THREE ESSAYS ON PEER EFFECTS AND APPLICATIONS IN ENVIRONMENTAL ECONOMICS AND FAMILY ECONOMICS

by

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To my parents and grandparents

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ABSTRACT

This dissertation focuses on analyzing peer effects in household decisions and the diffusion of renewable energy. The first chapter investigates peer effects in two family planning decisions among Chinese households – having a second child and having a son. The second chapter focuses on evaluating environmental policies (tax credit and Corporate Average Fuel Economy standard) on the diffusion of electric vehicles in the US. And the third chapter analyzes peer effects in residential solar panels adoption with a geographic focus on California. In summary, the first and third chapter adopt two structural peer effects models to analyze household behavior under two distinct decision-making context – family planning and solar panels adoption. And the second and third chapter focuses the diffusion of two renewable energy powered products – electric vehicle and solar panels.

Peer effect measures how much the decision made by an agent (usually refers to an household in this dissertation) is influenced by peers' decisions under the same decision context. Manski (1993) summarizes the obstacles in identifying peer effects. The first is to separate peer effects with contextual effects, or how much the observed similarity in decision making among peer group members are attributed to similar backgrounds between peers due to endogenous group formation. The second is to separate peer effects with correlated effects, which refers to unobserved household characteristics and are believed to be correlated with each other. We use static and dynamic structural peer effects models to analyze family planning decisions and solar panels adoption decision separately, and these models are capable of disentangling the difficulties mentioned above. For the demand estimation of electric vehicle, we use a random coefficient model which has been broadly used in industrial organization.

The first chapter is motivated by the increasingly unbalanced sex ratio in China. This phenomenon and associated social challenges have been widely documented, though few studies have rigorously investigated the role that peer effects have played in this unbalanced sex ratio. This paper fills this gap by focusing on peer effects in the decision to have a second child, and to have a son. The data we use comes from the 2016 data of China Family Panel Studies, and is a ten-year cohort of women aged 45-54 by 2016; we use a structural discrete choice model to estimate the peer effects. We find that peer choices significantly

influence the probability that a family has a second child, but not the probability of having a son. Instead, having a son is largely driven by contextual effects, and in particular, by the education level of one's peer group.

The second chapter uses the random coefficient model with post-estimation counterfactual analysis to answer two research questions: (1) How much the tax credit has facilitated the diffusion of EV; (2) How much the CAFE standard and penalty level have facilitated the diffusion of EV. We obtain the data from WardsAuto with a years range from 2012 to 2019. We find that the EV market share will decrease by 35.82% if there is no tax credit. CAFE marks down the price of EV in average by 3.4 percent but marks up the price of other types of vehicles by 3.26 percent, whose absolute value far exceeds the CAFE penalty itself. We also find that increasing the penalty level from $55 to $140 per vehicle per mpg below the standard will only increase the EV market share by 0.23% and decrease the non-EV market share by 0.12%.

The third chapter applies a utility-based structural optimal stopping time model developed by de Paula (2009) to analyze solar PV adoption. We use both econometrics model and nonparametric test to support the evidence of peer effects, using public solar PV data obstained from CaliforniaDGStats. And we apply the optimal stopping time model with a confidential data set obtained from PG&E. We find significant peer effects and correlated effects in a case study which contains 20 non-adjacent communities in the suburb of San Jose. And we predicted the adoption rate in this area will increase from 19.77% in 2019 to 39.65% in 2029.

1. INTRODUCTION

1.1 Identification of peer effects

Agents (usually refers to an household in this dissertation, henceforward households) within a peer group behave similarly under some circumstances. To explain in an economics perspective, households make decisions not only based on their own characteristics, but also their peers' performances and characteristics. Manski (1993) calls the effects sourced from a household's own characteristics “exogenous effects”, such as age and education of this household members themselves. And Manski (1993) names the impact from peers' behaviors as “peer effects”. Peer effect measures how much the decision made by a household is influenced by peers' decisions under the same decision context. In the fertility story this dissertation analyzes, the family planning decision faced by each household is whether to have a second child during the reproductive age. Peer effects in this case are measured as: if more peers from the same age cohort of this household are expected to have a second child, how it increases the probability that this household is going to have a second child. If there is no peer effects, this probability should not change by the expected outcome of their peers behaviors, ceteris paribus.

However, peer effects are not that easy to identify. Under a perfect experimental setting, we can randomly assign peers and attribute the behavioral similarity to peer effects. However, empirically, households do not become peers randomly. To be clear, the observed phenomenon that households behave similarly may not be purely because households intend to catch up with the expected behavior of their peers, but could be because they share similar background – one of the reasons they become peers – and happen to make similar decisions under the same context. To give an example, highly educated couples are less likely to have a second child for many reasons. Suppose we observe a household has a single child by the end of the wife's reproductive age (set as 45 in this dissertation) and many of its highly educated peers also have a single child. Part of the reason could be this household does not want to deviate from their peers' behaviors (we find evidence for this). But it also could be the case that their highly educated peers influence their family planning preference through other channels aside from the behavior directly, which motives this household to have a single child in the end (we find evidence for this too). Manski (1993) names the effect sourced from peers' characteristics as "contextual effects". For obvious colinearity reasons, we need to exclude the household itself when we form the contextual effects controls.

Unfortunately, not all peers' characteristics are observable to economists. For example, exogenous and contextual controls such as education and occupation are available in the fertility and son preference chapter, but important factors which could lead to similar behaviors such as social norm are not observable by economists. Manski (1993) calls it "correlated effect". Empirically, correlated effects are controlled using two approaches. One is adding rich fixed effects (e.g., Bollinger and Gillingham 2012). For example, the Chinese social norm of "the more the merrier" in child bearing is a common social nudge for every household, and the magnitude is heterogeneous across different regions. We add provincial and county level fixed effects – depending whether peer group is defined in a county or community level – to control the social norm and other unobserved characteristics which are highly correlated between peers. Another approach usually involves simulations by assuming the unobserved characteristics follows a random distribution but are allowed to be correlated across peers through a correlation coefficient ρ (e.g., de Paula 2009, Lee *et al.* 2014). In the solar PV adoption chapter, we adopt the second approach by assuming the unobserved characteristics in each time episode are correlated by coefficient ρ in a dynamic optimal stopping time model.

In general, peer effect is identified by the variation in leave-i-out mean of peer group behavior, variation in group size across the data sample (a relatively smaller group size is required if contextual effects is present), and a separation between peer, contextual and correlated effects (Manski 1993, Brock and Durlauf 2001, Lee 2007). In the dynamic optimal stopping time model that peer effects generate nudges for households to adopt solar PV within the same discretized time slot, peer effects is also identified by the observed simultaneous adoptions (de Paula 2009).

1.2 Research motivations and contributions

1.2.1 Fertility decision and son-preference

For the fertility and son preference paper, our contribution is that we investigate the role peer effects plays in the family planning decisions. Peer effects anecdotally exist in many aspects of the Chinese culture and society, but it is not widely discussed in economics literature related to family planning. This chapter is motivated by the policy change in 2016 that all households in China can have a second child. This is a relaxation to the one-child policy and conditional two-child policy which had been implemented for 37 years. Broad discussions have aroused among households that their "peer pressure" increases because of this policy. It has been a long tradition in China to have many children and at least one son to carry on the family name. But this tradition has been challenged when the one-child policy has reshaped the family structure and preference in China. After the implementation of the two child policy, many families have faced peer pressure when they expect or observe their peers to have a second child which has caused some intra-family tensions. Besides, the two child policy is expected to decrease the proportion of single daughter or no-son families, statistically. If peer effects exist in son preference, this may worsen the imbalanced sex ratio which has already been severe.

Even though our research is motivated by the two child policy, we are unable to study the peer effects for the current generation as we cannot observe the finalized family planning decisions of young mothers. Instead, we focus on a ten-year cohort of women (age 45-54 at 2016) prior the policy change. Note that even the one child policy has been implemented in 1979, we still observe many families have two children because of the conditional two child policy or because they had them illegally. Applying the method developed by Brock and Durlauf (2001) and Lee *et al.* (2014), we find significant peer effect in having a second child but not in having a son. We discuss the implications of our findings in the result session.

1.2.2 The diffusion of electric vehicle

Battery and plug-in hybrid electric vehicles (EV) can be operated fully on electricity and are considered as efficient substitutes for conventional engine vehicles. Currently the market share of EV is 1.8% in 2020 and has been growing steadily. There are two major environmental policies which facilitate the diffusion of EV – federal tax credit and Corporate Average Fuel Economy (CAFE). The former is equivalent to a $7,500 price deduction which is approximately 16.5% of the total retail price of an EV in average. CAFE standard is enacted by National Highway Traffic Safety Administration (NHTSA) and has been through major modifications since model year 2011. In general, NHTSA publishes the fuel efficiency target in unit of miles per gallon for each vehicle model based on its footprint (wheelbase $\times$ track width). And the overall target for each manufacturer under each vehicle type (passenger car and light truck) is calculated as the sales-weighted harmonic mean of the MPG attributes across all available models. If fails CAFE, a manufacturer needs to pay $55 per vehicle per MPG below the target.

This chapter is motivated by the fact that the penalty level, $55, hasn't been changed since 1983. There has been criticism for this unchanged penalty level as it does not catch up with the inflation rate and should be equivalent to $140 if taken into account. We investigate the role CAFE has played in the diffusion of EV. CAFE has been designed to encourage manufacturers to mark down the retail price of EV to increase the sales of EV. We quantify this effect as 3.4 percent. It is far below the impact of the tax credit, which decreases the price of EV by 24.97 percent. One feature that differentiates our study from others is that we focus purely on EV instead of hybrid which does not have a plug (these vehicles are more fuel efficient than gasoline vehicles but they operate only on gasoline). Another contribution is that we use a random coefficient model developed by Berry *et al.* (1995) and Miravete *et al.* (2018) to analyze the role CAFE standard has played in the diffusion of EV, and conduct counterfactual analysis on how an increased penalty level could impact the price and market share of EV.

1.2.3 Residential solar PV adoption

Previous research has focuses on finding evidence of peer effects on residential solar panels adoption (e.g., Bollinger and Gillingham 2012, Rode and Weber 2016). Different than the endogenous peer effects described in section 1.1, these studies usually set up a time lag when counting previous adoptions and current period's adoptions. They claim that by doing so, there is no simultaneity issue for identifying peer effects. In other words, their peer effects are instead "exogenous", which ignore the endogenous interactions among potential adopters within the long time lag (usually set as three to six months). And because their model is essentially a static model, the estimated peer effects coefficients cannot be used to predict a long-term adoption equilibrium.

de Paula (2009) proposes a structural optimal stopping time model which specifically allows for an estimation of peer effects. One advantage of this model is that both previous adoptions and concurrent adoptions generate accumulated impact on each household's decision – the optimal time to adopt solar PV. Another advantage is that each household's expected adoption time can be simulated separately which includes the flexibility of never adopting. This attribute allows us to predict a future adoption equilibrium. We obtain a confidential data set from utility company PG&E which contains residential addresses. It allows us to define peer group in a more flexible setting compared to Bollinger and Gillingham 2012 which defines peers in a zip-code level. Another contribution to this literature is that we apply a dynamic structural model which accommodate the features of residential solar PV adoption and proposes a strategy to predict future adoption equilibrium.

2. PEER EFFECTS ON FERTILITY AND SON-PREFERENCE IN CHINA

2.1 Introduction

Many Chinese families value male offspring relatively more than female offspring for many reasons. Traditionally, male children carry on the family name, inherit the family's wealth, and care for the parents in old age. As a result, convention obliges the male heir to honour the ancestry by having at least one male offspring. Combined with the infamous Chinese "one-child-policy" of recent decades, Chinese parents face substantial pressure to bear a son and within the restricted birth quota. At the same time, these motives are compounded by cultural and social norms that manifest in particularly strong peer-based pressures for preference on male offspring. Chinese culture values behavioral conformity. In all areas of China, but particularly in rural China where households are connected through low-degree (closely-linked) networks, family planning and fertility decisions – especially having (more) sons – are largely influenced by peers and neighborhood effects as individuals desire to "keep up with the Zhanges" (Ling 2009). In all, these forces have led to the well-known gender imbalance among recent generations.

Child choice and sex selection at birth are widely known and studied in Asian culture (Chinese, Indian, South Korean, etc.). Previous research has focused on the motivation of high sex ratio, such as the effect of sex-specific income (Qian 2008); outcomes related with high sex ratio, such as higher level of savings for sons (Wei and Zhang 2011) and lower labor market participation for women (Angrist 2002). The main focus of this research is to test whether peer and social pressures drive fertility decisions and son-preference in China. We focus on two family decisions in child planning. The first is whether to have an additional child, and the second is whether to have at least one son. We answer these questions via a model that explicitly allows for peer effects.

To provide context, the China Nationwide Census of 2010 reported a newborn male-female sex ratio of 1.18, which is substantially beyond the natural sex ratio at birth (which is about 1.05).[1] The sex ratio of infants born in urban area (1.16) was slightly lower than rural area (1.19). Indeed, son-preference is stronger in rural areas. According to a survey conducted in 1996 on rural families of Anhui Province in China, only 31 percent of single-daughter families are satisfied with having one daughter while for single-son families 58 percent are satisfied (Hardee *et al.* 2003). At the same time, people living in rural areas tend to rely more on neighbors or relatives for their well-being or livelihood, and thus peer influence from relatives tends to be stronger in these areas (Chan *et al.* 2002); son-preference also exists in urban areas, where people rely comparatively less on relatives and neighbors but are more exposed to social influences from friends and colleagues.

As a comparison of China to the rest of the world, the World Economic Forum ranks China in the 153rd position out of 153 countries in terms of the sex ratio at birth via the Global Gender Gap Report 2020.[2] These issues are important because population size, total fertility rate, and age structure plays an important role in economic growth and social development. Thus, understanding the motivation underlying the persistence of son-preference in modern China is of vital importance as serious social problems related to this phenomenon are already emerging, such as the soaring bride price and impending challenges associated with having approximately 30 million wifeless bachelors.

Peers are not assigned randomly. To identify peer effects, we need to separate it from contextual effects and correlated effects (Manski 1993). All three effects leads to observationally similar behavior among peers. A peer effect is an endogenous behavioral interaction among peer group members. Under the fertility context, peer effects mean that a family would like to have a second child if they observe or expect peers to have a second child; A contextual effect measures an “environmental” impact on household behavior, such that a family behaves differently under a different living environment captured by various demographics. For example, highly educated peers may pass on working spirits and pleasure of raising single child/daughter, which motivates a family to choose a smaller family size and has weaker son preference; A correlated effect represents the unobserved individual and

[1] ↑The sex ratio is with respect to new born infants at birth from one year before the census was conducted: Nov. 1st, 2009 - Oct. 31st, 2010.

[2] ↑http://www3.weforum.org/docs/WEF_GGGR_2020.pdf, page 125.

group characteristics that is believed to be highly correlated. Examples under the family planning context include local laws and social norms that are unobservable to economists.

Traditional Chinese social norms in family planning include having (male) offspring and "the more the merrier (*duo zi duo fu*)". For families that already have a son, it would also be a blessing to have both a son and a daughter (*er nv shuang quan*). Similar fertility behaviors among peers due to social norms is fundamentally different from peer effects, as the latter sources directly come from the outcome of peers, while social norms are built through intergenerational interactions following a long-term tradition. People following social norms will have an intrinsic motivation to have a second child or a son regardless of the choices of their peers.[3] The strategy to separate these two effects are explained in the model section in detail.

Several domestic and social disadvantages of being different from peers motivates a family to align with peers. Wives without sons are less respected in the original families of their husbands comparing with other daughter-in-laws with sons. No-son couples are also disadvantaged in resource allocation within the husbands' original families and have lower discourse power in their village. To improve their social status within a village and wives' status within the patriarchal family, no-son couples try hard to bear more children and hopefully have a son to catch up with their peers (Chan *et al.* 2002). Under the culture of son-preference, families with single daughters are in the most vulnerable situation. As rearing a large family and paying the fine for extra birth beyond the birth quota is is financially costly, many families will conduct sex-selective activities for unwanted girls during pregnancy until a desired son is detected via ultrasound.

Therefore, in this research we focus on the role of peer effects in child planning for families in China, including the decision of having a second child and ever having a son. From 1982 to 2016, China government had implemented several policies to relax the one-child quota

[3]↑An example to help differentiate the two effects: a conversation of "When are you planning to have the second child (as it is expected from seniors/society)?" under the context between a younger couple and senior relatives/superiors forms a typical channel of social norm. It is a homogeneous expectation for everyone living under the same regional culture. In the mean time, household could observe or perceive their peers' behavior and corresponding benefits in having a second child or a son. The pressure sourced from being different from others stimulates an adjustment of their behavior to align with the majority. A conversation of "When are you planning to have the second child (as we did)?" among friends and colleagues, or simply by observing/expecting their benefits from doing so, forms channels of peer effects.

to a two-child quota. These policies are designed to alleviate the high mortality rate of the firstborn daughters as well as boost the demographic dividend for future generations.[4] As low fertility rate and unbalanced sex ratio severely affect Chinese social and economic situation, a scientific understanding of the motivation of fertility decisions appears more important. As motivated, peer effects may be particularly salient in the Chinese context, and therefore we aim to measure the extent to which social factors influence the gender choice of their offspring. We find a significant peer effects in having a second child and no peer effects in son-preference. It suggests that fertility incentive policies, including the two-child policy, generates spillover effects in fertility decisions; With more families having sons after the two-child policy was implemented, sex ratio will not climb due to peer effects in having sons. To alleviate son-preference, increasing the education level of the whole population have great potentials.

2.2 Background

2.2.1 Evolution of child policies in China: 1979-2016

In 1979, the Chinese government announced the one-child policy that limited each married couple to have only one child. The penalty for violating this policy ranged from financial fines to forced abortions or sterilization, and civil servants or employees of state-owned enterprises faced the possibility of unemployment. The policy, requiring a small family size, was an effort to curb a dramatically rising population out of fear of increased poverty and food shortage in China (Greenhalgh and Bongaarts 1987). It was a brutal destruction of traditional family planning, and well-known results of these policies are rampant gender selection via sex-selective abortions or female infanticide, and birth registration of female children being delayed until the child is of school or marriage age (Shi and Kennedy 2016). The one child policy was soon revised so that if both the husband and wife were each the only child of their parents, the couple was allowed to have two children as a reward for their parents' contribution to population control. This policy adjustment was first implemented

[4]↑Demographic dividend arises when the share of working-age population is large enough. One-child policy has shifted the age structure of China dramatically and impaired the future demographic dividend.

in rural areas in 1982 and then expanded to urban areas in 1984; however, a very limited number of households fit that requirement.

