DISTRIBUTING THE NEW GOLD MINE: *INVESTINGATING THE EQUITABLE ALLOCATION OF CALIFORNIA'S GREENHOUSE GAS REDUCTION FUND*

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Abstract

California implemented a CO_2 cap-and-trade system in 2013. SB 535 and AB 1550 require that at least 35% of the revenue earned through the system must be allocated towards projects that benefit "priority populations". However, the competitive nature of the grant systems used to allocate most of the revenue is thought to conflict with this goal. This study used a variety of multivariate regression techniques to investigate if the expressed intentions Sb 535 and AB 1550 of are actually being followed. The results of this study suggest that the funding requirements given by SB 535 and AB 1550 have been successfully implemented, but have not fully rejected the prevailing forces economic and racial privilege has on competitive grant funding allocations. The results of this study also offere important conclusions surrounding the best functional form to use when explaining the allocation of cap-and-trade revenue in California.

KEYWORDS: (Climate Change, Cap-and-Trade, Grant Funding, Race, Class)
JEL CODES: (Q540, K230, I380, H230)

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Introduction

Reducing global CO_2 emissions by almost half in ten years is an urgent need and an ambitious goal. As the latest IPCC report (2018) states, if the world wishes to preserve biological diversity and maintain adequate environments for human life to flourish, global CO_2 emissions must be addressed. "[to have] no or limited overshoot of 1.5°C [of warming], global net anthropogenic CO_2 emissions [must] decline by about 45% from 2010 levels by 2030, reaching net zero around 2050" (IPCC 2018). In 2013 California implemented the world's fourth largest cap-and-trade system in an attempt to accelerate the reduction of CO_2 emissions in the state (*California Cap and Trade,* 2020). The development of this system has made California an international leader in successful climate mitigation strategies. The market-based nature of cap-and-trade systems make them one of the most economically efficient climate mitigation strategy known to date (Truong, 2014). The revenue raised from cap-and-trade systems is also highly valuable public revenue, sometime referred to as a new gold mine (Tokunaga, 2015). However, cap and trade systems are critiqued for their potential to exacerbate environmental and economic inequalities. Under cap-and-trade programs emissions fall overall, however emission may increase in some locations. Further, there is potential that increased energy costs resulting from cap-and-trade systems will be regressive in nature.

Californian academics, community organizers, and the general public anticipated that their cap-and-trade system could potentially widen environmental, health, and economic inequalities (Truong, 2014). They pushed the California state legislator to proactively pass Senate Bill 535 (SB 535): Warming Solutions Act of 2006: Greenhouse Gas Reduction Fund on September 30, 2012. This bill was an unprecedented attempt to address environmental justice concerns related to California's cap-and-trade program (De Leon, 2012). Subsequently, on September 14th, 2016 the California State legislator passed Assembly Bill 1550 (AB 1550) Greenhouse Gases: Investment Plan: Disadvantaged Communities, which has been seen by many stakeholders as an improvement to SB 535. The legislative directive created with SB 535 and then expanded by AB 1550 requires the state of California to ensure at least 35% of the revenue derived from the statewide cap and trade system, also referred to as the Greenhous Gas Reduction Fund (GGRF), is invested in projects that benefit communities comprised of "priority populations" (Gomez, 2016).

California's legislative attempt to directly target a portion of the GGRF to "priority populations" was a hopeful sign for many racially and economically marginalized communities in California (Truong, 2014). However, the competitive grant application process used to distribute almost all of the GGRF raises the concern that SB 535 and AB 1550 are potentially not being implemented effectively. Numerous studies of competitive grant programs have found that communities with more racial and economic privilege tend to receive more funding (Dull & Wernstedt, 2010; Frederickson, 2005). The least privileged "priority populations" in California may not be receiving investments from cap-and-trade revenues at the same rates as more resourced "priority populations", nor at the same rate as all Californian communities more broadly. This study studies this concern by asking, within the context of SB 535 and AB 1550, how does a community's racial composition and economic need impact the allocation of GGRF funding between "priority populations" and between all communities in California?

This study will address this two-part research question by quantitatively testing twelve hypotheses. The hypotheses have been formulated with an understanding of what racial and economic privilege looks like in the context of the United States. Broadly defined, privilege is the unearned benefits people receive from being in the dominant group (Mahalingam & Leu, 2005; Cole, 2009; Sanders & Mahalingam, 2012). In terms of racial identity, people racialized as White have been consistently privileged in the United States (Bonilla-Silva, 2013). To name a few examples, the consistent racial privileging of White people in the US is evident in greater access to housing, education, and employment opportunities when compared to people not racialized as White (Bonilla Silva, 2013). The racial privilege White people inherit within the US has been, and continues to be, institutionalized through a combination of explicitly racialized policies, such as the historic institution of slavery and Jim Crow laws, and less explicitly racialized societal norms, such as residential segregation and racially homogenous job networks (Bonilla Silva, 2013). Although less commonly accepted due to a flawed belief that the US is meritocracy, economic privilege is defined as the unearned benefits derived from being in a social class with greater income levels, access to credit, and economic stability (Sanders & Mahalingam, 2012). Tangible benefits of economic privilege include receiving better healthcare, jobs, government assistance, and education opportunities despite similar service providers (Phillips, 2015).

SB 535 and AB 1550 are attempts to disrupt the prevailing forces of racial and economic privilege. The legislation explicitly direct money towards communities that are not often privileged (Truong, 2014). Holding all else constant, if SB 535 and AB 1550 are being implemented as intended, communities that are less racially (less White) and economically privileged (less wealthy and economically stable) should be receiving more GGRF "priority population" designated funding and, ideally, receiving more GGRF funding generally (de Leon, 2012; Truong, 2014). The first six hypotheses offered below focus on the allocation of GGRF funding reported to be awarded to "priority populations" specifically, and assume that SB 535 and AB 1550 are being implemented as intended. The second six hypotheses stated below focus on the allocation of GGRF funding across all communities in California, and assume the effects SB 535 and AB 1550 being implemented correctly is reflected in the allocation of all GGRF funding.

H1: The proportion of non-Hispanic White people in a "priority population" has a negative association with the allocation of California cap and trade revenue among "priority populations".

H2: The proportion of non-Hispanic Black people in a "priority community" has a positive association with the allocation of California cap and trade revenue among "priority populations".

H3: The proportion of non-Hispanic Asian people in a “priority community” has a positive association with the allocation of California cap and trade revenue among “priority populations”.

H4: The unemployment rate of a “priority community” has a positive association with the allocation of California cap and trade revenue among “priority populations”.

H5: The median household income of a “priority community” has a negative association with the allocation of California cap and trade revenue among “priority populations”.

H6: The proportion of owner-occupied housing units of a “priority community” has a negative association with the allocation of California cap and trade revenue among “priority populations”.

H7: The proportion of non-Hispanic White people in a “priority community” has a negative association with the allocation of California cap and trade revenue among all Californian communities.

H8: The proportion of non-Hispanic Black people in a “priority community” has a positive association with the allocation of California cap and trade revenue among all Californian communities.

H9: The proportion of non-Hispanic Asian people in a “priority community” has a positive association with the allocation of California cap and trade revenue among all Californian communities.

H10: The unemployment rate of a "priority community" has a positive association with the allocation of California cap and trade revenue among all Californian communities.

H11: The median household income of a "priority community" has a negative association with the allocation of California cap and trade revenue among all Californian communities.

H12: The proportion of owner-occupied housing units of a "priority community" has a negative association with the allocation of California cap and trade revenue among all Californian communities.

This study begins with a section that provides the reader with background information on the specifics of how GGRF funding is distributed to "priority populations" under SB 535 and AB 1550. The next section of this study addresses the current scholarly conversation on the Climate Gap, inequities surrounding competitive grant administration, and community characteristics theorized as predictive of competitive grant funding allocation. The following section presents the model, data, and methodology used in this study. Subsequently, results are presented. Implications and final remarks conclude the study.

Policy Background

California's cap-and-trade system is the fourth largest cap-and-trade system in the world behind the systems of China, the European Union, and the Republic of Korea. A cap-and-trade system functions by putting an overall cap, often shrinking over time, on gross GHG emissions within a designated region (Truong, 2014). Emission allowances, equal in total to the overall emission cap, are then created by the governing agency and auctioned or given, depending on the design, to emitters (Stavins, 2008; Truong, 2014). California gives away a select number of allowances to public utility companies under their system and the rest of the allowances sold at auction (Stavins, 2008). Emitters can also trade emission allowances with one another on an emission allowance market. No one emitter is mandated to reduce emissions, but by trading emission allowances, emitters that can reduce emissions for less money than the cost of allowances will do so (Tokunaga, 2015). The money that the state of California earns through the auctioning of emission allowances is deposited into the Greenhouse Gas Reduction Fund (GGRF). During the subsequent year the California state legislator allocates the GGRF to a variety of state agencies through the state budget (*California Climate Investments*, 2020). The state agencies are then in charge of ensuring that the GGRF funding allocations are invested in successful projects throughout the state. As of this year $12 billion has been allocated from the Greenhouse Gas Reduction Fund since its inception (*California Climate Investments*, 2020). While each state agency has latitude in determining how their funds are distributed, the majority of fund administrating agencies rely on a competitive grant application system to determine distribution (Tokunaga, 2015; *California Climate Investments*, 2020).

