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政黨傾向對生育決策的影響：臺灣總統選舉實證
Partisan Fertility in Taiwan

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口試委員會審定書

意識型態對生育決策的影響：台灣總統選舉實證

Partisan Fertility in Taiwan

本論文係黃泓鈞君（R10323037）在國立臺灣大學經濟學系完成之碩士學位論文，於民國 112 年 7 月 24 日承下列考試委員審查通過及口試及格，特此證明

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摘要

支持不同政黨的人們可能對於不同議題會有不同看法，並依照這些看法來做未來決策，比方說經濟狀況。這篇論文藉由事件分析法（event study）、合成控制（synthetic control），分析台灣 2016、2020 年兩屆總統大選，發現黨派生育效果（partisan fertility effect），獲勝的選民傾向生育。不過，在連任的 2020 年，效果並不明顯。2016 年，估計的季節平均效果介於每千位女性提高 0.048 到 0.132 位小孩；2020 年則為 0.020。這三個數字分別佔平均的一般生育率（general fertility rate）1.27、3.93，與 0.70%。

關鍵字：政黨傾向、生育、政治兩極化、選舉、政權交替

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Abstract

People with different partisan affiliations may hold contrasting opinions on various topics, such as the state of the economy, and make decisions based on their beliefs. By analyzing the presidential elections of 2016 and 2020, this paper uncovers the presence of partisan fertility effects. This is achieved by implementing the DID event study and synthetic control method. The findings suggest that individuals are more likely to conceive children following the election victory. However, when examining the re-election in 2020, the partisan effect becomes less evident. On average, the estimated quarter effects range from 0.048 to 0.132 per 1,000 women in 2016, and 0.020 in 2020. These represent 1.27%, 3.93%, and 0.70% of the average quarterly general fertility rate, respectively.

Keywords: Partisanship, Fertility, Political Polarization, Election, Economic Evaluation, Transition of Power

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Chapter 1 Introduction

Voters in Taiwan have experienced three transitions of power in presidential elections since 2000. Many of them have started their families throughout these transitions. In terms of families, Dahl et al. (2022) conclude that partisanship is a determinant of fertility in the United States, as former President Trump unexpectedly won the election in 2016. Notably, individuals' partisanship and their optimistic outlooks have exhibited associations with birth rates in the United States. The decision of parents to have a child can be influenced by various factors, including their expectations of the future. This leads to an intriguing question: To what extent does partisan fertility express in Taiwan?

Partisan bias manifests when voters evaluate the economy (Bartels, 2002). In Taiwan, the Taiwan Election and Democratization Study (TEDS) data from 2012 to 2020 show that voters aligned with the winner of presidential elections tend to become more optimistic about the national economy, and vice versa (Huang, 2018). This implies the outcome of a presidential election can reduce uncertainties and potentially have an immediate impact on individuals' decisions regarding fertility. If the change in opinions based on partisan alignment is substantial enough, it may be possible to observe partisan fertility effects in a village with a mixture of different types of voters. Although the true mechanism remains unknown (Dahl et al. 2022), Taiwan has similar patterns to the United States with respect to economic evaluations. In Appendix A, I depict the instant-changing trend.

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To shortly conclude, this paper aims to provide empirical evidence of partisan fertility effects using the difference-in-differences (DID) event study in two presidential elections in Taiwan: the 2016 and 2020 elections and the synthetic control method. In the 2016 election, a transition of power occurred, along with huge vote share changes, and President Tsai from the Democratic Progressive Party (DPP) was re-elected in the subsequent election. The average partisan fertility effect for the DPP was $0.132(0.148)$ after President Tsai became the first female leader in Taiwan using DID event study (synthetic control). In the next election, the re-elected effect (discovered by focusing on the party vote share instead of the presidential vote share) was smaller. The average re-elected partisan effect by synthetic control is 0.020, and the effect by the other method is statistically insignificant. 0.148 accounts for 3.93% of the national general fertility rate.

To account for confounders affecting the treatment and the outcome (i.e. the fertility rate), a matching method is implemented to relieve selection bias. Since the distribution of village demographics such as the final education is different between the treated and the control group, matching could help eliminate the initial imbalance. In this paper, the nearest-neighbor (NN) matching method proposed by Ho et al. (2007) addresses the issue by pairing the treated unit with the most similar control unit. After pre-processing the data, The DID event study with matched observations exhibits the same evidence as the standard DID event study.

Further, to ensure the robustness of the findings, the outcome variable is altered to the general fertility rate from one year before the children were born, and the estimates are mostly insignificant before the real treatment date and differ from the original findings. The existence of partisan fertility was supported in both elections, but the partisan fertility in the transition of power is more obvious.

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Eventually, this paper contributes to the existing literature by providing supporting evidence of partisan fertility effects on the basis of two consecutive elections. However, the true mechanism underlying partisan fertility has yet to be identified. Nonetheless, this thesis sheds light on the possibility of partisan fertility effects being a widespread phenomenon, as observed not only during the transition of power in 2016 but also during the re-election in 2020. Future research can extend to more matching options that are available in Taiwan (e.g. village electricity consumption and income tax), argue the true mechanism (e.g. the partisan bias in economic expectation), or investigate how non-partisans in Taiwan influence the elections and whether non-partisans have partisan fertility. Particularly, the proportion of non-partisans in Taiwan increased during the election in 2016, yet, unknown for the election in 2020.

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Chapter 2 Related Literature

The supporters of the Democratic Progressive Party (DPP) and the Kuomintang (KMT) in Taiwan are deeply divided in terms of their national identities, satisfaction with the president, and economic expectations for the future. Decision-making is influenced by individuals' beliefs and perceptions. As the government is responsible for fostering national economic prosperity, its performance becomes a crucial criterion for evaluation. However, partisan bias can shape people's opinions and economic beliefs, as the perceptions of current economic indices (e.g. inflation rate) diverge between Republicans and Democrats (Bartels 2002). Voters have loyalties with parties they support (Bartels 2000) and have different strategies for congressional and presidential votes.Moreover, the distinction in opinions reinforces between them. Similarly, Huang (2018) suggests that partisan bias in economic evaluation was observed among Taiwanese voters before and after the 2016 presidential election.

Understanding the mechanism that links survey responses to actual behavior requires careful analysis. Gerber and Huber (2009) argue that analyzing local sales data helps uncover the channel through which partisanship influences consumption behavior, with individuals increasing their consumption after their preferred party wins. Individuals could change their consumption behavior after the announcement of a new president. Reproductive choices could possibly be influenced. While the underlying mechanisms of partisan

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fertility effects remain ambiguous, Dahl, Lu, and Mullins (2022) provide intriguing insights into the correlation between the election of Trump and an increase in Republican fertility rates compared to Democratic rates, as they argue that Trump attracted a new set of voters.

This study serves as a foundation for further exploration of the mechanisms linking declining fertility rates with growing political polarization, as the authors argued Trump had attracted to a new set of voters. Building upon this research, the purpose of this study is to argue for the ubiquity of partisan fertility effects and investigate their manifestations using data from Taiwan. Yet, the type of political polarization in Taiwan differs from that observed during Trump's election in 2016. Wang (2019) investigates the type of political polarization in Taiwan from 2002 to 2017 and concludes that ideologically moderate voters no longer support the DPP or the KMT, which corresponds to the shift in vote shares observed in 2016. This could lead to a distinct consequence from the US. In summary, while similarities are found in partisanship, the type of political polarization differs between Taiwan and the United States.

Partisanship can extend to various aspects. In line with the work of Gerber and Huber (2009), Benhabib and Spiegel (2019) investigate the impact of partisanship on spending behavior related to consumer goods using the Index of Consumer Sentiment from the University of Michigan. Furthermore, the application of natural language processing techniques, such as sentiment analysis, can provide valuable insights into voter sentiments using deep learning. For instance, Widmann and Tobias (2022) mention the use of sentiment analysis to analyze the government's communication strategies and the impact of fear on citizens' compliance with COVID-19 restrictions .

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Chapter 3 Data and Method

In this chapter, the variables for the analysis are defined and discussed first. Second, summary statistics are covered in section 3.2 to illustrate how fertility and vote shares change over time. Thirdly, the identification strategy (i.e. the difference-in-differences event study and the synthetic control method) is explained to verify my process to obtain partisan fertility effects in Taiwanese elections. In the last section, the matching method is introduced to validate the findings from the DID event study specification by further considering observable confounders.

3.1 Variable of Interests

The village-level fertility and population data are collected from the Taiwan open data platform [1] spanning the period from 2015 to 2022 collected and combined with vote share data from the Central Election Commission [2] to estimate the partisan effects in the 2016 and 2020 presidential elections. The election dates are in January 2016 and 2020, respectively. Besides, the presidential vote shares above the median in 2012 were added to identify partisanship for 2016.

In the US, the *shift*, defined by the increment of presidential vote share above the

[1] https://data.gov.tw/en
[2] https://db.cec.gov.tw/ElecTable/Election?type=President

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median, can capture new voters for Trump (Dahl et al. 2022). However, the same definition/variable in DPP's presidential vote share has the opposite correlation. This may stem from the growth of numbers of non-partisans departing from the pan-blue (KMT) side, failing to translate into the DPP side. Hence, the plummet (shift) in KMT's (DPP's) presidential vote share is mostly associated with KMT villages, not DPP villages. For detecting political polarization in partisan effect, instead, I use a larger winning margin. Lastly, the education data were merged for matching suggested by Ho et al. (2007) to further consider different distributions and characteristics between the treatment group and the control group in the last subsection.