In response to the growing gender imbalance, and out of recognition that rural families are generally unable to survive with a single child (at a minimum in terms of labor force requirements) the Chinese government proposed the one-and-a-half child policy (hereafter the 1.5 child policy) that allowed a family whose registered residence type was agricultural to have a second child if the first child was a girl. Between the years 1985 and 2011, 19 out of 34 provinces legalized this policy with 18 of the 19 provinces implementing the 1.5 child policy before 2003.[5] This policy adjustment was designed to protect females in rural areas where heavy labor demands males, in which case a first-girl would be less likely to be kept. This policy is believed to have saved many firstborn daughters: not only is having both a daughter and a son considered to be a blessing by Chinese tradition, but a first-born daughter is a source of household labor and brings a bride price when married that helps to offset the cost of the second child's (i.e., the son's) marriage.[6]

Over time the total fertility rate in China dropped to below 1.5 and remained low for at least two decades following the mid-1980s. A low fertility rate, as evidenced in, for example, Japan and Germany, leads to an aging population problem and pension gap. In 2014 the Chinese government further relaxed the one-child policy so that as long as (only) one parent is the only child of his or her parents the couple could have two children in both rural and urban areas. This policy adjustment did not lead to much change in child bearing: according to 2014 statistics from the National Health Commission of China, only 700,000 couples applied to have a second child out of 11 million couples that satisfied this requirement and were at reproductive age (roughly 6 percent of those eligible). In 2016, the Chinese government removed all restrictions on having a second child. The total fertility rate

[5]↑The 18 provinces where the 1.5 child policy was implemented before 2003 are (year implemented in parenthesis): Jiangxi (1985), Shandong (1986), Guangdong (1986), Hunan (1987), Hubei (1988), Liaoning (1988), Anhui (1988), Inner Mongolia (1988), Guangxi Zhuang Autonomous Region (1989), Shanxi (1990), Jilin (1993), Hebei (1994), Gansu (1997), Guizhou (1998), Heilongjiang (2000), Fujian (2002), Zhejiang (2002) and Shaanxi (2002).

[6]↑A traditional Chinese marriage requires a dowry (*cai li*) paid by the groom's family. As girls become increasingly rare in rural areas, the amount of the dowry increased sharply. Therefore having a first-born daughter who marries earlier than the second child (the son) helps to ease the family's financial burden. Despite modern criticism that a dowry system reflects the selling of daughters, the custom is still practiced today in most rural and some urban areas in China.

in 2016 was about 1.7, which is still far below the rate of 2.1 that is needed to maintain a stationary population. It has also been documented that these policy relaxations have led to increased gender discrimination in the labor market, with employers increasingly concerned that female employees may be less productive if they choose to rear larger families (Zeng and Hesketh 2016).

Overall it is estimated that these population control policies have decreased the population size by 200-400 million (Goodkind 2017), and have led to an unbalanced sex ratio in China with 30 million wifeless men. This problem leads to documented social problems that have real economic consequences: increased violence and spread of AIDS (Bhalotra and Cochrane 2010, MPH *et al.* 2006), and increased gender (female) discrimination in the labor market and thus a higher female unemployment rate. A shortage of brides in the rural marriage market has also pushed up the bride price, which many rural families with sons cannot afford to pay; one consequence of this is increased trafficking of women as brides.

2.2.2 Fertility decisions under a birth quota

The majority of urban families and many rural families were only allowed one child over the 1979 to 2016 period, with an exception for some rural families to schedule a second child if their first child is a girl. The birth quota contradicted the demand for children. Guo (2014) finds that, in rural China, aged parents with fewer or no children are more likely to be depressed and live a less satisfied life. The preference of having a large number of children – including a son – is deeply rooted, such that a family that did not meet the legal requirements allowing more than one child may decide to break the law and have a second child illegally, risking punishment.

The 2010 China Population Census shows that 70 percent of newborns in urban areas and 55 percent of newborns in rural areas over the November 2009 to October 2010 period are firstborns; see Figure 2.1. The 1.5 child policy affects many rural families that have a first girl: 36 percent of rural newborns are a second child (based on 2010 census data), while for urban areas this statistic is only 26 percent. Around 3 percent of urban newborns and 7 percent of rural newborns are the third child of the family; larger families with more than three children are rare. We can thus infer from these data that many urban families and some rural families break these laws. In general, the majority of Chinese families have one or two children. Our first research question focuses on a key decision in Chinese family planning: whether or not to have a second child.

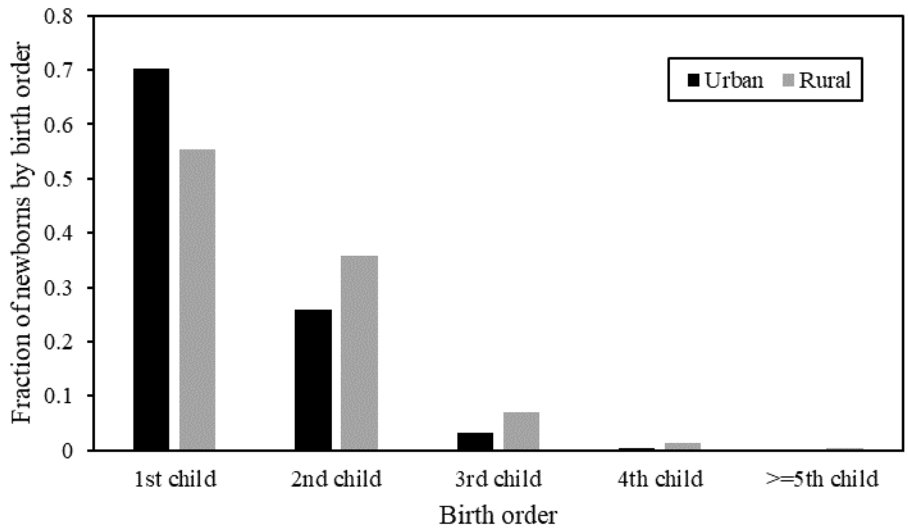


Figure 2.1. Fraction of newborns by birth order
Source. 2010 China Population Census: Nov. 1st, 2009 - Oct. 31st, 2010

The social influence motivating (in part) fertility decisions can also interact with the gender of the child being female. The economic burden of raising and supporting a (first) girl is typically lower than that of raising a son, and so a couple with a first girl may be more financially able to have a second child.[7] At the same time, a couple with a first girl may not be satisfied with not having a son, and want to try their luck on a second pregnancy in hopes of having a son. This influence is obvious in rural areas where the 1.5 child policy applies. For most urban families, having a second child is illegal; but we still observe families with two children among the urban population (see Figure 2.1).

In the mean time, different from western culture, kinsmen play an important role in Chinese family planning for young couples. Traditionally, married daughters detach from

[7]↑The most obvious economic burden of raising a son comes from the convention that parents prepare for their son's housing in future marriage. Usually parents have less or no burden preparing for their daughter's future housing.

their original families and take less responsibilities of taking care of their parents at old age. Elder people usually have no income source and they usually choose to live with one of their sons – usually the eldest, richest, or their favorite. On the one hand, as alluded to, a couple would like to have sons for security of old age; On the other hand, senior parents resides with sons have high bargaining power in family planning. Indeed, it is a moral code for a young couple to align with the elders' needs (Meng 2002, Chan *et al.* 2002). This inter-generational transmitted social norm of having more kids (especially sons) has had a long-term impact on local residents. Social norm is highly heterogeneous across different area. Each provincial-level administrative region (equivalent to a state in the US) has their own culture. e.g., Shanghai has a weaker social norm of having sons.

In the mean time, observing or expecting peers to have larger families generates peer impacts. Based on our estimates, the decision of having a second child is largely driven by peers' behavior in having a second child. Peer effects could be harmless, as a family want to enjoy the pleasure of having multiple children as their peers do; or it could be passive, as a family observes their peers (or the children of their peers) enjoy better intrafamily resource allocation from both sides of a couple's original families, and more respect from senior relatives, while they don't.

2.2.3 A preference for sons

Our second research question is related to son-preference. Under a strict birth quota, the economic difficulties of raising multiple children, and social pressure of having sons, many families succumb to these pressures and conduct sex-selective abortion or infanticide in response to unwanted girls. According to the 2010 China Population Census, the sex ratio of newborn infants over the November 1, 2009 to October 31, 2010 period is slightly higher than natural sex ratio at birth for the first child, and increasingly higher for the second and third child (see Figure 2.2). The probability of conducting sex-selective activities increases by birth order (less than four children) as families of larger size usually have a first girl or multiple girls before a desired son is born. In general sex ratio is higher in urban area compared to rural area (see Figure 2.2), mostly because of the more flexible birth quota in the rural area.

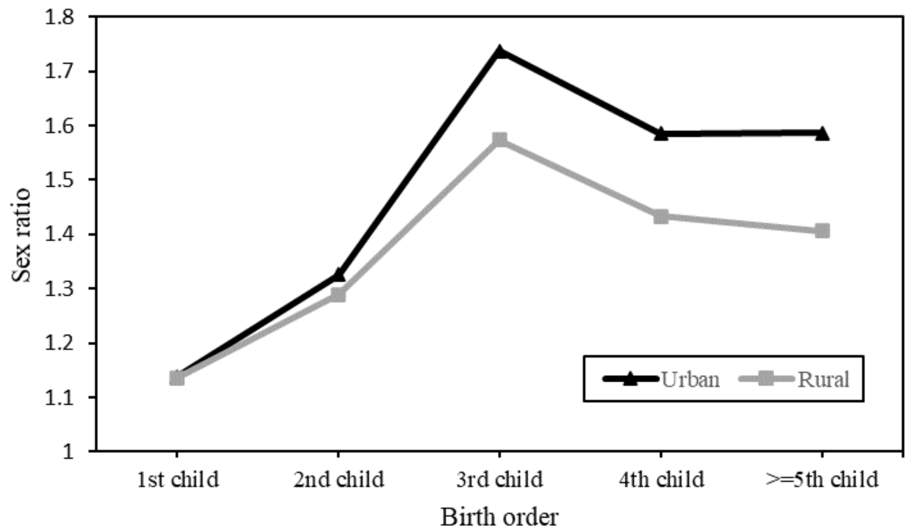


Figure 2.2. Sex ratio by birth order
Source. 2010 China Population Census: Nov. 1st, 2009 - Oct. 31st, 2010

For the second research question, we use the fertility record of ever having a son as a measurement of son-preference, regardless of the number of children a family ever has. The reason is twofold. For a single family, having at least one son is a signal of fulfilling the social obligation of carrying on the family line (*chuan zong jie dai*). The outcome of having a son, as our dependent variable, can be achieved either by having natural birth(s) until a son is born, or it could involve sex-selective activities for unwanted girls during the process. For peer effects measurement, it is whether a peer family is expected to have at least one son, rather than at which birth does the peer family have a son, that matters to a family. Therefore peer effects of having a son is reflected by the expected proportion of peers with at least one son.

2.2.4 Prenatal sex selection and unbalanced sex ratio

Ultrasound technology has been widely used since 1980s (Chen *et al.* 2013, Almond *et al.* 2019). Even though it is illegal to use it for sex detection of the infants, people can still manage to know the sex of the infants including bribing the doctor, finding an acquainted doctor through social connections to know the sex, visit a private clinic, or even sending blood sample to Hong Kong for sex detection has became popular in recent years. In general, if a family want to know the sex of the infant, they will find their channel. It is broadly known but silent in public for obvious legal reasons. Once an unwanted female infant is confirmed via ultrasound, the parents can use fake reasons, such as drug overdose during pregnancy, to conduct abortion with low medical fee in public hospital and private clinics. In general, abortion in China with a "valid" reason is legal and easily accessible. The sex ratio by age appears to have a large increase since the 1990s (see Figure 2.3). A person aged 20 in 2010 should be born at 1990, and the sex ratio increases dramatically since then (age moves backwards).

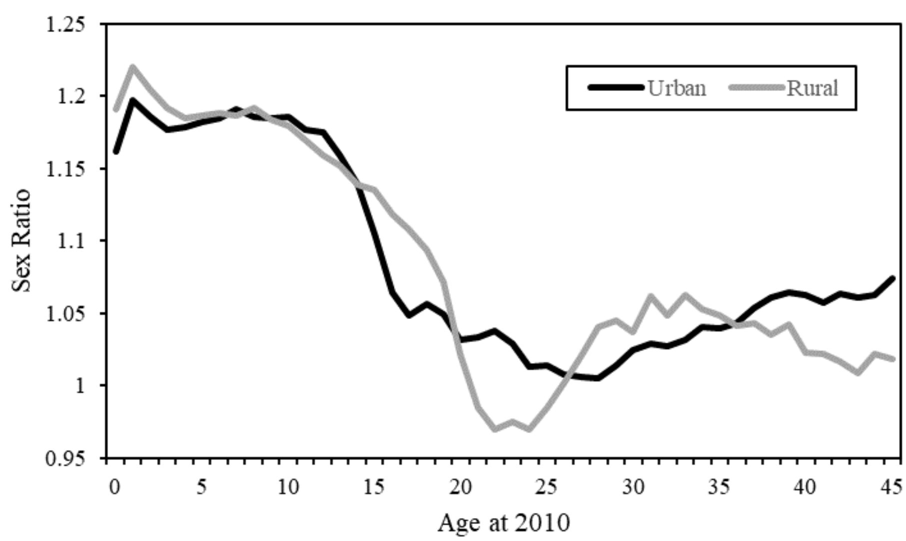


Figure 2.3. Sex ratio by age
Source. 2010 China Population Census

Abortion may cause lifelong infertility, and it comes along with a mental cost. Therefore it is difficult to understand the motivation of this dangerous and harmful choice. Even though modern biology has proved that sex-determining gene comes from men, the fertility pressure of having sons is still largely borne by women. Women without sons may suffer mentally in their domestic and social life. Therefore when there is an opportunity in prenatal sex selection and it could potentially erase their shame and guilty, increase their family and social status in lifetime, women may be self-motivated to take the risk with a temporary pain; or they may be urged by their husbands or senior relatives to do so, as filial obedience and respecting the seniors are of vital importance in Chinese morality (Chan *et al.* 2002, Bedford and Hwang 2003).

2.2.5 Late registration for early ages

Some literature (e.g., Goodkind 2011, Shi and Kennedy 2016) argues that late registration may causes an unbalanced sex ratio, and the number of registered girls is under-reported. This phenomenon exists for early ages but is less likely to affect the accuracy of our observations as the majority of children in our data sample are adults. We compare the population change on the same cohort over a ten year gap based on the two censuses of 2000 and 2010. Except for the cases of changing citizenship or death, the group of people who aged zero at 2000 should be the same cohort in 2010 who aged ten. The population change rate from 2000 to 2010 by age should be close or slightly less than one.[8] However, the population increases by five percent for both male and female aged zero at 2000, in which one obvious reason should be late registration (see Figure 2.4).

We see two bumps in Figure 2.4, one locates around age six to eight, and another is during age nineteen to twenty-two. The latter should be due to registration for marriage, and there is only a mild difference between sex. Comparing with age eleven (in 2000), only five percent male and three percent female delayed registration until age twenty-one (in 2010). The former case should be due to registration for school, in which there is a slight difference by gender. For the age group of seven for example, population "increases" by twelve percent for boys and twenty percent for girls from 2000 to 2010 (they should be age seventeen at 2010). In general, both girls and boys could be hidden for registration before they enter elementary school. The real sex ratio are believed to be lower than the reported data depicted in Figure 2.3. But after the age of twelve, the miss-registration problem should be mild. Our research sample is restricted to mothers who age 45 to 55 at 2016. A vast

[8]↑Population change rare from 2000 to 2010 at age t is calculated as the fraction of "population size at age $t+10$ at 2010 $-$ population size at age t at 2000" to "population size at age t at 2000".

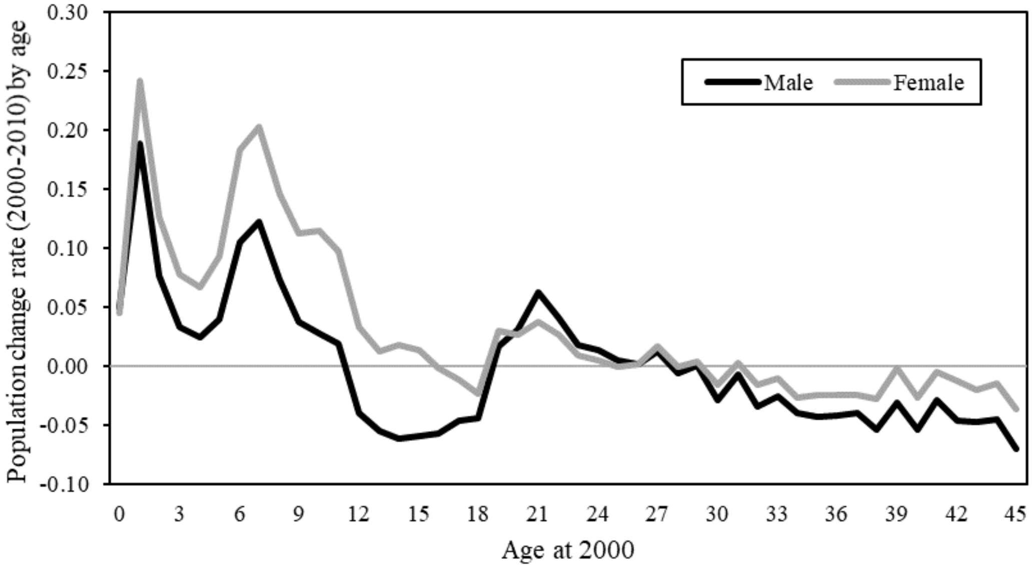


Figure 2.4. Population change rate by age
Source. 2000 and 2010 China Population Censuses

majority of their children's age is above twelve, with a average age of firstborns being 26 and 22 for second child. Therefore we believe most children in our sample are registered by 2016 (details can be found in the data section).