SB 535 (2012) and then the modifying AB 1550 (2016) were passed by the California State Legislator to ensure that GGRF funding is going to the most at need communities in California. Under SB 535, 25% of the Greenhouse Gas Reduction Funds must benefit “disadvantaged communities”, and at least 10% of the funds must be directly invested within those geographic regions (De Leon, 2012). AB 1550 modified SB 535 to increase the GGRF funding targets for “disadvantaged communities” and included funding targets for low-income communities (Gomez, 2016). California uses the term “priority populations” to simultaneously refer to “disadvantaged communities” and low-income communities (Gomez, 2016). Under AB 1550, 25% of the GGRF must be used for projects directly benefiting “disadvantaged communities”. An additional 5% of GGRF funding must be located in communities benefiting low-income households or low-income communities across the state. Finally, AB 1550 requires an additional 5% of the GGRF funding to be for projects located in and benefiting low-income households or low-income communities that are within half a mile of a “disadvantaged community”. These new funding requirements under AB 1550 mean that an additional 10% of the GGRF benefits “priority populations”. Furthermore, AB 1550 requires 15% more of the Greenhouse Gas Reduction Funds to be used in projects directly located in “disadvantage communities” than SB 535 did. Each state agency administrating GGRF funding is given a target of how much of their funds should go to projects directly located in or a benefiting “priority population” (*California Climate Investments*, 2020). Not all agencies must hit the funding requirements laid out in AB 1550 since AB 1550's requirements only apply to the GGRF as a whole (*California Climate Investments*, 2020).

Before distributing the GGRF in line with the legislative directive given by AB 1550, "priority populations" must be identified. AB 1550 clarified that low-income communities and households were those communities and households, "that are either at or below 80 percent of the statewide median income, or at or below the threshold designated as low-income by the California Department of Housing and Community Development's 2016 State Income Limits" (*California Air Resources Board*, 2018). "Disadvantaged communities" are much harder to define and AB 1550 did not change the designation process dictated by SB 535. As directed by SB 535, the California Environmental Protection Agency (CalEPA) is in charge of identifying what qualifies as a "disadvantaged community" (Truong, 2014). According to Rodriquez (2017) with CalEPA:

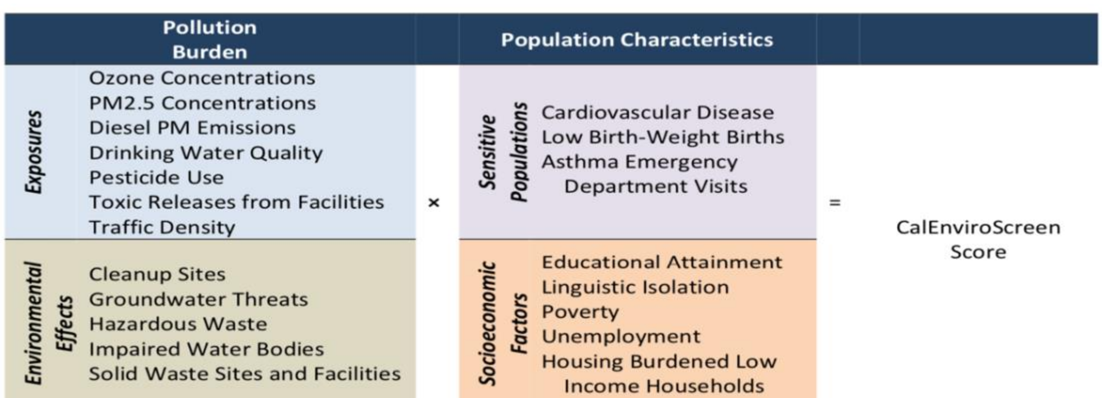
> [I]identifying disadvantaged communities remains a challenging task. In general, the term disadvantaged is commonly associated with economic indicators related to poverty and income. Many of the comments received from our SB 535 workshops and public comment period focus on poverty as being the most important factor in determining whether an area should be considered disadvantaged. At the same time, the term community has numerous definitions ranging from a neighborhood within a city, to a small town or unincorporated area. In some cases, communities have been identified as an entire region. A few

public comments pointed out that the use of census tracts as a proxy for a community might not give an accurate snapshot of an area where people associate with some type of commonality.

CalEPA currently uses the California Communities Environmental Health Screening Tool (CalEnviroscreen) to designate “disadvantage communities. CalEPa’s Office of Environmental Health Hazard Assessment (OEHHA) designed and then released the first version of the CalEnviroscreen in 2012 (Truong, 2014). Subsequently, OEHHA has been modifying the screen and they are currently on version 3.0 (Rodriquez, 2017). The CalEnviroscreen 3.0 identifies communities at a census tract level and utilizes a number of different indicators to identify “disadvantaged communities”. The overarching indicator groups and specific measures can be seen in *Figure 1.*

Figure 1:

CalEnviroscreen 3.0 Indicators



Source: Rodriquez, 2017

A community's CalEnviroscreen score is calculated once measures of the previously mentioned social and environmental indicators are entered into OEHHA's CalEnviroscreen 3.0 algorithm (Rodriquez, 2017). CalEPA decided that census tracts with a CalEnvrioscreen score in the75th percentile and above are classified as "disadvantaged communities" (Rodriquez, 2017). The threshold for what percentile score is needed to qualify as a "disadvantaged community" was controversial to determine during the design process. East Los Angeles communities wanted the threshold to be higher to provide more funds to the very highest scoring communities (Rodriquez, 2017). On the other hand, communities in the Bay Area advocated for a lower threshold to make funding available for a larger collection of the population (Rodriquez, 2014). CalEPA argues that the 75th percentile strikes a balance between these tradeoffs but acknowledges that the threshold can never satisfy all stakeholders (Rodriquez, 2014). Individual census tracts may hover between the status of being a "priority population" and not. If the funding for a project is allocated while the census tract is designated as a "priority population", the funding qualifies as benefiting a "priority population" for the duration of the project regardless of if there are any changes in "priority population" designation (*California Climate Investments*, 2020).

Literature Review

The first section of this literature review consists of a discussion of the *climate gap* in relation to California's GHG cap-and-trade policy. The next section of the literature review examines the scholarly conversation surrounding injustices in competitive grant programs. The literature review concludes with an analysis of previous research done investigating factors that influence the allocation of competitive grant funding.

The *Climate Gap*

Increased natural disasters and shifting precipitation patterns due to human induced climate change will disrupt countless people's lives throughout the world (Stern, 2007; Nordhouse, 2007). However, the impacts of climate change will not be evenly distributed, especially considering which countries are most responsible for causing it. Althor et al. (2016) find that only 16% of countries have an even balance between their carbon emissions and climate vulnerability.

First discussed in the work of Shonkoff (2009), the *climate gap* refers to the disproportionate distribution of climate change impacts that low income and/or People of Color face. While the *climate gap* exists on an international scale, the *climate gap* also exists in the United States and in each individual state. California exemplifies the climate gap. Shonkoff et al. (2011) argue that communities in California marginalized by class and race will experience greater climate change induced health and economic distress than less economically and racially marginalized Californians. Shonkoff et al. (2011) write that when analyzing the presence of a *climate gap*, climate mitigation strategies must also be reviewed for an inequitable distribution of both co-benefits and co-harms.

There is vigorous debate regarding whether California's cap-and-trade program widens the *climate gap*. Six years ago, in opposition to California's cap-and-trade system, scholars and environmental justice activist cited concerns of pollution “hot spots” developing near marginalized communities as a result of the system (Truong, 2014; Tokunaga, 2015). Pollution “hot spots” are defined as localized places where pollution emission levels are either maintained or increased while overall pollution emission levels decrease for the broader area (Truong, 2014). Opponents argued that the development of “hot spots” near communities marginalized by race and class under California’s cap-and-trade system would suggest that the system widens the *climate gap*. While most Californians would benefit both in terms of health and economic stability, certain Californians would not reap the benefits of the cap-and-trade policy.

Truong (2014) argues that California’s cap-and-trade system would create “hot spots” around select communities because polluting companies would increase emissions in the least desirable locations by buying emission allowances to continue emitting. Pollution hot spots were found to have developed around marginalized communities due to a regional NO_x and SO_2 cap and trade system in southern California (Grainger & Ruangmas, 2017). However, in regard to California’s still recently implemented cap-and-trade system, debate exists surrounding the existence of spatially unequal reductions in CO_2 emissions and other co-pollutants. Cushing et al. (2018) find that facilities regulated under California’s cap-and-trade system were disproportionately located in economically and racially marginalized communities, and 52% of these facilities actually increased their emissions since the cap-and-trade program was implemented in 2013. Furthermore, the anticipated reduction in co-pollutants has not been seen under California’s cap-and-trade system due to the limited type of facilities regulated under the system (Anderson et al. 2018). On the other hand, Meng (2019) and Walch (2018) find no evidence that pollution has increased near marginalized communities in California. It is likely that conclusive findings regarding the development or lack therein of pollution hot spots will only come once California's cap-and-trade system has been in place longer.

Despite the ongoing debate regarding the equity of the California cap-and-trade system, the California state legislature has attempted to shrink the potentially widening California *climate gap* through the passage of two key legislative bills: SB 535 in 2012 and then AB 1550 in 2016. As explained in detail in the background section, these bills seek to ensure that a minimum of 35% of revenue derived from the cap-and-trade system goes to projects that directly benefit people and/or communities that are on the wrong side of the *climate gap*. While largely quiet, the scholarly community has been supportive of these bill's ability to meaningfully shrink the *climate gap*. Truong (2014) argues that despite some of its limitations, SB 535 is an example of climate policy that is truly benefiting those most vulnerable to climate change and should be used as an example of how to protect the United States' most climate vulnerable communities on a national level. This opinion is echoed by the research of Tu and Marcantonio (2016). Two years after the enactment of SB 535, Tokunaga (2015) found that one agency administering GGRF funding was doing a very good job ensuring its funds were targeting the *climate gap*. An organization that works on issues central to SB 535's mission, is quoted as saying, "[SB 535] represents an exceptional opportunity for environmental justice issues to be addressed if these monies are invested [to serve] the interests of vulnerable, low-income households" (Russak, 2015). However, not all scholars agree that SB 535 and AB 1550 are being implemented in a way that sufficiently address the *climate gap*. Kingsley (2015) finds that while the bills are good in principle, the state agencies distributing the funding do not make adequate or creative efforts to attract the most vulnerable communities to apply for funding.

