Title
An Analysis of the Causal Effects of the Sustainable Groundwater Management Act on California Farm Organizational Structure

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Undergraduate

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Section 1: Introduction

The state of California is a major source of agricultural production for the entire country. With large-scale production, however, comes large-scale water usage. California farms account for roughly 40% of all water usage within the state. That being said, given that 50% of the state's water is considered environmental – which makes it inaccessible for agricultural or urban use – that 40% equates to 80% of the water allocated for businesses and homes ("Water Use in California"). Evidently, water is extremely important within the farming community. However, not all water is the same. There are two main sources of water California farms can draw from – surface water and groundwater. Surface water includes water from streams, rivers, lakes, reservoirs, and collected rain, whereas groundwater is drawn from underground basins called aquifers. While both are finite resources, groundwater is particularly scarce due to the amount of time it takes for a basin to replenish itself. This, in combination with the fact that these aquifers are responsible for roughly "40% of the water used by California's farms and cities" is a significant reason why many of these basins are being drawn at a rate that is unsustainable in the long-term, bringing into question the necessity for regulation ("Groundwater in California" 2019).

The Sustainable Groundwater Management Act (SGMA) was introduced in 2014 with the intention of ensuring the sustainable use of California aquifers through the creation of Groundwater Sustainability Agencies (GSAs) whose job is to enforce Groundwater Sustainability Policies (GSPs) for those basins deemed medium or high priority. Each GSA is responsible for crafting a unique GSP based on the needs of the individual basin. Although each GSP is different, there are many commonalities between them such as: administering pumping allocations, creating water markets to transfer allocations, assessing fees on pumping, registering groundwater wells, and ensuring a balance between withdrawal and recharge within 20 years (Newman 2018). Relating this information to an economic context, the GSPs effectively increase the cost of production for all farms under its jurisdiction by limiting the supply of groundwater and thus forcing prices upwards. Other, more subtle costs include the need to adopt new irrigation technologies and an increase in the time and energy farmers must allocate towards GSA representation. In the business world, a natural response to cost of production increases is to consolidate assets – most often seen with mergers and acquisitions and incorporation. The goal of this study is to analyze whether the SGMA resulted in an increase in the share of corporate farms and a decrease in the share of small farms among those counties affected by the designation. My hypothesis is that as farms adjust to the enforcement of the SGMA, it could force smaller, family-owned farms to either exit the market or consider incorporation as a means to remain operational. The reasoning behind this thesis is that incorporated firms tend to have more assets and therefore have the flexibility to incur higher input costs. Smaller farms, on the other hand, are more likely to be less equipped to follow the guidelines of the SGMA and must therefore turn to larger companies to consolidate their assets and stay in business.

Understanding the effects of SGMA on organizational structure is important because of the social ramifications that could come as a consequence. Over the past few decades, agriculture has become an industry dominated by few organizations who hold control over the majority of the market. As researchers from Pew Environmental Group point out, this trend effectively works to squeeze out small and medium sized farms, reducing competition within the market ("How Corporate Control Squeezes Out Small Farms" 2012). Data from the Economic Research Service (ERS), a branch of the USDA, suggests that this trend is here to stay based on the economics at play and the financial advantage large farms have over smaller farms. Using operating profit margin (OPM) as their metric of choice, the ERS highlights the fact that 50-75% of small farms have an OPM less than 10% with many of them having negative margins. This contrasts with the 40% of large farms with OPMs of 25% or higher ("America's Diverse Family Farms" 2016). The market, as it stands, heavily favors large farms, and the SGMA could potentially accelerate the inequality present within agriculture if it truly does lead to an increased share of corporate farms and decreased share of small farms. This would not only affect the small-farm owners and workers, but also the rural communities which are reliant on small-farms, consumers who could see produce prices and selection affected, and the environment as it has been shown that large farms are responsible for greater waste and pesticide use ("How Corporate Control Squeezes Out Small Farms" 2012).

Using data from the NASS agricultural censuses, I analyze my hypothesis using a panel-data analysis where I estimate whether counties with more SGMA jurisdiction experience a larger shift away from small farms and toward corporate farms, as opposed to non-SGMA enforced counties. These results provide the basis for evaluating the effect of the SGMA on farm incorporation trends.

After careful analysis, we find that there is insufficient evidence to reject the null hypothesis that the SGMA had no effect on the share of corporate and small farms in California. We find that although the share of small farms decreases by a statistically significant amount, we do not see similar significance in the increased share of corporate farms. It should be acknowledged that a potential shortcoming arises from a lack of data further removed from 2014, the year of the bill's implementation. With the passing of more time and with the ability to collect data points from future censuses, it is possible that a more conclusive link could be established between farm organizational structures and the SGMA.