2.3 Literature Review

Many papers have empirically documented the unbalanced sex ratio in China (e.g., Chan *et al.* 2002, Hardee *et al.* 2003, Ding and Hesketh 2006, George 2006, Zhu *et al.* 2009), as well as in India (e.g., Gupta 1987, Griffiths *et al.* 2000, Dubuc and Coleman 2007), and South Korea (e.g., Park and Cho 2009). Evidence shows that, in China, this preference for sons has manifested in different ways under the different policy regimes. Before the one-child policy was implemented and ultrasound technology became accessible, most families had multiple children; and yet, the mortality rate was higher for female offspring (Zhang 1990). After the one-child policy was implemented, girls in higher birth orders were less likely to be kept so as to save the child quota for a boy (Ebenstein 2010).[9] For instance, Ebenstein (2010) shows that male births come about 0.34 years later than female births, based on the 2000 China census, and this extended interval indicates (with a high probability of) ongoing pregnancy and sex selection prior to the arrival of the male child. Bhalotra and Cochrane (2010) estimate that 480,000 girls were aborted in China over the 1995 to 2005 interval.

This documented evidence of son-preference stimulates discussion on the reasons for this phenomenon. One reason is that boys are more economically valuable than girls through the labor market. Land reforms implemented during the 1978 to 1984 period allowed families to keep extra self-produced crops to themselves. This policy intensified son-preference as farming is heavy labor and families prefer having son(s) (Almond *et al.* 2019). Similarly, Qian (2008) shows that when females bring more income into the household, for instance from the female-preferred labor market of tea-leaf harvesting, sex selection at birth is less frequent. Ebenstein (2011) finds that the average value of a first son in China is 1.85 times the annual family income, whereas the value of a first girl is only 0.43 times the annual family income. The two-child policy recently implemented in China in 2016 has further led to a crowding out of females in the labor market, as employers are reluctant to hire women with higher expected frequency of maternal leave and overall fewer working hours (Zeng and Hesketh 2016). It is clear that these policies affect the economic value of women relative to men, which in turn affects family sex selection.

Education also matters; highly educated women prefer a smaller family size and have statistically weaker preference for sons (e.g. Zhang and Spencer 1992, Abrevaya 2009). It is worth noting that McElroy and Yang (2000) find no evidence that highly educated women have fewer children in rural China. Others have investigated the use of ultrasound technology as a factor that influences the sex ratio. Abrevaya (2009) finds that one reason for the 2,000 missing Chinese and Indian girls in the United States over the 1991 to 2004 period is because of widely accessible ultrasound technology. By 1985, Chinese residents in more than 60 percent of counties had access to ultrasounds for prenatal testing (Chen

[9]↑The pressure to have a boy, conditional on previous children being girls, increases with the birth order of the child in China (Chen *et al.* 2013), India (Bhalotra and Cochrane 2010), South Korea (Park and Cho 2009), and even among Chinese living in the United States (Abrevaya 2009).

et al. 2013), though by the same time ultrasound technology was available in all provincial capitals, such that families could travel to their provincial capital for an ultrasound (Almond *et al.* 2019).

In addition to these economic motives, peer effects and social norms influence family planning. In China, not having a son can lead to shame, especially in rural areas, and so households face enormous pressure to have a son (Chan *et al.* 2002). A higher female suicide rate in rural areas of China has been linked to low female status in family decision-making under the traditional patriarchal structure (Chan *et al.* 2002, Meng 2002). Woman with a firstborn son has higher bargaining power inside the family, lower probability to be underweight, and better nutrition intakes (Li and Wu 2011). More broadly the culture of shame is more prevalent across Asia compared with other parts of the world; shame caused from deviating from others would push people to align with the majority (Bedford and Hwang 2003). Nevertheless, while peer pressure is believed to play an important role in child planning in China, it has not been widely modeled in economics (e.g., Qian 2008, Abrevaya 2009, Ebenstein 2010, Ebenstein 2011).[10]

Beyond these motivations underlying child gender selection that lead to a high gender ratio, there are economic and social impacts of this high ratio and associated population control policies. A high sex ratio is correlated with higher marriage rates for women and lower female participation in the labor market (Angrist 2002). A high sex ratio also motivates household saving, as Chinese families with sons anticipate a more competitive marriage market for their son (Wei and Zhang 2011). Rosenzweig and Zhang (2009) find weak evidence that the one-child policy increased the education and health conditions of the post-policy generation as a result of increased human capital investment on each child. Families also come up with multiple ways to avoid financial punishment of having extra children beyond the birth quota, such as late registration of unwanted daughters (Shi and Kennedy 2016) and fake twins (Huang *et al.* 2016).

[10]↑Peer/network effects are more widely studied in other areas of economics, including finance and investment (e.g., Banerjee *et al.* 2013, Bursztyn *et al.* 2014), academic performance (e.g., Zimmerman 2003, Bramoullé *et al.* 2009, Carrell *et al.* 2009), and teenage smoking behavior (e.g., Lee *et al.* 2014), to name a few examples.

2.4 The Empirical Model

Brock and Durlauf (2001) develop a structural binary choice model that accommodates peer effects. In this model each member within a peer group has a homogeneous expectation on the leave-out group average behavior, which directly impacts each member's utility – the more individual behavior deviates from the group mean, the lower the utility. Lee *et al.* (2014) expands this model with a heterogeneous expectation on each group member. Both papers use a maximum likelihood estimator to estimate the peer effects and contextual effects. With sufficient socio-cultural evidence of peer pressure of having more children and potentially a son, ignoring peer effects may lead to biased estimation for other controls such as the use of ultrasound technology and education. Therefore we adopt Brock and Durlauf (2001) and Lee *et al.* (2014)'s model to fill the gap of the existence of peer effect in Chinese fertility choices.

We answer two research questions in this paper. First, does the probability that a Chinese family has a second child depend, in part, on an expectation that their peers have a second child? Second, does the probability that a Chinese family has a son depend, in part, on an expectation that their peers have a son?

We answer both research questions using the utility structure described below, in the context of our first research question. Our model follows Brock and Durlauf (2001) and Lee *et al.* (2014): conditional on already having one child, each household faces the decision of whether or not to have a second child. Letting $y_i \in \{1, -1\}$ define whether or not the household has a second child, household i's utility $V(y_i)$ is:

$$\begin{aligned} V(y_i) &= u(y_i) + S(y_i, M) + c(F_p, y_i) + \epsilon(y_i) \\ &= x_i \alpha y_i + (w_i X_2 \delta y_i + \gamma w_i M y_i) + F_p y_i + \epsilon(y_i) \end{aligned} \tag{2.1}$$

where $u(y_i)$ captures the household's private utility, $S(y_i, M)$ captures the social component of utility, $c(F_p, y_i)$ represents correlated effects with F_p as the provincial fixed effect. $\epsilon(y_i)$ is the error term, and is independently and identically distributed across households.

2.4.1 The private component of household utility

The private component of utility, $u(y_i)$, depends on the characteristics of the household, such as level of income and education, and is independent of other households' characteristics or child choices. For tractability, we parameterize this utility component as:

$$u(y_i) = x_i \alpha y_i \tag{2.2}$$

where x_i is a vector of household characteristics and α is the corresponding coefficient vector. That is, the private utility in the household when there is a second child (i.e., when $y_i = 1$) is $x_i\alpha$, while the private utility without a second child (i.e., $y_i = -1$) is $-x_i\alpha$. Hence, a positive $x_i\alpha$ indicates that the family's net private utility is greater with a second child. In x, we include the education of both the husband and wife, family income, a farming indicator, whether the household lives in a rural or urban area, the sex of the first child, type of registered residence (agricultural or non-agricultural *hukou*), whether the household qualifies for the 1.5 child policy, the wife's age when having the first child, and whether or not the husband's parents live with the family.

2.4.2 The social component of utility

The second component of the household's utility function captures social effects, or the importance of both peer characteristics and decisions on the household's decision to have a second child (or to have a boy in the case of our second research question). That is, it is essential to recognize that there are different ways in which a household's decisions are influenced by its peers, only one of which is typically referred to as "peer effects". Colloquially, the term "peer effects" refers to the decisions of households $j \neq i$ influencing the decisions of household i. Using the terminology laid out by Manski (1993), these peer effects are endogenous social effects, and arise in equilibrium as each household makes its decisions based on the decisions (or an expectation of the decisions) of neighboring households. Conceptually, these endogenous social effects are distinct from exogenous social effects, generally called contextual effects, in reference to the idea that a household's decisions may vary with the characteristics of others in the group – e.g., the average level of income or education in the social group. Finally, Manski (1993) refers to commonalities in the social environment (e.g., similar laws or cultural norms) as correlated effects. As is well-known, differentiating between these types of social effects is not only important for accurately describing our research interests, but for developing an appropriate empirical strategy for identifying the endogenous social effects (which we are calling peer effects) from contextual and correlated effects.

Theoretically, there are different ways in which endogenous peer effects might arise. One common formulation is that of social norms, or that a household does not want to deviate from typical group behavior (i.e., keeping up with the Zhangses). In this formulation, we expect that a household forms an expectation of the average decision among other households within their reference group, and then makes an individual decision, in part, based upon this expectation. In the case of a binary decision, this expectation amounts to an expected percentage of households in the reference group that have a second child or choose to have a boy as a second child (in the case of our second research question).[11] Hence, in this framework, a positive peer effect would indicate that – all else equal – the probability that a household chooses to have a second child (or chooses a boy for their second child) is increasing with the expected share of their peers that choose to have a second child (or choose a boy as a second child).

On the other hand, contextual effects references the idea that a given household is likely to make different decisions in different environmental contexts, regardless of their own individual characteristics (e.g., income or education) or expectation of group decisions. For example, all else equal, a household may be less likely to have second child if a majority of their peers are highly educated as neighborhood groups characterized by higher average education may have different preferences regarding labor market participation, family planning, or adherence to traditional customs. A household's desire to have a second child may be influenced by this contextual setting. Perhaps more importantly, identification of peer ef-

[11]↑Since our model is static and so all household decisions are made simultaneously, we do not differentiate between expected reference group decisions and actual birth outcomes. In a dynamic framework, one might differentiate between past (observed) outcomes and expected future outcomes.

fects requires that we can statistically distinguish between endogenous group influences and these contextual effects; in general, these types of social influences can be collinear, making identification challenging (Brock and Durlauf 2001).[12] Brock and Durlauf (2001) describe how nonlinearities inherent in probability models of binary choice facilitate identification of peer effects in discrete outcome models; it is on their basic insight on which we base our identification strategy. Details of how nonlinearities facilitate the identification will be introduced at the end of this section.

To parameterize the model, we write the social utility component, $S(y_i, M)$, to be additive in the contextual and peer effects:

$$S(y_i, M) = w_i X_2 \delta y_i + \gamma w_i M y_i \tag{2.3}$$

where w_i is a $1 \times N$ social network vector with element w_{ij} being positive if i and j are in the same peer group, and zero if not. That is, to completely define the social component of utility, one must first define the household's peer reference group or network. In our models, we use a group network structure such that each household peer has an equally weighted influence on household i given by $w_{ij} = 1/N_i$. This way, w_{ij} sums to one across $j \neq i$ for each household i, noting that $w_{ii} = 0$ so that household i is excluded from its own peer reference group. More specifically, we define the peer group at the county level. In China, a county is smaller than a city, but larger than a village, and each county will be made up of roughly 15 villages. Further, the county level is typically the level at which local economic interactions are conducted, the level at which government policies are implemented, and the level at which may individuals generally interact (in both urban or rural areas). In the Chinese context, and in the absence of an exact peer-to-peer friendship network, the county group level is a natural definition of peer reference group. In (2.3), $X_2 = [x_1, x_2, ..., x_n]$ is the matrix of household characteristics, and thus $w_i X$ is the leave-i-out mean of i's reference

[12]↑Indeed, a large literature since Manski (1993) has focused on different ways of identifying endogenous peer effects from contextual effects. Some examples include the use of dynamic models (Brock and Durlauf 2001) , explicit networks (Bramoullé *et al.* 2009), or heterogeneity in peer group size (Lee 2007).

group characteristics.[13] δ is the vector of contextual effects coefficients: the higher the parameter δ_k, the larger the impact of the leave-i-out mean of peer characteristic $x^k_{j\neq i}$.

The second term captures the endogenous peer effects, for which γ is the coefficient and the vector $M = E(Y)$ is i's expectation of peer behavior regarding a second child. Following Lee *et al.* (2014), this expectation is allowed to be heterogeneous across households; further mathematical details regarding M are explained below.

2.4.3 Correlated effects

Finally, and as noted, identification of peer effects also requires that we can adequately account for factors common to all members within the same group, such as similar laws or traditional customs that may be apparent in one provincial region but not another. These are the correlated effects, and in general may not be observed. These traditional customs related to family planning vary largely across China, but the variance within provinces is much smaller than across provinces as Chinese people commonly identify their residence and social image by province. In turn, each province has its own features/stereotypes known across the country. And, as noted earlier, the Chinese child policies are usually implemented at the provincial level, such as the 1.5 child policy or other relevant incentives favoring single-child families, including bonus points on the college entrance examination for rural single child, and endowment subsidies for couples with a single child (e.g. Li 2020). We control for these province-level differences via the province fixed effects, F_p. A higher F_p means that all else equal, household i has higher utility if they have a second child living in current province comparing with living in other provinces with lower F_p.

$$c(F_p, y_i) = F_p y_i \tag{2.4}$$

2.4.4 Maximum likelihood estimator

Estimation of the econometric model is a straightforward logistic regression model under the assumption that the error term is logistically distributed. That is, household i will choose

[13]↑X_2 includes chosen contextual characteristics that are believed to influence the outcome decision, and does not necessarily equal to the own characteristics matrix X.

to have a second child, $y_i = 1$, whenever $V(1) > V(-1)$ but will not have a second child, $y_i = -1$, if $V(1) < V(-1)$. The probabilities of having a second child, $Prob(y_i = 1)$, and not having a second child, $Prob(y_i = -1)$, are:

$$
\begin{aligned}
Prob(y_i = 1) &= \frac{1}{1 + exp[-2(x_i\alpha + w_i X_2 \delta + \gamma w_i M + F_p)]} \\
Prob(y_i = -1) &= \frac{1}{1 + exp[2(x_i\alpha + w_i X_2 \delta + \gamma w_i M + F_p)]}
\end{aligned} \tag{2.5}
$$

and the coefficients $[\alpha, \delta, \gamma]$ can be estimated using maximum likelihood.

The model is complicated by M, as M is a equilibrium expectation among all members in the group and thus must be solved for simultaneously. Brock and Durlauf (2001) and Lee *et al.* (2014) make a rational expectations assumption, or that the expected outcome behavior of i, M_i, equals to the objective expected outcome $E(y_i)$ calculated based on each i's information set. From (2.5), we can solve for the expected behavior of having a second child for each household i, M_i, as:

$$
\begin{aligned}
M_i &= E(y_i) \\
&= 1 \cdot Prob(y_i = 1) + (-1) \cdot Prob(y_i = -1) \\
&= \frac{1}{1 + exp[-2(x_i\alpha + w_i X\delta + \gamma w_i M + F_p)]} - \frac{1}{1 + exp[2(x_i\alpha + w_i X\delta + \gamma w_i M + F_p)]} \\
&= \frac{exp[x_i\alpha + w_i X\delta + \gamma w_i M + F_p] - exp[-(x_i\alpha + w_i X\delta + \gamma w_i M + F_p)]}{exp[x_i\alpha + w_i X\delta + \gamma w_i M + F_p] + exp[-(x_i\alpha + w_i X\delta + \gamma w_i M + F_p)]} \\
&= tanh(x_i\alpha + w_i X\delta + \gamma w_i M + F_p)
\end{aligned} \tag{2.6}
$$

such that M_i is a function of vector M, the heterogeneous expectations of peers' behavior. In other words, each household i behaves optimally based on each peer j's expected behavior M_j ($j \in i$'s peer group set), which is heterogeneous across different j. If we stack the expected outcome M_i for each household $i \in \{1, 2, ..., N\}$, we can solve for the heterogeneous expectation vector M through a system of nonlinear equations:

$$
M = tanh(X\alpha + WX\delta + \gamma WM). \tag{2.7}
$$

The *tanh* function is linked with the assumption that the error term follows the logistic distribution. It is of vital importance that M is a non-linear function of the contextual effects (WX) for identification of peer effects and contextual effects (Brock and Durlauf, 2001). And the assumption that the error term is logistically distributed guarantees that M is a non-linear function of the contextual effects (see function (2.7)). Intuitively, if M is a linear function of WX and we replace M with this linear function in the maximum likelihood function, we cannot identify the peer effects parameter γ and the contextual effects δ because of obvious linearity issue.

Thus, following Lee *et al.* (2014), we solve for the parameter vector $\Omega = (\alpha, \delta, \gamma)$ using a maximum likelihood estimator that iteratively solves both the M system of equations and the optimal model parameters.For the second research question of whether the second child is a boy, we use the same method by replacing the dependent binary choice variable with z_i, with $z_i = 1$ as having at least one son and $z_i = -1$ as no son.

2.5 Data

Our data comes from the China Family Panel Studies (CFPS), a bi-annually collected, household-level panel database that was started in 2010. For both research questions, we focus on a ten-year cohort of females between the ages of 45 and 54 (i.e., born between 1962 and 1971), in order to focus on women who have most likely completed their fertility planning by the time the survey was conducted, but not so old that their children were born before any child control policies were implemented. This sample of females corresponds to those interviewed in the 2016 wave of the survey, so we focus on the 2016 sample of 58,179 individuals from 14,763 households in urban and rural China.

CFPS contains household-level economic data (e.g., annual income, occupation) and individual-level demographics data (e.g., education, age) of all members inside a household, including individual, spouse, individual's parents and children. We first merge the individual-level and household-level data by household ID, and then keep only male individuals whose spouses are 45-54 years old. By selecting males as "individuals", we are able to include variables of whether the mother or father of the male (which is also the mother-in-law or father-in-law of the female partner) lives together with the family. As alluded to, parents-in-law of females typically generate intra-family pressure inside a Chinese family.

An additional advantage of this sample is that women get married and start to have children at an early age, with the average age of becoming a mother being 23.64. Therefore, on average, females in our sample have a long reproductive period to have a son if they wish, either by having multiple children or sex-selective abortion(s) during pregnancy.

2.5.1 Peer group definition

We define peer group by county. The administrative divisions in China contain five levels: provincial level (1st), prefectural level (2nd), county level (3rd), township level (4th) and community level (5th). The CFPS data contains information of province (1st level), county (3rd level) and community (5th level) for each household. A county in China is a subordinate level of a city (prefectural level) and could be geographically smaller than counties in the United States.[14] Usually each county has one "county center" where people cluster and socialize. Rural villagers living nearby go to these centers (*xian cheng*) for supplies. On the contrary, community usually refers to a living community or street, which is too narrow a criterion to partition peers.