While the preliminary findings regarding SB 535 and AB 1550's ability to reduce the *climate gap* are largely hopeful, none of the authors have investigated how successful the funding allocation has been in benefiting those communities most vulnerable to climate change. The author is unaware of any researchers that have done a quantitative assessment of how equitably allocated GGRF funding has been as a result of SB 535 and AB 1550. Theory related to the competitive grant funding systems suggests that SB 535 and AB 1550 may only work in theory but not practice.

Competitive Public Grant Administration

While SB 535 and AB 1550 are attempts to address the inequalities in a cap-and-trade system, competitive grant systems are used by almost all of the state agency's responsible for allocating GRRF funding (Tokunaga, 2015). Collins and Gerber (2008) find that competitive grant programs can often increase inequalities. Social equity is better served when there are other factors taken into consideration when determining the distribution of grants (Collins & Gerber, 2008). Empirical evidence was found in support of this theory when Dull and Wensredt (2010) concluded that the EPA's competitive

Brownfields Award program was not successfully targeting communities affected by environmental inequality despite that being the program's stated goal. The competitive nature of the Brownfield Award program makes it hard for communities with limited resources and the most need to successful apply for grant funding when they were competing against more resource-endowed applicants. (Dull & Wensredt, 2010). There is an inherit tradeoff between performance and equity in competitive grant programs. Applicants that have the capacity to gain the most performance out of grant funding are often those that do not need the grant funding the most (Liang, 2018).

Six broadly defined community characteristics are seen to impact the allocation of competitive grant funding. First, measures of a community's size are seen to be very important factors to control for when explaining competitive grant funding allocations. More funding is generally allocated to projects that will serve more people and/or cover more area (Dull & Wernstedt, 2010; Tokunaga, 2015; Liang, 2018). While the importance of accounting for a community's size is widely recognized within the public administration literature, scholars disagree about how it should be measured. Tokanaga (2015) accounts for a community's size in their study by measuring a community's total population. Liang (2018) also uses total population but includes a measure of population density as well. Measuring population density helps account for differences in funding allocation between more densely populated areas and sparsely populated areas (Hall 2008, Liang 2018). The association between a community's size and allocation of competitive grant funding is usually found to be positive (Hall, 2008; Dull & Wernstedt, 2010; Tokunaga, 2015).

Scholars find that the racial composition of a community has mixed effects on the allocation of competitive grant funding. Dull and Wensredt (2010) find that, on average, higher rates of non-White people in a community are associated with the community receiving less funding from the competitive Brownfield Award program run by the Environmental Protection Agency. In contrast, Collin and Gerber (2008) find that the racial composition of a community is not a significant predictor of Community Development Block grant distributions in four states. On the other hand, in a study looking at one California state agency's specific grant program regulated under SB 535, higher proportions of non-Hispanic Black residents in a community were positively associated with increased grant allocation (Tokunaga, 2015). These last two findings are surprising given the limited participation and decision making historically afforded to less racially privileged communities in public administration processes across the United States (Frederickson, 2008).

While these conflicting findings do not conclusively explain how the racial compositions of a community influences the allocation of competitive grant funding, it is evident that race may play a role in predicting the allocation of funding in some grant programs (Tokunaga, 2015). Furthermore, measures of a community's racial composition are frequently included in studies of competitive grant application funding because many grant programs explicitly attempt to target funds towards less racially privileged communities (Tokunaga, 2015). Race is generally operationalized throughout the literature using the Census Bureau's racial and ethnic classifications (Dull & Wensredt, 2010; Tokunaga, 2015). Tokunaga (2015) and Collins and Gerber (2008) operationalized race by measuring the proportions of non-Hispanic Black people and Hispanic people in each community. Dull and Wensredt (2010), used the proportion of non-White people in a community to operationalize race in their study.

A community's education level is another factor that scholars find influences the allocation of competitive grant funding (Dull & Wensredt, 2010; Tokunaga, 2015). Dull and Wernstedt (2010) argue that when dealing with environmentally focused funding programs, increased education levels may be associated with increased civic engagement which can be associated with increased competitive grant funding allocation. Dull and Wensredt (2010) operationalize education in their study by including a measure of the proportion of people in a census tract that have a bachelor's degree. Slightly differently, Tokunaga (2015) operationalizes education in their study by measuring the proportion of people in a census tract that have a bachelor's degree or higher.

A community's economic need is the fourth characteristic that scholars throughout the public administration literature frequently cite as important when explaining the distribution of competitive grant funding. Studying the impact of a community's economic need is the central focus in multiple studies investigating determinants of competitive grant funding allocation (Tokunaga, 2015; Dull & Wernstedt, 2010; Collins & Gerber, 2008). At the very least, studies investigating the allocation of competitive grant funding control for a community's economic need (Hall, 2008). Across a number of studies, greater economic need is found to be associated with receiving less competitive grant funding (Collins and Gerber, 2008; Hall, 2008; Dull and Wernstedt, 2010). This result is understandable due to the inverse relationship Hall (2008) finds between a community's economic need and their capacity to utilize funding.

Collins and Gerber (2008) operationalize economic need by measuring the unemployment rate. Collins and Gerber (2008) find a community's unemployment rate is statistically significant in their research. Alternative ways of operationalizing economic need include measuring a community's, poverty rates (Tokunaga, 2015), median household income (Tokunaga, 2015), per-capita income (Hall, 2008), or the proportion of owner-occupied housing units (Dull & Wernstedt, 2010; Liang, 2018). The proportion of owner-occupied housing units in a community can be used as a unique measure of economic stability and a community's ability to build wealth (Dull & Wernstedt, 2010; Liang, 2018). Many studies do not rely on just one measure of economic need but instead rely on multiple measures of economic need simultaneously to create a more comprehensive picture of economic need (Dull & Wernstedt, 2010; Tokunaga, 2015).

Scholars have repeatedly found that a community's government capacity is highly predictive of the amount of competitive grant funding the community receives. A community with greater government capacity is thought to be better equipped to put more time and money into writing more competitive grant applications, thereby increasing their funding allocation (Hall, 2008; Dull & Wernstedt, 2010; Collins & Gerber, 2008;

Tokunaga, 2015). A community's government capacity is operationalized in a variety of ways across the literature; Dull and Wernstedt (2010) use property taxes while Collins and Gerber (2008) and Tokunaga (2015) use government workers per 1,000 residents. Researchers often find that government capacity dominates economic need when predicting the allocation of competitive grant allocation (Collins and Gerber, 2008; Tokunaga, 2015).

Finally, the last community characteristic that scholars often determine to be predictive of competitive grant funding allocations is a community's political alignment with those in charge of selecting grant recipients. A variety of scholars have tried to determine the influence voting for or supporting those in charge has on the amount of funding allocated to different communities (Hall, 2008; Dull & Wernstedt, 2010; Tokunaga, 2015). Hall (2008) finds that political alignment, in part, explains the distribution of competitive grant funding for certain competitive grant programs (Hall, 2008). However, Dull and Wernstedt (2010) find mixed results in regard to a community's political alignment influencing the distribution of the EPA's Brownfield Awards. Measures of political alignment are often constructed depending on the relationship between where the grant is being distributed from and who is applying for the grant. Political alignment measures for grant programs that are distributed at the federal level are often operationalized by measuring the community's voter support for the party in control of congress or measures of the community's congressional delegation power (Hall, 2008; Dull & Wernstedt, 2010). Scholars working with competitive grant programs run at the state level use similar measures of political alignment, but translate the measures to state governments (Tokunaga, 2015).

Many of the community characteristic (greater government capacity, lower economic need, and privileged racial identities) associated with greater distributions of competitive grant funding are often not associated with communities that are the least racially and economically privileged. In line with the findings of many scholars, this makes it appear very hard for equity to be pursued under competitive grant systems (Collins & Gerber, 2008; Dull and Wernstedt, 2010). SB 535 and AB 1550 explicitly attempt to allocate money towards less racially and economically privileged communities within the confines of a competitive grant system. The goal of increasing GGRF investments in Californian communities that are less racially and economically privileged is important since California's cap-and-trade system may be widening the state's *climate gap*. Currently, there is very limited comprehensive, quantitative research assessing the implantation of SB 535 and AB 1550. This research seeks to fill this gap in the existing literature by identifying how a community's racial composition and economic need predict a community's allocation of GGRF "priority population" funding, and general GGRF funding.

Methods and Data

The following section begins by providing a conceptual model based off of the literature discussed above. A discussion of the variables used to operationalize the conceptual model follows. The models used in this this study are then specified. Data sources are presented at the end of this section.

Conceptual Model and Variables

The public administration literature suggests successful competitive grant program funding can be explained as a function of a number of community characteristics. These community characteristics can be broadly described as measures of a community's size, racial composition, education, economic need, political alignment, and government capacity (see *Table 1*).

Conceptual Model:

Competitive Grant Funding = Size + Racial Composition + Education + Economic Need + Political Alignment + Government Capacity

Four response variables and thirteen explanatory variables will be used to operationalize the conceptual model presented above. Variable groupings, names, and brief descriptions for each variable are presented in *Table 1.* Based off of the conceptual model, nine different models will be used to test the hypotheses presented in the introduction Model group one consists of Models 2, 3, 4, and 5 and model group two consists of Models 6, 7, 8, and 9. Model 1 is excluded from the model groups because it is a probit model used to conduct a Heckman Correction for the models in Model Group One, as explained more below.