Section 2: Literature Review

The objective of this section is to present the existing evidence of SGMA implementation on agricultural outcomes, as well as other relevant studies for this paper. To begin, *Drivers of Consolidation and Structural Change in Production Agriculture* from Langemeier et al. (2017) provides background on the causes of consolidation in the agricultural sector. To motivate my hypothesis, it is important for "economies of scale" to be defined. Economies of scale exist when average cost per unit declines as production expands. Given that in theoretical micro-economic models, profit per unit is a function of price and average cost (revenue and total cost if you multiply through by quantity), it makes sense for profit maximizing firms to expand their businesses. This is the argument the authors make when applying this economic concept in the context of the agricultural industry, an industry suited for economies of scale, they note. They argue that larger firms have an advantage in terms of adopting new technologies as well as negotiating bulk orders for production inputs. In the case of SGMA implementation, large California farms could likely be more adept at adopting new irrigation technologies and negotiating water deals, providing an advantage over smaller farms who do not have the resources to do so. For instance, it has been shown that production has been shifting towards larger farms for many years in part due to the greater profits associated with increasing size – a 2015 Agricultural Resource Management Survey found that 69% of all farms had a profit margin of less than 10% but that for farms with $1,000,000 to $5,000,000 in sales and for farms with greater than $5,000,000 in sales, only 36% and 26% of them, respectively, had profit margins less than 10%. As Langemeier et al. (2017) notes, these profits can be moved to retained earnings for future business growth, indicating a compounding effect that could lead to an even greater disparity between small and large farms. In total, Langemeier and his team list seven advantages large farms have that could be drivers of potential future consolidation: capital and labor market access, cost economies, managerial resources, profitability and growth focus, risk tolerance, technology, and value chain alliances. Although the SGMA does not influence all of these drivers directly, there is reason to believe it could accentuate the advantage large, consolidated farms have in this industry – specifically in terms of their capital market access, managerial resources, and technology, which could induce changes in organizational structure in the future. Having touched on the big picture benefits of consolidation within the agriculture industry, it is important to understand the role, if any, of the SGMA on farm consolidation within California. *The Sustainable Groundwater Management Act challenges the diversity of California Farms* by Rudnick et al. (2016) details the potential effects of the SGMA on California farms. Describing how the SGMA will be enforced, Rudnick and her colleagues provide testimonials[i] [ii] [iii] from members of the farming community from both small and large farms that explain the challenges that the bill will bring them as well as other farmers in their same position. These challenges include the need for new irrigation technologies, higher pumping costs, and a lack of time to attend local GSA meetings – a major impediment in the construction of unbiased GSPs. These obstacles serve to highlight the implications of the SGMA and its potential for a loss in farm diversity (in size). As is made evident, the SGMA will almost certainly lead to new expenses and an increased dependence on human resources. Existing studies have discussed the mechanisms through which the SGMA might have a higher impact on small farms. For instance, Rudnick et al. (2016) proposes qualitative evidence and testimonials from farmers suggesting that smaller farms could bear the burden of higher operational costs, as well as suffer from a lack of participation in local GSA meetings. To my knowledge, however, quantitative evidence is non-existent, highlighting the need for a more rigorous study. The purpose of this paper is to analyze whether the SGMA can potentially affect the share of small farms and increase farm consolidation. Utilizing both articles, there appears to be evidence suggesting that the hypothesis I have set forth has legitimate standing. The Langemeier article is intended to provide a big picture idea of the drivers of consolidation in the agriculture industry as well as the current trends that exist. The second article by Rudnick is used to form a better understanding of how the SGMA relates to all of the drivers introduced in the article before it. As the theory suggests, many of the advantages brought up by Langemeier and team were voiced in the testimonials of the farmers in the Rudnick piece which is encouraging as it suggests a link between the theory and the real-world. The goal of my paper is to solidify this link.

Section 3: Empirical Strategy

The estimation model used in this study looks at how the share of corporate and small farms in California, by county, in the years 2007, 2012, and 2017 are affected by the share of a county on top of a medium or high priority basin. The purpose of having three years' worth of data is to establish pre-treatment trends in order to make a comparison to post-treatment levels. This model will also include several relevant controls – precipitation, unemployment, as well as fixed effects for each county and year. We will, however, run different models that may contain some or none of these controls as a way to compare results. In addition, these models may also include population and average temperature, variables we chose to omit from our "optimal model," as controls. The independent variable is "basin share " which measures the "treatment intensity" of basin prioritization for each county and is calculated by finding the overlap of a county with a basin that is designated to be either medium or high priority. Moreover, it should be noted that the literature does not provide conclusive guidance on how to account for differences in treatment designation[1]. Therefore, although the share of high and medium priority basins is simple, we believe it best captures the effect of the SGMA. The following empirical model is used for both the corporate and small-farm dependent variables.

$$Y_i = \beta_0 + \beta_1 BasinShare_i + \beta_3 Unemployment_i + \beta_4 Precipitation_i + CountyFixedEffects_i + YearFixedEffects_i + \varepsilon_i$$

Where:

Y_i: the share of a certain farm type (corporate or small) within a county; measured using $\frac{\#\ of\ farms\ of\ a\ specific\ type}{\#\ of\ total\ farms}$

$BasinShare_i$: the share of a county overlapping a medium or high prioritization basin

[1] Each basin is assigned a numerical score that correlates to either a very low, low, medium, or high priority. This score is the treatment designation. Unfortunately, there is a lack of information on how scores impact treatment decisions. In other words, there is no indication as to how treatment scales up with the scores.

$Unemployment_i$: the unemployment rate of a county measured using the average of the previous 5 years (i.e. 2007 Unemployment rate observation is the average rate from 2003-2007)

$Precipitation_i$: the total amount of rain within a county measured using the average of the previous 5 years

$CountyFixedEffects_i$: county fixed effects account for average differences between counties and are useful in eliminating omitted variable bias

$YearFixedEffects_i$: year fixed effects account for average differences between years and are useful in eliminating omitted variable bias

ε_i: unobserved errors; to account for heteroskedasticity, we use robust standard errors in our model

The reasoning behind using a fixed effect model is due to the panel structure of our dataset. Fixed effects greatly control for differences between counties which would lead to omitted variable bias (Blumenstock "Fixed Effect Models"). As constructed, this model provides reasonably accurate coefficient estimates for our basin share variable by accounting for the year implementation took place as well as the counties it took place in. Another characteristic of our model is that we choose not to run a true difference in difference (DID) because of the continuous variable type we want our basin share to have. Having basin share be continuous as opposed to an indicator allows for high basin shares to be differentiated from lower basin shares, something we feel should be accounted for in the model. This intuitively makes sense as you would expect that counties with higher basin shares would have less alternatives to turn to and would therefore be more exposed to GSP implementation. There, unfortunately, is not much literature that covers this topic and so both methods could conceivably be viable, yet we feel that our current model makes fewer assumptions about how treatment is administered and is therefore safer to use.

Now that we have established the structure and the intuition behind our model, this is how we interpret results. Using the R statistical software tool, I estimate these models with an alpha level of 0.05 (95% confidence). I set up my hypothesis test in this way:

Null Hypothesis (H_0): There is no difference in farm share as a result of how much a county overlaps with enforced basins

Alternative Hypothesis (H_A): The difference in farm share for more regulated counties is greater than the difference for less regulated counties (regulation refers to overlap with GSA enforced basins)

We first check the results to make sure that the directions of the coefficients fall in line with what we would expect. The expectations are that basin share increases would lead to the share of corporate farms increasing and the share of small farms decreasing. The next metric of interest is statistical significance. A p-value lower than 0.05 for both the corporate share model and the small share model would allow us to reject the null hypothesis in favor of the alternative. This would suggest that there is sufficient evidence for the hypothesis to be correct. Any p-value higher than 0.05 would have the opposite effect.