Therefore we define peers at the county level, recognizing that the county represents a regional center where relatives, colleagues and friends communicate and socialize. Each county in the CFPS contains enough households that not only share the same cultural background but could also be connected through their social networks. On average, there are 20 representative households in each county in Sample I, which makes 19 neighbors for each household. There is a large group size variation with a standard deviation of 7.35. Small peer group sizes and sufficient variations in group sizes lead to a more precise estimate of peer effects and contextual effects (Lee 2007). For models with province fixed effects, we drop provinces with fewer than five counties from our sample to increase the variation in leave-i-out mean of peers' expected behavior and contextual characteristics across counties

[14]↑For example, Beijing and Shanghai are cities and each of them contains sixteen counties.

within the same province. This strategy helps the identification of peer effects and contextual effects with the presence of province FE.

2.5.2 Data description of Sample I

For the first research question of having a second child, we keep only families having one or two children and obtain a sample size of 2,206. They are distributed in 168 counties out of 21 provincial-level administrative regions.[15] We exclude provinces with more than 10 percent of minority population including Tibet and Xinjiang, as the birth quota for minorities is complicated and varies by region. By doing this, the families in Sample I (for analyzing having a second child) who are not restricted by the general birth quota account for a very small proportion.[16]

Table 2.1 shows the descriptive statistics of Sample I. 58.98 percent of families have a second child. On average, men have two more years of education than women.[17] 42 percent of women and 62 percent of men hold a junior high school diploma, which takes nine years to finish.[18] The average education years for women are 5.85 years, and the average years foe men are 7.82 years.[19] Average annual family income is 71,500 *yuan* (roughly $10,500) with a standard deviation close to the mean.[20] "First child is a girl" is a binary variable

[15]↑21 provincial-level administrative regions are: Beijing, Tianjin, Hebei, Shanxi, Jilin, Heilongjiang, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Chongqing, Sichuan, Shaanxi, Gansu.

[16]↑The top 10 provincial-level administrative regions with respect to the proportion of minority population are: Tibet (93.94%), Xinjiang Uygur Autonomous Region (59.43%), Qinghai (45.97%), Guangxi Zhuang Autonomous Region (38.38%), Guizhou (37.84%), Ningxia Hui Autonomous (34.56%), Yunnan (33.42%), Inner Mongolia (20.83%), Hainan (17.38%), Liaoning (16.06%) based on the 2000 China Population Census. We exclude provinces with a minority percentage higher than 10 percent.

[17]↑We define education years as follows: 0 if illiterate/semi-literate, 6 if the highest degree is primary school, 9 if the highest degree is junior high school, 12 if the highest degree is senior high school/secondary school/tech, 15 if the highest degree is 3-year college, 16 if the highest degree is 4-year college, 18 if the highest degree is a Master's degree.

[18]↑In Sample I, 32.46% of women are illiterate, 25.75% have primary school diploma, 27.29% have finished junior high school, 11.15% have finished senior high school, and 3.35% have college degree or above; the percentages of men with the same order of education categories are: 15.32% (illiterate), 22.93% (primary), 38.35% (junior high), 17.86% (senior high), and 5.53% (college or above).

[19]↑Based on the 2010 census, the average years of education for all women aged 39 - 48 (45 - 54 at 2016) are 8.65 years. For men, the average education years for the same age cohort are 9.43 years. Therefore, women in our sample receive 2.80 years less of education compared to the national average, and men receive 1.61 years less of education compared to the national average.

[20]↑We exclude the observations that are below 1 percent or above 99 percent percentile regarding the family income.

Table 2.1. Summary statistics of sample I

Variable	mean	s.d.	min	max
Individual controls				
Mother's education years	5.85	4.59	0	18
Father's education years	7.82	4.12	0	18
Annual family income in unit of 50,000 *yuan*	1.43	1.2	0.06	8.7
Whether engaged in ag production	0.57	0.49	0	1
Rural indicator	0.51	0.5	0	1
First child is a girl	0.45	0.5	0	1
Either of parent has ag *hukou*	0.76	0.43	0	1
Qualified for 1.5 child policy	0.22	0.42	0	1
Mother's age at first birth	23.64	7.35	16	45
Living with father-in-law of the mother	0.1	0.3	0	1
Living with mother-in-law of the mother	0.18	0.38	0	1
Contextual controls				
Education years of peers	6.8	1.96	0	13.44
Annual income of peers in unit of 50,000 *yuan*	1.42	0.62	0.26	5.83
% of peers with firstborn daughter	0.45	0.14	0	1
Mother's age at first birth among all peers	23.61	1.41	19.75	33
% of peers living w/ either in-law of the mother	0.21	0.12	0	1
Other descriptive statistics				
Number of households in each county	20.02	7.35	1	36
Age of the 1^{st} child	25.72	4.46	1	37
Age of the 2^{nd} child if applicable	21.65	6.03	1	34

which takes the value of one if the firstborn is a girl, and zero if a boy. Only 45 percent of the single-child and two-children families have a first daughter. 95 percent of mothers gave birth to the first child between 19 and 32 years old, with an average age of 23.64. In Sample I, only 10 percent of households live with their father-in-law and 18 percent live with their mother-in-law. Families with two generations living together indicate higher tension between the female and mother-in-law, in which the elder generation may put more pressure on the younger generation to bear children (Chan *et al.* 2002, Meng 2002).

51 percent of households are registered as rural residents and 57 percent rely on farming as part of their income source. In China, the types of registered residence (known as *hukou*)

include agricultural and non-agricultural, which are linked with policy implements. For example, the 1.5 child policy was restricted to families who have the agricultural *hukou* with a firstborn daughter and live in the provinces where the policy was implemented. 76 percent of households have agricultural *hukou* but only 22 percent are qualified for the 1.5 child policy. The three variables, “Rural indicator”, “Whether engaged in ag production” and “Either parent has ag *hukou*” have some conceptual similarities, but they reflect different aspects of household characteristics: geographical location as “Rural indicator”, occupation as “Whether engaged in ag production” and policy-related registered type as “Either parent has ag *hukou*”. The full correlated coefficients of controls in Sample I are shown in Appendix A.2, and the three variables are not collinear.

To capture the observable neighborhood characteristics, *i.e.* contextual effects, we include the leave-i-out mean of education, income and age of having the first child. We also include the percentage of peers with firstborn daughters, and the percentage of peers living with in-law(s). “Education years of peers” in the contextual effects is the leave-i-out mean of education year for both fathers and mothers within the peer group. The variable “% of peers living w/ either in-law of the mother” is defined as living with either of the in-laws.[21] We use province fixed effects to control correlated unobservables such as social norm and unobserved provincial child policies. Corresponding own and contextual characteristics are usually positively correlated but the highest correlated coefficient is only 0.362 (see Appendix A.1).

Figure 2.5 shows the sex composition of child(ren) in Sample I. G and B represent single daughter and single son families, and ij represents families having two children with sex i for the first child and sex j for the second child (i,$j \in \{G, B\}$). More than half of urban families have a single child due to the one-child policy, with slightly more single sons than single

[21]↑We do not have contextual controls X_2 as the same list of individual controls. One reason is the group average of some individual characteristics is less likely to be relevant to individual fertility decisions. For instance, peers' education level is obviously an important demographic which affects a peer's behavior, but the proportion of peers holding agricultural *hukou* is less likely to be relevant to a fertility decision. Another reason is the high correlation of some contextual controls. As shown in A.2, individual controls – whether living in rural area, agricultural *hukou*, farming indicator and qualification for the 1.5 child policy – are not highly correlated, but the group averages of these controls are highly correlated to each other. Including these contextual controls would lead to biased estimates of all individual and contextual controls. Therefore we only include relevant contextual controls.

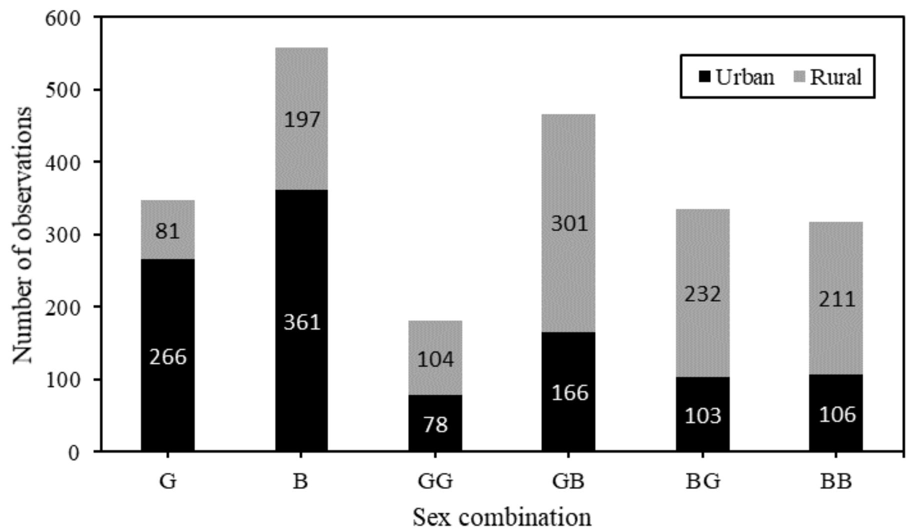


Figure 2.5. Sex composition of child(ren) for single child and two children families
Source. China Family Panel Studies (year 2016)

daughters. Very few rural families have single daughters partly because of the availability of 1.5 child policy. 75 percent of rural families and 42 percent of urban families choose to have two children, with having two girls being the least popular choice. When the first child is a boy, the family has less pressure regarding the sex of the second child. Therefore, the numbers of BG and BB families are close. But the number of GB families doubles in comparison to GG families in the urban area and triples in the rural area. One reason is that families with two girls first may choose to have a third child and would not be included in the sample. Another reason is that sex-selective activities exist on the second child when the first child is a girl. We believe that some of the GG families are those who have given up trying to have a son, while others of the GB families are those who have succeeded. In general, there is a large proportion of urban and rural families who didn't follow the birth quota policies.

The firstborn of a family was on average 25.7 years old in 2016, and the second child was 21.6 years old. 95 percent of the firstborn who were born after the first child policy was implemented in 1979 are between 16 to 33 years old (born between 1983 to 2000). 95 percent of the second children, if applicable, were born between 1985 to 2007 (and are 9 to 31 years old in 2016), during which a series of restrictive two-child policies have been implemented.[22]

Figure 2.6 shows the age gap between two children (if applicable) in Sample I. Overall, the age gap is smaller for rural families compared to urban families, except for the case of GG. Some rural families who ended up with two daughters are believed to have had sex-selective abortions once or multiple times before another unwanted girl was tested and they gave up, which enlarges the age gap between the two girls. With potential sex-selective abortions in between, the age gap between GB is still small in the rural area, as rural households schedule a second child earlier when they have firstborn daughters. Figure A.1.1 shows the corresponding density functions of the age gaps by sex combination and area type. We see clearly that many rural households ended up having a son sooner after their first daughter is born. Therefore, contrary to what Ebenstein (2010) find, that boys come later than girls by 0.34 year, we find that boys actually come sooner than girls if the first child is a girl. We find no significant difference in age gap between BG and BB families.

[22]↑The 95 percent interval is measured based on an evenly tailed distribution.

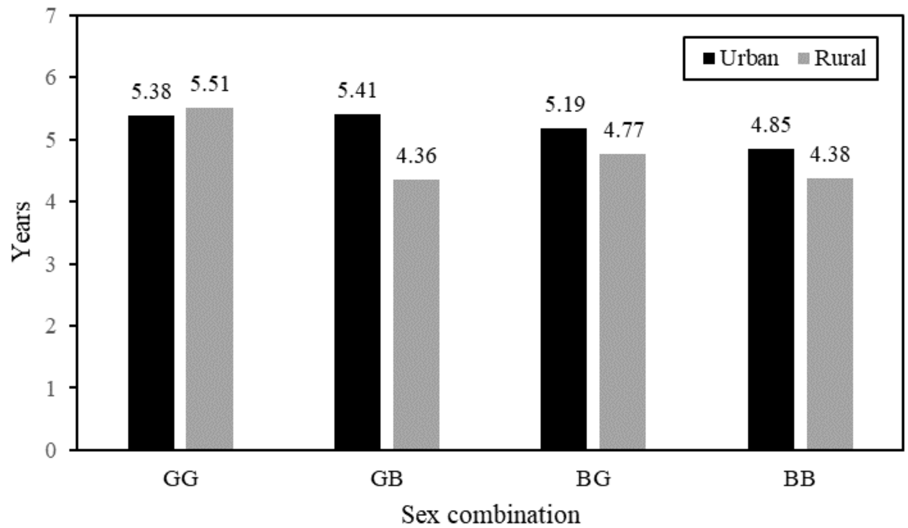


Figure 2.6. Age gap between two children (if applicable) in sample I
Source. China Family Panel Studies (year 2016)

2.5.3 Data description of Sample II

The second research question is to test whether peer effects play a significant role in son-preference. We choose a binary variable of ever having a son as the outcome measure of son-preference.[23] Peer effects on this behavior are supposed to capture how much a family would be more likely to end up having a son if the expectation of the percentage of neighbors with son(s) increases. We focus on the same age cohort with mothers aged 45 to 54, and record the sex of child(ren) they ever have. In this cohort, 17 percent of families have more than two children. As we are interested in the behavior of ever having a son, our scope is not restricted to households with one or two children. We also keep the minority provinces with various child policies. Sample II contains 3,348 observations, in which 36 percent of families have a single child, 47 percent have two children, and 13 percent have three children. Families

[23]↑In general, there are two ways to reach the goal of having a son. First, conduct sex-selective activities within the birth quota. That is, try to have a firstborn boy for urban families and make sure the second child is a boy if the firstborn is a girl for rural families; second, keep bearing children until a son is born. However, there are still families that either do not have a son-preference or they do not try "hard" enough until a son is born. These families may end up not having a son and we use the outcome of ever having a son as a measure of son-preference.

with more than three children account for only 4 percent. In Sample II, 79.24 percent of families have at least one son.

Table 2.2. Summary statistics of sample II

Variable	mean	s.d.	min	max
Individual controls				
Mother's education years	5.51	4.55	0	18
Father's education years	7.47	4.16	0	18
Annual family income in unit of 50,000 *yuan*	1.39	1.18	0.06	9.29
Whether engaged in ag production	0.62	0.49	0	1
Rural indicator	0.56	0.5	0	1
Either of parent has ag *hukou*	0.8	0.4	0	1
Mother's age at first birth	23.4	3.29	16	45
Living with father-in-law of the mother	0.1	0.3	0	1
Living with mother-in-law of the mother	0.17	0.37	0	1
Province indicator with 1.5 child policy implemented	0.71	0.46	0	1
Province indicator of minority > 10%	0.17	0.38	0	1
Contextual controls				
Education years of peers	6.42	1.91	1.15	13.44
Annual income of peers in unit of 50,000 *yuan*	1.38	0.55	0.43	5.83
Mother's age at first birth among all peers	23.36	1.2	20	32.5
% of peers living w/ either in-law of the mother	0.21	0.1	0.03	1
Other descriptive statistics				
Number of households within a county	23.66	7.44	1	37
Age of 1st child	26.06	4.42	1	37

Figure 2.7 shows the sex composition (in birth order) for families with less than 4 children in Sample II. We see a consistent pattern that shows the sex preference of children: before a boy is born to a family, sex ratio on the next parity is very high; but once a boy is born, the sex ratio on later parities appears to be more balanced. We can see this pattern by comparing the number of *GG* and *GB*, *GGG* and *GGB* families. Recall that families with more than three children account for only 4 percent in Sample II. But even for families with more than three children, which Figure 2.7 does not show, the number of *G...GB* sex combination is still much more than the *G...GG* case.

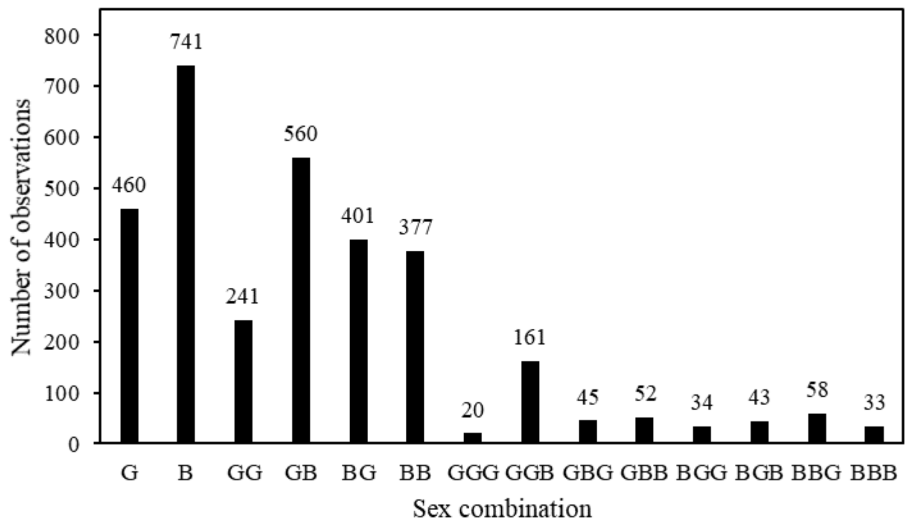


Figure 2.7. Sex composition of children for families with less than 4 children in sample II
Source. China Family Panel Studies (year 2016)

Table 2.2 shows the summary statistics of Sample II. Since we include families with more than two children, as well as those in minority provinces, we have more observations. But the characteristics of Sample II are very similar to those of sample I. We add the province indicator as whether the 1.5 child policy was implemented at that province and minority province indicator to show whether minority accounts for more than 10 percent of the total population in that province. The average education years for women are 5.51 years (7.32 years for urban area and 4.10 years for rural area). For men, the average education years are 7.47 years (8.68 years for urban area and 6.52 years for rural area).[24]

[24]↑Based on the 2010 census, the average years of education for all urban women aged 39 - 48 (45 - 54 at 2016) are 9.75 years. For urban men, the average education years for the same age cohort are 10.39 years. Therefore, urban women in our sample receive 2.42 years less of education compared to the national average, and urban men receive 1.71 years less of education compared to the national average. The average years of education for all rural women aged 39 - 48 (45 - 54 at 2016) according to 2010 census are 7.52 years. For rural men, the average education years for the same age cohort are 8.40 years. Therefore, rural women in our sample receive 3.42 years less of education compared to the national average, and rural men receive 1.88 years less of education compared to the national average.