The critical differences between the nine models lie in the response variables. The two model groups use different classifications for which GGRF funding allocations count when measuring the response variables. Within the two model groups, the response variables also differ in order to identify the preferred functional form of the models. The response variables used in two of the models in each model group are log transformed to determine if taking the log of the response variable is the preferred functional form. Furthermore, within the pairs of non-log transformed and log transformed models in each model group, one model is run using a technique to correct for spatial autocorrelation while the other model is not. These systematic variations in the models will offer insights into how consistent the study's results are across different functional forms.

A community in this study is defined as an individual census tract in California. This is a rough proxy for community because many different communities may exist within one census tract or one community may exist across multiple census tracts. However, defining a community by census tract matches the way CalEPA identifyees "priority populations", GGRF funding is allocated, and provides an easy unit of analysis for which to gather community data.

Table 1:

Variable Descriptions

Variable Group	Variable	Variable Name	Description
Response Variables			
Funding Allocation	Total GGRF Funding	*tot_GGRFF*	Total GGRF funding aggregated across years and projects for each census tract
	Total GGRF "Priority Population" Funding	*tot_dis_fu*	Total GGRF "priority population" funding aggregated across years and projects for each census tract
	Log Transformed Total GGRF Funding	*tot_GGRFF_log*	The log transformation of the total GGRF funding aggregated across years and projects for each census tract
	Log Transformed Total GGRF "Priority Population" Funding	*tot_dis_fu_log*	The log transformation of the total GGRFF "priority population" funding aggregated across years and projects for each census tract
Continuous Explanatory Variables			
Size	Total Population (logged)	*tot_pop_log*	Total population by census tract log transformed
	Population Density	*pop_den*	Population density within each census tract
	Census Tract Area	*area*	Census tract area in square miles
Education	Proportion with Bachelors Degree or Higher	*prop_bach*	Total population in a census tract with a bachelors degree or higher divided by the total population of the census tract
Economic Need	Unemployment Rate	*unemploy*	Unemployment rate of the census tract
	Median Household Income (logged)	*med_inco_log*	Log transformed median household income in census tract
	Proportion of Owner Occupied Housing Units	*prop_own*	Proportion of housing units in a census tract that are owner occupied

Government Capacity	Percapita Government Employees	*percap_gov*	Number of people in census tract employed in public administration divided by the total population of the census tract
Race	Proportion White	*prop_white*	Proportion of the census tract that self identifies as non-Hispanic White
	Proportion Black	*prop_black*	Proportion of the census tract that self identifies as non-Hispanic Black
	Proportion Asian	*prop_asian*	Proportion of the census tract that self identifies as non-Hispanic Asian
Categorical Explanatory Variables			
Community Type	Disadvantage Community	*dis_numtim*	Number of times a census tract has been determined to be a disadvantaged community under CalEnvrio Screen 2.0 and 3.0. Levels: 0 = Never classified as a disadvantaged community, 1= has been classifies as a disadvantaged community 1 time. 2 = has been classified as a disadvantage community every time
Political Alignment	Political Alignment	*political*	Number of time a census tract has chosen the winning governor in the last three elections. 0 = zero times out of three, 1 = one or two times out of three, 2 = all three times

The models that make up Model Group One test which community characteristics impact the allocation of GGRF "priority population" funding. The two response variables (*tot_dis_fu, tot_did_fu_log*) used in these four models measure the total amount of GGRF funding distributed to each census tract that can be classified as benefiting "priority populations", as defined first by SB 353 and then by AB 1550. 1,960 census tracts out of the 8,057 census tracts in California have received GGRF funding that is classified as benefiting "priority populations". These 1,960 observations will be the only observations used when estimating the models in Model Group One because these models are only meant to explain the associations between different community characteristics and the allocation of GGRF "priority population" funding across communities that have received at least one dollar of GGRF "priority population" funding. As explained in more detail below, the Heckman correction is used to eliminate the selection bias introduced by only estimating the models in Model Group One based off of communities that have been allocated at least one dollar of GGRF "priority population" funding.

The models that make up Model Group Two investigate which community characteristics affect the allocation of GGRF funding across all communities in California. The two response variables (*tot_GGRFF_fun_*, *tot_GGRFF_fun_log*) used in these four models are measures of the total GGRF funding allocated to all communities in California. As evident in *Table 2,* all census tracts in California have received at least some GGRF funding because the ranges of *tot_GGRFF_fun_* and *tot_GGRFF_fun_log* do not include zero.

As seen in the summary statistics presented in *Table 2,* the unlogged response variables, *tot_dis_fu* and *tot_GGRFF_fun,* are highly skewed to the right with the means being substantially higher than the medians. The observation that drags *tot_GGRFF_fun*'s mean much higher than the median is an observation from a census tract in the city of San Leonardo that includes the Oakland Airport. The census tract is one of the most "disadvantaged communities" in California and is also located near the headquarters of the Greenlining Institute. The Greenlining Institutes was very influential in getting SB 535 and AB 1550 passed and their political power surrounding this legislation may give this census tract more access to GGRF funding (Turong, 2014). The observation that pushes *tot_dis_fu*'s mean higher than the median is an observation from a census tract in Los Angeles. The tract has a very high rate of people living below the poverty line which may have helped them get more funding. The distributions of the response variables are much more normally distributed when a log transformation is applied (*tot_dis_fu_log, tot_GGRFF_fun_log)*.

As previously stated, the explanatory variables used in this study can be broadly categorized as variables that measure a community's size, race, education, economic need, political alignment, and government capacity. Within this study some of these broad variable's groups will be operationalized with just one explanatory variable while others will be operationalized with multiple explanatory variables. Many of the explanatory variables used in this study are endogenous by nature; for example, a community's median household income is a function of numerous factors such as the community's education levels and racial composition. However, for the purpose of this study all explanatory variables are assumed to be exogenous because it is difficult to find census tract specific variables that are truly exogenous.

Measures of a community's size will be operationalized in this study in three ways. The log transformed total population (*Tot_pop_log*) of each census tract will be used to account for the population size of a census tract. *Tot_pop_log* is the only continuous explanatory variable that has observations recorded for all 8,057 census tracts in California. Measuring community size by total population is supported by the work of Hall (2008), Dull and Wernstedt (2010), and Tokunaga (2015). As articulated by Tokanaga (2015) and Ling (2018), the logged form of total population will be used because of the expectation that total population has a diminishing marginal effect on grant funding allocation. The second measure of size that will be used in this study is population density, *Pop_den*. This explanatory variable helps account for differences in funding allocation between densely populated areas and sparsely populated areas (Hall, 2008; Ling, 2018).

The final measure of size that will be used in this model is the area of each census tract in square miles, *Area*. This measure may be important to include because larger census tracts may require more funding in order to implement projects. This measure of size was not found to be important within the literature. However, due to the environmental and land-based nature of many of the projects funded by GGRF funding, a larger community, as measured by its land area, may attract more funding for projects. All three measures of community size are expected to be positively associated with the allocation of both GGRF "priority population" funding, and general GGRF funding.

In this study the racial composition of each census tract will be operationalized by measuring the proportion of non-Hispanic White people (*Prop_white*), non-Hispanic Black People (*Prop_black*), and non-Hispanic Asian People (*Prop_asian*). The proportion of Hispanic people in a census tract has been excluded from this study to due to the potential for multicollinearity when including all categories in an exhaustive and mutually exclusive list of categories. The association between the proportion of Hispanic people in a census tract and the allocation of GGRF funding is assumed to be represented in the intercepts of the models and is therefore the racial reference group for this study. Measuring the racial composition of a census tract by the proportion of select racial and ethnic groups is supported by the research of Tokunaga (2015) and Collins and Gerber (2008). However, using the proportion of Hispanic people in each census tract as the reference group instead of the proportion of non-Hispanic White people makes this study unique. The proportion of Hispanic people in each census tract was chosen because Hispanic identifying people are the largest racial group in California, and it is important to reimagine which racial groups can be the "reference group". According to the US Census Bureau, the term Hispanic refers to an ethnic identifier not a racial identifier, but for the purpose of this study it will be assumed to act much like a racial identifier. Since SB 535 and AB 1550 specifically attempt to make sure GGRF funding is allocated to less privileged groups, the proportion of non-Hispanic White people in a community is expected to be negatively associated with the allocation of both GGRF "priority population" funding, and general GGRF funding. The proportions of non-Hispanic Black people and Asian people are expected to be positively associated with the allocation of both GGRF "priority population" funding, and general GGRF funding.

As done in the work of Dull and Wernstedt (2010) and Liang (2018), a community's education level will be operationalized in this study by measuring the proportion of residents in a census tract that have a bachelor's degree or higher, *Prop_bach*. In this study *Prop_bach* is expected to be negatively associated with the allocation of both GGRF "priority population" funding, and general GGRF funding. This predictions is based on reasoning that SB 535 and AB 1550 try to directly target money towards communities with less racial and economic privilege, and less racial and economic privilege is often linked to depressed education rates (Bonia-Silva, 2013).

Economic need will be operationalized in three ways in this study. First, economic need will be accounted for by the unemployment rate (*Unemploy*) in each census tract. Operationalizing economic need this way to is supported by the work of Collins and Gerber (2008). Another measure of economic need used in this study is median household income (*Med_inco_log*). Using median household income is supported by the work of Tokunaga (2015). Hall (2008) uses per-capita income in their study, but median household income deals with outliers more effectively. In this study the logged transformation of median household income will be used due to the predicted diminishing returns increased median household income will have on grant funding allocation (Tokunaga, 2015). The final way that economic need will be operationalized in this study is by measuring the proportion of owner-occupied housing units in each census tract (*Prop_own*). These three measures of economic need provide a measure of a community's access to job opportunities, income levels, and economic stability. As stated numerous times, SB 535 and AB 1550 require that GGRF funding is allocated to communities that are less racially and economically privileged. Therefore, the association between the unemployment rate and the allocation of both GGRF "priority population" funding, and general GGRF funding is expected to be positive. The explanatory variables that measure a community's median household income logged and the proportion of owner-occupied housing units are expected to be negatively associated with the allocation of both GGRF "priority population" funding, and general GGRF funding.