The outcome variable of interest is defined as the *deseasonaliezed* quarterly general fertility rate over a span of three quarters (*fertility rate*). It is defined as

$$1000 \times \frac{\text{total births conceived}}{\text{female population aged from 15 to 49 years old}}.$$

For better data visualization, each conception rate is deseasonalized by its village × month-of-year average using the full dataset. I assumed that some households plan for pregnancy right after observing the treatment, and the presidential election, and adjusting their expectations. Thus, the delivery of the child will be as earliest as three quarters later. In each election, it occurred in January, the first quarter and the babies would be delivered over a nine-month period, which is three quarters later.

The treatment variables are constructed based on winning margins. Each of them is the median, 50%, and 60%. The main reason why Dahl et al. (2022) used *shifts* is conditional on the previous Republicans, us that the new supporters attracted by Trump. These new supporters may be critical such that the partisan fertility is larger in polarized

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regions as they are associated with Republican county, in some sense that the biased expectations like found could amplify the effect or shape these opinions. Nonetheless, those shifts toward the DPP are correlated with the KMT in Taiwan.

Note that in 2020, the pandemic started. However, whether or not to control for COVID does not affect the estimates. The immediate and effective isolation of the virus led to almost no virus in Taiwan in 2020. Thus, the COVID controls are omitted in this analysis.

3.2 Summary Statistics

Table 1 summarizes the birth, the population, and the election data from the 2012 to 2020 presidential elections. The numbers of villages were merged so as to be immune from the institutional changes, such as combining two villages if one of them is created after a time period; $(deseasonalized)$ $FertilityRate$, or $Excess\ Fertility\ Rate$, is the births conceived divided by the female population from 15 years old to 44 years old, as I assumed it takes nine months (three quarters) for a full pregnancy; The standard deviations of village population implicate the fewer births and the aging population. For the election data, Table 1 describes both the legislative and the presidential party vote share data. The elections took place on the same date in 2016 and 2020 respectively. From the legislative vote share data, the vote share shift patterns are different between the legislative and the presidential results. This could originate from the non-partisans choice of legislative votes against a president's power. Eventually, more voters prefer Ing-Wen Tasi, the DPP candidate, but they do not support legislators from the DPP simultaneously.

Does partisan fertility exist and persist in Taiwan? Figure 3.1 might interpret that

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partisan fertility might exist in 2016, and persist in 2020. The first row of Figure 1 plots the fertility trend in 2016, while the second row is for the next election. Notably, the distinct deviations exist at first in 2016. The shaded areas suggest that the replacement of the KMT candidate in October 2015, and the participation of the PFP candidate in August 2015, could have influenced voters' beliefs before the election. In fact, the poll rates for the KMT had been decreasing since then. After the treatment date (2016Q1), the gap in fertility rates between DPP and non-DPP narrows down. In the second column of Figure 3.1, both the High Shift and the DPP village in 2016 may exhibit partisan fertility since the gaps narrow down. Each election shows a bigger fertility gap, whereas the thinner gap in the second election suggests a smaller partisan effect. In addition, the excess fertility rate in DPP villages flipped over and became higher than that in KMT villages. No adverse partisan effects are observed in the re-election. Figure 3.2 presents the same setup using matched data. Similar patterns from it validate the finding above.

In terms of the results in 2020, the patterns indicate the partisan fertility *persists* or the re-elected effect is ambiguous. If the winners' expectations or the vote shares do not alter, the excess fertility would not increase after the election. In general, partisan fertility appears to be far more difficult to detect as a consequence of the involatile vote shares between elections unless partisan bias emerges in the re-elected process.

To sum up, it is evident that the fertility rates in the DPP villages, the winners of the election, exhibit a greater increase compared to the losers. The shifts above the median in Taiwan fail to capture new advocates for President Tsai. The plummet of the KMT votes did not proportionally transform into DPP's votes in each election as a result of a negative correlation between the shift and the DPP village. The deviations between the legislative and the presidential vote share shifts shown in Table 1 may reflect the strategy for voters to

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separate the powers. Notice that the vote share shift deviates in the DPP villages in 2020. Whether this leads to smaller partisan fertility needs more caution for future extensions to argue the DPP supporters would be less willing to give birth since the power is more separated.

3.3 Identification Strategy

3.3.1 DID Event Study

The DID event study method is chosen to identify and interpret partisan effects in the Taiwanese presidential elections with the following model specification:

$$Y_{vt} = \sum_{t=-3}^{t=8} \beta_t Treat_{vt} + \mathbf{x_{vt}}'\gamma_{\mathbf{vt}} + \delta_{\mathbf{v}} + \eta_{\mathbf{t}} + \epsilon_{\mathbf{vt}} \tag{3.1}$$

Here, Y_{vt} denotes the fertility rates in village v in t quarters after the election. The treatment variable $Treat_{vt}$ represents the DPP or the KMT complier, which is a dummy variable. The regression model includes village and time fixed effects (δ_v and η_t) to control for unobservable factors. Eventually, the $\mathbf{x_{vt}}$ are COVID or other controls. In this setup, one could analyze whether the partisan effect is long-term or not, or further argue that it could be delayed.

3.3.2 Synthetic Control

Apart from matching methods and the variant of DID called the DID event study, the synthetic control method provides another approach to estimating treatment effects. By constructing a *linear* combination of control groups the counterfactual outcomes of

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a treated group can be simulated. The underlying assumption in this method is that the control groups can closely mimic the treated unit's outcomes in the absence of treatment. By comparing the treated unit's actual outcome with the synthetic control outcome, the treatment effect can be observed.

To accommodate the thousands of villages in Taiwan, the generalized synthetic control framework introduced by Xu (2007) is employed for synthetic control estimation since the **gsynth** package developed by Xu and Liu is fast. The model specification for synthetic control can be represented as follows:

$$Y_{vt} = \sum_{t=-3}^{8} \beta_{vt} Treat_{vt} + \mathbf{x_{vt}}' \boldsymbol{\gamma_{vt}} + \boldsymbol{\delta_v} + \boldsymbol{\eta_t} + \boldsymbol{\epsilon_{vt}}, \tag{3.2}$$

where Y_{vt} is the outcome variable of interest for village v at time t, β_{vt} represents the treatment effect for village v at time t, $Treat_{vt}$ is the treatment indicator for village v at time t, $\mathbf{x_{vt}}$ is a vector of control variables for village v at time t, γ_{vt} denotes the coefficients of the control variables, δ_v captures village fixed effects, η_t represents time fixed effects, and ϵ_{vt} is the error term.

For simplicity, I omit the more generalized specification with time-variant factor loadings (Xu 2007), as the algorithm recommended no factor loadings being the best fit. Other variables in model (3.2) are the same as in model (3.1). Hence, the estimator of the average treatment effect of the treated (ATT) is

$$\frac{1}{N_{treated}} \times \sum_{v \in Treatment} (Y_{vt}(1) - \hat{Y}_{vt}(0)),$$

where v stands for village and t stands for quarter *or month*, N_{treated} is the number of treated villages, $Y_{vt}(1)$ is the actual outcome of village v at time t under treatment, and $\hat{Y}_{vt}(0)$ is

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the counterfactual outcome estimated in the absence of treatment. Note that, in order to estimate, one should have a time span long enough before the treatment date; otherwise, the estimation would fail as a consequence of lack of data[3]. Therefore, in 2016, switching to monthly analysis is required to obtain $\hat{ATT}$, while for the re-election in 2020, quarterly analysis is applied to provide less noisy estimates.

3.4 Matching

If the model specification (3.1) is correct, then I could argue that partisan fertility exists in Taiwanese presidential elections. However, from Figure 3.1, the deviations of excess fertility rate before the election in 2016 could suggest there could be some confounders missing in the model since no open birth data were available to prove the partisan fertility in 2008. Hence, I cannot reject the possibility of confounders. Matching data then becomes an approach to validate the evidence. To address the issues, Ho et al. (2007) suggested a semi-parametric or a non-parametric method to pre-process/match the treatment group. The goal is to create a dataset such that my treated group was matched with a control group with a resembling structure (i.e. the mean differences of the matched variables are close to zero).

Considering village demographics, The matching ratios, which are denoted as the number divided by every ten thousand village population), chosen for the treatment variable, the DPP villages, are the death ratio, the ratio of final degree above university, and the female population ratio from 15 years old to 65 years old. To avoid high computational costs, the nearest neighbor method is selected. Eventually, the matched datasets are

[3]https://github.com/xuyiqing/gsynth/issues/21

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constructed based on different margins of vote shares as treated groups. Other variable choices such as village-level electricity consumption and income tax could be introduced at the cost of more missing data.

In summary, the mean differences in matching ratios are almost zero in the pairs of the treatment and control groups. The distribution of *UnivRatio* accumulated at a lower speed than one in the KMT villages, implicating the DPP supporters have lower final education on average. The final education can associate with both the fertility rate and the preferences of parties. If more people with lower education level votes for the DPP, I cannot identify whether the increase in fertility is due to the partisan or the education associated with the vote share (treatment). This could be important when a researcher states an argument about a true mechanism, though not covered in this paper.