A potential question of interest is the relationship between the SGMA and farm size (acres and asset worth) and production (value of receipts). For the purpose of organization and scope, I focus on the topic of organizational structure. However, for the sake of a complete analysis, findings for farm size and production are referenced in the results and do serve as possible indicators of consolidation.

Section 4: Data

Sources

The basin prioritization data was obtained by creating a Public Records Data Request to the Department of Water Resources (B118 SGMA 2014 Basin Prioritization). The data contains the geographic location of all California basins and its prioritization level designated in 2014. We obtained counties' basin share area by geographically merging the area of each basin to the respective total county area by prioritization level. Therefore, we calculated four measures: the high prioritization share, medium prioritization share, low prioritization share, and very low prioritization share for each county in 2014 which are seen in Figure 5.

Most of the remaining data comes from the USDA's agricultural censuses. This covers information from 2007, 2012, and 2017 which allows for analysis from before and after the SGMA was passed in 2014. Dependent variables of interest include the number of farms by organizational structure, sales, acres operated, net income, asset worth, and expenses. The censuses' lowest level of granularity is county-specific data, meaning all 58 of California's counties are included in the analyses. Descriptive statistics of these variables are included in Tables 1, 8-14.

Data was collected using the USDA Quick Stats tool which produces csv files for each county for each year. Using Microsoft Excel's index-match function, I joined each table by row to get the 2007, 2012, and 2017 observations for a county. This was repeated for each variable (Number of Operations, Sales, Acres Operated, etc.) as the tables from Quick Stats had limitations as to the amount of information that could be grabbed. We then created our master table, which has information for each county from each year (i.e. the panel-data structure) and is used for our regression analysis.

One potential shortcoming of this analysis is that 2017 is close to 2014 and so there may not have been enough time for significant effects to have already occurred, especially given the 20 year time frame that basins have to establish a balance between recharge and withdrawal. This is quite possible given the lengthy nature of business acquisitions – in general 4-6 months "from inception through consummation," and often longer in the agricultural sector (Harroch; Klinefelter). Another issue that we ran into was an absence of data for asset worth in 2007. This was a potential indication of consolidation, and so we must be cognizant of potential data-integrity issues when analyzing the results for that variable. A few other notable sources of data are the articles from Langemeier et al. and Rudnick et al, the California Natural Resources Agency (CNRA), the National Climatic Data Center (NCDC), the Bureau of Labor Statistics (BLS), and the government census website. The CNRA describes the mechanisms for assigning a priority level to a basin while the article from Rudnick and colleagues provides a visual in Figure 4 for which counties lay over which basins and how significant those basins are as well as how diverse (in terms of size) farms in those counties are. Additionally, the other resources, described in Tables 2 and 15, are useful as potential controls where the NCDC produces precipitation and temperature data, the BLS includes unemployment information, and the census is useful for population levels. Our thought process when selecting these controls was that it would make sense for an industry like agriculture to be dependent on weather and macro-economic influences. We ultimately do not use population and average temperature in our optimal model due to concerns about their relationship to the dependent variable; however, we include other models which contain these controls as a means for comparison.

Descriptive Statistics

The following summary-statistics tables are useful for a high-level look into the changes from 2007 to 2012 to 2017 of the relevant dependent variables.

Table 1 – Variable Means by Year (Aggregated and per-Operation)

Year	Variable	Statistic	Value per Operation	Value Aggregated
2007	Farm Assets	Mean	NA	NA
2007	Commodity Sales	Mean	$379,449	$604,920,393
2007	Income Farm Ops	Mean	$47,758	$14,917,927
2007	Farm Acres	Mean	427	394,477
2007	Corporation NoO	Mean	82	82
2007	Small farm NoO	Mean	1,103	1103
2007	Number of Operations	Mean	1,397	1397
2012	Farm Assets	Mean	$2,107,531	$2,799,017,351
2012	Commodity Sales	Mean	$495,281	$761,097,250
2012	Income Farm Ops	Mean	$45,734	$21,899,236
2012	Farm Acres	Mean	473	456,200
2012	Corporation NoO	Mean	102	102
2012	Small farm NoO	Mean	1,030	1,030
2012	Number of Operations	Mean	1,342	1,342
2017	Farm Assets	Mean	$3,062,467	$3,915,914,776
2017	Commodity Sales	Mean	$556,749	$806,178,804
2017	Income Farm Ops	Mean	$73,743	$26,215,821
2017	Farm Acres	Mean	519	422,807
2017	Corporation NoO	Mean	109	109
2017	Small farm NoO	Mean	903	903
2017	Number of Operations	Mean	1,089	1,089

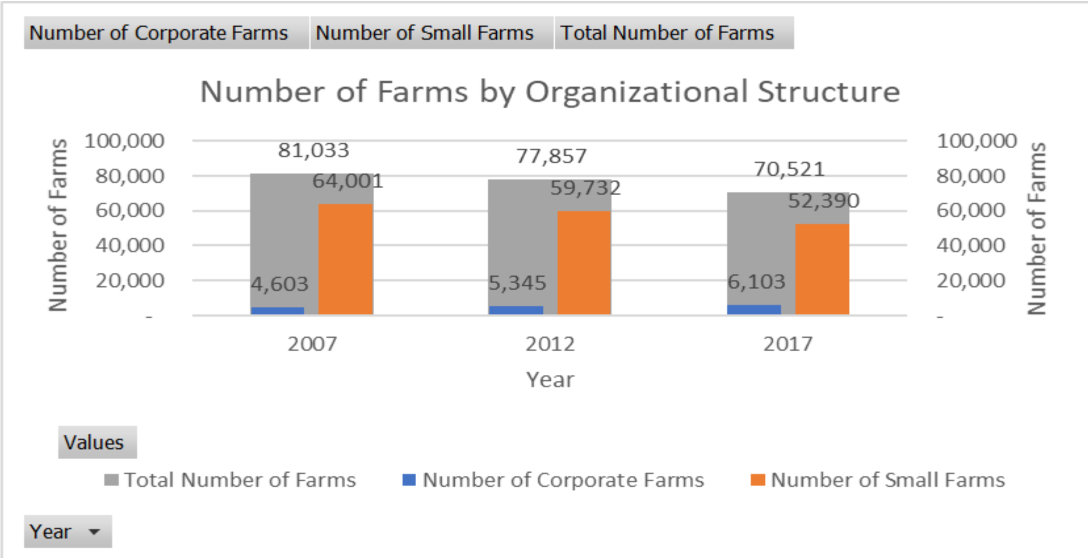
Notes: Aggregated is measured using the total for each county and finding the average of those totals. Per Operation takes the total for each county, divides that total by the number of operations within that county, and then finds the average of those amounts – Source: USDA