Using census tracts as this study's unit of analysis makes operationalizing government capacity difficult. Government employees are not employed by census tract and property tax revenue is not calculated by census tracts. In light of this challenge, this study will operationalize government capacity by measuring the number of people living in each census tract that are employed in public administration and divide that number by the total population of the census tract (*Percap_gov*). The government capacity measure used in this study can be described as a community's per-capita government employees. Using a per-capita government employee method to measure government capacity is similar to the work done by Collins and Gerber (2008) and Tokunaga (2015). Using this measure of government capacity assumes that public administrators work close to home, and if they work in government that serve multiple census tract, they advocate for publicly funded projects to be located within their own census tract. It would be very interesting if the implementation of SB 535 and AB 1550 disrupts the commonly found positive association between government capacity and competitive grant funding. In line with the predominate findings throughout the literature, government capacity is expected to be positively associated with the allocation of both GGRF "priority population" funding, and general GGRF funding.

Finally, a community's political alignment will be measured in this model by counting how many times a majority of people in a census tract voted for the winning governor candidate in the last three governors' elections (*Political_*). Measuring political alignment by assessing the voter support in past elections for those in charge of a grant program is supported by the work of Hall (2008) and Dull and Wernstedt (2010). The last three governors' elections were chosen because that represents who has had political power during the creation and execution of California's cap and trade program. Only 886 census tracts in California did not vote for the winning governor's candidate over the last three governors' races. 2,736 census tracts only voted for the winning candidate once or twice out of the three races. A slim majority of the census tracts, 4,435, voted for the winning candidate every time. This is not that surprising since California is a very solidly blue state and in all three governors' races the Democratic candidate won. Although relatively unsettled, based on the literature, the measure of political alignment used in this study is expected to be positively associated with the allocation of both GGRF "priority population" funding, and general GGRF funding.

With the expectation of one explanatory variable, all nine models will use the same twelve explanatory variables. The one exception to this is the categorical variable that measures if a community was designated as "disadvantaged community" under Calenviro screen 2.0 and 3.0. Of all the census tracts in California, 2,317 census tracts have been designated as a "disadvantaged community" under one Calenvrio screen or another. Of those 2,317 census tracts, 1,659 have been designated as a "disadvantaged community" under both. This variable will only be used in the models that make up Model Group Two. The reasons for only including this variable the models that make up Model Group Two are explained in detail further below.

Summary statistics of all the response and explanatory variables used in this study can be seen in *Table 2.* As seen by the values of N in *Table 2,* only *tot_pop_log,* and *political* have observations recorded for all census tracts in California. All but three of the explanatory variables are skewed to the right. None of the variables used in this study include values that are below zero. With the conceptual model operationalized and these summary statistics in mind, the nine different models will be specified in the following section.

Model Specifications

As previously mentioned, Model 1 is a probit model that will only be used to conduct a Heckman correction for the models that make up Model Group One. The response variable used in the probit model is a dichotomies variable that assess if a census tract received any "priority population" funding or not. Predicting whether or not a census tract received any funding is a critical step in eliminating bias that is caused by non-random selection bias that varies systematically across the communities that received no "priority population" funding and those that received even just one dollar. To eliminate this non-random selection bias, an inverse mills ratio will be constructed from the Model 1 and used to conduct a Heckman correction in Models 2, 3, 4, and 5. Tokunaga (2015) and Collins and Gerber (2008) both use a similar probit model to conduct a Heckman correction in their studies of competitive grant funding allocation. The probit model used in this study can be seen below:

Model 1 (probit):

$$Priority\_pop\_funding = Tot\_dis\_fun\_log = \beta 1\ Tot\_pop\_log + \beta 2 Pop\_den + \beta 3 Area + \beta 4 Prop\_white + \beta 5 Prop\_black + \beta 6 Prop\_asian + \beta 7 Prop\_bach + \beta 8 Unemploy + \beta 9 Med\_inco\_log + \beta 10 Prop\_own + \beta 12 Political\_ + \beta 13 Percap\_gov + \beta 14 Inverse + u$$

The models that make up Model Group One will assess which community characteristics explain differences in the amount of GGRF funding only allocated to "priority communities". Model 2 and 4 use a spatially lagged two stage least squares regression technique in an effort to assess how spatial autocorrelation affects the results of the study. This correction can be seen in the modified error terms of the models. This regression technique corrects a model for any bias that exists as a result of the error terms' of the response and explanatory variables being spatially correlated. Spatial autocorrelation between census tracts and the amount of GGRF funding they receive could significantly affect the results of this study. A substantial portion of GGRF funding is supposed to be allocated to projects that are in or benefit priority communities. As

Table 2:

Variable Summary Statistics

Variable Name	N	Mean	SD	Median	Min	Max	Range	Skew	Kurtosis
Response Variables									
tot_GGRFF	7941	186519.23	713506.51	87185.00	4.00	44799158.00	44799154.00	36.51	2019.82
tot_dis_fu	1960	113017.35	242214.64	46525.50	2.00	5100000.00	5099998.00	8.43	120.56
tot_GGRFF_log	7941	11.32	1.20	11.39	2.20	17.62	15.42	-0.27	1.88
tot_dis_fu_log	1960	10.69	4.70	10.75	1.10	15.44	14.35	-0.56	2.36
Continuous Explanatory Variables									
tot_pop_log	8057	8.34	0.81	8.44	0.00	10.57	10.57	-6.80	64.68
pop_den	8036	8691.88	9706.26	6425.97	0.00	151487.00	151487.00	3.68	26.25
area	8036	15.16	78.76	0.73	0.02	829.15	829.13	8.17	73.04
prop_bach	8010	0.32	0.21	0.28	0.00	1.00	1.00	0.59	-0.62
unemploy	7990	0.07	0.04	0.06	0.00	1.00	1.00	2.81	35.40
med_inco_log	7965	11.14	0.48	11.15	7.82	12.43	4.61	-0.13	0.22
prop_own	7984	0.51	0.23	0.52	0.00	1.00	1.00	-0.24	-0.84
percap_gov	8012	0.02	0.02	0.02	0.00	0.16	0.16	2.16	8.86
prop_white	8012	0.39	0.26	0.38	0.00	1.00	1.00	0.17	-1.22
prop_black	8012	0.06	0.09	0.03	0.00	0.84	0.84	3.74	19.68
prop_asian	8012	0.14	0.15	0.08	0.00	0.93	0.93	1.90	3.62
Categorical Explanatory Variables									
			Levels						
		"0"	**"1"**	**"2"**					
dis_numtim	8034	5717	658	1659					
political	8057	886	2736	4435					

discussed in the policy background section, the factors that determine if a census tract is designated as disadvantaged or not are socioeconomic, linguistic, education and pollution characteristics. Many of these factors are likely to be more similar between neighboring census tracts than distant census tracts (Kissling & Carl, 2008). Chun et al. (2012) argue that because the distribution and effects of environmental pollution are not often contained within political boundaries, it is critical to assess and adjust for spatial autocorrelation. Cutter et al. (1996) write that correcting for spatial autocorrelation has often been overlooked in many environmental justice studies. This failure has led to miss specified models that produce inaccurate results (Cutter et al., 1996). Using a spatially lagged two stage least squares regression technique will offer insights into how spatial autocorrelation impacts the results of this study and assist in determining the preferred functional form. All four models in Model Group One include a Heckman correction. The inverse mills ratio (*inverse*) created from the first model is used in these models to perform this correction. The models that make up Model Group One can be seen below:

Model 2: Spatially Lagged Technique Used and Response Variable Log Transformed

$$Tot\_dis\_fun\_log = \beta_1\ Tot\_pop\_log + \beta_2 Pop\_den + \beta_3 Area + \beta_4 Prop\_white + \beta_5 Prop\_black + \beta_6 Prop\_asian + \beta_7 Prop\_bach + \beta_8 Unemploy + \beta_9 Med\_inco\_log + \beta_{10} Prop\_own + \beta_{12} Political\_ + \beta_{13} Percap\_gov + \beta_{14} Inverse + rWu + \varepsilon\ u$$

Model 3: Response Variable Log Transformed

$$Tot\_dis\_fun\_log = \beta_1\ Tot\_pop\_log + \beta_2 Pop\_den + \beta_3 Area + \beta_4 Prop\_white + \beta_5 Prop\_black + \beta_6 Prop\_asian + \beta_7 Prop\_bach + \beta_8 Unemploy + \beta_9 Med\_inco\_log + \beta_{10} Prop\_own + \beta_{12} Political\_ + \beta_{13} Percap\_gov + \beta_{14} Inverse + u$$

Model 4: Spatially Lagged Technique Used

$$Tot\_dis\_fun = \beta_1\ Tot\_pop\_log + \beta_2 Pop\_den + \beta_3 Area + \beta_4 Prop\_white + \beta_5 Prop\_black + \beta_6 Prop\_asian + \beta_7 Prop\_bach + \beta_8 Unemploy + \beta_9 Med\_inco\_log + \beta_{10} Prop\_own + \beta_{12} Political\_ + \beta_{13} Percap\_gov + \beta_{14} Inverse + rWu + \varepsilon\ u$$

Model 5:

$$Tot\_dis\_fun = \beta_1\ Tot\_pop\_log + \beta_2 Pop\_den + \beta_3 Area + \beta_4 Prop\_white + \beta_5 Prop\_black + \beta_6 Prop\_asian + \beta_7 Prop\_bach + \beta_8 Unemploy + \beta_9 Med\_inco\_log + \beta_{10} Prop\_own + \beta_{12} Political\_ + \beta_{13} Percap\_gov + \beta_{14} Inverse + u$$