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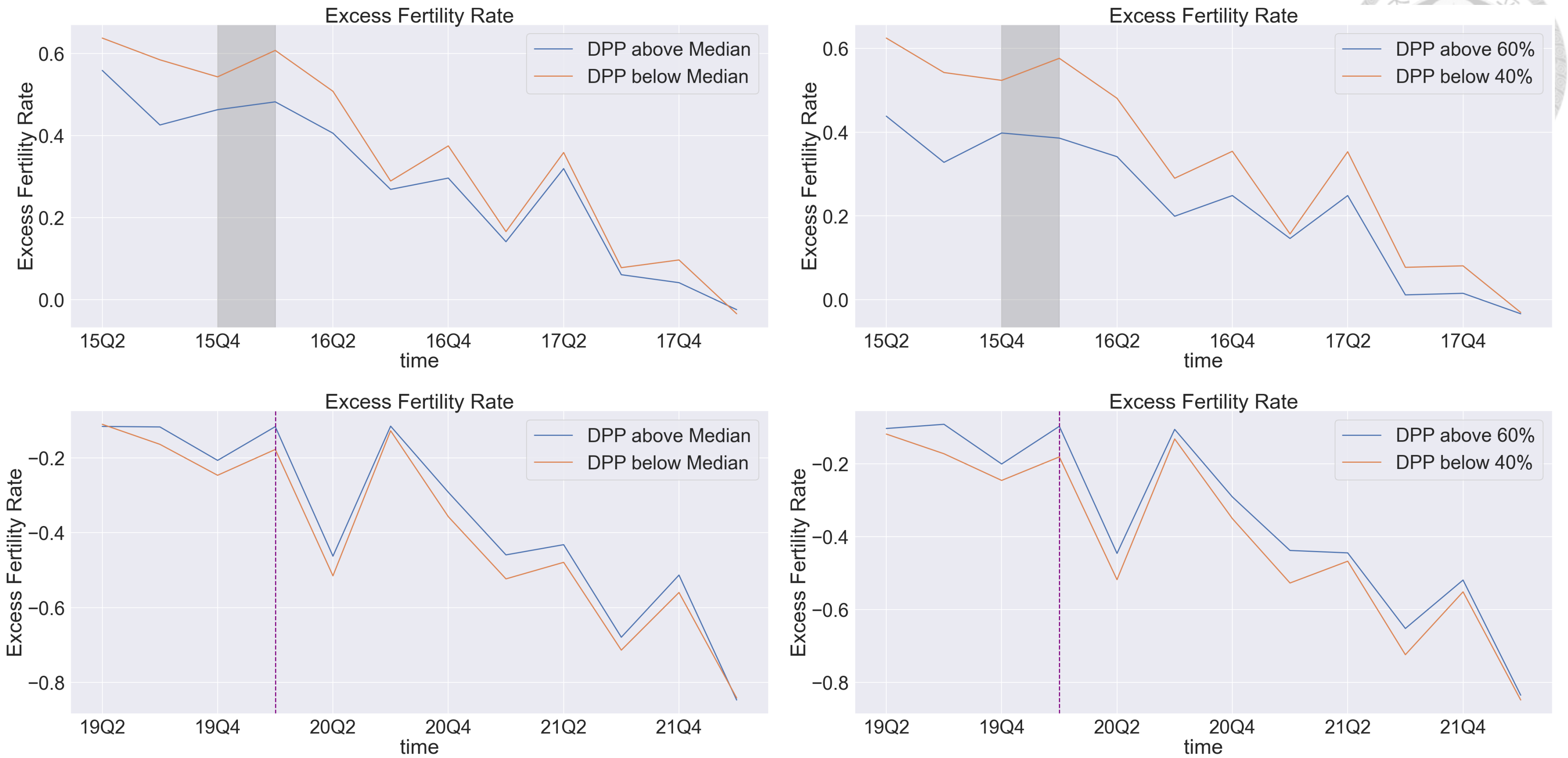

Figure 3.1: In the first row, the figure shows the general trend of the deseasonalized conception rate in DPP villages. In addition, the conception rate in the DPP village increases gradually. Note that, on the top right, the DPP High Shift equals one when both the vote share shift to the DPP (2016 vs. 2012) and the vote share are above the median. In the DPP's re-election, (C) and (D) show less evidence of the increases in conception rates.

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Figure 3.2: This Figure shows the general trend with matched data using (above) the median and 60% in the previous election as treatment variables.

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Table 3.1: Summary Statistics

Time	2012			2016			2020		
Village Demographics	median	mean	std	median	mean	std	median	mean	std
FemalePop1544	-	-	-	1,358	1,948	1,830	1,300	1,867	1,807
FemalePop1565	-	-	-	2,371	3,363	3,056	2,357	3,338	3,135
N(Household)	-	-	-	2,311	3,266	2,909	2,457	3,469	3,179
Population	-	-	-	6,649	9,025	7,708	6,707	9,171	8,119
Fertility Rate	-	-	-	2.92	3.10	2.14	2.39	2.61	2.04
Election Data	median	mean	std	median	mean	std	median	mean	std
DPPVoteShare (Party)	35.70	35.99	11.16	45.36	44.68	14.06	35.38	35.13	9.85
DPPVS (President)	47.05	47.95	14.10	57.80	55.39	13.32	58.52	56.78	12.14
KMTVS (Party))	42.98	43.80	12.03	26.27	27.50	9.82	32.46	34.58	11.12
KMTVS (President)	49.17	50.18	13.75	29.01	30.60	10.68	37.17	39.20	11.94
DPPVS Shift (Party)	-	-	-	9.19	9.10	3.52	-9.63	-9.80	4.02
DPPVS Shift (President)	-	-	-	9.84	9.50	3.12	0.56	0.28	3.43
KMTVS Shift (Party)	-	-	-	-16.45	-16.41	4.87	6.47	7.20	4.13
KMTVS Shift (President)	-	-	-	-19.66	-19.61	4.92	8.63	7.75	4.61

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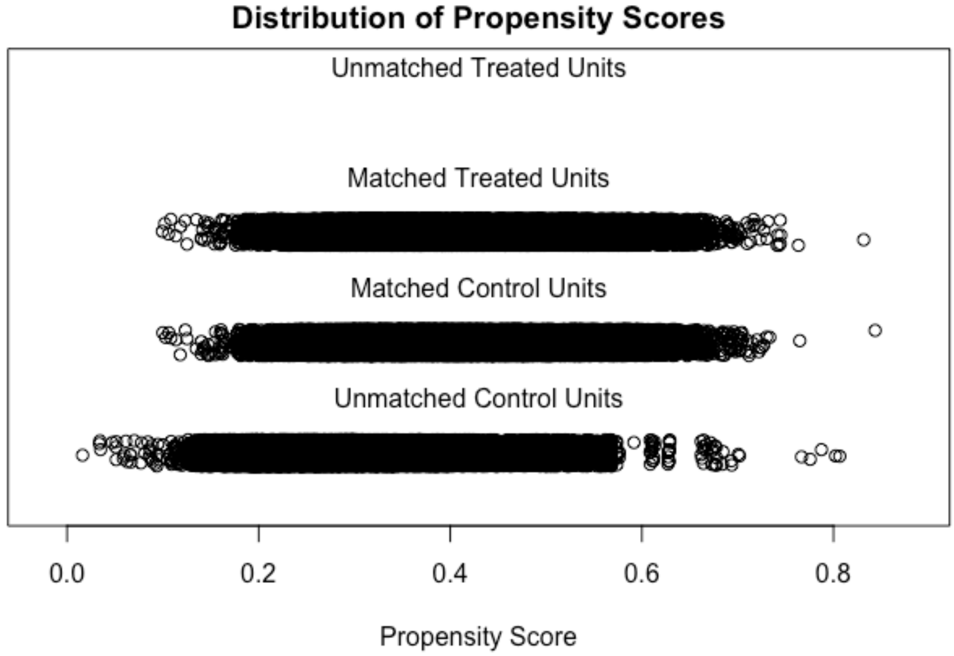

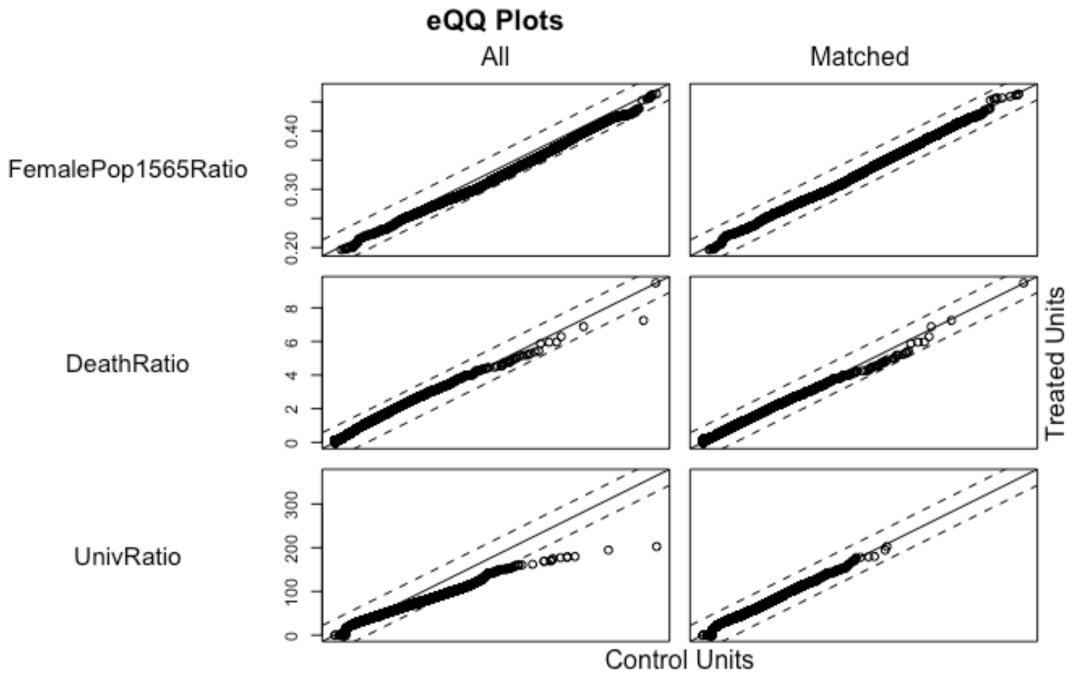

Figure 3.3: The first plot shows that there are no unmatched treatment units. Every treated village is paired with a controlled village. In the second plot, the cumulative CDF in the matched data has interpretations of similar distributions in each ratio. Note that *Female-Pop1565Ratio* denotes the female population ratio from 15 years old to 65 years old for every ten thousand people, incorporating both females with fertility and the age distribution within a village.