Table 2 – Controls (Measured using previous 5-year Average)

	Precipitation (Inches)			Avg. Temp (Farenheit)			Unemployment Rate (%)			Population		
Year	Mean	Median	Std. Dev	Mean	Median	Std. Dev	Mean	Median	Std. Dev	Mean	Median	Std. Dev
2007	27.63	22.04	15.84	57.67	58.42	5.65	7.1	6.5	2.37	616,990	174,585	1,382,350
2012	27.56	22.67	15.27	57.21	57.97	5.77	12.1	11.9	3.34	643,008	178,952	1,406,749
2017	24.57	19.99	14.88	59.23	60.14	5.72	7.9	7.6	3.15	670,005	181,899	1,450,196

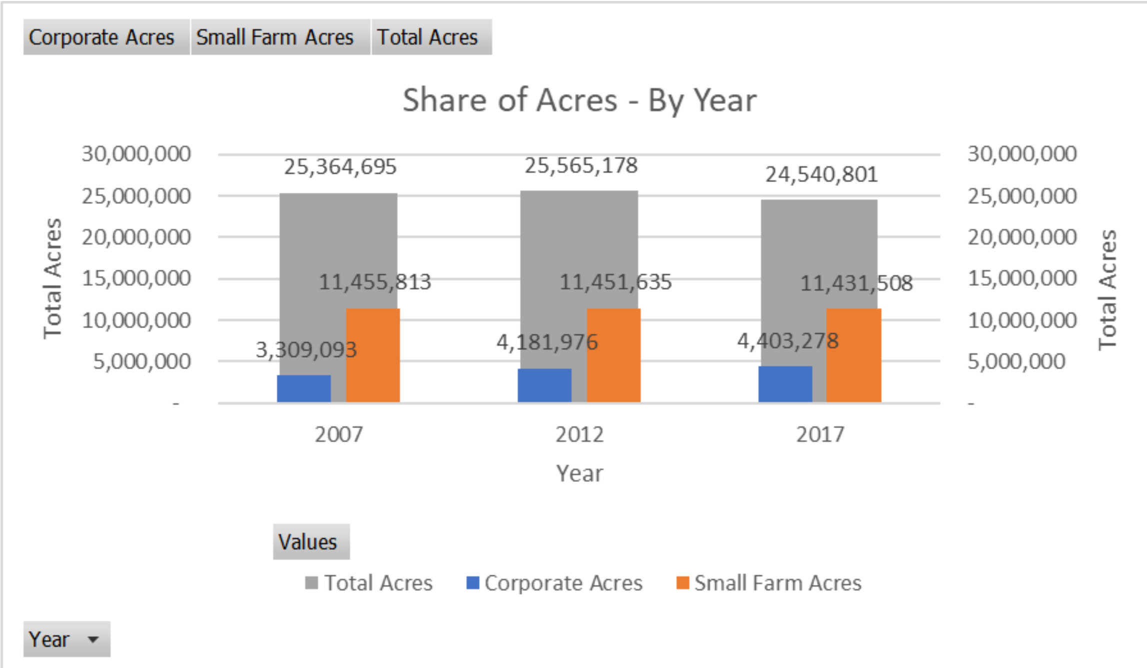
Notes: 2007 observations take the averages from 2003-2007. 2012 observations take the averages from 2008-2012. 2017 observations take the averages from 2013-2017 – Source: USDA

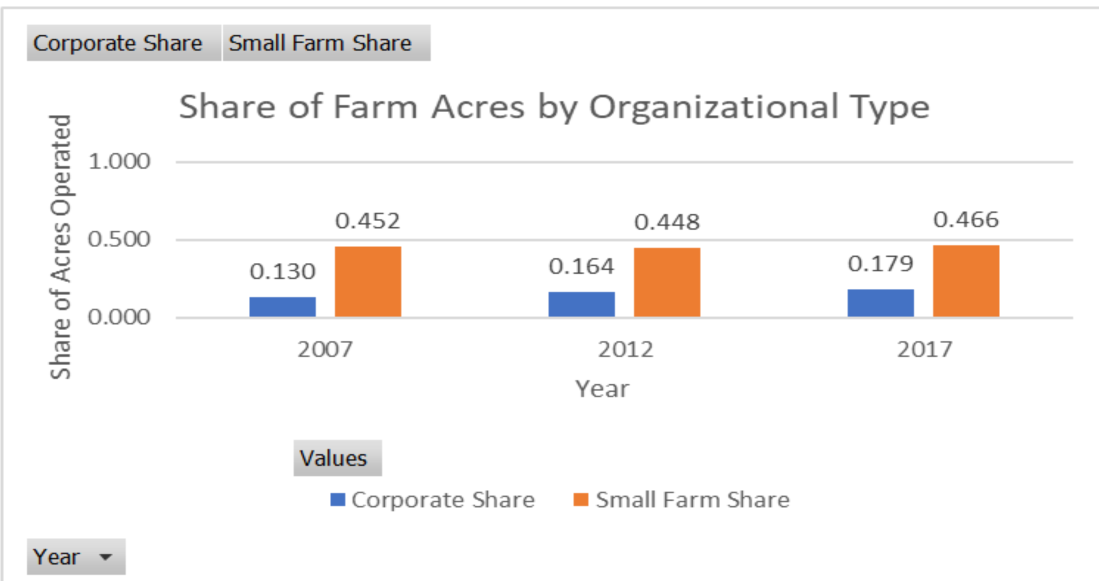
Figure 1 – Share of Farms by Organizational Structure by Year



Notes: A look at the share of farms by organizational structure as both a gross value and percentage – Source: USDA

Figure 2 – Share of Land Operated by Organizational Structure by Year





Notes: A look at the share of land by organizational structure as both a gross value and percentage – Source: USDA

The preliminary results in Figure 1 shows that the share of small farms has been decreasing while the share of large farms has been increasing. While encouraging, it is worth noting that these are aggregate trends within California, and they do not account for the treatment variable at the county level. More results from Figure 2 gives mixed conclusions about the share of land by each type of farm. There is a noticeable uptick in share of land by corporate farms, but a bit more noise for small farms as the share goes down in 2012 but back up in 2017.

