intervals.

Latin hypercube sampling (LHS), on the other hand, divides each range $[l_i, u_i]$ into k_i intervals. It then randomly samples one value from each interval, ensuring that each interval is represented exactly once. This approach provides a more efficient exploration of the hyperparameter space, especially when dealing with a large number of hyperparameters.

4.4.3 Cross-Validation for Robustness

The metric used to select the best models was the survival Brier score, which measures the accuracy of survival predictions at a given time (Gerds and Schumacher, 2006). Cross-validation allows one to evaluate the performance of models on different subsets of data, taking into account censored data. This metric considers the values of the estimated survival function of the model, using a fixed time as a reference to compare survival in censored cases. As a reference in the case of censoring, the overall median of times in the dataset, obtained from a simple Kaplan-Meier equation, was considered.

Cross-validation evaluates the robustness of the model and assesses its performance on unseen data. This method involves dividing the data into multiple subsets (folds), training the model on a portion of the data (the training folds) and evaluating its performance on the remaining folds (the validation folds).

- **K-Fold Cross-Validation:** The most common type of cross-validation, where the data is split into k folds, and the choice for this robustness check. The model is trained on $k-1$ folds and tested on the remaining fold. This process is repeated k times, with each fold serving as the validation set once.
- **Leave-One-Out Cross-Validation (LOOCV):** A special case of k-fold cross-validation where k equals the number of observations. The model is trained on all observations except one, and then tested on the single observation left out. This method is computationally expensive but can be useful for small datasets.

4.4.4 Applications in Environmental Permitting Research

Gradient boosting regression trees can be used for analyzing the duration of environmental permitting processes. This method can capture complex relationships between numerous variables, including those related to:

- **Governance Structures:** The impact of different levels of government involvement in permitting (e.g., federal, state, municipal) and the degree of agency independence.
- **Transparency:** The effects of transparency in the permitting process, including access to information on environmental regulations and impact assessments.
- **Political Influences:** The influence of political affiliations (e.g., conservative vs. progressive parties) and the role of specific political figures.
- **Economic Factors:** The influence of economic variables, such as GDP per capita, unemployment rates, and industry sector.

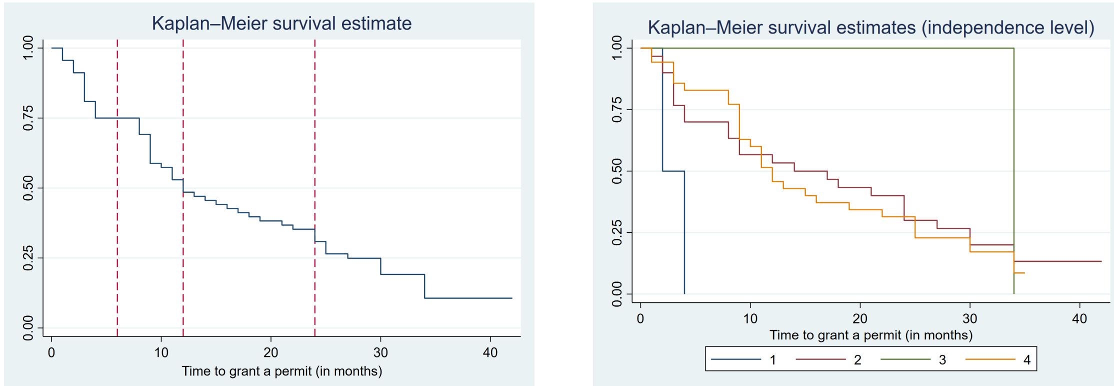

Figure 1: Hazard function for permit requests - for all and by independence levels.

5 Results and Discussion

5.1 Nonparametric Models

Figure 1 shows the survival function for our sample of permit applications for high impact projects. Through the Kaplan-Meier function $\hat{S}(t_j)$ we see the maximum likelihood estimate of the probability after t months that the average application change status from under analysis to approved. Dashed lines show the 6, 12 and 24-month periods.