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Chapter 4 Results

Before diving into the estimates, what are the possible reasons for fertility differences by partisanship? In Taiwan, they could be different national identities (the People's Republic of China vs. the Republic of China), distinguishable expectations of the economy, etc. The TEDS offers abundant periods of data for those aspects and the participants' characteristics and political affiliations. Still, discovering partisan fertility is not sufficient to claim the true mechanism. In terms of the limitation, I do not claim any true mechanism in this paper, only providing the trend of economic evaluation for each party in Appendix A. There may be attenuation (downward) bias in the estimates. If people decide to give birth, they must not be capable of doing that again right after the pregnancy.

4.1 DID Event Study

To analyze results in 2016, I argue that some potential treatments before the 2016 election, such as the controversial replacement of the presidential candidate from the Kuomintang (KMT) and the inclusion of a new candidate from the People First Party (PFP) in the second half of 2015 would impact the estimates (shaded area in Figure 3.1 & 3.2). These events significantly affected the odds of the KMT and, assuming rational voters adjust their expectations based on media poll rates, the partisan effect could be ob-

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served before the election. Hence, I also set the treatment date in 2015Q4 to run the same specifications.

The results are presented in Table 4.1 $\sim$ 4.3 and Figure 4.1 $\sim$ 4.3. First, on the top of Figure 4.1, only extreme DPP villages won by 60% accompanied by a significant estimate. In the second row, the coefficients are negative mostly before and after 2016Q1. Hence, I consider another treatment date setting that is one-quarter earlier in Figure 4.2. Note that since the matching method is conducted at a cost of efficiency, the estimates become volatile, especially for extreme DPP villages. Second, Figure 4.2 shows more evidence of partisan fertility in a transition of power, except for the DPP 60% match. The direction is counter-intuitive and the number of observations is small.

For President Tsai's re-election in 2020, only some DPP villages using matched data have a positive partisan effect, and most of them are still insignificant. However, the re-election may deteriorate the losers' expectations by making them more pessimistic, as the results show that the effects are negative. However, if I use the shift of DPP's party vote share above the median in this case in DPP villages (DPP Median), a short-term positive effect is captured in the matching data. Considering the voter shift as Dahl et al. have done, the legislative party vote share shift could capture the positive correlation with the DPP identifier, whereas the presidential votes have a negative one. The latter might indicate the influence of the non-partisans. The short-term partisan effect is observed in the shift.

In terms of assuring the validity of these regressions, I apply a falsification test to check the robustness of my results by transforming the outcome variable to one year earlier. The treatment variable is set as the DPP median. In the last column from Table 4.1 to 4.3, the existence of partisan fertility is supported since there is no repeated significance

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with the same direction, at least for the excess fertility before the real treatment date.

In brief, in the 2016 presidential election, different vote share cutoffs and treatment variables have been examined to explore whether more polarized villages have partisan effects more often. In addition, Figure 3.1 interprets the larger gap may be attributed to more polarized areas. In Figure 4.1, this insignificant outcome can be attributed to the participation of the People First Party (PFP) in the election or the replacement of the KMT candidate. Voters should have adjusted their predictions in response to other voters choosing not to support the KMT party due to the replacement of the original candidate in 2016. Thus, they would make fertility decisions based on the adjustment of odds. On the other hand, as indicated in Figures 4.2 and 4.3, the results may recommend partisan effects for the winner, the DPP, although the re-elected effect is smaller. Lastly, the falsification tests suggest the results might not come from coincidences.

4.2 Synthetic Control

Applying model (3.2), monthly basis estimation for 2016 and quarterly basis for 2020 are conducted with standard two-way fixed effects. The number decided for bootstrapping is 1,000. In addition, control variables are the same as those used in the matching method. Similar to the event study, the treatment date of 2015Q4 is set. For simplicity, I show only the results from the 60% DPP identifier.

Figure 4.4∼4.6 shows the trend of excess fertility and the estimated average treatment effect of the treated (ATT) in Taiwan. In general, partisan fertility exists, but the re-election effect appears to be relatively small. To address data limitations, I use monthly data for 2015Q4 and 2016, allowing for sufficient observations for pre-treatment periods

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and ensuring convergence in the synthetic control approach. Figures 4.4 and 4.5 demonstrate that DPP villages exhibit a higher willingness to give birth. The initial insignificant coefficients may be attributed to the noise in the monthly data. In terms of the scale of the ATTs, the estimates are 0.093, 0.106, and 0.008 if the treatment dates are 2016Q1, 2015Q4, and 2020Q1.

Beyond the ATT, researchers may be more interested in examining the cumulative partisan effect since a *perfect* control group does not exist; everyone is affected by the election results. It is plausible that election losers might be less inclined to have children, while winners might be more motivated to do so. This might be valid if the true mechanism is economic evaluation as Figure A.1 and Appendix A show. To ascertain that winners have a greater propensity to give birth compared to *nothing happens*, a larger partisan effect is necessary. Consequently, I calculate the cumulative ATT over two years. During the transition of power, the 2-year cumulative ATTs are 0.55 (0.67) when the treatment dates are 2016Q1 and 2015Q4, respectively. In contrast, the 2-year cumulative ATT is 0.09 in the case of re-election. Specifically, the DPP villages, on average, exhibit 0.55, 0.67, and 0.09 more births per 1,000 women two years after the election, compared to villages with a DPP vote share of less than 60

In conclusion, the partisan fertility effect in Taiwan is more pronounced during the transition of power. The re-elected partisan effect may only be short-term, as indicated in the last graph in Figure 4.3. The synthetic control approach does not support a significant partisan effect in 2020.

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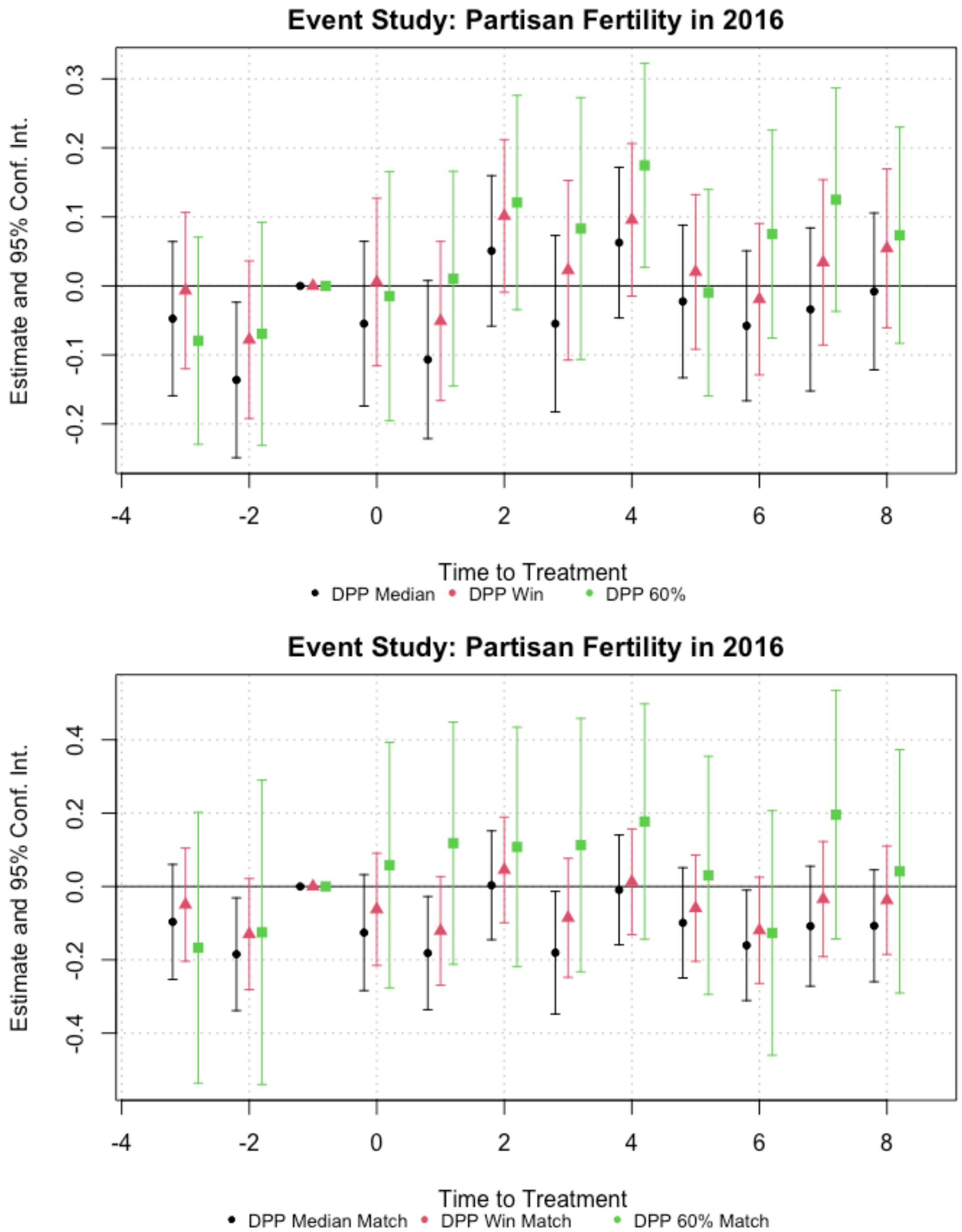