The models that make up Model Group Two do not need a Heckman correction because they assess which community characteristic explain differences in the total GGRF funding allocation between all communities in California. All census tracts in California have received at least one dollar of GGRF funding over the course of the program's lifetime, so no Heckman correction is needed. For the same reasons presented above, Models 6 and 8 use a spatially lagged two stage least squares regression technique to test how correcting for spatial autocorrelation changes the results of this study. Unlike the models that make up Model Group One, the models in Model Group Two all include an explanatory variable (*dis_numtim*) that measures the number of times a community was designated as a "disadvantaged community". It is important to account for this difference in census tracts because at least 35% of GGRF funding must be designated to projects benefiting these communities under SB 535 and AB 1550. This variable was not included in the models included in model group one because almost all of the observations used to run the models are from communities classified as "disadvantaged communities"

Model 6: Spatially Lagged Technique Used and Response Variable Log Transformed

$$Tot\_GGRFF\_fun\_log = \beta_1\ Tot\_pop\_log + \beta_2 Pop\_den + \beta_3 Area + \beta_4 Prop\_white + \beta_5 Prop\_black + \beta_6 Prop\_asian + \beta_7 Prop\_bach + \beta_8 Unemploy + \beta_9 Med\_inco\_log + \beta_{10} Prop\_own + \beta_{16} Dis\_numtim + \beta_{12} Political\_ + \beta_{13} Percap\_gov + \beta_{14} Inverse + rWu + \varepsilon\ u$$

Model 7: Response Variable Log Transformed

$$Tot\_GGRFF\_fun\_log = \beta_1\ Tot\_pop\_log + \beta_2 Pop\_den + \beta_3 Area + \beta_4 Prop\_white + \beta_5 Prop\_black + \beta_6 Prop\_asian + \beta_7 Prop\_bach + \beta_8 Unemploy + \beta_9 Med\_inco\_log + \beta_{10} Prop\_own + \beta_{16} Dis\_numtim + \beta_{12} Political\_ + \beta_{13} Percap\_gov + \beta_{14} Inverse + u$$

Model 8: Spatially Lagged Technique Used

$$Tot\_GGRFF\_fun = \beta_1\ Tot\_pop\_log + \beta_2 Pop\_den + \beta_3 Area + \beta_4 Prop\_white + \beta_5 Prop\_black + \beta_6 Prop\_asian + \beta_7 Prop\_bach + \beta_8 Unemploy + \beta_9 Med\_inco\_log + \beta_{10} Prop\_own + \beta_{16} Dis\_numtim + \beta_{12} Political\_ + \beta_{13} Percap\_gov + \beta_{14} Inverse + rWu + \varepsilon\ u$$

Model 9:

$$Tot\_GGRFF\_fun = \beta_1\ Tot\_pop\_log + \beta_2 Pop\_den + \beta_3 Area + \beta_4 Prop\_white +$$

$$\beta_5 Prop\_black + \beta_6 Prop\_asian + \beta_7 Prop\_bach + \beta_8 Unemploy +$$
$$\beta_9 Med\_inco\_log + \beta_{10} Prop\_own + \beta_{16} Dis\_numtim +$$
$$\beta_{12} Political\_ + \beta_{13} Percap\_gov + \beta_{14} Inverse + u$$

Data Sources

The data used in this research has been collected from four primary sources and merged using GEOFIPS identifiers. The record of GGRFF funding and "priority population" specific GGRFF funding allocations by census tract was gathered from the historical GGRFF projects dataset made publicly available by California's Climate Investments Office (California Climate Investments, 2020). GGRFF funding allocations that are not identified by census tract have been excluded from this study. These excluded GGRFF funding allocations consist predominately of large transportation projects that span numerous census tract and wildfire prevention projects that are identified by longitude and latitude coordinates instead of census tracts. GGRFF funding allocations are identified by project and year in the rat dataset. In line with the work of Collins and Gerber (2008) and Bickers and Stein (2004), GGRF funding allocations across years and projects has been aggregated to identify total GGRF funding received by each census tract since the inception of the funding program. A project is usually given a small amount of funding initially for planning and then larger amounts of funding for implementation (Collins & Gerber, 2008). Aggregating funding eliminates the noise that would be introduced into the models due to these short-term fluctuations in funding. Eliminating this noise is important when working with demographic explanatory variables that do not differ dramatically over such a short time period (Collins & Gerber, 2008).

The political alignment variable used in this study was constructed from statewide assembly district voting records over the past three California governors' elections (2010, 2014, 2018) publicly available through California's Secretary of State's Election Division (*Statewide Election Results*, n.d.). All census tracts within an assembly district were assumed to have voted the same way since the researcher could not find a smaller geographic entity that was identifiable across the state with state level voting data. Census tracts were either given a one or a zero depending on if the majority of the tract had voted for or against the winning candidate. The ones and zeros were summed for each census tract across all three elections to produce a categorical political align variable for each census tract that represents how many times the census tract's voting records aligns with those in power.

Besides the measures of total GGRFF funding, total "priority population" funding, and political alignment, the variables used in this study have been gathered from the five year (2015-2019) American Community Survey estimates accessed through the dataset builder, Social Explorer. Five-year estimates were chosen for this project because they provide detailed and accurate census tract level demographic, occupation, and socioeconomic data that were collected over the duration of the GGRFF funding program. Geometric data used to correct for spatial autocorrelation was gathered from the US Census Bureau.

Results

This section will briefly mention the results of Model 1. Then the results of the models that make up Model Group One and Two will be discussed in detail.

Model 1 Results

The probit model, Model 1, was run in an effort to create and Inverse Mills Ratio. The coefficient signs and significances for most of the variables were in line with most of the theoretical expectations articulated when operationalizing each explanatory variable. As expected, *tot_pop_log, prop_asian, dis_numtim* above zero*, political* above zero, and *percap_gov* are all positively associated with the probability a census tract receives at least one dollar of GGRF "priority population" funding. Also as expected, *prop_bach, med_inco_log* were negatively associated on average with the probability a census tract receives at least one dollar of GGRF "priority populations" funding. It was surprising to see that the results of Model 1 indicated that, *pop_den, area, prop_black,* and *unemploy* were negatively associated with the probability that a census tract receives GGRFF funding as a "priority population" while *prop_white and prop_own* are positively associated on average with the probability that a census tract receives GGRF "priority populations" funding. These surprising results go against the expressed goals of SB 535 and AB 155, but do affirm common findings throughout the public administration literature. The probit model is only used in this study to create an Inverse Mills Ratio for the full models that make up Model Group One. Marginal effects from Model 1 generally align as expected. However, they are not displayed in this paper because the results of the Model 1 do not inform the conclusions drawn from this study.

Model Group One Results

T*able 3* provides a summary of the results from the models that make up Model Group One. While *Table 3* presents each explanatory variable's coefficient sign, magnitude, and significance, sign and significance are what matters when testing the hypotheses of this study. The explanatory variables' coefficient magnitudes while interesting and worth further investigation, are beyond the scope of this presentation of the study's results.

The results from the models that make up Model Group One offer important insights into the preferred function form. A model's f-statistic assesses the explanatory variables' ability to explain the response variable in a model. Holding the degrees of freedom constant, the higher the f-statistic, the better job the model does at explaining variations in the response variable. While all the models' f-statistics were statistically significant at a significance level of 0.01, Models 2 and 3 have f-statistic that are 43.5 and 51.5 points higher than the f-statistics from models 4 and 5 respectively. The models where total GGRF "priority population" funding is logged, Models 2 and 3, have a much better fit than the models that do not use a log transformed response variable. Interestingly, in Model 2 the *Rho* variable is not statistically significant above a significance level of 0.05, but *Rho* is statistically significant above a significance level of 0.01 in Model 4. However, there is very limited differences in the sign, significance, and magnitude of the variable coefficients when comparing Model 2 to Model 3. This further demonstrates the insignificance of correcting for spatial correlation when the response variable is logged.

The Heckman correction that was done to all models in Model Group One was an important step. The inverse mill ratio variable, *invers*, is statistically significant above a significance level of 0.01 in all four of the total GGRF "priority population" funding models. The higher f-statistics produced by Model 2 and 3, significance of the *inverse* variable across all four models, and the *Rho* variable not being statistically significant in Model 2 tentatively suggests that the preferred functional form when studying factors that influence the allocation of total GGRF "priority population" is a Heckman corrected model that uses a log transformed response variable but does not necessarily account for spatial autocorrelation. Model 2 and 3 both fit this preliminary description of preferred functional form.

Table 3:

Model Group One Results

Variable	Model 2		Model 3		Model 4		Model 5	
Rho	-0.009		-		0.29	***	-	
(Intercept)	10.171	***	10.000	***	301490		578300	*
tot_pop_log	1.159	***	1.156	***	108020	***	116600	***
pop_den	0.000	***	0.000	***	-3.92	***	-4.89	***
area	-0.001	**	-0.001	**	-23.73		-50.09	
prop_white	-0.340		-0.336		-13645		16470	
prop_black	0.900	***	0.900	***	28438		29470	
prop_asian	1.056	***	1.045	***	124540	**	161800	***
prop_bach	1.320	***	1.331	***	157040	*	121400	
unemploy	1.805	**	1.792	**	242150	*	314200	**
med_inco_log	-0.887	***	-0.877	***	-115240	***	-146900	***
prop_own	1.356	***	1.346	***	125540	***	150300	***
political_1	-0.228	*	-0.228	*	23238		29510	
political_2	-0.005		-0.005		29958		39490	*
percap_gov	9.970	***	9.841	***	1132600	**	1655000	***
invers_final	-0.429	***	-0.424	***	4641.80		4102.00	
f-statistic	64.8 on 15 and 1994 df	***	70.2 on 14 and 1945 df	***	21.3 on 15 and 1994	***	18.7 on 14 and 1945 df	***

(*=10% significance level, **=5% significance level, ***=1% significance level)

Note: The coefficients from Models 2 and 3 must be interpreted differently than the coefficients from Model 4 and 5 due to their respective differences in the form of the response variables used.