Although we cannot say whether either of these results lead to significant results, it is at least reassuring that the directions of the trends in farm share point to where we would expect them to, and that the direction of corporate acreage share does as well.

Other subsidiary results such as those for assets, sales, and net income indicate that per-operation values are increasing. This is a potential indicator for consolidation as it shows that the average farm does increase in size from 2007-2017. Again, these must be taken with a grain of salt as it does not consider county-level trends. However, much like the results for farm share and acreage share, the direction is encouraging.

Section 5: Results & Evidence

From looking at the output tables in Table 3, we see that basin share is only significant towards corporate share when we exclude any controls. This suggests that although the share of corporate farms is increasing – as revealed in the summary statistics bar charts – the trend is not associated with SGMA implementation based on the data collected. This is contrasted by the significant results obtained in Table 4, our small farm share model. In all three model scenarios, we observe a significant negative relationship between small farm share and basin share. We can infer that although there was a pre-existing movement away from the proportion of small farms, being under SGMA jurisdiction works to accelerate this movement.

Table 3 – Regression Output using Corporate Share (Levels)

	No Controls	All Controls	Optimal Model
	(1)	(2)	(3)
Basin_share	0.036***	−0.005	−0.004
	(0.010)	(0.009)	(0.010)
avg.temp		0.004	
		(0.016)	
Rain_inches		0.003**	0.003**
		(0.001)	(0.001)
population		0.00000	
		(0.00000)	
unemployment_rate		0.006*	0.006*
		(0.003)	(0.003)
Note:		*p<0.1; **p<0.05; ***p<0.01	

Notes: Models and their respective coefficients and robust standard errors (in parenthesis). Fixed Effects for County and Year included in "All Controls" and "Optimal Model" – Source: Hlavac

Table 4 – Regression Output using Small Farm Share (Levels)

	No Controls	All Controls	Optimal Model
	(1)	(2)	(3)
Basin_share	-0.103^{***}	-0.053^{**}	-0.055^{**}
	(0.027)	(0.027)	(0.027)
avg.temp		0.005	
		(0.022)	
Rain_inches		0.005	0.004
		(0.005)	(0.005)
population		−0.00000	
		(0.00000)	
unemployment_rate		−0.006	−0.006
		(0.006)	(0.006)
Note:		*p<0.1; **p<0.05; ***p<0.01	

Notes: Models and their respective coefficients and robust standard errors (in parenthesis). Fixed Effects for County and Year included in “All Controls” and “Optimal Model” – Source: Hlavac

When looking at Table 5, the output table for acreage operated, we see that although acres per small farm is the only significant coefficient, the direction of all coefficients fall in line with what the hypothesis indicates. This tells us that not only are corporate farms operating more land per operation and small farms less land per operation, but that of all land being farmed, more of that is going to corporations and less to small farms.

Table 5 – Regression Output using Acreage

	Corp. Acres	Small Acres	Corp. Acres Share	Small Acres Share
	(1)	(2)	(3)	(4)
Basin_share	170.604	-153.488^{**}	0.046	−0.066
	(500.070)	(73.862)	(0.054)	(0.051)
Rain_inches	−5.799	12.081	0.007	−0.0001
	(67.112)	(11.795)	(0.004)	(0.007)
unemployment_rate	−23.362	−3.117	−0.008	−0.003
	(70.757)	(14.186)	(0.008)	(0.010)
Note:				*p<0.1; **p<0.05; ***p<0.01

Notes: Models and their respective coefficients and robust standard errors (in parenthesis). Corp Acres and Small Acres are the total number of acres operated by that farm type divided by the number of farms of that type at the county level. Corp Acres Share and Small Acres Share are the total number of acres operated by that farm type divided by the total number of acres operated at the county level. Fixed Effects for County and Year included in all models – Source: Hlavac

Other metrics for consolidation are observed in Table 6, where per-operation variables such as net income, expenses, sales, and assets all seem to have positive relationships with basin share. Although basin share has strong t-statistics (t>1) for all of the variables, assets per operations is the only model that experiences a statistically significant relationship with basin share. We should, however, be cautious to draw conclusions as asset data is missing in 2007.

Table 6 – Regression Output of other Indicators of Consolidation

	Net Income	Expenses	Sales	Assets
	(1)	(2)	(3)	(4)
Basin_share	7,645.958	125,899.700	96,369.210	1,427,547.000***
	(5,537.588)	(104,823.800)	(78,682.420)	(480,371.100)
Rain_inches	616.821	1,871.508	2,279.149	99,739.730
	(553.965)	(13,540.380)	(8,742.003)	(98,642.600)
unemployment_rate	1,201.257	11,546.200	128,464.700***	376,854.000**
	(2,207.932)	(47,570.300)	(48,750.620)	(173,809.800)
Note:				*p<0.1; **p<0.05; ***p<0.01

Notes: Models and their respective coefficients and robust standard errors (in parenthesis). Each dependent variable is measured by taking the total and dividing by the total number of operations at the county level ($\frac{Value\ of\ Assets\ in\ a\ county\ in\ USD}{Number\ of\ Operations\ in\ that\ county}$). Fixed Effects for County and Year included in all models – Source: Hlavac

The last table that we analyze is Table 7, a true difference in difference model. In this model, year takes on a value of 1 when it is 2017 (post SGMA implementation) and 0 otherwise. Treatment takes on the value 1 when a county overlaps with a medium or high priority basin and 0 otherwise. The difference in difference term is the interaction between year and treatment and can be interpreted as the effect of being under SGMA jurisdiction after its passing in 2014 (Christoph). As described in the Empirical Strategy section, we deliberately do not use a DID, but instead include it to compare its results to our desired optimal model. Based on the output table, the DID term is significantly negative for small farm share without fixed effects but loses its significance when fixed effects are included. No other coefficients are statistically significant. Much like the other tables, though, we check for direction of the coefficients and see that they line up with what we would expect. The DID terms suggest that being treated has a positive association with corporation share and a negative association with small farm share.