2.6 Results

2.6.1 Fertility decision: Having a second child

Table 2.3 shows the estimation result for the first research question. The dependent variable is whether to have a second child. Model (1) is the baseline model without any social effects, and it is equivalent as a logit model with the dependent variable defined as $\{-1, 1\}$; Model (2) adds contextual effects, based on Model (1), which account for the social effects of only the exogenous neighborhood characteristics; Models (3) and (4) add peer effects based on Model (1) and Model (2) separately. Therefore, Model (4) contains both endogenous peer effects and exogenous contextual effects as social effects; Models (5) and (6) add province FE based on Models (3) and (4). As mentioned, we drop provinces with fewer than or equal to 5 counties for Models (5) and (6). In particular, Model (6) contains complete social effects: peer effects, contextual effects, and province fixed effects controlled for correlated unobservables. The estimates of Model (1)-(5) are based on assumptions that one or multiple parts of social effects are ignored and are for comparison with the complete Model (6).

2.6.1.1 Interpretation of peer effects estimate, as well as social and policy implications

We find significant peer effects in Models (3)-(6), which means families make their decision of having a second child according to the average of expected behavior of their peers in having a second child. Based on the estimates of Model (6), all else being equal, if a family lives with all peers expected to have two children versus all peers expected to have a single child, this family will increase their probability of having a second child by 35 percent (see the marginal effects Table 2.4 for the fertility choice and Table 2.6 for the son-preference). On the margin, the average expected behavior of peers $w_i M$ across i is 0.1968, or equivalently the average expected probability of having a second child among peers is 59.84 percent.[25] If 10 percent more of peers are expected to have a second child (or proportion of peers having

[25]↑This statistic is calculated by first solving the expected behaviors M through equation (2.7), and then calculate the average of $w_i M$ across all households.

Table 2.3. Whether to have a second child on peer effects

	(1)	(2)	(3)	(4)	(5)	(6)
Peer effects			0.464***	0.250**	0.516***	0.388***
			(0.064)	(0.118)	(0.091)	(0.146)
Individual controls						
Mother's education years	-0.031***	-0.021***	-0.036***	-0.021***	-0.041***	-0.032***
	(0.007)	(0.007)	(0.006)	(0.007)	(0.008)	(0.009)
Father's education years	0.017**	0.017***	0.017**	0.016**	0.009	0.019**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
Annual family income in unit of 50,000 *yuan*	0.002	0.048	0.014	0.053**	0.075***	0.069**
	(0.022)	(0.024)	(0.019)	(0.023)	(0.026)	(0.028)
Whether engaged in ag production	0.256***	0.087	0.231***	0.079	0.123*	0.102
	(0.063)	(0.066)	(0.057)	(0.064)	(0.075)	(0.080)
Rural indicator	0.387***	0.377***	0.336***	0.347***	0.367***	0.340***
	(0.059)	(0.060)	(0.052)	(0.059)	(0.068)	(0.074)
First child is a girl	0.065	0.081	0.090	0.062	0.403***	0.341***
	(0.062)	(0.065)	(0.058)	(0.068)	(0.080)	(0.068)
Either of parent has ag *hukou*	0.297***	0.326***	0.158**	0.257***	0.389***	0.370***
	(0.077)	(0.080)	(0.066)	(0.075)	(0.087)	(0.091)
Qualified for 1.5 child policy	0.726***	0.689***	0.573***	0.618***	0.655***	0.669***
	(0.092)	(0.093)	(0.080)	(0.094)	(0.122)	(0.126)
Mother's age at first birth	-0.063***	-0.063***	-0.042***	-0.060***	-0.068***	-0.084***
	(0.008)	(0.008)	(0.007)	(0.008)	(0.009)	(0.009)
Living with father-in-law of the mother	-0.166*	-0.139	-0.114	-0.127	-0.122	-0.127
	(0.093)	(0.095)	(0.091)	(0.097)	(0.113)	(0.115)
Living with mother-in-law of the mother	0.173**	0.115	0.100	0.103	0.188*	0.124
	(0.074)	(0.075)	(0.077)	(0.098)	(0.097)	(0.080)
Contextual controls						
Education years of peers		-0.105***		-0.073***		-0.092***
		(0.018)		(0.022)		(0.030)
Annual income of peers in unit of 50,000 *yuan*		-0.129**		-0.102**		-0.010
		(0.053)		(0.048)		(0.073)
% of peers with firstborn daughter		-0.518***		-0.531***		-0.373*
		(0.189)		(0.162)		(0.198)
mother's age at first birth among all peers		0.076***		0.066***		0.064***
		(0.011)		(0.010)		(0.012)
% of peers living w/ either in-law of the mother		-0.145		-0.146		0.039
		(0.225)		(0.196)		(0.260)
Constant	1.011***	0.346	0.600***	0.314	0.969***	0.118**
	(0.215)	(0.255)	(0.189)	(0.254)	(0.234)	(0.303)
Province FE					Y	Y
Number of obs.	2,206	2,206	2,206	2,206	1,901	1,901
log-likelihood	-1,182	-1,140	-1,172	-1,141	-844	-831

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Contextual controls are leave-i-out mean of peers' characteristics for each individual.

Table 2.4. Marginal effects of having a second child in percentage points

	(1)	(2)	(3)	(4)	(5)	(6)
Peer effects			42.53	23.70	45.83	35.08
Individual controls						
Mother's education years	-1.47	-1.01	-1.71	-1.00	-1.85	-1.46
Father's education years	0.81	0.79	0.83	0.75	0.40	0.85
Annual family income in unit of 50,000 *yuan*	0.08	2.25	0.66	2.53	3.42	3.12
Whether engaged in ag production	12.06	4.14	10.99	3.75	5.65	4.65
Rural indicator	18.03	17.65	15.80	16.36	16.60	15.29
First child is a girl	3.05	3.81	4.23	2.92	17.99	15.15
Either of parent has ag *hukou*	14.34	15.81	7.61	12.44	18.46	17.43
Qualified for 1.5 child policy	29.19	28.24	24.27	25.95	25.59	25.75
Mother's age at first birth	-2.96	-2.98	-1.99	-2.85	-3.08	-3.78
Living with father-in-law of the mother	-8.00	-6.73	-5.51	-6.16	-5.68	-5.91
Living with mother-in-law of the mother	7.89	5.34	4.65	4.79	8.20	5.44
Contextual controls						
Education years of peers		-4.96		-3.48		-4.17
Annual income of peers in unit of 50,000 *yuan*		-6.12		-4.86		-0.46
% of peers with firstborn daughter		-24.33		-24.99		-16.91
Mother's age at first birth among all peers		3.59		3.11		2.87
% of peers living w/ either in-law of the mother		-6.98		-7.05		1.75

For continuous variable, the marginal effects is the change of probability in having a second child (in percentage points) if the continuous variable increases by one unit; for discrete variable, the marginal effects is the difference between the probabilities of having a second child when the discrete variable changes from zero to one; for the endogenous effects, the marginal effects is the difference between the probabilities of having a second child when the leave-out mean of peer's outcome expectation M changes from -1 to 1, as the way it is defined.

a second child increases from roughly 60 percent to 70 percent), the probability of having a second child for each household will increase by 3.42 percent on average.

The significance of the peer effect parameter indicates that households do not make fertility decisions independently from each other. Whether or not this dependence improves a family's welfare improving is a complex question, and naturally depends on a variety of factors. Though a complete welfare analysis is beyond our current scope, it is worth considering the following possible channels through which a significant peer effect might generate an unanticipated impact.

First, understand that the presence of a significant peer effect in one's utility function changes the marginal two-child family, relative to a marginal two-child family we would have otherwise identified in a model absent peer effects. That is, the significant peer effect in the utility function influences the utility function in the direction of having another child (because the estimate is significantly positive). This means that a marginal household in the traditional model absent peer effects would no longer be a marginal household in the model that incorporates peer effects. In the peer effects model, that household would choose to have a second child, whereas the same household in the model absent peer effects would have been indifferent to having or not having a second child. By considering this change in marginal household from the traditional (non-peer) model to the peer effects model, we can begin to anticipate some of the potentially welfare-influencing effects of the dependence in decision-making that were previously unrecognized.

One channel of impact may be through intra-household resource allocation between both children, such as a change in consumption and/or savings. Clearly, the birth of a second child requires an adjustment in household resource allocation. While there are a variety of ways that a household can reallocate resources, one possible reallocation that may be both prevalent (at least anecdotally) and concerning, would be a reallocation of resources away from the first child and towards the second. Given the 1.5 child policy statutes, it is likely that the first child is a girl. Since sons are preferred traditionally, as discussed, it stands to reason that households may choose to invest a relatively greater share of their wealth in the second child if the second child is a son. Of course, it need not be the case that the family would make such a resource reallocation, or that the second child is a son. It is also possible that the household chooses to allocate an even share of resources to both children regardless of gender, or that the family accommodates the birth of the second child by reducing consumption or savings. However, given broader evidence of gender discrimination in China (Li and Wu 2012, Zheng 2015), it may be worth further study to understand how an incorporation of peer effects into household resource allocation among children may be warranted and insightful.

Another channel of impact may be through female labor market participation. With prevalent understanding of the negative relationship between the number of children a female has and the probability of her labor market participation, the two-child policy implemented in 2016, which has boosted the total fertility rate, may lower the labor supply of married females in the long run (Zeng and Hesketh 2016). Accounting for peer effects, this potential direction in the change of female labor market participation may be further enhanced during the two-child policy era. Of course, this paper does not study the peer effects in females leaving the labor market, but the spillover effects of fertility choices may generate an indirect impact on labor market participation of women.

From the population policy perspective, a significant peer effect interacts with policy objectives and eventually could facilitate the achievement of policy goals. When the Chinese government aimed at a population control in the 1980s, it implemented the one-child policy which has curbed the size of multi-child families. During this policy period, a positive and significant peer effect would have decreased a family's willingness to have a second child, to keep up with other single-child families. Since 2016, the Chinese government has implemented a general two-child policy. Under this population expansion goal, a positive and significant peer effect would motivate more families to have a second child, in order to keep up with other two-child families. That is, with more families planning to have a second child under the two-child policy, there would be more single-child families trying to have a second child because of peer effects. In general, peer effect works as a momentum towards population goals.

2.6.1.2 Interpretation of individual controls estimates

Based on Model (6), one more year of education for the mother decreases the probability of having a second child by 1.46 percent, while one more year of education for the father increases, by 0.85 percent, the probability of having a second child. This dilemma reflects a conflict in fertility preference between highly educated couples. The negative relationship between education years of women and their fertility preference is as expected: on average, women in Sample I received 5.85 years of education. A large number of illiterate women and elementary school graduates are most likely to be off the labor market because of low productivity. Therefore, longer education years increase the chance of being employed and spending less time raising children. However, the positive relationship between fertility preference and the education level of a male is interesting. One possible explanation is that highly educated males are more likely to support a larger-size family. But another explanation is that highly educated males have stronger ability to break the birth quota and realize their willingness to have more children carrying on their family names and genes. We are not able to distinguish these two conjectures based on our estimates.

Families with higher income are more likely to have a second child, as they could likely afford to raise another child and also because they could afford to pay a potential penalty for breaking the birth quota. A 50,000 *yuan* (roughly $7,400) raise in family income increases the probability of having a second child by 3.12 percent. Either parent holding the agricultural type of registered residence increases the probability of having a second child by 17.43 percent. Ceteris paribus, families with a first daughter are 15.15 percent more likely to have a second child according to Model (6). More interestingly, a relaxed birth quota from one child to two, or "Qualified for 1.5 child policy", increases the probability of having a second child by 25.75 percent. This suggests that relaxing the birth quota, such as implementing the two-child policy, could largely motivate fertility willingness. The higher the age of a mother giving birth to the first child, the less likely the family is to have a second child because of a shortened reproductive period. Living with in-laws of females has no significant impact on having a second child after we control for contextual effects and province fixed effects.

2.6.1.3 Interpretation of contextual effects estimates

Contextual effects play an important role in the decision of having a second child, especially the education of level peers. Living with highly educated peers decreases the probability of having a second child, and this contextual effect of education has an even larger magnitude of influence than one's own education level. Based on the estimate of Model (6), one more year of education for the whole population (mother and father of a family and all peers) decreases the probability of having a second child in a family by 4.78 percent. The contextual effects of the percentage of peers with a firstborn daughter reflect the magnitude of son-preference. Statistically it should be close to 0.5 if there were no gender selection at birth. A higher percentage of peers with a firstborn daughter suggests a weaker son-preference and therefore the household to having less pressure in having a second child (potentially a son). Based on Model (6), the probability of having a second child decreases by 16.91 percent if a household lives with peers all having firstborn daughters compared to those with all peers having firstborn sons.

The contextual effects of income based on Models (2) and (4) suggest that if a household lives with richer peers, they are less likely to have a second child. But these effects are not significant after province FE is added. The contextual effects of the age of mothers among the peers when having the first child shows interesting dynamics regarding the choice of having a second child. If a woman becomes a mother at an older age, she is less likely to have a second child, and the individual control of "Mother's age at first birth" supports this statement. However, keeping a woman's age of having a first child unchanged, her probability of having a second child varies by her relative age compared to the her peers. Model (6) suggests that having more older mothers as peers increases the probability of having a second child. A possible explanation is that, when a mother is relatively younger among her peers, the environment motivates this woman to use her age advantage to have more children (and potentially a son). On the other hand, living with peers who become mothers in their younger years actually discourages this "older" mother from having more children.

2.6.1.4 Comparison of peer effects estimates across models

Comparing Model (3) with Model (4), the magnitude of peer effects decreases after we add contextual effects – similarly as we compare Model (5) with Model (6). These comparisons reflect that some of the social effects come from contextual effects, and ignoring the contextual effects leads to an upward bias estimate of peer effects. Intuitively, the fact that peer group members behave similarly is not only directly stimulated by peer expected behaviors, but also partly because they share similar background. In this specific second choice question, contextual controls are in general positively correlated with peer effects. Therefore ignoring contextual effects lead to upward bias estimate of peer effect.

The majority of province FE estimates not shown in Table 2.3 are significant, which suggests a heterogeneity in unobserved provincial characteristics. Comparing Model (3) with Model (5), or Model (4) with Model (6), we find that peer effect increases after controlling for province FE. Province FE captures the correlated unobservables including social norm and province level child policies. In this specific second choice problem, ignoring correlated effects leads to a downward bias of peer effects and most individual/contextual effects in the fertility decision. This feature reflects that the unobserved province-level characteristics are negatively correlated with peers' expected behavior and most of individual/contextual characteristics. Intuitively, if an area (province in this case) already has stronger social norms of having a second child or stronger policy incentive to have a second child, households care less about what their peers are expected to do and care more about following the social norms.

2.6.2 Son-preference: Having a son during reproductive period

Intuitively, sex selection is a follow up research question of having a second child. However, if we only include two-child families (e.g., GG and GB families, or all two-child families) and use the sex of the second child being a boy as the dependent variable, we would ignore peer effects sourced from single-son neighbors and/or three-child families with sons around each household. After all, it is whether a household had a son that matters for fulfilling the traditional obligations, instead of at which birth a son was born. Therefore, for the second research question of peer effects on son-preference, we use whether a family ever had a son as the outcome variable without putting restrictions on the number of children they ever had.

Table 2.5 shows the estimates for Models (1) to (6) under the same setting with the fertility question. We find significant peer effects for Models (3) and (5) without contextual effects, but peer effect is no longer significant after we control for contextual characteristics. Similarly to the second child question, the contextual effects of neighbors are in general positively correlated with peer effects and ignoring the contextual effects leads to upward bias of peer effects estimates. Intuitively, if a household lives with peers whose characteristics (e.g., education level, income, etc.) motivate this household to have a son, this household would also care more about what their peers are expected to do regarding having a son. In this specific sex choice question, our baseline estimates in Model (6) show that the social effects are majorly driven by the contextual living environment instead of keeping up with the others. As a comparison with the fertility decision of having a second child, son-preference has different nature regarding the role of peer effects.

Highly educated females are less likely to have a son, or tend to be against the prevalent son-preference. One more year of education for a female decreases the probability of having a son by 0.33-0.87 percent. But this estimate is not significant after contextual effects and province FE are added simultaneously while the sign is still negative. Interestingly, the education level of a male plays an opposite role in sex preference. One more year of education for a male increases the probability of having a son by 0.34-0.50 percent. And this effect stays significant to at least a 10 percent level across all six models, which means the traditional thought of having a son actually gets strengthened through higher education of the male. One possible explanation is that the deep-rooted tradition exists broadly, but a highly educated male has better chance to implement the son-preference as he is able to utilize his social resources and strengthen the bargaining power in his marriage regarding having a son. Another supplementary possibility is that highly educated males have higher pride in themselves and are more obsessed with having a son to carry on their family name as well as their genes.