Model diagnostics were used to ensure that the four conditions required to use a multivariate least squares linear regression technique were met before continuing to interpret the results from Model Group One. Model diagnostics were only run on Model 3 since it is more efficient to run model diagnostics on a model that does not correct for spatial autocorrelation, and the results of Model 2 and 3, the preferred functional form models, are essentially the same. If the model diagnostics had raised concerns about using Model 3, then model diagnostics would have been run on Model 2. However, since the results were very similar, as described next, the model diagnostics did not raise concerns about using Model 3. The first condition that must be met in order to use a multivariate least squares linear regression technique is that a linear enough relationship between the explanatory variables and the response variable must exists. A residual verse fitted plot was used to check this condition. The residuals of Model 3 were evenly dispersed across the fitted values around zero with no obvious patterns. Therefore, there appears to be a straight enough relationship between the explanatory variables and the response variable.

Independence of the residuals is the second condition that must met in order to use a multivariate least squares linear regression technique. By comparing Models 2 and 3, and finding no substantial differences in the sign, magnitude and significance, there was not obvious signs of spatial autocorrelation, so the residuals are assumed to be spatially independent. The residuals were also checked for lagged correlations using the Pearson correlation technique. No substantial evidence of lagged autocorrelation was detected among the residuals. The third condition that must be met when making inferences with multivariate least squares linear regressions is that there must be constant variance of the residuals across the range of the predictor. A spread-location plot was created to test Model 3 for this condition. The residuals appeared to be spread fairly evenly across the range of predictors with a few exceptions. No alarming patterns were detected meaning that condition three is met. The final condition is that the residuals must be normally distributed. A normal Q-Q plot was created to check if the residuals are normally distributed. Based on the plot, the residuals appeared to be normally distributed. All four conditions for using a multivariate least squares linear regression technique were met for Model 3.

The results of the models that make up Model Group One provide interesting results related to hypotheses 1 through 6. Although found to have a negative sign in 3 of the 4 models, the coefficient for *prop_white* was not found to be statistically significant in any of the four models even at a significance level of 0.1. Therefore, hypothesis 1 is not accepted. It is unclear exactly why *prop_white* is not statistically significant. It may be because the communities that qualify for GGRF "priority population" funding may not have enough non-Hispanic White people to make *prop_white*'s coefficient significant. More research is needed to investigate this result. *Prop_black* and *prop_asian* are found to be statistically significant at a significance level of 0.01 and positively associated on average with the total allocation of GGRF "priority population" funding in Model 2 and 3. *Prop_asian*'s positive association and statistical significance above a 0.05

significance level is confirmed in the results of Model 4 and 5. *Prop_black's* positive association is only confirmed by Model 4, but not found to be statistically significant at a 0.1 significance level in either Model 4 or 5. Given the decisive results from Model 2 and 3, the preferred functional form models, hypothesis 2 and 3 is accepted, but this acceptance should be understood within the mixed results from Model 4 and 5. While hypothesis 1 could not be accepted due to a lack of statistical significance, accepting hypothesis 2 and 3 based on the results of Model 2 and 3 tentatively suggests that the allocation of GGRF "priority population" funding is being successfully targeted towards communities that are less racial privileged as directed by SB 535 and AB 1550.

Compared to the results related to hypothesis 1, 2, and 3, the results related to hypothesis 4, 5 and 6 are clearer across all four models that make up Model Group 1. In Model 2, 3, and 5 *Unemploy* is statistically significant at a significance level of 0.05 and positively associated on average with allocations of GGRF "priority population" funding. While *Unemploy* is positively associated with allocations of GGRF "priority population" funding in Model 4, it is only statistically significant at a significance level of 0.1. The significance and positive association consistently found for *Unemploy* across three of the four models that make up Model Group One means that hypothesis 4 is accepted. As seen in table 2, *med_inco_log,* and *prop_own* are statistically significant above a 0.05 significance level across Models 2, 3, 4, and 5. Across all models in Model Group One, *med_inco_log* is found to have a negative association with allocations of GGRF "priority population" funding. These noteworthy and consistent results related to the coefficient of *med_inco_log* means that hypothesis 5 is accepted. *Prop_own* is found to have a positive association, on average, with allocations of GGRF "priority population" funding across all models in Model Group One. Therefore, hypothesis 6 is not accepted. Accepting hypothesis 4 and 5 but rejecting hypothesis 6, suggests the allocations of GGRF "priority population" funding are successfully being targeted towards communities that are less economically privileged in terms of job opportunities and income levels, but not economic stability and wealth creation. Even among communities receiving GGRF "priority population" funding, increased levels of economic stability and ability to create wealth, as measured by *prop_own,* are associated with increased levels of GGRF funding. Therefore, it is hard to say that SB 535 and AB 1550's expressed goal to effectively allocate GGRF funding towards less economically privileged communities is being fully implemented correctly.

While not presented exhaustively, the results surrounding the variables that measure other community characteristics in addition to racial composition and economic need generally align with the results found throughout the public administration literature. Measures of community size (*tot_pop_log),* education level (*prop_bach)* and government capacity (*percap_gov*) were found to be statistically significant at a significance level of at least 0.1 and positively associated on average with the allocation of GGRF "priority population" funding across all but the final model in Model Group One. The other two measures of a community's size, *pop_den* and *area,* were less significant across all four models that make up Model Group One and have very little economic significance. Across all the models in Model Group One, the very small magnitudes of the *pop_den* and *area* coefficients imply that very little of a community's allocation of GGRF "priority population" funding is explained by the community's *pop_den* and *area.* Finally, contrary to the predominate theories in the public administration literature, the categorical measure of political alignment was not statically significant for either level (*political_1* and *policital_2*) of political alignment used in this study. This may be the result of the very rough way a community's political alignment is measured in this study.

Model Group Two Results

The results from the models that make up Model Group Two can be seen in *Table 4.* In the same vein as the results derived from Model Group One, the results found across the models in Model Group Two offer insight into which functional form is best when studying the factors that explain the allocation of GGRF funding across all communities in California. Across all Model Group Two models the f-statistics were statistically significant at a significance level of 0.01. However, Models 6 and 7 have f-statistic that are 476.2 and and 450.16 points higher than the f-statistics calculated for models 8 and 9 respectively. Similar to, but at a greater extent than Model Group One, the models where total GGRF funding is logged, Models 6 and 7, have a much better fit than the models that do not use a log transformed response variable. In Model 6 and 8, the spatially adjusted models in Model Group Two, the *Rho* variable is statistically significant above a significance level of at least 0.1. This indicates that controlling for spatial correlation is important when explaining the allocation of total GGRF funding. However, there are very few differences in the sign, significance, and magnitude of the variable coefficients between the spatially adjusted and non-spatially adjusted models within each model paired by response variable form. This demonstrates the limited effect correcting for spatial correlation has on the results of this study. The higher f-statistics produced by Model 6 and 7, and the *Rho* variable not substantially impacting the primary results of the models, suggests that the preferred functional form for this part of the study is a model that uses a log transformed response variable but does not necessarily account for spatial autocorrelation. Model 6 and 7 both fit this preliminary description of preferred functional form. This description of preferred functional form is very similar to the preferred functional form found from the results of the models that make up Model Group One.

Table 4:

Results from Model 6, 7, 8, and 9

Variable	Model 6		Model 7		Model 8		Model 9	
Rho	0.224	***	-		0.14	*	-	
(Intercept)	-1.332	**	0.017		-1271700	***	-1353000	***
tot_pop_log	0.933	***	0.977	***	135410	***	139500	***
pop_den	0.000	***	0.000	***	-10.28	***	-11.06	***
area	0.000		0.000		157.22		163.80	
prop_white	0.154		0.110		-14089		-18620	
prop_black	-0.024		-0.128		205990	**	234500	**
prop_asian	1.241	***	1.523	***	297820	***	345500	***
prop_bach	2.392	***	2.798	***	292750	***	306400	***
unemploy	-0.898	***	-0.922	***	-227750		-243000	
med_inco_log	0.104	**	0.168	***	21960		28630	
prop_own	0.207	***	0.199	***	-96207	*	-103600	*
dis_numtim1	0.608	***	0.688	***	113560	***	119000	***
dis_numtim2	1.043	***	1.165	***	186870	***	201100	***
political_1	0.037		0.029		2848.10		3214	
political_2	0.104	***	0.104	***	21992		25000	
percap_gov	-1.725	***	-2.772	***	-818370	*	-995700	**
f-statistic	496.3 on 16 and 7756 df	***	473.3 on 15 and 7757 df	***	20.1 on 16 and 7756 df	***	23.14 on 15 and 7756 df	***

(*=10% significance level, **=5% significance level, ***=1% significance level)

Note: The coefficients from Models 6 and 7 must be interpreted differently than the coefficients from Model 8 and 9 due to their respective differences in the form of the response variables used.

As in Model Group One, model diagnostics were tested to make sure that the four conditions to use a multivariate least squares linear regression technique were met before further interpreting model results from Model Group Two. Once again, model diagnostics were only run-on Model 7 since it is more efficient to run model diagnostics on a model that does not correct for spatial autocorrelation, and the results of Model 6 and 7, the preferred functional form models, are essentially the same. If the model diagnostics had raised concerns about using Model 7, then model diagnostics would have been run on Model 6. A fitted verse residuals plot showed that there appears to be a linear enough relationship between the explanatory variables and the response variable in Model 7. Finding no substantial differences in the sign, magnitude and significance of the coefficients in of Model 6 and 7 and Models 8 and 9 implies that any spatial autocorrelation that may exist in the residuals creates no obvious and substantial impacts on the models. The residuals of Model 7 were also checked for lagged correlations using the Pearson correlation technique. No substantial evidence of lagged autocorrelation was detected among the residuals thereby confirming that the residuals are independent of each other. A spread-location plot of Model 7 showed the residuals to be spread fairly evenly across the range of predictors with a few exceptions. No alarming patterns were detected in Model 7 meaning that there appears to be constant variance of the residuals across the range of the predicted values. In an effort to check if the residuals of Model 7 are normally distributed, a normal Q-Q plot was created to. Based on the plot the residuals of Model 7 appear to be normally distributed. After two standard deviations they trend away from the line measuring normality. However, this trend is not large enough to indicate that a multivariate least squares linear regression technique, like Model 7, cannot be used.