Table 7 – Regression Output of Difference in Difference using Farm Share

	Corp - No FE	Corp - FE	Small - No FE	Small - FE
	(1)	(2)	(3)	(4)
Year_indicator	0.005		0.132	
	(0.016)		(0.085)	
Treatment_indicator	0.025		0.013	
	(0.016)		(0.074)	
Year_indicator:Treatment_indicator	0.018	0.018	−0.161*	−0.161
	(0.018)	(0.025)	(0.087)	(0.101)
Note:			*p<0.1; **p<0.05; ***p<0.01	

Notes: Models and their respective coefficients and robust standard errors (in parenthesis). Year is coded as 1 for 2017 (post SGMA) and 0 otherwise. Treatment is coded as 1 when basin share is greater than 0 and 0 otherwise. The No FE models use no controls and the FE models use County Fixed Effects and Year Fixed Effects – Source: Hlavac

Section 6: Conclusion

After many variations of the models proposed in the Empirical Methods section, we do not have sufficient evidence to reject the null hypothesis that the SGMA had no impact on farm organizational structure. While this conclusion is certainly unsatisfying, there is still a lot of reason to be optimistic about results in the future. First and foremost, we see that in every model, the share of small farms decreases significantly at the 5% level. This is to be expected as the literature suggests smaller farms would be more adversely affected by the SGMA. A possible explanation for why we do not see the same level of significance with corporate farm increase could be the longer amount of time it would take for incumbent farms to transition to corporate status or for new farms to enter the industry as corporate, a theory that draws on research from Harroch and Klinefelter (Harroch; Klinefelter). As was noted earlier, census data at the county level is only available every five years and so the latest available data is from 2017, only three years after the SGMA was passed. It is easy to conceive a situation in which these business processes take a considerable amount of time to realize as farms wait to analyze how GSPs will be constructed and what their effects will be. I believe that with more data further removed from 2014, we would have a much more accurate answer to the hypothesis. Another explanation for the lack of significance in our corporate share models could be the way in which we define consolidation. It is possible that consolidation occurs in ways we do not track. Although we account for acreage by farm type, data limitations do not allow us to do the same granular analysis with sales, net income, expenses, and assets. As a result, we only see the changes within the counties as a whole and cannot make any claims as to how corporate and small farms are being affected with regards to the aforementioned variables.

Despite the not being able to reject the null hypothesis, there are still other reasons to be optimistic for future results. This optimism stems from the summary statistics presented in section 4 and the regression outputs from section 5. From 2007 to 2017, there is a noticeable decrease in the number of small, family farms in conjunction with an increase in the number of large, corporate farms. We see this is true in terms of both the gross amount and the share in Figure 1. In terms of acreage operated, the gross number of acres operated by corporate farms is increasing and the gross number of acres operated by small farms is decreasing. This is supplementary to the regression output in Figure 5 which highlights the direction of the coefficients, despite lacking significance. With more datapoints, we could potentially see this noise reduced and obtain more significant coefficients. In addition to the previous variables, many of the other measures such as sales, assets, expenses, and net income – calculated per operation – all increased which shows for a fact that farms are getting bigger, both monetarily and spatially. So, while we cannot yet prove that these trends are linearly related to the share of a basin under GSA jurisdiction, we are hopeful that future research will yield a more significant link.