From data collection, we already observed that a common outcry from the period, which claimed that the environmental permit process was detrimental to economic development, seemed unwarranted, as there was a substantially low number of permit applications for high-impact projects. We observed only 13 requests filed with the national authority, IBAMA, 21 for the Brazilian state with the highest gross domestic product (GDP), São Paulo, and 14 in Rio de Janeiro. At any rate, the number of requests turned out to be low in every Brazilian state where we could look for the entire 2011 period. Rio Grande do Sul had 13 applications, Mato Grosso do Sul 7, Ceará 8, while in Tocantins and Maranhão, despite cheking for applications for the entire 2011 year, we found none. Moreover, from a total of 68 applications, just one was rejected and another was submitted without merit decision. This low number call into question the idea that the environmental permitting process could hinder investments, specially by posing risks and unwarranted delays to large-scale projects.

The Kaplan-Meier plotting also contradicts popular voice. A quarter of the applications were deferred in up to six months from their fillings, and slightly more than half after a year. Almost three quarters had a decision before two years, which seems pretty good since we are talking about projects with high environmental impact. However, there are some applications that exceed 40 months, with no sign of resolution.

When we plot survival function curves separated for independence levels of the permitting organ, we clearly see different standards for each measure. The coding of the variable is intended to capture how independent regulatory and permitting organs are in each Brazilian state and at the national level. We combined three different pieces of information in this indicator, whether the organ is part of direct or indirect administration, whether it has an advisory or executive council and, finally, conditional on having a council, how the chairs are divided amongst members from government

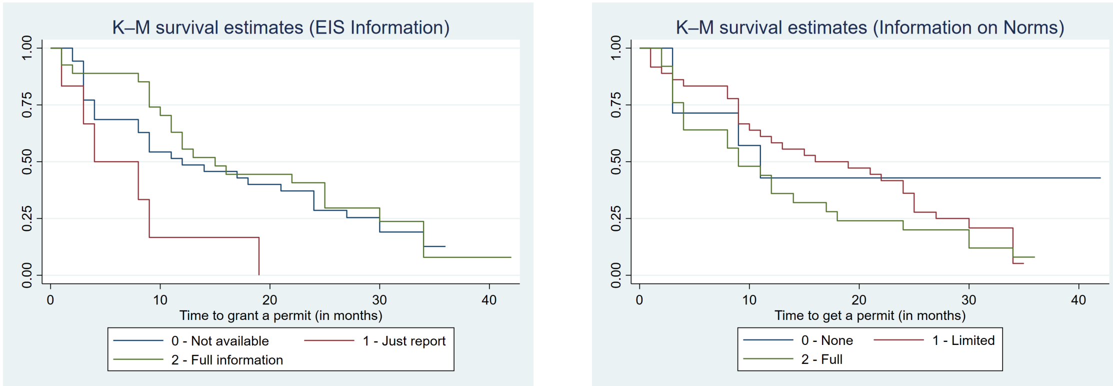

Figure 2: Hazard function for permit requests - for all and by independence levels.

Permitting Agency Structure	**Coding**
Direct administration, without board	0
Direct administration, board with no parity	1
Direct administration, parity board	2
Indirect administration, board with no parity	3
Indirect administration, parity board	4

Table 1: Independence level.

and from society, that is, whether there is parity for the composition of the board or not. The resulting combinations are presented in Table 1, and it is expected that they show how independent the organ is, ranging from 0 (less independent) to 4 (more independent).

There are few observations for levels 1 and 3, and none for level 0, but as for levels 2 (permitting agency as part of direct administration having a board with parity) and 4 (permitting agency as part of indirect administration, parity board), there is a fairly good portion. Panel B in Figure 1 shows the hazard function for these different independence levels, and log rank tests show that the hazard ratios are indeed different between groups (Table 2).

The meaning of the independence variable can be disputed. The measure could assess both how far the permitting body is from the elected officials in a local or national government, or it could show the openness of government to its constituents. In the latter case, the reduction in the time to have a permit granted could arise from a more negotiated relationship, and one might wonder if there is some sort of self-selection.