Richer families have higher chance of having a son. The estimate of income level remains significant across all six models. The richer the family, the higher the chance of realizing the "son dream". A 50,000 *yuan* increase in annual income increases the chance of having a son by 2.1 percent based on Model (6). This is possibly because having a son indicates a higher economic burden on a family, as it is the parents' obligation to prepare the future housing for their son's marriage. Therefore richer families are more likely to afford the economic burden and are more emboldened to schedule/welcome a son. Families holding agricultural type of registered residences (or *hukou*) are 10.34 percent more likely to have a son. This a reasonable estimate as *hukou* is usually linked with government policies – the 1.5 child policy is one example, and there are other unobserved child and financial policies linked with *hukou*. For example, a household could acquire land contract, and/or enjoy more flexibility of house building if holding an agricultural *hukou*. Such policy incentives generate obvious motivations to have a son. Each year older that a woman becomes a mother, it is 0.87 percent less likely the family will have a son in the end. Similar to the fertility decision,

Table 2.5. Whether to have a son during reproductive age

	(1)	(2)	(3)	(4)	(5)	(6)
Peer effects			0.445***	-0.053	0.441***	-0.059
			(0.109)	(0.240)	(0.128)	(0.268)
Individual controls						
Mother's education years	-0.028***	-0.016***	-0.027***	-0.014**	-0.025***	-0.011
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
Father's education years	0.011*	0.017***	0.013**	0.014**	0.013*	0.013*
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
Annual family income	0.044**	0.050**	0.038**	0.049**	0.083***	0.073***
in unit of 50,000 *yuan*	(0.020)	(0.022)	(0.017)	(0.020)	(0.022)	(0.023)
Whether engaged in	0.128**	0.106*	0.111**	0.100	0.161*	0.063
ag production	(0.058)	(0.060)	(0.056)	(0.061)	(0.064)	(0.069)
Rural indicator	0.160***	0.130**	0.152***	0.130**	0.097*	0.117*
	(0.055)	(0.056)	(0.050)	(0.056)	(0.056)	(0.065)
Either of parent has	0.299***	0.283***	0.221**	0.317***	0.292***	0.321***
ag *hukou*	(0.066)	(0.068)	(0.065)	(0.072)	(0.075)	(0.084)
Mother's age at first birth	-0.028***	-0.018***	-0.020***	-0.021***	-0.031***	-0.030***
	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)
Living with father-in-law	0.029	0.036	0.032	0.042	-0.005	0.001
of the mother	(0.085)	(0.086)	(0.084)	(0.087)	(0.094)	(0.098)
Living with mother-in-law	0.065	0.032	0.024	0.041	0.076	0.053
of the mother	(0.066)	(0.066)	(0.066)	(0.067)	(0.073)	(0.074)
Province indicator with 1.5	0.194***	0.216***	0.142***	0.236***		
child policy implemented	(0.048)	(0.052)	(0.038)	(0.066)		
Province indicator of	-0.142**	-0.215***	-0.096**	-0.247***		
minority > 10%	(0.058)	(0.058)	(0.042)	(0.074)		
Contextual controls						
Education years of peers		-0.099***		-0.098***		-0.122***
		(0.016)		(0.029)		(0.036)
Annual income of peers		-0.020		-0.017		-0.020
in unit of 50,000 *yuan*		(0.046)		(0.046)		(0.069)
Mother's age at first birth		0.044***		0.045***		0.056***
among all peers		(0.008)		(0.014)		(0.017)
% of peers living w/ either		-0.056		-0.101		-0.040
in-law of the mother		(0.227)		(0.231)		(0.282)
Constant	0.869***	0.217	0.519***	0.270	0.810***	0.446
	(0.185)	(0.239)	(0.176)	(0.246)	(0.215)	(0.288)
Province FE					Y	Y
Number of obs.	3,348	3,348	3,348	3,348	2,811	2,811
log-likelihood	-1,587	-1,569	-1,584	-1,569	-1,270	-1,263

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Contextual controls are leave-i-out mean of peers' characteristics for each individual. Province indicator with 1.5 child policy implemented and province indicator of minority population accounts for more than 10 percent of population are removed from control list when province FE are added.

Table 2.6. Marginal effects of ever having a son in percentage points

	(1)	(2)	(3)	(4)	(5)	(6)
Peer effects			35.00	-3.07	33.07	-3.22
Individual controls						
Mother's education years	-0.87	-0.49	-0.84	-0.42	-0.71	-0.33
Father's education years	0.34	0.50	0.40	0.43	0.37	0.37
Annual family income in unit of 50,000 *yuan*	1.34	1.50	1.16	1.48	2.39	2.10
Whether engaged in ag production	3.99	3.25	3.47	3.06	3.54	1.83
Rural indicator	4.97	3.95	4.75	3.98	2.81	3.36
Either of parent has ag *hukou*	10.19	9.46	7.37	10.77	9.35	10.34
Mother's age at first birth	-0.87	-0.54	-0.62	-0.63	-0.90	-0.87
Living with father-in-law of the mother	0.88	1.06	0.96	1.24	-0.14	0.04
Living with mother-in-law of the mother	1.93	0.96	0.72	1.22	2.12	1.48
Province indicator with 1.5 policy	7.71	6.89	4.55	7.59		
Province indicator of minority $> 10\%$	-4.59	-7.07	-3.09	-8.25		
Contextual controls						
Education years of peers		-3.00		-2.96		-3.48
Annual income of peers in unit of 50,000 *yuan*		-0.62		-0.52		-0.57
Mother's age at first birth among all peers		1.34		1.35		1.60
% of peers living w/ either in-law of the mother		-1.72		-3.17		-1.16

For continuous variable, the marginal effects is the change of probability in ever having a son (in percentage points) if the continuous variable increases by one unit; for discrete variable, the marginal effects is the difference between the probabilities of ever having a son when the discrete variable changes from zero to one; for the endogenous effects, the marginal effects is the difference between the probabilities of ever having a son when the leave-out mean of peer's outcome expectation M changes from -1 to 1, as the way it is defined.

we find no evidence to support that living with either parent-in-law of the mother affects the son-preference of a family.

Contextual effect plays a vital important role in having a son. One more year of education in the peer group decreases the probability of having a son by 3.48 percent based on Model (6). One possible explanation is that highly educated peers (especially mothers) are more likely to have jobs and live economically independently. The highly educated peers could have passed on their values to the wife of the household about the advantages of participation in the labor market, thus encouraging her to work and reduces the probability of having a larger-sized family (then statistically reduces the probability of having a son). Another possible explanation is that highly educated peers have more concerns about abortions and may enjoy more in raising daughters. And their views may influence a household's decision on sex selection.

Older mothers are less likely to have a son, but if a family lives with peers that are even older mothers, they are more likely to have a son. One explanation is that having a son is a game and a family chooses the optimal strategy to play considering their age advantage. When a mother is younger among her peers, it reminds the mother of her age advantage among her peers and motivates her to have a son. On the other hand, if a mother lives with younger peers which makes her a relatively older woman, she is more likely to give up the son-preference and accept living with a daughter she already has; after all, competing with younger peers in having a son brings a lot of pressure because of the age disadvantage. More interestingly, the magnitude of contextual effect of "Mother's age at first birth among all peers" (-0.87% as the marginal effect) exceeds the individual effect of "Mother's age at first birth" (1.60% as the marginal effect). Therefore, the encouragement of "late marriage and late fertility" for the sample cohort generation, which has increased the mother's age at first birth, could have worsened the unbalanced sex ratio according to our estimates. If all mothers postpone having the first child by one year, the probability for them to have a son would increase by 0.73% ($-0.87\% + 1.60\%$).

Comparing the estimates of Model (1) with Model (6), we find the individual controls estimates vary not only by magnitude but also significance. Ignoring social effects may lead to biased estimates. We can also see the consequences of adding peer effects while ignoring the contextual and correlated effects. For the first research question, ignoring the contextual effects could lead to an overestimate of peer effects; as for the son-preference, we could have credited the contextual effects to peer effects mistakenly.

2.6.3 Separate rural and urban peer effects

The baseline model in equation (2.1) remains the flexibility to divide a single peer effects estimate for the whole sample into separated peer effects estimates for rural and urban area. To achieve this goal, we replace $\gamma w_i M$ in equation (2.1) with $\gamma^{rural} w_i M \mathbb{I}_{Rural_i=1} + \gamma^{urban} w_i M \mathbb{I}_{Rural_i=0}$ where indicators $\mathbb{I}_{Rural_i=1}$ and $\mathbb{I}_{Rural_i=0}$ equal to either one or zero depending on whether household i lives in a rural or an urban area. The proportion of households in the sample living in a rural area across counties varies from 0% to 100%. This means that for some counties, the proportion of households living in the rural area could be very low (0% would indicate that everyone in that county lives in an urban area). For some counties, this statistic could be very high (If this is 100%, it indicates that everyone living there is from a rural area). Within each county, rural and urban households may have different peer effects. We use the heterogeneous peer effects model for one robustness check, as peer effects for a subgroup of households may be different from others.

Table 2.7 shows the separated peer effects estimates for both research questions – having a second child as in Model (1) and having a son as in Model (2). Recall in the baseline Model (6) for having a second child, we find significant peer effects for the whole sample (see Table 2.3). But if we allow for heterogeneous peer effects in the rural and urban areas, only peer effects in the urban area are significant. Even though anecdotally the tradition of raising a larger family could be more deeply-rooted in the rural area, the evidence that the behavior of having a second child is caused directly by expected peers' behavior in rural area is weak. One possible explanation is that rural households are more realistic in family planning decisions when it comes to peer comparison. Peer pressure from expecting others to have a second child is not strong enough to cause a behavioral change in having a second child for rural households whose basic needs for food and clothing could be more of a concern, compared with urban households. Surprisingly, urban families' behavior in having a second child is more sensitive to the expected behavior of the surroundings compared to rural households. One explanation is that "keeping up with the Zhanges" is an advanced need beyond the basic needs of food and clothing. Urban families are more likely to shift their behavior towards their peer group's average behavior for an increased utility. The positive peer effects of having a second child in the urban area and the insignificant peer effects for rural households suggest that the two-child policy generates spillover effects mostly for urban families instead of rural families.

Peer effects on son-preference are in opposite directions for rural and urban families but are insignificant. Recall in the baseline model, we find insignificant peer effects for the whole sample, with coefficient estimate as -0.059 (see Model (6) in 2.5). Under the separated peer

Table 2.7. Separate rural and urban peer effects

	2nd child	Son
	(1)	(2)
Rural Peer effects	0.124	0.123
	(0.186)	(0.346)
Urban Peer effects	0.348***	-0.121
	(0.161)	(0.294)
Individual controls		
Mother's education years	-0.032***	-0.014*
	(0.009)	(0.007)
Father's education years	0.020**	0.014*
	(0.008)	(0.007)
Annual family income in unit of 50,000 *yuan*	0.067**	0.063**
	(0.028)	(0.023)
Whether engaged in ag production	0.150*	0.052
	(0.081)	(0.069)
Rural indicator	0.417***	0.032
	(0.078)	(0.074)
First child is a girl	0.335***	
	(0.085)	
Either of parent has ag *hukou*	0.400***	0.316***
	(0.092)	(0.084)
Qualified for 1.5 child policy	0.619***	
	(0.126)	
Mother's age at first birth	-0.080***	-0.023***
	(0.009)	(0.007)
Living with father-in-law of the mother	-0.106	-0.003
	(0.115)	(0.098)
Living with mother-in-law of the mother	0.112	0.052
	(0.098)	(0.074)
Contextual controls		
Education years of peers	-0.099***	-0.115***
	(0.032)	(0.037)
Annual income of peers in unit of 50,000 *yuan*	-0.022	-0.011
	(0.078)	(0.069)
% of peers with firstborn daughter	-0.309	
	(0.217)	
Mother's age at first birth among all peers	0.061***	0.058***
	(0.012)	(0.018)
% of peers living w/ either in-law of the mother	0.083	-0.099
	(0.283)	(0.281)
Constant	0.571*	0.290
	(0.311)	(0.285)
Province FE	Y	Y
Number of obs.	1,901	2,811
log-likelihood	-835	-1,263

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Contextual controls are leave-i-out mean of peers' characteristics for each individual.

effects setting, neither rural nor urban peer effect is significant but the estimate is positive for the rural area and negative for the urban area. In general, negative peer effects indicate that households tend to have a daughter if they expect their peers to have sons. It would be a more reasonable reaction, considering the decreasing probability for a man to get married in China due to high sex ratio, but we will not draw this conclusion as the estimates are insignificant.

2.6.4 Alternative definition of peer group

The baseline Model (6) in Table 2.3 and Table 2.5 are estimated based on the assumption that the peer group is defined at a county level. Part of the reason is that the peer-to-peer network is not available at CFPS, but, more importantly, we believe the social and economic lives of Chinese households happen at the county level as explained in 2.5.1. CFPS contains geographic information of three levels: province, county and community. It gives us the flexibility to conduct a robustness check if peer influence is believed to be at a narrower level, such as the community level. Community is the lowest level of administrative divisions of China, even smaller than the township level, which is commonly used in applied micro-analysis in China. A community in a rural area may include several natural villages or a subset of a natural villages, depending on the village size. An urban community may include only 100-700 households living within a few blocks, depending on the population density. If we define peers in a community level – only households living in each community are peers to each other, we can re-estimate the baseline Model (6). Table 2.8 shows the estimation for both research questions under the narrower definition of peers.

Models (1) and (3) include provincial level fixed effects while Models (2) and (4) use county level FE. Recall that the baseline Model (6) in Table 2.3 and Table 2.5 defines peers in a county level with province FE. With community level peers, we have the flexibility to choose either provincial FE or county FE. If we believe all unobserved characteristics are correlated only in a provincial level, such as social norms and child policy, Models (1) and (3) should be referred to. If we believe there is heterogeneous unobserved household characteristics across counties within each province, Models (2) and (4) provide a more

Table 2.8. Peer group defined at the community level

	Having a second child		Having a son	
	(1)	(2)	(3)	(4)
Peer effects	0.118	0.690***	0.056	0.278
	(0.145)	(0.134)	(0.180)	(0.191)
Individual controls				
Mother's education years	-0.027***	-0.007	-0.015**	-0.004
	(0.009)	(0.007)	(0.006)	(0.008)
Father's education years	0.016*	0.013	0.018***	0.015*
	(0.007)	(0.010)	(0.007)	(0.008)
Annual family income in unit of 50,000 *yuan*	0.065**	0.025	0.106***	0.062**
	(0.028)	(0.035)	(0.024)	(0.030)
Whether engaged in ag production	0.173**	0.100	0.129*	0.072
	(0.081)	(0.092)	(0.068)	(0.080)
Rural indicator	0.325***	0.140*	0.069	0.032
	(0.084)	(0.076)	(0.065)	(0.074)
First child is a girl	0.233***	0.417***		
	(0.085)	(0.118)		
Either of parent has ag *hukou*	0.477***	0.276**	0.335***	0.368***
	(0.099)	(0.116)	(0.083)	(0.106)
Qualified for 1.5 child policy	0.567***	0.541***		
	(0.121)	(0.157)		
Mother's age at first birth	-0.073***	-0.057***	-0.017**	-0.036***
	(0.009)	(0.011)	(0.007)	(0.008)
Living with father-in-law of the mother	-0.139	-0.133	0.045	-0.047
	(0.110)	(0.136)	(0.097)	(0.115)
Living with mother-in-law of the mother	0.175*	0.167	0.048	0.049
	(0.093)	(0.109)	(0.072)	(0.083)
Contextual controls				
Education years of peers	-0.018	0.007	-0.054***	-0.034**
	(0.017)	(0.018)	(0.015)	(0.016)
Annual income of peers in unit of 50,000 *yuan*	0.002	-0.002	-0.074**	-0.045
	(0.049)	(0.056)	(0.037)	(0.046)
% of peers with firstborn daughter	-0.392***	-0.388***		
	(0.120)	(0.138)		
Mother's age at first birth among all peers	0.014*	0.007	0.021***	0.008***
	(0.007)	(0.008)	(0.007)	(0.008)
% of peers living w/ either in-law of the mother	0.022	0.138	0.023	0.047
	(0.137)	(0.144)	(0.121)	(0.136)
Constant	0.973	0.597*	0.429*	0.860**
	(0.261)	(0.320)	(0.221)	(0.345)
Province FE	Y		Y	
County FE		Y		Y
Number of obs.	1,987	1,701	3,009	2,436
log-likelihood	-894	-715	-1,344	-1,114

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Contextual controls are leave-i-out mean of peers' characteristics for each individual. (1) and (3) drop observations if less than 5 counties in each province; (2) and (4) drop observations if less than 3 counties in each county.

flexible estimation. Peer effects estimates in having a son are insignificant in both models. But for having a second child, the peer effects estimate varies by the FE choice.

In Model (1), we find insignificant peer effects on having a second child with provincial FE. One explanation is that we believe households living across communities while within a county could also be peers. Ignoring the part of the peer effects across communities (with a county) leads to omitted variable bias. Model (2) adds the flexibility of heterogeneous FE across counties compared to Model (1) and we find significant community-level peer effects. We think part of the ignored cross-community peer effects are accommodated to the county level FE; therefore, the bias of community-level peer effects is reduced. In general, we find significant peer effects in either county or community level peer effects with an upper-level FE.

2.6.5 Placebo test

For the first research question of having a second child, both peer effects and contextual effects should be insignificant if peers are randomly assigned. This is because contextual effects come from "real" peers' characteristics and peer effect is sourced from "real" peers' expected behavior. If peers are "fake", the estimates of contextual and peer effects should be theoretically insignificant.[26] We conduct 100 placebo estimates with re-sampling strategy as follows: randomly draw a household by its original ID without replacement within each province and form a new reordered data set. In the mean time, keep the original network structure, the "W" matrix, unchanged. By doing this, we keep the same number of observations with no repeated observation and the same distribution of peer group size. Each re-sampled household still "lives" in its original province; therefore it faces the same social norm and provincial child policies. But each household's new peer group members will not be its true peers. We estimate the baseline Model (6) in having a second child for each placebo and repeat the process 100 times.

Table 2.9 shows the percentage of estimates that are 1%, 5% and 10% significant. Recall that the baseline model (6) shows peer effects estimate is of 1% significant with true peers.

[26]↑This will hold only if the characteristics of fake peers are uncorrelated with the characteristics of true peers. And we provide supporting statistics in the following text.

Table 2.9. Placebo test of baseline Model (6) of having a second child

Numbers in the table are the percentage of placebo estimates that are of 1%, 5%, and 10% significance.

	1%	5%	10%
	(1)	(2)	(3)
Peer effects	0%	5%	11%
Individual controls			
Mother's education years	100%	100%	100%
Father's education years	3%	37%	61%
Annual family income in unit of 50,000	20%	44%	71%
Whether engaged in ag production	80%	99%	100%
Rural indicator	100%	100%	100%
First child is a girl	100%	100%	100%
Either of parent has ag *hukou*	100%	100%	100%
Qualified for 1.5 child policy	100%	100%	100%
Mother's age at first birth	100%	100%	100%
Living with father-in-law of the mother	0%	0%	0%
Living with mother-in-law of the mother	0%	5%	10%
Contextual controls			
Education years of peers	3%	14%	21%
Annual income of peers in unit of 50,000 *yuan*	4%	11%	21%
% of peers with firstborn daughter	1%	3%	5%
Mother's age at first birth among all peers	48%	82%	89%
% of peers living w/ either in-law of the mother	0%	0%	0%
Constant	8%	38%	73%
Province FE	Y	Y	Y
Number of obs.	1,901	1,901	1,901

Number of placebos: 100.

But when we assign "fake" peers, we find zero peer effects estimates are of 1% insignificant based on 100 placebos. In the baseline Model (6) of having a second child, education years of peers and mother's age of having a second child are of 1% significance, and "% of peers having a firstborn daughter" is 10% significant. In the placebo result, only 3 of the 100 placebo estimates of peers' education years are of 1% significant, and only 5 out of 100 placebos have "% of peers having a firstborn daughter" shows up as 10% significant.