Appendix A

Figure 3 – Map of Water Usage in California

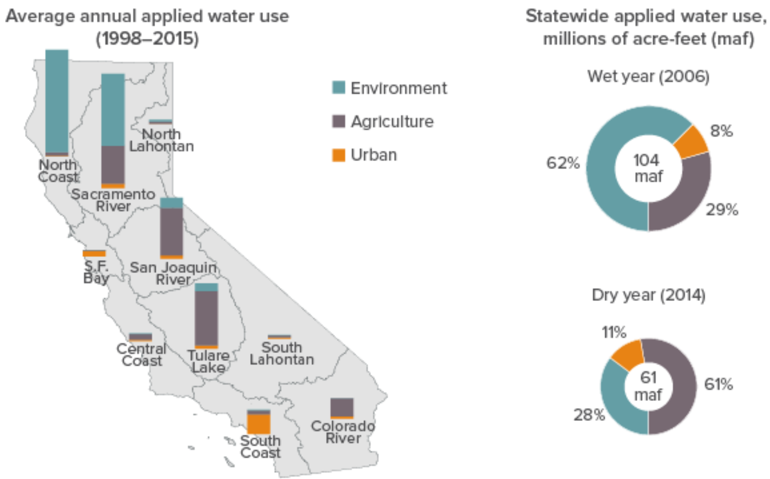
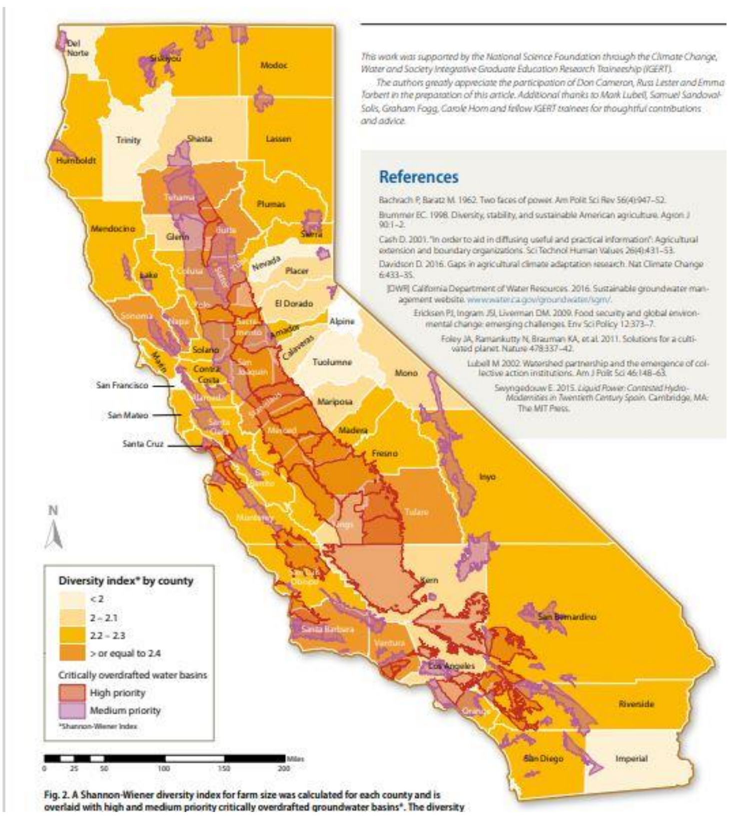
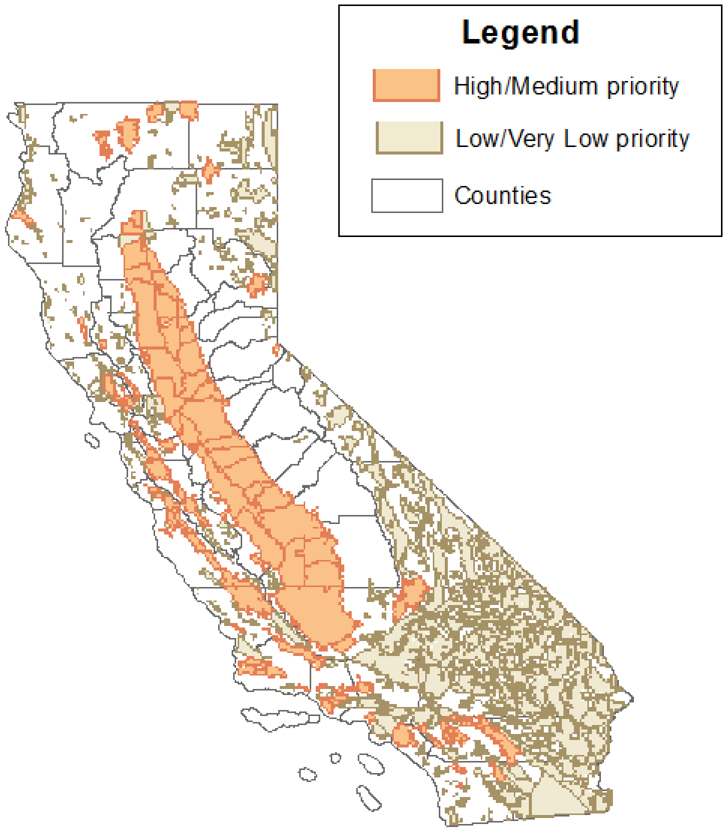


Figure 4 – Map of California Counties



Notes: Diversity index is a measure of the distribution of different sized farms within a county. The purple and red shading refers to medium and high priority basins, respectively

Figure 5 – Map Produced Using ArcGIS



Notes: The source for the basin share independent variable

Table 8 – Number of Operations

Year	Variable	Statistic	Value per Operation	Value Aggregated
2007	Number of Operations	Mean	1,397	1397
2007	Number of Operations	Median	937	937
2007	Number of Operations	Std.Dev	1,441	1441
2012	Number of Operations	Mean	1,342	1,342
2012	Number of Operations	Median	967	967
2012	Number of Operations	Std.Dev	1,326	1,326
2017	Number of Operations	Mean	1,089	1,089
2017	Number of Operations	Median	751	751
2017	Number of Operations	Std.Dev	1,099	1,099

Notes: The mean, median, and standard deviation of the number of farms in a county within California

Table 9 – Number of Corporate Operations

Year	Variable	Statistic	Value per Operation	Value Aggregated
2007	Corporation NoO	Mean	82	82
2007	Corporation NoO	Median	47	47
2007	Corporation NoO	Std.Dev	87	87
2012	Corporation NoO	Mean	102	102
2012	Corporation NoO	Median	59	59
2012	Corporation NoO	Std.Dev	105	105
2017	Corporation NoO	Mean	109	109
2017	Corporation NoO	Median	69	69
2017	Corporation NoO	Std.Dev	116	116

Notes: The mean, median, and standard deviation of the number of corporate farms in a county within California

Table 10 – Number of Small Farms

Year	Variable	Statistic	Value per Operation	Value Aggregated
2007	Small farm NoO	Mean	1,103	1103
2007	Small farm NoO	Median	738	738
2007	Small farm NoO	Std.Dev	1,152	1152
2012	Small farm NoO	Mean	1,030	1,030
2012	Small farm NoO	Median	751	751
2012	Small farm NoO	Std.Dev	1,023	1,023
2017	Small farm NoO	Mean	903	903
2017	Small farm NoO	Median	667	667
2017	Small farm NoO	Std.Dev	878	878

Notes: The mean, median, and standard deviation of the number of small farms in a county within California

Table 11 – Acres Operated

Year	Variable	Statistic	Value per Operation	Value Aggregated
2007	Farm Acres	Mean	427	394,477
2007	Farm Acres	Median	294	316,241
2007	Farm Acres	Std.Dev	460	360,242
2012	Farm Acres	Mean	473	456,200
2012	Farm Acres	Median	328	337,442
2012	Farm Acres	Std.Dev	449	442,294
2017	Farm Acres	Mean	519	422,807
2017	Farm Acres	Median	350	287,472
2017	Farm Acres	Std.Dev	544	425,697

Notes: The mean, median, and standard deviation of the number of acres operated in a county within California