Figure 4.1: DPP Median, DPP Win, and DPP 60% stand for vote share above median, 50%, and above 60%. To those adding *Match* at the end, the matched data discussed in section 3.4 is used. When the treatment date is set in 2016Q1, negative estimates exist because of the potential treatment such as the replacement of the KMT candidate leading to a decrease in poll rates in October 2015.

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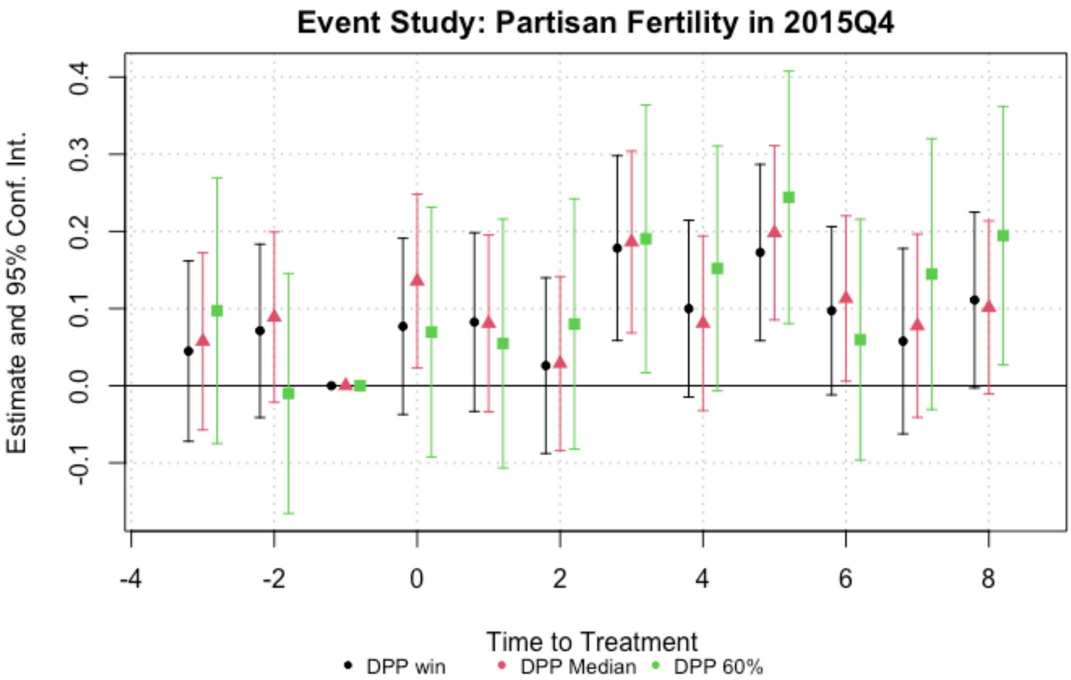

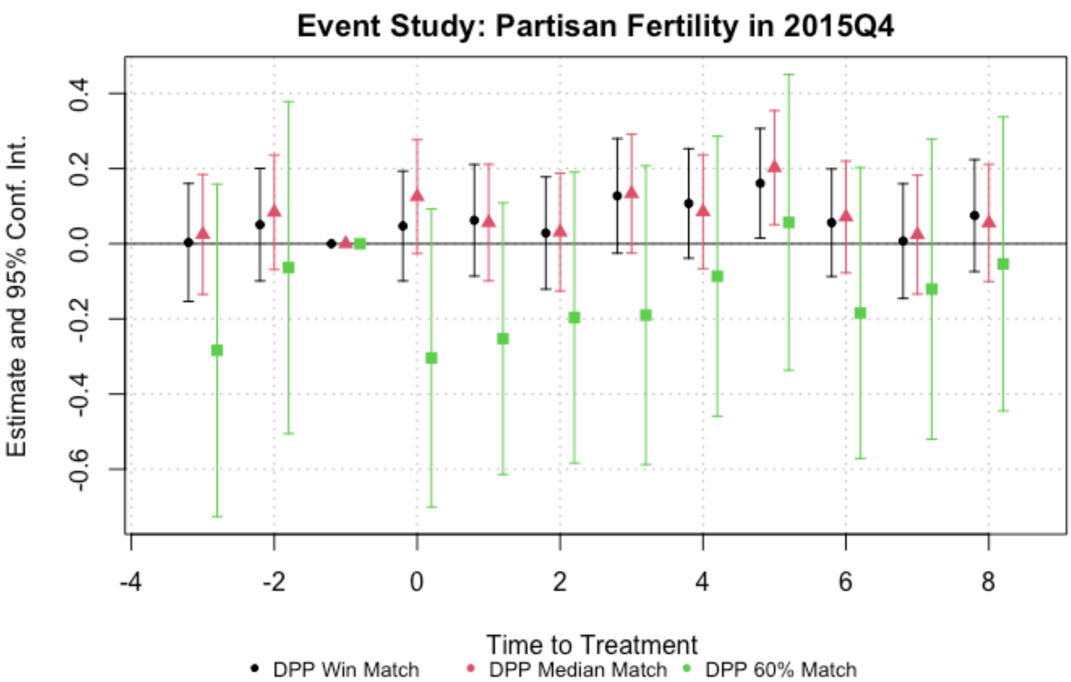

Figure 4.2: Given another treatment date to incorporate earlier treatments (i.e. the original candidate from the KMT substituted and the participation of the PFP), both DID event studies with or without matching offer the same evidence — the existence of partisan fertility.

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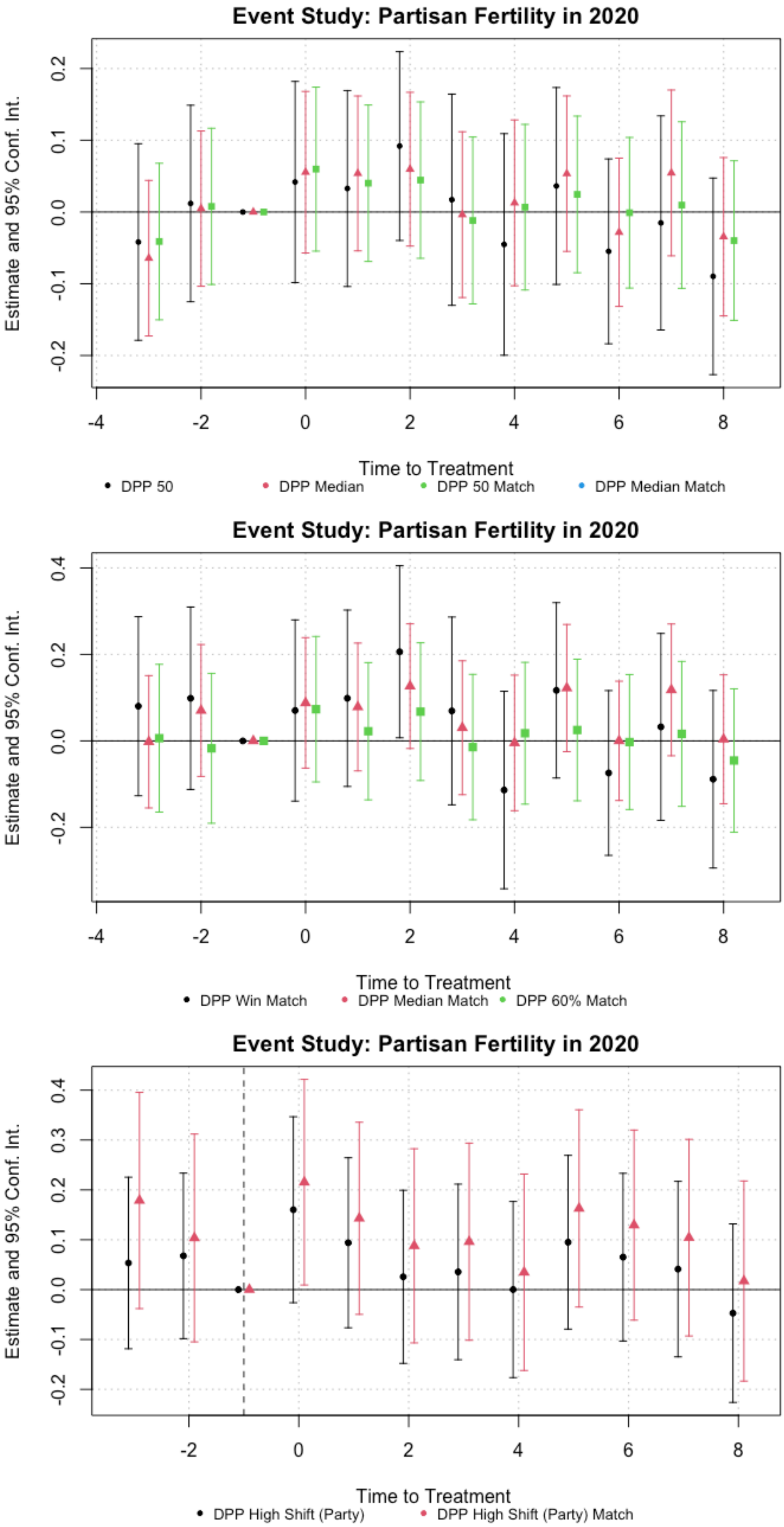