But there are still 48 of 100 placebos showing the mother's age at first birth among all peers as being 1% significant. The reason for this phenomenon is that "mother's age of having a second child" has a dense distribution centered around 23-24. The re-sampling process still generates highly correlated fake contextual effects with respect to real contextual effects. Figure 2.8 shows the distribution of real contextual effects (in red) and placebo contextual

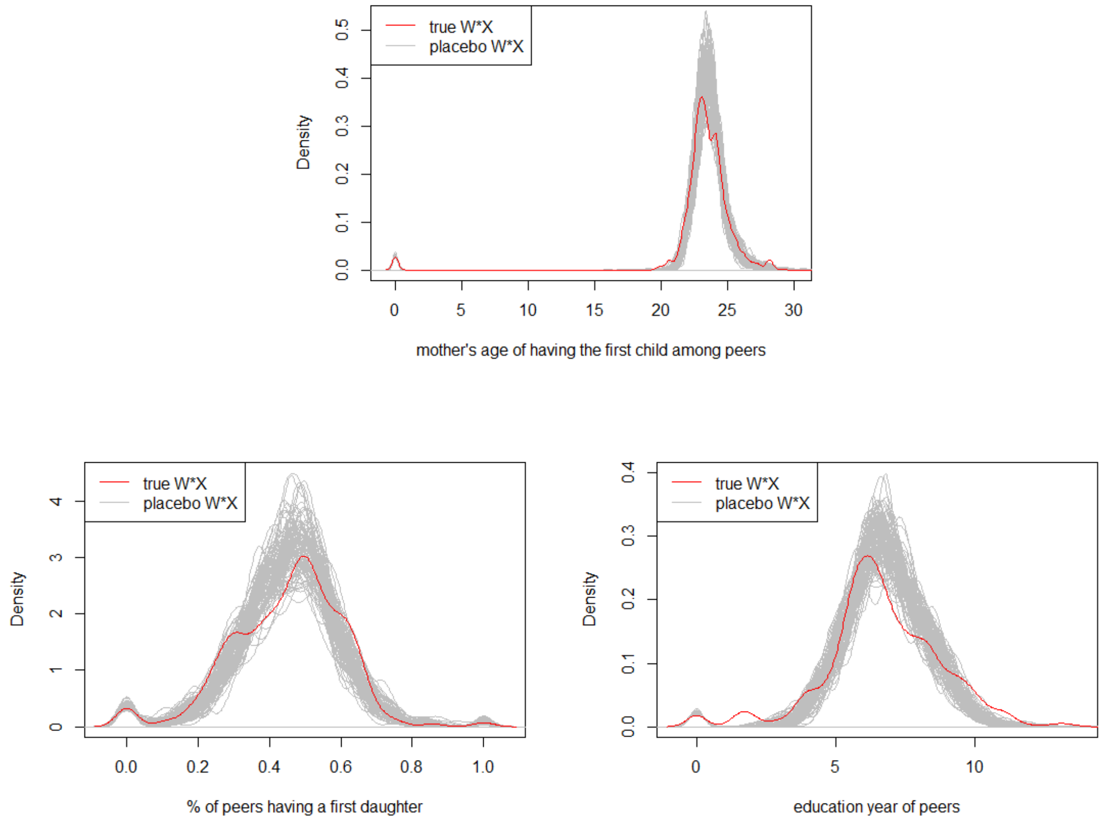


Figure 2.8. Comparing the density distribution of real contextual effects and placebo contextual effects

effects (in grey) of "mother's age at first birth among all peers", "% of peers with firstborn daughter" and "education year of peers". We can see that with peers randomly assigned, a mother's age of having a first child still has less variant distribution compared to the other two contextual effects. In fact, the average correlation coefficient of real contextual effects (WX^{real}) and the ith placebo contextual effects ($WX_i^{placebo}$) is 0.894. While the correlation coefficient for the contextual effect "education year of peers" is 0.546 and for the "% of peers with firstborn girl" is only 0.263. We believe this is the reason that there are still 48 out of 100 placebos with the contextual effect of mother's age of having a second child as 1% significant.

2.6.6 Peer effects comparison across age cohorts

In the baseline Model (6), we focus on a ten-year cohort of women aged 45-54 , whose first child was basically born under the one child policy and their second child was basically born under the 1.5 child policy. One interesting extension of our research is that whether peer effects become weaker or stronger for younger generations. Ideally, we can estimate peer effects among a younger cohort (35-44 years old) and an elder cohort (50-54 years old) for comparison with the baseline cohort. However, we do not believe the younger cohort of women have finished their child bearing plan. For the elder cohort (55-64), their children are very likely to be born without a birth quota (before the one-child policy). Therefore, to compare the cross-age peer effects, we divide the ten-year cohort into an elder cohort (50-54) and a younger cohort (45-49), estimate baseline Model (6) and separated rural-urban peer effects in each sub-cohort.

Table 2.10 shows the result of having a second child. Models (1) and (2) are estimated based on the baseline model – Model (1) is for the elder cohort and Model (2) is for the younger cohort. Model (3) and Model (4) estimate rural and urban peer effects separately. We see that peer effects are stronger for the elder cohort compared to the younger cohort. The negative impact of the number of mother's education years on having a second child gets intensified for the younger cohort. However, the number of father's education years still remains a positive effect on having a second child across the two age groups. Whether the household is engaged in farming plays an important role in having a second child for the elder cohort but not for the younger cohort. One explanation is that increased total factor productivity has reduced the intra-family labor demand. The first child being a girl remains an important factor in having a second child, but the impact has become smaller for the younger cohort. The younger cohort follows the demographic policy more closely compared to elder cohort, as the coefficient of "qualified for 1.5 child policy" is higher for the younger cohort. One possible explanation is that the punishment of violating the birth quota is more severe for the younger cohort.

The contextual effects show interesting dynamics across the two cohorts. First, the younger cohort is more sensitive to peers' education level, with a lower willingness to have a

Table 2.10. Peer effects comparison across age cohorts for having a second child

	50-54	45-49	50-54	45-49
	(1)	(2)	(3)	(4)
Peer effects	0.361**	0.249		
	(0.171)	(0.204)		
Rural Peer effects			0.123	0.064
			(0.226)	(0.245)
Urban Peer effects			0.400**	0.318
			(0.185)	(0.208)
Individual controls				
Mother's education years	-0.020*	-0.048***	-0.018	-0.053***
	(0.011)	(0.013)	(0.012)	(0.013)
Father's education years	0.022*	0.025*	0.020*	0.026**
	(0.011)	(0.013)	(0.011)	(0.013)
Annual family income in unit of 50,000 *yuan*	0.069*	0.039	0.067*	0.052
	(0.037)	(0.050)	(0.037)	(0.049)
Whether engaged in ag production	0.232**	0.066	0.273**	0.062
	(0.111)	(0.117)	(0.112)	(0.118)
Rural indicator	0.452***	0.351***	0.486***	0.393***
	(0.106)	(0.111)	(0.111)	(0.115)
First child is a girl	0.393***	0.252*	0.409***	0.238*
	(0.114)	(0.129)	(0.115)	(0.130)
Either of parent has ag *hukou*	0.318**	0.483***	0.361***	0.528***
	(0.132)	(0.140)	(0.133)	(0.141)
Qualified for 1.5 child policy	0.493***	0.633***	0.535***	0.689***
	(0.180)	(0.178)	(0.182)	(0.181)
Mother's age at first birth	-0.079***	-0.071***	-0.082***	-0.074***
	(0.015)	(0.012)	(0.016)	(0.012)
Living with father-in-law of the mother	-0.257	-0.026	-0.251	-0.042
	(0.169)	(0.161)	(0.172)	(0.162)
Living with mother-in-law of the mother	0.084	0.255*	0.076	0.279*
	(0.133)	(0.144)	(0.135)	(0.145)
Contextual controls				
Education years of peers	-0.070**	-0.093**	-0.083**	-0.097**
	(0.032)	(0.043)	(0.033)	(0.045)
Annual income of peers in unit of 50,000 *yuan*	0.197**	-0.300**	0.209***	-0.346***
	(0.077)	(0.127)	(0.079)	(0.132)
% of peers with firstborn daughter	-0.152	0.101	-0.129	0.098
	(0.208)	(0.280)	(0.218)	(0.286)
Mother's age at first birth among all peers	0.025*	0.056***	0.029**	0.059***
	(0.013)	(0.015)	(0.014)	(0.016)
% of peers living w/ either in-law of the mother	0.028	0.215	0.016	0.241
	(0.324)	(0.295)	(0.346)	(0.309)
Constant	0.702	0.570	0.704	0.643
	(0.432)	(0.410)	(0.448)	(0.415)
Province FE	Y	Y	Y	Y
Number of obs.	950	1,046	950	1,046
log-likelihood	-439	-420	-440	-419

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Contextual controls are leave-i-out mean of peers' characteristics for each individual.

second child if peers are highly educated. Second, the sign of peer's income estimate switches from positive to negative (both significant at least to the 5 percent level) across the two cohorts. The richer the peers are, the more likely an elder-cohort family is willing to have a second child, but less likely that a young-cohort family would have a second child. If a family is relatively poor compared to its peers, on the one hand, this family may prefers to have a second child (hopefully a son) as a compensation of not being as rich as their peers; on the other hand, a son born to this family has lower chance to marry well compared to his richer peers – we think one explanation to the opposite signs of contextual income coefficients is that the elder cohort weights more on the former factor, and the younger cohort weights more on the later. Third, those in the younger cohort are more sensitive to the peers' age when they had their first child. When there are more elder mothers around the younger cohort, they are more likely to have a second child. As mentioned before, one possible explanation is that the younger-cohort women realize more about their age advantage compared to the elder-cohort and are more likely to have a second child when they become mothers at a younger age.

Table 2.11 shows the cross-age result of having a son. Similarly, Models (1) and (3) are based on the elder-cohort (50-54) and Models (2) and (4) are based on the younger-cohort (45-49). Neither cohort shows significant peer effects. The mother's education level plays a more important role in reducing son-preference for the younger-cohort compared to the elder-cohort. The positive impact of the father's education in having a son is largely weakened and becomes insignificant for the younger cohort. Income plays an important role in having a son for the elder-cohort, but not for the younger-cohort. We find that the mother's age of having a first child plays a different role in the fertility decision of having a second child and son-preference. As alluded to, a female who becomes a mother at an older age will be less likely to have a second child for both cohorts (see table 2.10); As for son-preference, the negative impact of a mother's age for having a son is largely reduced for the younger cohort, which means elder mothers (those with a higher value of "mother's age in having a first child") in the younger cohort (45-49) may still try to have a son. Since their willingness to have a second child remains unchanged compared to those in the elder cohort, those in the younger cohort are more likely to conduct sex-selective abortions.[27] Based on Model (4), we fail to find evidence that elder mothers from the younger cohort are less likely to have a son compared to younger mothers.

Those in the younger-cohort are more sensitive to the education years of peers, as well as the "mother's age at first birth among all peers". It is interesting to notice that the education of peers works in the same direction as the mother's education years. If a woman has more years of education, son-preference is reduced; if her peers have more education years, her son-preference is reduced even more. This is true for both younger and elder cohorts, but the "mother's age at first birth among all peers" works in the opposite direction compared to own effect (mother's own age of having the first child). If a mother's age of having a first child increases at a population level, the probability of having a son will barely change for the elder cohort as the coefficient of own effect "mother's age at first birth" and contextual effect "mother's age at first birth among all peers" almost cancel each other out. For the younger cohort however, the magnitude of contextual effect exceeds own effect, which means an increased age of having a first child in the whole population will even increase the probability of having a son. Our finding in Table 2.11 provides further support for our main conclusion that son-preference is not triggered directly through the expected outcome of peers, but through another channel of social effect – contextual effect.

2.7 Conclusion

It is traditionally a social obligation for a male heir to have multiple children and for at least one son to carry on the family honor. These traditional values have been challenged due to a series of child policies implemented since 1979. These policies, initially aimed to control the population size of China, have restricted families under a strict birth quota. Whether to have a second child and whether to aim for a son became judgement calls for

[27]↑Consider a representative woman from the younger cohort and another representative woman from the elder cohort who become mothers at the same age. Now consider if they become a mother one year later: the probability of having a second child decreases at a similar level based on the result shown in Table 2.10; but the probability of having a son for the younger-cohort woman decreases much less than the elder-cohort woman. One possible explanation is that the young-cohort woman is more likely to conduct sex-selective abortion to increase the probability of having a son for a future pregnancy.

Table 2.11. Peer effects comparison across age cohorts for having a son

	50-54	45-49	50-54	45-49
	(1)	(2)	(3)	(4)
Peer effects	0.170	-0.098		
	(0.271)	(0.376)		
Rural Peer effects			0.165	0.189
			(0.383)	(0.423)
Urban Peer effects			0.027	-0.245
			(0.295)	(0.402)
Individual controls				
Mother's education years	-0.016*	-0.020**	-0.015	-0.017**
	(0.010)	(0.010)	(0.010)	(0.010)
Father's education years	0.021**	0.009	0.022**	0.008
	(0.010)	(0.010)	(0.010)	(0.010)
Annual family income in unit of 50,000 *yuan*	0.079**	0.058	0.077**	0.040
	(0.031)	(0.035)	(0.031)	(0.036)
Whether engaged in ag production	0.195**	-0.014	0.215**	-0.023
	(0.096)	(0.095)	(0.098)	(0.095)
Rural indicator	0.190**	0.078	0.127	-0.096
	(0.088)	(0.086)	(0.185)	(0.147)
Either of parent has ag *hukou*	0.296***	0.349***	0.354***	0.359***
	(0.113)	(0.111)	(0.114)	(0.112)
Mother's age at first birth	-0.036***	-0.020**	-0.030***	-0.016
	(0.010)	(0.010)	(0.011)	(0.010)
Living with father-in-law of the mother	-0.041	0.017	-0.038	0.003
	(0.150)	(0.125)	(0.149)	(0.125)
Living with mother-in-law of the mother	0.085	0.072	0.095	0.062
	(0.112)	(0.098)	(0.112)	(0.098)
Contextual controls				
Education years of peers	-0.070*	-0.120***	-0.063*	-0.115***
	(0.033)	(0.044)	(0.033)	(0.044)
Annual income of peers in unit of 50,000 *yuan*	-0.008	0.053	-0.014	0.043
	(0.064)	(0.094)	(0.067)	(0.094)
Mother's age at first birth among all peers	0.034**	0.044**	0.037**	0.046**
	(0.016)	(0.020)	(0.017)	(0.021)
% of peers living w/ either in-law of the mother	0.039	-0.004	-0.025	-0.036
	(0.296)	(0.272)	(0.313)	(0.267)
Constant	0.443	0.459	0.303	0.397
	(0.382)	(0.367)	(0.388)	(0.366)
Province FE	Y	Y	Y	Y
Number of obs.	1,471	1,574	1,471	1,574
log-likelihood	-647	-725	-648	-724

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Contextual controls are leave-i-out mean of peers' characteristics for each individual.

Chinese families since the 1980's. Chinese culture values conformity, and deviating from the majority and social norm is costly, especially under the peer pressure to "keep up with the Zhanges". Our paper estimates peer effects in two family planning decisions: whether to have a second child, and whether to have at least one son; more specifically, if a family tends to have a second child (or a son) because they expect more of their peers to have a second child (or a son). To identify peer effects, we add contextual characteristics of the peers and provincial FE to control for the endogenous group formation and correlated unobservables such as social norms and provincial child policies.

We find significant peer effects on having a second child. That is, if a family expects more peers to have a second child, they are more likely to have a second child. All else being equal, if a family lives with all peers expected to have two children versus all peers expected to have a single child, this family will increase their probability of having a second child by 35.08 percent. Since January 1, 2016, each Chinese family can legally have a second child. Accounting for peer effects, families who are interested in having two children would motivate other one-child families to follow them. A significant peer effect on fertility decision-making could facilitate the effectiveness of policies that encourage a larger family size (e.g., the two-child policy). For the choice of having a son, peer effect is insignificant after controlling for contextual effects. Instead, the social influence in son-preference is attributed to contextual effects (captured by peers' education level, etc.) and unobserved correlated effects (such as provincial social norms). Even though the traditional concept of son-preference has been deeply rooted, it has a potential to be alleviated through an increase in education level of the whole population (especially that of females).

3. THE DIFFUSION OF ELECTRIC VEHICLES UNDER TAX CREDIT AND CAFE STANDARD

3.1 Introduction

Electric vehicles (EV) were first introduced to the automobile market around 2010, and the market share of battery EVs has increased to 1.8 percent in 2020 according to IHS Markit.[1] In this paper, we specifically focus on electric vehicles that store electricity in a rechargeable battery through which it operates fully on electricity (henceforward BEV), and plug-in hybrid vehicles which have a potential to be fully operated by electricity (henceforward PHEV), instead of gasoline-electric hybrid vehicles which do not have the option to operate fully on electricity (henceforward hybrid). Both BEV and PHEV are generally taken to be more environmentally friendly than hybrid or conventional engine vehicles; further, EVs provide an opportunity to substitute away from the reliance on fossil fuels. This assertion is, of course, based on the condition that the electricity is produced from clean sources, and/or that the life-cycle of EVs is cleaner than conventional engine vehicles and hybrids. This paper takes this assertion as true.

Various financial incentives and environmental policies have been implemented to accelerate the diffusion of EVs, including the income tax credit offered to consumers and the Corporate Average Fuel Economy (CAFE) standard created for manufacturers. This paper aims at evaluating how current incentives including the tax credit and CAFE standard have facilitated the market share of EVs and whether they have improved consumer welfare. We also conduct counterfactual analysis regarding the EV market share, prices and consumer welfare if the tax credit were not available; CAFE standard were implemented at a different level, or the penalty of violating the CAFE standard was higher than the current value.

The maximum federal tax credit for purchasing an EV (including BEV and PHEV) is \$7,500. Once a manufacturer has sold more than 200,000 EVs, the tax credit for purchasing an EV from this specific manufacturer will gradually phase out. For example, Tesla has reached the sales quota of phasing-out, with no claimable tax credit for each purchased EV

[1] ↑https://ihsmarkit.com/research-analysis/ev-registrations-exceed-2-of-overall-us-market-share-in-decemb.html

of Tesla starting 2020. This phasing-out tax credit policy is designed to encourage early adopters of EV. The median price of 35 EV models offered in the market at March 2020 is \$45,445. A full tax credit saves 16.5 percent for a median-price EV consumer. It also helps in balancing the market competition regarding the diffusion pace for each manufacturer. For example, some of current potential EV consumers may switch to EVs with higher tax credit before it fades. Therefore, this policy temporally paces down the diffusion of the fast sellers after the incentives fades, and accelerates the sales of their competitors whose incentives are still high, to increase EV market competition.