Another explanation for the effect of this independence measure could be related to some variant of a *grease theory*. By being far from elected officials, more independent permit bodies could be hard to supervise and could engage in bribery. We plotted hazard functions for different levels of state corruption (high and low)[4], and fitted curves seem mostly to overlap, something confirmed in log rank tests.

Visual inspection of panel B also shows that the plotted lines for the independence levels 2 and 4 cross, which could be a violation of the proportional hazard assumption. This crossing of plotted lines for hazard functions occurs also for other variables, such as our indicator of transparency. We tested whether the proportional hazard (PH)

[4]Cutoff on 0.44 for the indicator suggested by Boll (2010).

Independence level	Observed	Expected
1	2	0.37
2	26	27.28
3	1	2.00
4	29	28.35
Total	58	58.00

$$\chi^2\,(3) = 8.59$$

$$\Pr > \chi^2\,(3) = 0.0353$$

Table 2: Log rank test for independence level.

assumption holds, examining the Schoenfeld residuals, and so far we could not find an instance where the PH assumption does not hold[5]

The plot of hazard functions for transparency on the results of environmental impact studies (EIS information) suggests that there would be a positive effect arising from the more easily accessible information. This difference between the transparency levels was confirmed by a log rank test, with the likelihood that the survival curves were different below 5%. We examine again this influence in the Proportional Hazard Cox models, with some suggestive results.

Finally, the communication of information on the websites of local permitting agencies about regulations also seems, according to the KM plot, to have some influence, in this case not supported by the log-rank tests (not always significant).

5.2 Semi-parametric and Parametric Models

Although informative, non-parametric models do not allow for the examination of the influence over hazard ratios coming from specific covariates, especially the ones of continuous nature. We show in Tables 3 and 4 the results from Cox proportional Hazard models[6].

To facilitate the reading of the results, we present the coefficients for each covariate with respective standard errors between parentheses. Some studies report instead the hazard ratios (HR) - as shown in equation (3), the Cox proportional hazard model assumes a multiplicative effect for these covariates. However, the reporting of the coefficients still demands some interpretation effort. A positive coefficient means that the covariate increases risks, which, in turn, reduces the survival time, that is, the time to have a permit granted. In a nutshell, a positive coefficient is good, and a negative coefficient is bad.

[5]We report the statistics for Shoenfeld residuals for each regression using the Cox model in the next section.

[6]As some authors suggest hazard ratios could be modeled as a Weibull distribution, e.g. Decker (2003), we run fully parametric models as a robustness check, informed in the electronic annex. We report in the footnotes when these tests differ from the results from the semi-parametric models.

5.2.1 Governance Structure and Transparency Effects

The level of independence of the local permitting agency seems, in general, to have a positive (time-reducing) effect in most models (Table 3). The effect vanishes a little when we consider political and environmental result covariates (Table 4, except for specification in column 11). As discussed in Section 3, independence is an indicator compounded from three other pieces of information. In some models, we substitute this indicator for a dummy, showing if the permitting local agency is part of the direct or indirect administration. In this latter case, the results in columns 6 and 7 suggest a stronger and positive effect of this variable alone.

A more robust result emerges from the effect of providing information on the rules for the permitting process. This variable takes up integer values between 0 and 2, with zero meaning that there is no information available on the agency website, 1 meaning that there is information on the applicable norms <u>or</u> having an online system to simulate the fit of the project to the various regulatory regimes for the permitting process. Coding 2 means that the agency provides both the information on the norms and the fitting test system. The results show that information has a positive (time-reducing) influence in the more parsimonious models of Table 3 and in the models of Table 4, with political and environmental result variables.

Finally, the publicity given to the studies on environmental impact also seems to have a positive effect, a result that shows when we examine only governance structure and transparency, and that seems to be enhanced when we include political and environmental results covariates.