Figure 4.3

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Table 4.1: 2016 Partisan Fertility

	DPP median (1)	DPP win (2)	DPP 60% (3)	DPP median match (4)	DPP win match (5)	DPP 60% match (6)	Falsification test last-year fertility (7)
$Treat_{-3}$	−0.047	−0.007	−0.079	−0.097	−0.050	−0.167	−0.017
	(0.057)	(0.058)	(0.077)	(0.080)	(0.079)	(0.188)	(0.058)
$Treat_{-2}$	−0.136**	−0.078	−0.069	−0.185**	−0.130*	−0.125	−0.015
	(0.057)	(0.058)	(0.083)	(0.078)	(0.077)	(0.212)	(0.056)
$Treat_0$	−0.055	0.006	−0.015	−0.126	−0.062	0.058	−0.029
	(0.061)	(0.062)	(0.092)	(0.081)	(0.078)	(0.171)	(0.060)
$Treat_1$	−0.107*	−0.051	0.011	−0.182**	−0.121	0.118	0.029
	(0.058)	(0.059)	(0.079)	(0.079)	(0.076)	(0.168)	(0.058)
$Treat_2$	0.051	0.101*	0.121	0.003	0.045	0.108	−0.090
	(0.056)	(0.056)	(0.079)	(0.076)	(0.073)	(0.167)	(0.058)
$Treat_3$	−0.055	0.023	0.083	−0.181**	−0.086	0.113	0.081
	(0.065)	(0.066)	(0.097)	(0.085)	(0.083)	(0.176)	(0.062)
$Treat_4$	0.063	0.096*	0.175**	−0.009	0.013	0.177	0.000
	(0.056)	(0.056)	(0.075)	(0.076)	(0.074)	(0.164)	(0.062)
$Treat_5$	−0.023	0.020	−0.010	−0.099	−0.059	0.030	−0.027
	(0.056)	(0.057)	(0.076)	(0.077)	(0.074)	(0.166)	(0.058)
$Treat_6$	−0.058	−0.019	0.075	−0.161**	−0.120	−0.127	0.123**
	(0.055)	(0.056)	(0.077)	(0.077)	(0.074)	(0.170)	(0.057)
$Treat_7$	−0.034	0.034	0.125	−0.108	−0.034	0.196	0.012
	(0.060)	(0.061)	(0.083)	(0.083)	(0.080)	(0.173)	(0.065)
$Treat_8$	−0.008	0.054	0.073	−0.107	−0.037	0.041	0.115**
	(0.058)	(0.059)	(0.080)	(0.078)	(0.075)	(0.169)	(0.057)
Num.Obs.	91 202	91 202	91 202	68 294	68 294	24 116	91 202
R2	0.090	0.090	0.089	0.089	0.089	0.089	0.091
FE: location	Y	Y	Y	Y	Y	Y	Y
FE: Quarter	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: All standard errors are clustered by village name. Control variables are FemalePop1565, DeathRatio, and UnivRatio, mentioned in the matching section.

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Table 4.2: 2015Q4 Partisan Fertility

	DPP win	DPP median	DPP 60%	DPP win match	DPP median match	DPP 60% match	Falsification test last-year fertility
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Treat_{-3}$	0.045	0.058	0.097	0.003	0.025	−0.284	0.086**
	(0.060)	(0.059)	(0.088)	(0.080)	(0.081)	(0.226)	(0.041)
$Treat_{-2}$	0.071	0.089	−0.010	0.051	0.084	−0.063	−0.002
	(0.057)	(0.056)	(0.079)	(0.076)	(0.078)	(0.225)	(0.056)
$Treat_0$	0.077	0.136**	0.070	0.047	0.125	−0.304	0.016
	(0.058)	(0.057)	(0.083)	(0.075)	(0.077)	(0.202)	(0.056)
$Treat_1$	0.082	0.081	0.055	0.062	0.056	−0.253	−0.013
	(0.059)	(0.058)	(0.082)	(0.076)	(0.079)	(0.184)	(0.059)
$Treat_2$	0.026	0.029	0.080	0.028	0.031	−0.196	0.045
	(0.058)	(0.057)	(0.083)	(0.076)	(0.080)	(0.197)	(0.057)
$Treat_3$	0.178***	0.186***	0.190**	0.127	0.133*	−0.190	−0.074
	(0.061)	(0.060)	(0.089)	(0.078)	(0.081)	(0.203)	(0.061)
$Treat_4$	0.100*	0.081	0.152*	0.107	0.085	−0.087	0.096
	(0.058)	(0.058)	(0.081)	(0.074)	(0.077)	(0.190)	(0.058)
$Treat_5$	0.173***	0.198***	0.244***	0.161**	0.202***	0.057	0.016
	(0.058)	(0.058)	(0.083)	(0.074)	(0.077)	(0.201)	(0.059)
$Treat_6$	0.097*	0.113**	0.060	0.056	0.071	−0.184	−0.011
	(0.056)	(0.055)	(0.080)	(0.073)	(0.076)	(0.197)	(0.058)
$Treat_7$	0.058	0.078	0.145	0.007	0.024	−0.121	0.138**
	(0.061)	(0.061)	(0.090)	(0.078)	(0.081)	(0.204)	(0.060)
$Treat_8$	0.111*	0.101*	0.195**	0.075	0.055	−0.054	0.028
	(0.058)	(0.057)	(0.085)	(0.076)	(0.079)	(0.199)	(0.059)
Num.Obs.	91 126	91 126	91 126	68 294	68 294	24 116	91 126
R2	0.094	0.094	0.094	0.092	0.092	0.092	0.096
FE: location	Y	Y	Y	Y	Y	Y	Y
FE: Quarter	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: All standard errors are clustered by village name. Control variables are FemalePop1565, DeathRatio, and UnivRatio, mentioned in the matching section.

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Table 4.3: 2020 Partisan Fertility

	DPP win	DPP median	DPP 60%	DPP win match	DPP median match	DPP 60% match	Falsification test last-year fertility
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Treat_{-3}$	−0.042	−0.064	−0.041	0.080	−0.002	0.006	0.002
	(0.070)	(0.055)	(0.056)	(0.106)	(0.078)	(0.087)	(0.058)
$Treat_{-2}$	0.012	0.005	0.008	0.099	0.070	−0.017	0.033
	(0.070)	(0.055)	(0.056)	(0.108)	(0.078)	(0.088)	(0.058)
$Treat_0$	0.042	0.055	0.060	0.070	0.088	0.073	0.049
	(0.072)	(0.057)	(0.058)	(0.107)	(0.077)	(0.086)	(0.061)
$Treat_1$	0.033	0.054	0.040	0.099	0.078	0.022	−0.006
	(0.070)	(0.055)	(0.056)	(0.104)	(0.075)	(0.081)	(0.061)
$Treat_2$	0.092	0.060	0.044	0.206**	0.127*	0.068	0.057
	(0.067)	(0.055)	(0.056)	(0.102)	(0.074)	(0.081)	(0.060)
$Treat_3$	0.017	−0.004	−0.012	0.069	0.030	−0.014	0.043
	(0.075)	(0.059)	(0.059)	(0.111)	(0.079)	(0.086)	(0.062)
$Treat_4$	−0.045	0.013	0.007	−0.114	−0.005	0.018	0.100*
	(0.079)	(0.059)	(0.059)	(0.117)	(0.080)	(0.084)	(0.060)
$Treat_5$	0.036	0.053	0.025	0.117	0.122	0.025	0.116**
	(0.070)	(0.055)	(0.056)	(0.103)	(0.075)	(0.084)	(0.058)
$Treat_6$	−0.055	−0.028	−0.001	−0.074	0.000	−0.003	0.116**
	(0.066)	(0.053)	(0.054)	(0.097)	(0.070)	(0.080)	(0.059)
$Treat_7$	−0.015	0.054	0.010	0.032	0.118	0.016	0.048
	(0.076)	(0.059)	(0.059)	(0.110)	(0.078)	(0.086)	(0.062)
$Treat_8$	−0.090	−0.034	−0.040	−0.089	0.004	−0.045	0.058
	(0.070)	(0.056)	(0.057)	(0.105)	(0.076)	(0.085)	(0.064)
Num.Obs.	91 717	91 717	91 717	68 678	68 678	58 464	91 717
R2	0.101	0.101	0.101	0.113	0.113	0.113	0.086
FE: location	Y	Y	Y	Y	Y	Y	Y
FE: Quarter	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: All standard errors are clustered by village name. In general, the re-election in 2020 had some short-term partisan fertility. For the falsification test, the positive and significant estimates validate larger fertility rates in the treated group (DPP median), since the one-year earlier fertility rate in $Treat_4$ is the same as $Treat_0$ in column (2)'s dependent variable. Control variables are FemalePop1565, DeathRatio, and UnivRatio, mentioned in the matching section.