Interesting results related to hypotheses 7 through 12 are found from the results of the models that make up Model Group Two. Although the sign flips between the models that have a log transformed response variables (Models 6 and 7) and those that do not (Models 8 and 9), the coefficient for *prop_white* was not found to be statistically significant in any of the four models even at a significance level of 0.1. Therefore, hypothesis 7 is not accepted, just like hypothesis 1. While Models 6 and 7 find *Prop_black* to have a negative association on average with the allocation of GGRF funding, *Prop_black* is only found to be statistically significant in the models that do not have the preferred function form and substantially worse fit (Models 8 and 9). Therefore, hypothesis 8 is not accepted. Across all models that make up Model Group Two, *prop_asian* is found to be statistically significant at a significance level of 0.01 and positively associated on average with the total allocation of GGRF funding. Given the consistent results from Models 6, 7, 8, and 9, hypothesis 9 is accepted. Accepting hypothesis 9 based on the decisive results across all four models that make up Model Group Two suggests that allocations of GGRF funding are being successfully targeted towards communities with higher concentrations of people racialized as non-Hispanic Asian and thereby less racially privileged communities. Not being able to accept hypothesis 7 and 8 due to a lack of statistical significance, points to the need for continued research on the association between a community's racial composition and allocation of GGRF funding.

Accepting or rejecting hypothesis 10, 11 and 12 depends on the results from the variables that measure economic need. Each of the three variables that measure economic need (*unemploy*, *med_inco_log*, and *prop_own*) in the models that make up Model Group Two are only statistically significant at a significance level of 0.05 or below in the preferred functional form models, Models 6 and 7. Across all models in Model Group Two, u*nemploy*, *is* shown to be negatively associated on average with allocations of GGRF funding. The consistent negative association with the respective response variables found for *unemploy* across Model Group Two, means that hypothesis 10 is not accepted. Contrastingly, across all models in Model Group Two, *med_inco_log*, and *prop_own*, are found to be positively associated on average with allocations of GGRF funding. The exclusively positive association with the respective response variables found for *med_inco_log*, and *prop_own* across Model Group Two, means that hypothesis 11 and 12 are not accepted. Not being able to accept any of the hypotheses related to the association a community's economic need has on its allocation of GGRF funding raises serious concerns regarding the allocation of GGRF funding. These results suggest that, holding all else equal, smaller amounts of GGRF funding have gone to less economically privileged communities in California.

The results from Model Group Two related to the variables that measure other community characteristics besides racial composition and economic status, compare with the results found throughout the public administration slightly differently than the results found in Model Group One. As found in the literature and in the results of the models that make up Model Group Two, a community's size, as measured by total population (*tot_pop_log),* is positively associated with the allocation of GGRF funding and statistically significant at a significance level of 0.01 across all models in Model Group Two. Compared to the results of the models that make up Model Group One, the other two measures of a community's size, *pop_den* and *area*, were slightly more significant across all four models but continued to have very little economic significance. Measures of a community's education levels (*prop_bach)* and political alignment (*political_2*) were found to be statistically significant at a significance level of at least 0.01 and positively associated on average with the allocation of GGRF "priority population" funding across at least Models 6 and 7. These results are in line with findings in the literature and the results of the models in Model Group One.

A very surprising results was that *percap_gov* was statistically significant at a significance level of at least 0.1 or below, and negatively associated, on average, with the allocation of GGRF funding. This result contrasts with the vast majority of the public administration literature and the results of the all the models that make up Model Group One. This surprising result may be a result of the crude way *percap_gov* is measured in this study. Both included levels (*dis_numtim1* and *dis_numtim2)* of the categorical variable measuring the total number of times a community was designated as a "disadvantaged community" are positively associated the allocation of GGRF funding and statistically significant at a significance level of 0.01 across Models 6, 7, 8, and 9. While it appears that this variable was an important measure to include in these models, the endogenous nature of the variable may distort the results of the models that make up Model Group Two.

Implications

The results of this study lead to three overarching implications. First, this study has implications for scholars seeking to identify the most appropriate functional form to use when explaining the allocation of GGRF funding across California. In both Model Group One and Model Group Two, the models in which the measures of GGRF funding allocations went through a log transformation had a much better fit than the models that did not undergo this transformation. The improved fit caused by applying a log transformation to the respective response variable signals that the explanatory variables used in this study have an exponential relationship with the response variables used in this study. Although unclear from the literature, this exponential relationship may exist for other competitive grant programs.

Scholars may be interested to note that applying the log transformation to the response variables had a much bigger impact on the results of this study than accounting for the spatial autocorrelation. Within both model groups, the results of the study varied very little between the models were identical in terms of response variable but differentiated in terms of adjusting for spatial autocorrelation. Overall, these results suggest that when explaining the distribution of specifically GGRF "priority population" funding and general GGRF funding, the preferred functional form uses a response variables that is log transformed but the model does not necessarily correct for spatial autocorrelation. Additional research should be done to further investigate if this proposed functional form continues to hold true as additional GGRF funding is allocated, and if the preferred functional form proposed in this study successfully explains the allocation of funding in other competitive grant systems, especially when different explanatory variables are used.

The second overarching implication from this study is that SB 535 and AB 1550 are, for the most part, being implemented in the way they were intended to be. Holding all else constant, by all but one measure (the proportion of owner-occupied housing in a community), on average communities less racially and economically privileged are being allocated more GGRF "priority population" funding. Scholars should investigate whether this result continues or whether the allocations improve as additional GGRF funding is distributed. Based on the results of this study, the policy makers and community organizers that pushed for the passage for SB 535 and AB 1550 can be assured that these policies are mostly being implemented as intended. However, policy makers and community organizers may want to develop potential amendments to the legislation that directs more GGRF funding into communities that are less economically stable and lack an ability to build wealth, as measured by the proportion of the housing units in a community that are owner occupied.

The success of SB 535 and AB 1550 described above also implies that with the right program design, competitive grant systems can successfully allocate funding in a way that disrupts the prevailing effects of racial and economic privilege. Scholars, policy makers and community organizers may want to push for similar funding allocation requirements in other competitive grant programs.

The final overarching implication that may be drawn from this study is that despite the success of SB 535 and AB 1550, when explaining the allocation of all GGRF funding, decreased levels of economic need are associated with more GGRF funding when all else is held equal. The amount of GGRF funding allocated under the requirements of SB 535 and AB 1550 is not enough to counteract the commonly found inverse relationship between a community's economic need and the amount of competitive grant funding awarded. This finding confirms the need for SB 535 and AB 1550. Policy makers and community organizers may want to push to increase the amount of GGRF funding subjected to the requirements of SB 535 and AB 1550. However, it is important to understand that this final implication is drawn from the models that made up Model Group Two. These models may have been mis-specified due to the inclusion of the categorical explanatory variable that measures the number of times a community was designated as a "disadvantaged community". The inclusion of this variable may have taken important explanatory power away from the variables that measure a community's racial composition and economic need because the screen used to designate "disadvantaged communities" is, at least in part, a function of a community's racial composition and economic need. Additional research is needed to confirm the validity of this final implication.

Conclusion

California implemented a CO_2 cap and trade system in 2013. To date, the sale of CO_2 emission allowances under this program has generated $12 billion dollars for the state of California. California places the revenue generated from the cap and trade program into the Greenhouse Gas Reduction Fund (GGRF). The GGRF is distributed to specific projects throughout the state by a variety of state agencies. Almost all of the state agencies use a competitive grant system to allocate GGRF funding. Collectively, the state agencies must allocate at least 35% of GGRF funding towards projects that benefit "priority populations" due to funding requirements set by Senate Bill 535 (SB 535) and Assembly Bill 1550 (AB 1550). The expressed intention, at least in part, of SB 535 and AB 1550 is to ensure that GGRF funding is targeted towards less racially and economically privileged communities. However, the competitive nature of the grant systems used to allocate most of the GGRF funding is thought to conflict with these expressed intentions. This study used a variety of multivariate regression techniques to investigate if the expressed intentions of SB 535 and AB 1550 are actually being followed in the allocation go GGRf funding.

The results of this study suggest that the funding requirements given by SB 535 and AB 1550 have successfully targeted the portion GGRF funding regulated under the legislation to communities less racially and economically privileged. However, when looking at all GGRF funding allocations, economically privileged communities tend to receive more funding. Expanding the amount of funding regulated under SB 535 and AB 1550 could increase the amount of GGRF funding distributed to less racially and economically privileged communities throughout California. The results of this study also offered important conclusions surrounding the best functional form to use when explaining the allocation of GGRF funding. Model estimations that used a log transformed response variable had a substantially better fit. Adjusting for spatial autocorrelation was not found to alter the results of models that used the same response variable.

The necessity of addressing climate change means that cap-and-trade systems may become much more prevalent throughout the world. Through SB 535 and AB 1550, California has taken progressive action to ensure that at least some of the revenue derived from its cap-and-trade system benefits communities that are less racially and economically privileged and thereby more exposed to climate change. Policy makers designing cap and trade systems and concerned with climate equity may want to implement similar funding allocation requirements in their systems.

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