Table 3: Proportional Hazard Cox Model - Social, Economic and Governance Variables

	(1)	(2)	(3)	(4)	(5)	(6)[a]	(7)[a]
Independence	0.240	0.641**	0.612**	0.116	0.219	1.312*	1.319**
	(0.257)	(0.319)	(0.283)	(0.237)	(0.303)	(0.725)	(0.673)
Information on EIS	-0.109	0.589*	0.570*	-0.074	0.326	0.477	0.470
	(0.233)	(0.321)	(0.301)	(0.242)	(0.293)	(0.370)	(0.334)
Information on Regulation	0.507*	1.285***	1.018**	1.029**	0.724***	1.135***	0.858
	(0.267)	(0.322)	(0.456)	(0.403)	(0.279)	(0.300)	(0.434)
National Jurisdiction		-0.427	-0.575	-0.299	-0.341	-0.484	-0.593
		(0.443)	(0.452)	(0.340)	(0.432)	(0.431)	(0.440)
Urban Population (%)		-0.212***	-0.175***			-0.164***	-0.144**
		(0.052)	(0.067)			(0.056)	(0.070)
GDP per capita		2.766**	3.214**		-1.026	1.476	1.157
		(1.187)	(1.522)		(0.646)	(1.559)	(1.843)
Corruption				-5.929**	1.927		
				(2.580)	(3.554)		
Quality of Courts				-0.048***			
				(0.018)			
Courts' Backlog					-0.061**		
					(0.025)		
Controls	No	No	Yes[b]	Yes[c]	No	No	Yes[b]
Obs/failures	68/58	68/58	68/58	68/58	68/58	68/58	68/58
Schoenfeld[d]	0.74	0.66	0.60	0.45	0.66	0.74	0.59

Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. a - Indirect administration, b - Schooling & IDH, c - GINI, d - Pr $> \chi^2$.

Table 4: Proportional Hazard Cox Model - Political and Environmental Variables

	(8)	(9)	(10)	(11)	(12)	(13)[a]	(14)[a]
Independence	0.445	0.0897	0.476	0.548**	0.409	0.243	0.522
	(0.304)	(0.312)	(0.298)	(0.259)	(0.298)	(0.433)	(0.487)
Information on EIS	0.583**	0.584**	0.628**	0.632**	0.623**	0.513	0.353
	(0.293)	(0.284)	(0.314)	(0.313)	(0.291)	(0.332)	(0.391)
Information on Regulation	1.015***	1.050**	1.061***	0.960**	0.986***	0.743*	1.219***
	(0.364)	(0.451)	(0.339)	(0.464)	(0.353)	(0.444)	(0.306)
National Jurisdiction	-0.528	-0.830*	-0.668	-0.684	-0.689*	-1.804**	-1.435
	(0.398)	(0.459)	(0.442)	(0.440)	(0.407)	(0.897)	(1.115)
Urban Population	-0.202***	-0.136**	-0.216***	-0.234***	-0.219***	-0.167***	-0.252***
	(0.0559)	(0.0636)	(0.0574)	(0.0806)	(0.0522)	(0.0626)	(0.0762)
GDP per capita	1.575	5.539***	3.461***	2.521	2.710**	5.153	7.858
	(1.288)	(1.700)	(1.245)	(1.636)	(1.081)	(5.222)	(5.073)
Conservative	0.0418**	0.0677***			0.0297*	0.0470*	
	(0.0166)	(0.0220)			(0.0166)	(0.0266)	
Degradation Index			0.0247**	0.0258**	0.0162*		0.0138
			(0.0103)	(0.0123)	(0.00966)		(0.0125)
Controls	No	Yes[b]	No	Yes[b]	No	Yes[c]	Yes[c]
Obs/failures	68/58	68/58	68/58	68/58	68/58	60/50	60/50
Schoenfeld[d]	0.30	0.35	0.89	0.32	0.35	0.39	0.55

Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. a - Indirect administration, b - Schooling & IDH, c - IDH, d - Pr $> \chi^2$.

5.2.2 Political and Environmental Results Covariates

(Decker, 2003) finds that the share of votes in the state for a more conservative party (the Republicans) is associated with a reduced length of permitting processes. We computed the share of votes for president of Jair Bolsonaro, the running candidate for Social Liberal Party (PSL), in the first-round of 2018 elections. The results show that this percentage is significantly associated with a shorter time to have a permit granted, a result that stands even when we include covariates for environmental results, perhaps indicating a *grease money* or lobbying effect[7]. This finding suggests that conservative (right-wing) governments may issue shorter environmental permits as part of a broader strategy to facilitate economic growth by reducing regulatory burdens. By streamlining or simplifying the permit process, the government aims to attract more investment in sectors like agribusiness and mining, which are seen as pivotal for the country's economic development but often come with significant environmental impacts.