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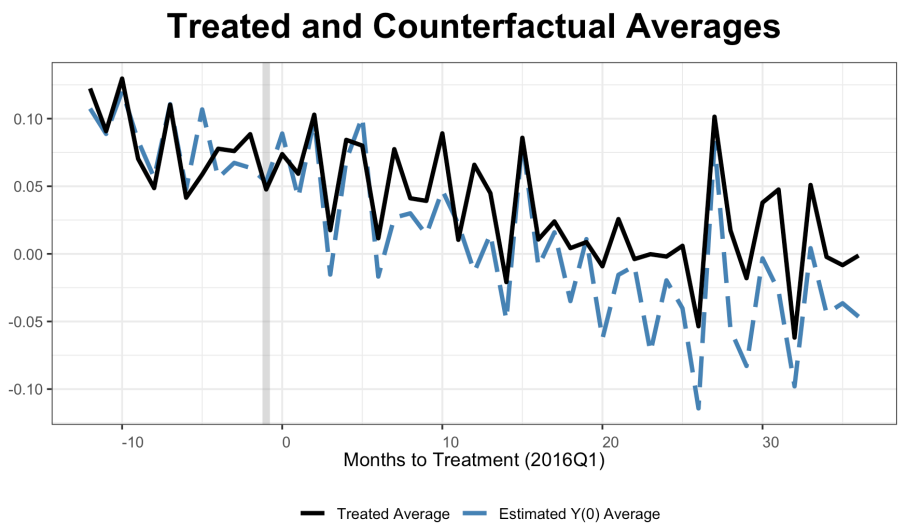

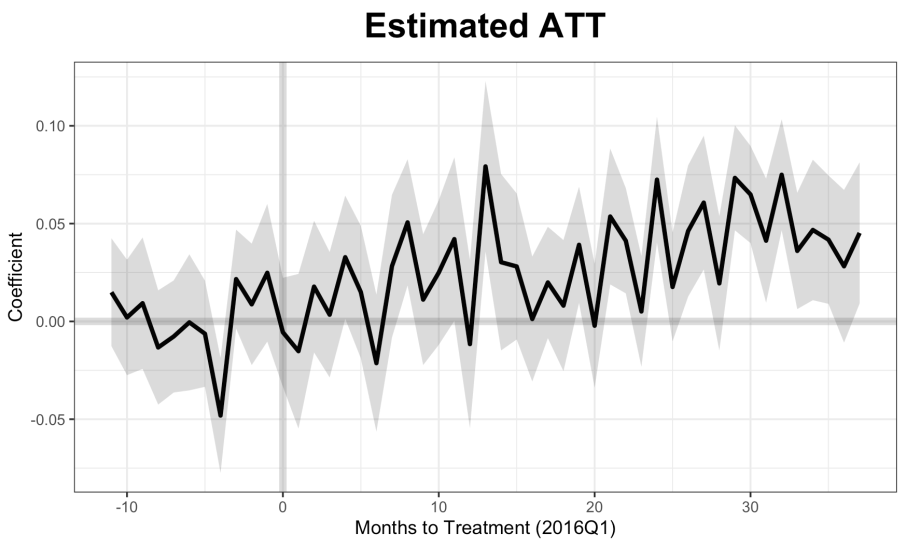

Figure 4.4: By the general synthetic control method, the counterfactual trend of the DPP villages is estimated, which is how the excess fertility should be when the vote share is less than 60%. Over time, the partisan effect (ATT) is larger, particularly in roughly 30 months after the election. Different from the results from the DiD event study, the ATT is larger when the treatment date is 2016Q1.

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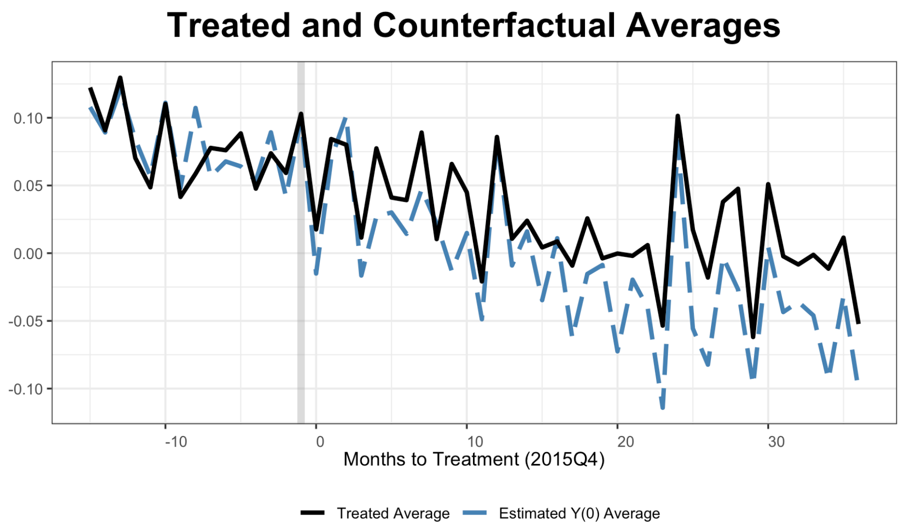

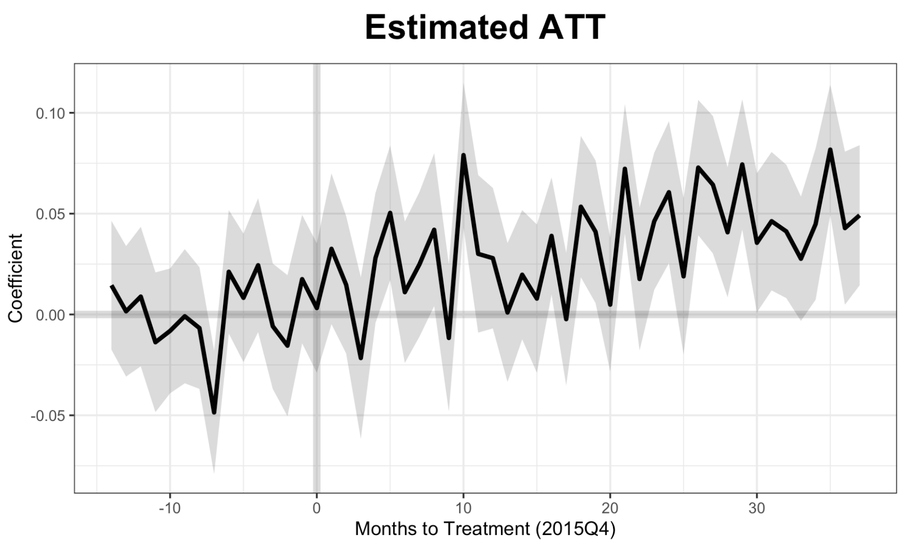

Figure 4.5: In general, the results are similar with Figure 4.4, but the estimates are more significant.

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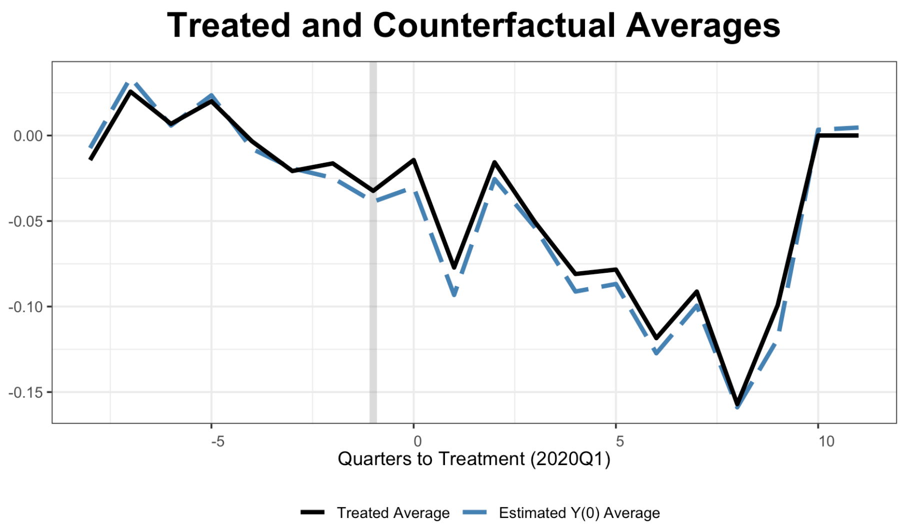

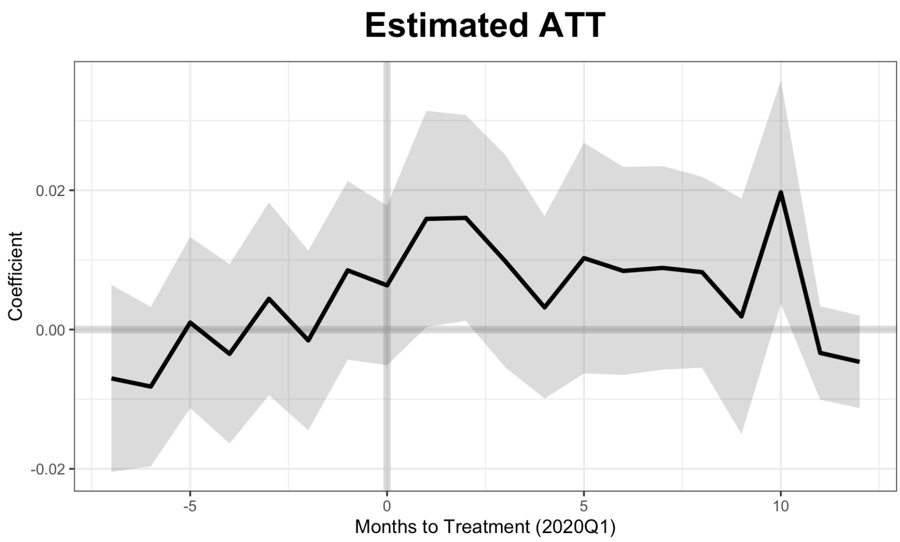

Figure 4.6: Although the estimates are mostly positive after the election, the scale of the ATT is slight.