Table 12 – Commodity Sales

Year	Variable	Statistic	Value per Operation	Value Aggregated
2007	Commodity Sales	Mean	$379,449	$604,920,393
2007	Commodity Sales	Median	$211,136	$240,111,000
2007	Commodity Sales	Std.Dev	$492,919	$875,924,799
2012	Commodity Sales	Mean	$495,281	$761,097,250
2012	Commodity Sales	Median	$249,549	$231,957,000
2012	Commodity Sales	Std.Dev	$727,020	$1,127,979,044
2017	Commodity Sales	Mean	$556,749	$806,178,804
2017	Commodity Sales	Median	$276,052	$222,878,500
2017	Commodity Sales	Std.Dev	$838,283	$1,262,055,255

Notes: The mean, median, and standard deviation of the nominal value of commodity sales in USD in a county within California (not adjusted for inflation)

Table 13 – Net Income

Year	Variable	Statistic	Value per Operation	Value Aggregated
2007	Income Farm Ops	Mean	$47,758	$14,917,927
2007	Income Farm Ops	Median	$45,145	$7,984,000
2007	Income Farm Ops	Std.Dev	$27,061	$17,919,502
2012	Income Farm Ops	Mean	$45,734	$21,899,236
2012	Income Farm Ops	Median	$38,024	$10,907,000
2012	Income Farm Ops	Std.Dev	$32,002	$26,472,549
2017	Income Farm Ops	Mean	$73,743	$26,215,821
2017	Income Farm Ops	Median	$58,228	$16,624,500
2017	Income Farm Ops	Std.Dev	$60,784	$29,300,586

Notes: The mean, median, and standard deviation of the nominal value of net income in USD in a county within California (not adjusted for inflation)

Table 14 – Farm Assets

Year	Variable	Statistic	Value per Operation	Value Aggregated
2007	Farm Assets	Mean	NA	NA
2007	Farm Assets	Median	NA	NA
2007	Farm Assets	Std.Dev	NA	NA
2012	Farm Assets	Mean	$2,107,531	$2,767,671,534
2012	Farm Assets	Median	$1,842,878	$1,504,054,500
2012	Farm Assets	Std.Dev	$1,360,100	$2,983,241,741
2017	Farm Assets	Mean	$3,062,467	$3,921,458,448
2017	Farm Assets	Median	$2,594,387	$1,887,562,500
2017	Farm Assets	Std.Dev	$2,392,356	$4,637,283,996

Notes: The mean, median, and standard deviation of the nominal value of assets in USD in a county within California (not adjusted for inflation)

Table 15 – Controls (Measure in Observed Years)

	Precipitation (Inches)			Avg. Temp (Farenheit)			Unemployment Rate (%)			Population		
Year	Mean	Median	Std. Dev	Mean	Median	Std. Dev	Mean	Median	Std. Dev	Mean	Median	Std. Dev
2007	17.42	13.14	12.17	57.56	58.1	5.66	6.8	6.1	2.4	625,005	177,121	1,380,832
2012	31.12	25.44	20.61	58.03	58.8	5.73	12.1	12	3.6	654,290	179,225	1,425,835
2017	37.43	30.17	22.4	59.05	60.05	5.95	6	5.5	2.8	678,595	185,164	1,459,838

Notes: The mean, median, and standard deviation of the controls data

Table 16 – Regression Output using Corporate Share (Logged)

	All Controls - Logged	Optimal Model - Logged
	(1)	(2)
Basin_share	−0.032	−0.021
	(0.119)	(0.123)
avg.temp	0.096	
	(0.190)	
Rain_inches	0.048**	0.047**
	(0.020)	(0.019)
population	0.00000	
	(0.00000)	
unemployment_rate	0.030	0.030
	(0.030)	(0.028)
Note:		*p<0.1; **p<0.05; ***p<0.01

Notes: Models and their respective coefficients and robust standard errors (in parenthesis). Models vary by the controls used and corporate share is logged. Both models include County and Year Fixed Effects – Source: Hlavac

Table 17 – Regression Output using Small Farm Share (Logged)

	All Controls - Logged	Optimal Model - Logged
	(1)	(2)
Basin_share	−0.073*	−0.077*
	(0.038)	(0.039)
avg.temp	0.003	
	(0.032)	
Rain_inches	0.008	0.008
	(0.008)	(0.008)
population	−0.00000	
	(0.00000)	
unemployment_rate	−0.011	−0.011
	(0.010)	(0.010)
Note:		*p<0.1; **p<0.05; ***p<0.01

Notes: Models and their respective coefficients and robust standard errors (in parenthesis). Models vary by the controls used and corporate share is logged. Both models include County and Year Fixed Effects – Source: Hlavac

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[i] Don Cameron is the general manager of a 6000-acre farm and a chair of the Environmental Farming Act Science Advisory Panel. As head of Terranova Ranch, Cameron oversaw the adoption of drip irrigation technologies and is widely regarded as one of the leaders in water conservation over the decades. With that being said, Cameron and his farm are extremely subject to the SGMA as over 95% of the water used for the farm's irrigation is pumped from groundwater wells. One of the key takeaways from Cameron was the importance of attending as many GSA meetings as possible in order to have a voice in SGMA implementation. This is a privilege that he acknowledged many smaller farms do not have due to their lack of human resources. This highlights another example of the obstacles that smaller farms face.

[ii] Russ Lester is the owner of a 1400-acre farm who has been forced to reconsider the crops that he will plant, as the restrictions on water usage forces his hand. This would imply switching from higher revenue crops that require a lot of water, to lower margin crops in order to be in accordance with the SGMA. Mr. Lester's situation is similar to that of other medium-small sized farms who must make important decisions on how to allocate their resources.

[iii] Emma Tolbert is the co-manager of a small, 4-acre farm which is entirely dependent on groundwater for irrigation. In order to comply with SGMA ordinances, she will need to make and has already made major investments in infrastructure just to get by. She has already begun experimenting with reduced irrigation schedules, even going as far as cutting her water usage by nearly 50%. Tolbert fears that because she needs to dedicate so much time to her land, she will miss out on important GSA meetings and risk having her voice be left out, a sentiment Rudnick and her colleagues surmise other small-scale farmers share. The purpose of these testimonials was not only to develop a better idea of the challenges each specific farm-size faces, but also understand the collective challenges that they all face.