Curiously, a better indicator of the quality of courts, measuring how pro-business state courts are, also shows the reversion of the results observed in the models of Table 3. Regardless of the local support for the Workers Party, better courts result in reduced time for permitting processes.

In order to reduce problems with no observed characteristics we included the covariates described in Section 3, accounting for environmental results ahead of the time of the granting (or not) of the requested permits. The rationale here is that, although a future result could not influence the permit process that occurred beforehand, both the time for the analysis of applications and the determinants of environmental results could have a common cause.

In our results, bad environmental results are significantly associated with expedite analysis of the environmental permit requests. We could conjecture that there is some lobbying effect – companies with bad projects could exert its economic power to have the permit exam hurried, and the approval of bad projects could result in worse environmental indicators. In this case, although investing companies could foresee a shorter time for the concession of permits, there would be externalities coming from this lobbying activity that would need fix.

5.3 Machine Learning Models

Table 5 presents the results of the fitted models, including the optimal hyperparameters and performance metrics.

[7]The results hold for the share of votes both from Serra and Aécio, showing that even the endorsement to a moderate and non-populist candidate results in shorter permitting processes. In fact, the correlation between 2018 Bolsonaro's votes and the voting of PSDB candidates are highly correlated (respectively, 0.72 and 0.80).

Table 5: Performance of Adjusted Models - Gradient Boosting Regression Trees

	(1)	(2)	(3)	(4)	(5)	(6)[a]
Brier Score	0.255	0.305	0.278	0.277	0.230	0.233
Number of predictor variables considered	12	15	4	15	18	12
Number of trees in the model	55	494	48	96	1	5
Minimum number of observations in a terminal nodel	17	33	13	5	7	10
Maximum depth of the trees	6	10	6	3	4	2

Table 6: Variable Importance - Gradient Boosting Regression Trees Models

	(1)	(2)	(3)	(4)	(5)	(6)[a]	(7)[a]
Independence	0.216	0.138	0.118	0.001	0.000		
Information on EIS	0.734	0.043	0.195	0.015	0.048	0.054	0.044
Information on Regulation	0.631	0.423	0.409	0.124	0.134	0.651	0.486
National Jurisdiction		0.120	0.218	0.498	0.107	0.132	0.264
Urban Population (%)		0.257	0.109			0.700	0.398
GDP per capita		0.061	0.045		0.044	0.229	0.112
Quality of Courts				0.119			
Corruption			0.527	0.431			
Courts' Backlog					0.113	0.026	
Indirect Administration						1.046	0.300
Education Index		0.670					0.730
Human Development Index		0.461					0.550
Controls	No	No	Yes[b]	Yes[c]	No	No	Yes[b]
Obs/failures	68/58	68/58	68/58	68/58	68/58	68/58	68/58

a - Indirect administration, b - Schooling & IDH, c - GINI.

The importance of the variables was evaluated using the FIRM (Feature Importance Ranking Measure) technique (Lundberg and Lee, 2017). Table 6 presents the importance of the variables for each adjusted model.

These results indicate that Information on Regulation is consistently important across all adjusted models, as shown in Table 6. The machine learning technique generated results similar to those found in Table 3, but with different importance of variables in some situations.

For example, the variable **Independence**, representing the level of autonomy and insulation of the local permitting agency, emerged as not so significant in some of the adjusted models, particularly model (1) in Table 6. This finding aligns with previous analyses suggesting that greater agency autonomy can lead to faster and more efficient permitting processes in some circumstances. (Mostafavi et al., 2022; Woods, 2021) It's important to note that while independence can lead to a streamlined process, it can also create opportunities for regulatory capture, where special interests might exert undue influence on the agency (Barrett et al., 2006). Therefore, the importance of balancing agency autonomy with mechanisms to ensure transparency and accountability remains paramount.