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Chapter 5 Conclusion and Discussion

This paper supports the perspective of partisans as a determinant of fertility. As Dahl et al. suggested, in the transition of power, the partisan effect in Taiwan is also economically significant. The DiD event study method shows that the average treatment effect on the treated equals $0.111(0.132)$ in the transition of power using the DPP median (60%) treatment variable. In addition, the basic falsification tests provide some validity in this thesis by distinguishable estimates before the treatment occurred. Moreover, the matching method provides similar estimates. Eventually, the quarterly ATTs for the synthetic control approach are 0.093, 0.106, and 0.008, and the two-year cumulative ATTs are 0.55, 0.67, and 0.09 if the treatment dates are 2016Q1, 2015Q4, and 2020Q1.

Different from what had been discovered in the US, the shifts to DPP's president vote share fail to capture new DPP supporters. Instead, it appears that the party vote shares in the legislative election in 2020 would correspond to the same correlation. Thus, researchers might need to devote more effort to non-partisans' voting strategy in Taiwanese elections, since the proportion of swing voters rose substantially from 2002 to 2017 (Wang 2019). One extension of this research can investigate what the partisan effects are in this type of political polarization. Another direction can focus on the identification of a true mechanism. (Huang, C. 2018) argued that partisan bias in economic assessments existed in the presidential election before and after 2016 using a panel survey.

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How the pandemic would affect fertile decisions may need a more sophisticated model, as linear COVID cases and death rates estimator in each city do not explain any variation after 2020. In addition, introducing matching variables like village electricity consumption may also decrease selection bias. On the other hand, the synthetic control method is also capable of identifying partisan effects by simulating the counterfactual outcomes of the treatment group not being treated.

Future research in this area could explore the partisan fertility within the context of this political polarization, delving into the mechanisms that underlie such effects. For instance, one avenue for investigation could be to examine the extent of partisan bias in economic assessments during presidential elections, both pre-and post-2016, utilizing the TEDS projects as demonstrated by Huang (2018). Another focus could be the *negative* partisanship in Taiwan, as many of the non-partisans dislike the DPP and the KMT at the same time. It is intriguing to ask what non-partisans' fertile decision would be affected by the elections. In this paper, I use presidential vote share trying to identify a DPP village. To include the inclination of voting (voter turnout rates), the total votes divided by the total valid votes might be able to reflect the actions from the non-partisans since they might vote a less dislike party for a new president to avoid a worse one.

It is important to acknowledge the potential interference of significant events prior to 2016, which may have impacted the causal inference. Finally, this paper contributes to the evidence of partisan fertility, especially in the transition of power, shedding light on one step toward understanding non-partisans' fertility choices in relation to elections and identifying the true mechanisms through which voters contemplate having new children.

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Appendix A — Mechanism

Understanding the true mechanism of how voters make their decisions is a fascinating endeavor. There are numerous factors that may influence voter choices, including equity, economy, sovereignty (especially in Taiwan), and others. In the Appendix, I aim to depict the trend of partisan voters' economic evaluations from 2012 to 2023. It is important to note that some periods have missing values due to data formatting issues, and time constraints limit our ability to address these problems.

Economic Evaluation

The TEDS (2012~2023) provides valuable and consistent quarterly survey data on how people assess the performance of the incumbency and their political affiliations. The survey covers various topics related to the nation, such as national defense and diplomacy, as well as personal characteristics of the president, such as leadership. Huang (2018) argue that partisan bias in economic evaluations exists.

If partisan economic assessments are one of the true mechanisms, voters should be influenced by election results, and their economic assessments should adjust accordingly. In Figure A.1, the survey questions are: "Compared to the economy six months ago, is the current economy better, worse, or unchanged?" and "What do you expect about economic

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conditions in the next six months, better, worse, or unchanged?” I define ”net better” as the mean score of economic evaluation, with +1 indicating better, -1 indicating worse, and 0 for other responses (indifferent, no opinions, etc.). Notably, there are only a few instances of no opinions and refusals to answer, and several missing values exist after 2017.

The figure reveals interesting patterns. For instance, in 2016Q1, the net better of current economic evaluations increased, despite the DPP taking office in May 2016 (2016Q2). Moreover, a deviation in economic assessments occurred in 2014Q4, when the DPP won most of the regional mayoral elections. In addition, the pandemic has different influences between current and future economic evaluation.

In conclusion, voters who support the winning party tend to change their economic evaluations instantly and expect a better economy before the election. These findings shed light on how partisan biases might influence economic perceptions and family planning decisions among voters.

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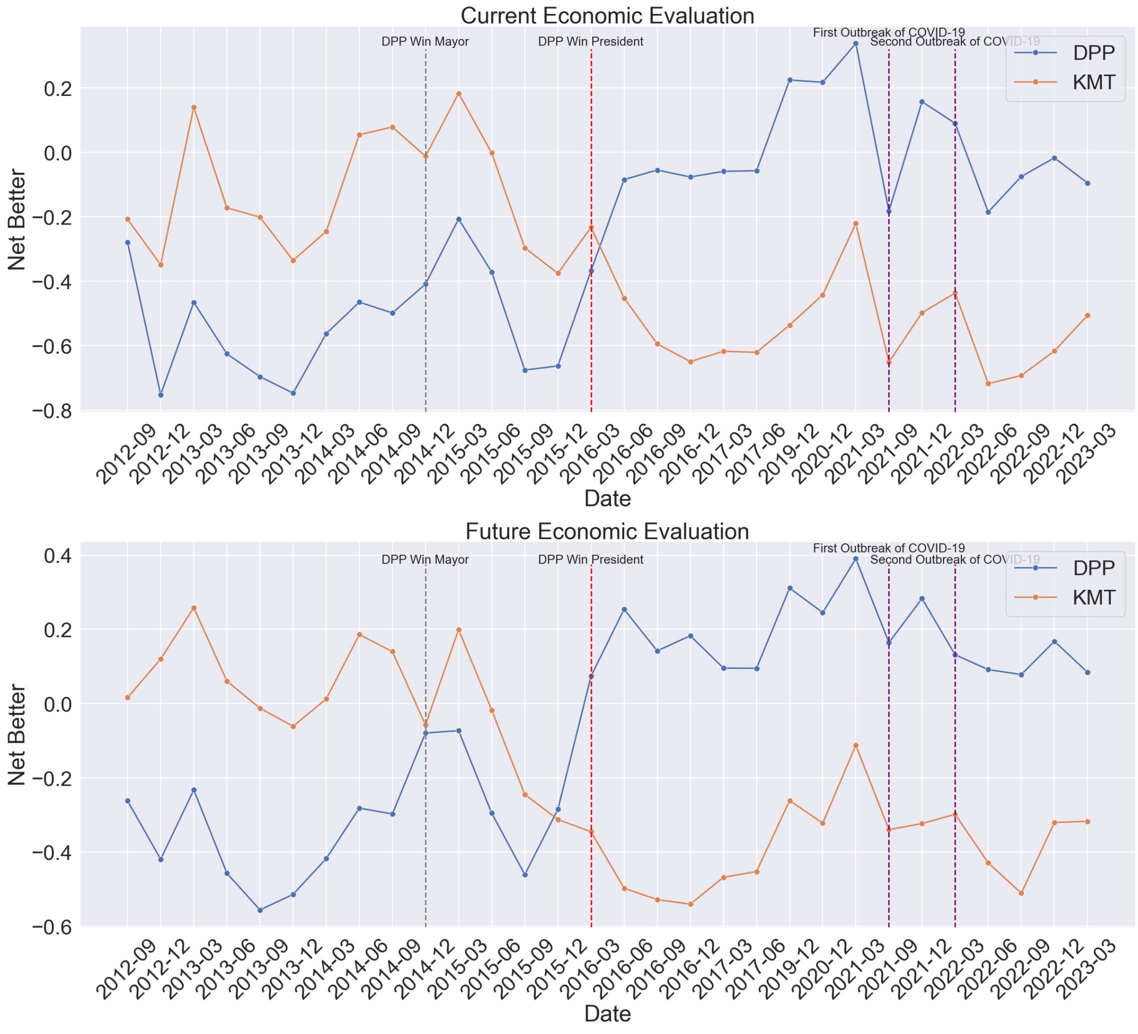

Figure A.1: The economic evaluations change right after the election in 2016. Notice that the re-election has missing values. There is no observations in 2020Q1 due to time limitation and incorrect data formats.

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