Information on EIS and **Information on Regulation**, representing the accessibility of information on environmental impact studies and regulations, also emerged as influential factors across models (particularly models 1 and 5). This aligns with our previous findings demonstrating that greater transparency can lead to shorter permitting times (Mostafavi et al., 2022; Woods, 2021). For instance, model (1) in Table 6 assigns a significant weight to **Information on EIS**, suggesting that easy access to environmental impact studies is a crucial factor in speeding up the approval process. The availability of information reduces information asymmetry, allowing stakeholders to more effectively participate in the decision-making process, potentially leading to more efficient outcomes. (Stiglitz, 1985; Arrow, 1985) This reinforces the need for transparent regulatory processes, where information about the permitting process and the criteria used to make decisions is readily accessible to all stakeholders.

The robust clustered error calculated for each state, taking into account the potential for differing variances across states, further supports the findings and demonstrates the reliability of the results.

While this subsection provides a more detailed discussion of the machine learning models and their results, it's essential to emphasize the importance of interpreting these findings in the broader context of the research. These results, in conjunction with the survival analysis results, provide a richer understanding of the complex factors influencing the duration of environmental permitting processes in Brazil.

In addition to the variables discussed above, our machine learning models also shed light on the influence of other factors on permitting outcomes. For instance, the **Quality of Courts** index emerged as a promising factor, to be further explored in extensions of this research. Our hypothesis is that the perceived quality of the judicial system can play a role in influencing the duration of the permitting process, potentially due to the greater likelihood of legal challenges or the need for more robust legal documentation in states with lower perceived judicial quality.

Finally, the **Corruption** index, representing the level of corruption in the state, emerged as a significant factor in model (3) of Table 6. This aligns with previous research, suggesting that a more corrupt environment can negatively impact environmental policymaking, potentially by increasing the influence of special interest groups and weakening the enforcement of regulations. However, the relationship between corruption and environmental permitting is complex, as highlighted by several studies. Further research is needed to understand the specific mechanisms through which corruption impacts the permitting process.

6 Conclusion

In conclusion, the study explored the complexities and nuances of the expedited environmental permitting processes in Brazil, highlighting the delicate balance between economic development and environmental protection. The analysis of high impact projects seeking environmental permits revealed a relatively low number of applications and an overall efficient process, challenging the conventional wisdom that environmental permits hinder economic growth, at least in the period examined (2011-2014). The study emphasized the significant impact of governance structures and transparency on the timing of permit approvals, with more independent permitting agencies and greater transparency associated with shorter processing times. Moreover, political factors, such as the share of votes for conservative parties, were found to influence the duration of permitting processes, with the worsening of the environmental indexes, underscoring the potential trade-offs between political agendas and environmental protection.

Indeed, the inclusion of covariates related to environmental results revealed a worrying trend in which expedited approval of permits was linked to poor environmental results, suggesting the possibility of lobbying effects from companies seeking faster approvals for projects with potential environmental hazards. This highlights the importance of robust environmental impact assessments and careful consideration of the long-term environmental implications of expedited permitting processes.

In contexts with greater transparency and independence of permitting bodies, expedited processes were found to have positive outcomes. However, in situations where political influences prevail, such as in Brazil under President Jair Bolsonaro, expedited processes may compromise environmental protection efforts. This underscores the importance of carefully evaluating the trade-offs between shorter and longer permitting processes to strike a balance that promotes both economic development and environmental integrity.

The extensive data collection efforts conducted in this study, particularly in mapping the various institutional and regulatory settings for environmental permit bodies across Brazilian states, have provided a comprehensive understanding of the factors that influence the timing of environmental permit approvals. By examining governance structures, transparency levels, and political influences, the research has elucidated the complexities inherent in environmental permitting processes, offering valuable information to shape effective policy decisions in environmental governance.

Ultimately, recent environmental disasters, such as the collapse of the Brumadinho and Mariana dams, serve as reminders of the need for regulatory oversight and environmental impact assessments in the permitting process. These events underscore the need for transparent decision-making mechanisms and robust regulatory frameworks to prevent environmental catastrophes and ensure sustainable development practices in the future.

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