How much the current tax credit has promoted the diffusion of EV is the first research question we focus on. To be more specific, if there no tax credit available for consumers, what percentage of potential customers will switch from EV to other types of vehicles. Besides the impact on EV market share, we also focus on the mark-up for EV and non-EV models if the tax credit is not available. Tax credit has been available since EV entered the market in early 2010s, and it is a federal incentive applied to every consumer. Causal inference methods such as regression discontinuity, difference-in-difference or matching are not suitable to identify the counterfactual when tax credit is not available. Therefore, we use a structural model (i.e., the random coefficient discrete choice model) to estimate the demand of each vehicle model accommodating heterogeneous consumer tastes for various vehicle attributes. We build the tax credit as a price deduction inside the utility function of each consumer, and obtain counterfactual market share when tax credit is taken off using the coefficients we estimated.

The CAFE standard is enacted by National Highway Traffic Safety Administration (NHTSA). In each year the CAFE specifies a set of miles per gallon (MPG) standard for each vehicle type (passenger cars and light trucks) such that the harmonic mean of MPG weighted by sales in each vehicle type is expected to meet the target. Failure to meet the standard will induce a fine charged by \$55 per car per unit of MPG that it exceeds. This policy aims at encouraging producers to invest in fuel efficient technologies and equipment, and further reduce greenhouse gas emission. NHTSA usually publishes the standard years beforehand, such that manufacturers have time to develop new models or improve incumbent models to reduce the potential penalty. While the penalty level has been kept flat since 1983, the CAFE standard has increased more than 40 percent since 2010. Starting 2012, NHTSA introduced a model-specific calculation of CAFE standard which applies on the footprint of a vehicle. Smaller cars are expected to meet a higher CAFE standard. The footprint-based rule in the U.S. is safer compared to Japan, whose fuel economy standard is weight-based, which has motivated manufacturers to produce lighter cars with less crash protection.

Developing an EV model is one strategy to help meet the fleet fuel economy standard, as its miles per gallon equivalent (MPGe) is generally much higher than the MPG of a gasoline-engine vehicle. The average MPG of non-EV models is 24.37 in our data set and the average MPGe for EV models is 96.62. However, the fleet economy performance is calculated by a weighted harmonic mean, which means the CAFE of a manufacturer will not improve significantly if the sales of EV is low.[2] Therefore the CAFE standard is considered as a nudge for manufacturers to mark down and sale more fuel-efficient vehicles, which facilitate the diffusion process of EVs.

The CAFE standard has increased from 18 MPG in 1978 to 38.5 in 2017 for domestic passenger cars. However, the penalty level has only increased by ten percent since 1983. The total penalty per vehicle (in dollars), $55 multiplies by a few MPG points below the target, only accounts for a small proportion of the average retail price of a vehicle. Based on our data obtained from WardsAuto, The average penalty per vehicle if the manufacturer fails to meet CAFE standard in 2012 - 2019 is $217, while the average retail price of all vehicle models is $48,700 – the penalty level is only 0.45 percent of an average-priced vehicle. Besides, the inflation rate has increased more than 100 percent since 1983. There has been a proposal of increasing the penalty level to $140, which catches up with the inflation rate, but has not been enacted by 2020. Previous research (e.g., Goldberg 1998) has also criticized the low penalty issue, as manufacturers were not responding actively to increase the fuel efficiency of the models they produce because of the unchanged penalty level for many years.

[2]↑For example, suppose a manufacturer produces three non-EV models with MPG being 25, 22 and 20 separately. The CAFE standard for current period to meet is 30. This manufacturer develops a new EV model whose MPGe is 100, and it sales one vehicle for each model in current period. The observed CAFE of this manufacturer in current period will only be $\frac{4}{\frac{1}{25}+\frac{1}{22}+\frac{1}{20}\frac{1}{100}} = 27.5$ under the calculation rule. Therefore developing one fuel efficient EV while keeping the polluting incumbent product set may not be sufficient to improve the CAFE in practice; unless the sales of the new EV model is sufficiently large.

This paper focuses on how CAFE standard and penalty have accelerates the diffusion of EV. We answer this question by conducting counterfactual analysis on how the market share of EV changes if penalty level and the CAFE standards by NHTSA is set at different levels. Similarly as tax credit, the new CAFE system exists right after the introduction of EV to the auto market, and it applies to all manufacturers in the U.S.. Reduced-form causal inference models such as matching or synthetic control cannot be used to identify a causal counterfactual when CAFE is not available. We use a structural model in the spirit of Berry *et al.* (1995) in which the CAFE penalty is build inside the profit margin of each manufacturer. If a manufacturer fails CAFE, the profit margin of each vehicle is deducted by the penalty times the MPG below the target. The counterfactual of no CAFE or a different level of CAFE penalty is obtained by replacing the penalty to zero or an assigned value (e.g., $140).

Our data combines car characteristics (e.g., MPG, horsepower, weight, size), retail price and monthly sales obtained from WardsAuto. This data set starts from 2012, which is the time EV models first became available in the market; and ends at 2019 right before the pandemic generated a non-negligible impact on the passenger vehicle market. We use a structural random coefficient model for vehicle demand estimation. The major advantage of this model is that the substitution between similar vehicle models is flexible which accounts for both observed and unobserved car attributes. Besides, it allows for consumer heterogeneity on observed car attributes which also relaxes the Independence of Irrelevant Alternatives (IIA) property imposed by Logit or AIDS. More importantly, a variety of instrument variables (to be introduced shortly) are available to account for the endogeneity of car attributes.

The relationship between safety driving and fuel economy is believed to be negative to some extent. An unrealistically high CAFE standard not only harms the small-sized manufacturers through heavy R&D investment, but also motivates manufacturers to produce lower weight vehicles which may cause higher fatal accident rate. However, on the other hand, rolling back or remaining a low fuel economy standard could slow down the diffusion of EV production, increase EV prices and worsen the environment by producing more greenhouse gas emissions. The economic and environmental consequences under a enhanced fuel economy standard in the predictable future is of vital relevance to the environment, health and consumer welfare.

3.2 Literature Review

Previous research has evaluated the impact of tax credit or rebate on the diffusion of hybrid or EVs. Chandra *et al.* (2010) account the tax rebate for hybrids in Canada for 26 percent of its sales. But they also mention some of the tax rebate claimers would have bought hybrid cars without the rebate, which suggests an inefficiency of the policy design. Xing *et al.* (2021) quantifies the proportion of consumers who would buy EVs in the United States regardless of the tax credit as 70 percent. They also find the tax credit benefits the diffusion of EV and explains 29 percent of the sales. The availability of EVs substitutes mostly the clean models such as hybrids and other fuel efficient gasoline models. Their simulations on a redesigned income-differentiated tax credit policy suggests that offering a higher tax credit for the low income group of consumers works more effective in EV diffusion. Similar conclusion is drawn by DeShazo *et al.* (2017), that a differentiated tax credit regarding consumer income and type of cars (battery EVs, plug-in hybrid and EVs) would generate a more effective policy for the penetration of cleaner energy vehicles.

Policy evaluation of the CAFE standard in general also has a rich literature. Goldberg (1998) analyzes the effectiveness of the CAFE level together with the penalty level across three different groups of manufacturers: good performers who always pass the standard, the ones who basically obey the standard, and the rule breakers who would rather pay the fine instead of following the rule. The effectiveness of the CAFE standard regarding the fuel efficiency lies on the last group, and increasing the CAFE standard marginally while keeping the penalty level unchanged (the penalty level has only increased by 10 percent since 1978) will not nudge the rule breakers to achieve better behaviors. A similar conclusion is found by Shiau *et al.* (2009), with a robust extension of treating firm design of CAFE-related attributes as endogenous. Shiau *et al.* (2009) also find firm design, such as engine scaling, as a response to CAFE adjustment is more sensitive to fuel prices relative to CAFE standard. It suggests that manufacturers are less likely to adjust other attributes, besides more direct attributes such as MPG and weight of a vehicle, just for meeting the CAFE standard. Both Ito and Sallee (2018) and Jacobsen (2013) find the current CAFE standard benefits the foreign firm more than the domestic, even though the CAFE standard holds almost even for imported and domestic manufacturers.

Even though models such as diffusion models, time series models and agent-based method summarized by M.Al-Alawi and Bradley (2013) have been used in automobile-related research, especially for policy evaluation (e.g., Sen *et al.* 2017), the random coefficient discrete choice model is still the most broadly used method for counterfactual analysis related with automobiles (Goldberg 1998, Petrin 2002, Jacobsen 2013, Blonigen *et al.* 2017, Miravete *et al.* 2018, Ito and Sallee 2018, Xing *et al.* 2021) and other research questions related to heterogeneous choices (e.g., cereal industry, Nevo 2001; video game industry, Lee 2013; school choices, Bayer *et al.* 2007). For example, Blonigen *et al.* (2017) analyze the effectiveness of model redesign in automobile market competition. Consumers have strong preference for redesigned cars, and it takes a large R&D investment in redesigning the old models. The authors build a random coefficient model allowing for heterogeneous consumer taste on car attributes, recover the marginal cost of each model following Berry *et al.* (1995), and build the model redesigning with a dynamic process which allows for old models exit and new model redesign following Bajari *et al.* (2007).

Miravete *et al.* (2018) adopt a method similarly to Berry *et al.* (1995) to evaluate several European tariff policies which benefits domestic manufacturers in the diffusion of diesel vehicles in Spain. This paper assumes the observed model-specific characteristic follows an AR(1) process with more flexibility in attributed evolution over time. A similar approach has been used by Grennan (2013) and Sweeting (2013). Even though the focus of Miravete *et al.* (2018) is not on EV, we adopt a similar structure of the random coefficient model for demand estimation. Our contribution is we use a structural model to evaluate policy incentives in the U.S., especially CAFE penalty level and CAFE standard, in terms of the diffusion of EV. Understanding whether current policy environment is effective in the diffusion of EV is of vital importance to environmental and health concerns, as well as energy replacement.

3.3 Policy Background

Since model year 2011, NHTSA has updated the calculation rule of CAFE from a flat rate to model-specific, which depends on the footprint of a vehicle model. Footprint is the area of a car based on the center points of four wheels. It is calculated by:

$$\text{Footprint} = \text{Wheelbase} \times \frac{\text{Track width (front)} + \text{Track width (rear)}}{2} \tag{3.1}$$

Compact vehicles have smaller footprint than SUVs and are expected to meet a higher CAFE target by NHTSA. Figure 3.1 and Figure 3.2 shows the CAFE target for passenger cars and light trucks separately. The target CAFE for a small size car (less than 41 square feet) is 35.95 miles per gallon in 2012, and the target level for a large size car (more than 56 square feet) in 27.95 miles per gallon. During 2012 to 2019, the CAFE target for large size car has increased by 25 percent to 35.07 miles per gallon. For small size cars, the CAFE target has increased by 30 percent to 46.87. Compact cars are facing a slightly stricter requirement regarding fuel efficiency over the years. For light trucks, the CAFE target for small vehicles (less than 41 square feet) is on average 40 percent higher than large vehicles (more than 67 square feet). But it has increased relatively slower during 2012 to 2019 for large light trucks.

For each model year, the observed or real CAFE performance of a manufacturer under each vehicle type (passenger car or light truck) is calculated as the harmonic mean of MPG for all models weighted by the sales volume of each model. The attribute MPG is calculated as the the summation of 45 percent weight on MPG on highway and 55 percent of MPG on city road. The observed CAFE of manufacturer f under vehicle type c at time t is calculated as:

$$CAFE_{fct}^{observed} = \frac{\sum_{j \in \mathcal{F}_{fct}} q_{jt}}{\sum_{j \in \mathcal{F}_{fct}} \frac{q_{jt}}{MPG_{jt}^{observed}}} \tag{3.2}$$

where q_{jt} is the number of cars sold for model j at time t, and $\mathcal{F}_{fct}$ represents a set of models sold by manufacturer f and under vehicle type c at time period t where $c \in$ {passenger car, light truck}. $MPG_{jt}^{observed}$ is the observed car attribute MPG for model j at time t. The CAFE standard for each manufacturer under vehicle type c is calculated as the harmonic

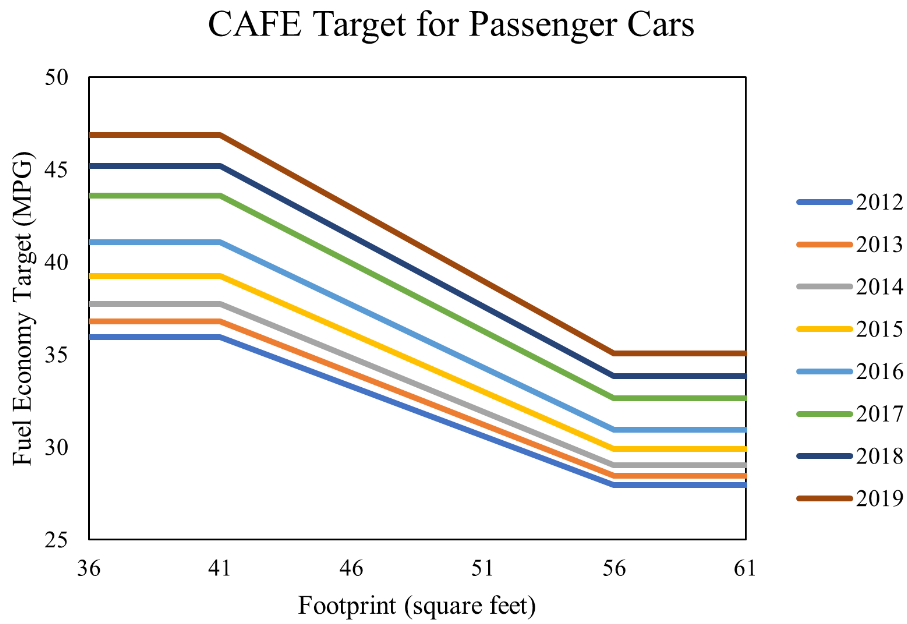


Figure 3.1. CAFE target for passenger cars (2012 - 2019)

mean of the sales-weighted CAFE targets for all models shown in Figure 3.1 and Figure 3.2:

$$CAFE_{fct}^{target} = \frac{\sum_{j \in \mathcal{F}_{fct}} q_{jt}}{\sum_{j \in \mathcal{F}_{fct}} \frac{q_{jt}}{MPG_{jt}^{target}}} \tag{3.3}$$

where MPG_{jt}^{target} is the CAFE target for model j at year t. If manufacturer f fails to meet the CAFE target under under vehicle type c, or $CAFE_{fct}^{observed} < CAFE_{fct}^{target}$, manufacturer f will pay \$55 times the total sales under vehicle type c times MPG by which the observed CAFE falls below the standard. If manufacturer f fails to meet the standard for vehicle type c at model year t, it needs to pay a total penalty as:

$$\text{Total penalty} = 55 \times \sum_{j \in \mathcal{F}_{fct}} q_{jt} \times (CAFE_{fct}^{target} - CAFE_{fct}^{observed}). \tag{3.4}$$

For simplicity, we drop the subscript t for the rest of the paper.

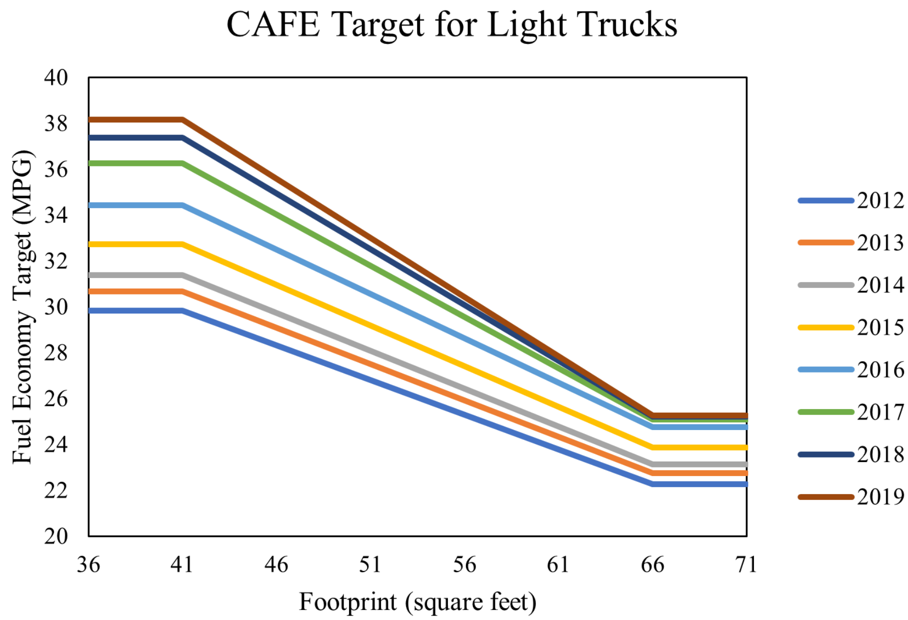


Figure 3.2. CAFE target for light trucks (2012 - 2019)

3.4 Model

This chapter summarizes the random coefficient model used for consumer demand estimation and marginal cost estimation. It is a structural model starting with a consumer utility optimization, followed by a profit maximization structure for each manufacturer. It is also a static model with a general assumption that the product set is exogenous.[3]

For the rest of this section, we will first introduce the demand estimation model with consumer choices (including an outside choice of not purchasing a car), followed by the supply side with producer's optimization process through which we can recover the marginal cost of each model for cost function estimation, and then introduce the methodology that uses the equilibrium data to recover the coefficients in both demand and supply sides.

[3]↑Even though it is a general assumption that the product set is exogenous, we acknowledge that if CAFE standard or penalty level is set to be high enough to trigger a change in the product set (e.g., change in MPG, weight, or even the introduction of a new EV model), the accuracy of the counterfactual analysis will be impacted. However, a manufacturer would face a finalized attributes when it decides the optimal price to maximize their profit in current period.

3.4.1 Consumer demand of automobiles

Vehicles are typical differentiated products with a large variety of car attributes, such as fuel efficiency, size, horsepower, and weight. Consumers are price sensitive and could have heterogeneous taste towards different attributes. It is important to consider the flexibility of substitution between similar vehicles among consumers for demand estimation (Chandra *et al.* 2010, Xing *et al.* 2021). That is, automobile purchases are highly sensitive to consumer taste. Yet, since the price of an EV is, in general, higher than a similar vehicle with a conventional engine, a consumer on a limited budget may be unlikely to purchase an EV. Consumers who select to purchase an EV are likely to be ones with sufficient budget and have relatively strong preferences for environmentally friendly products. Consumers on the margin between purchasing a gasoline-engine vehicle and an EV make their decision by evaluating the horsepower, fuel economy and weight.

Each potential consumer (i.e. every household in the U.S. at period t) faces a choice pool of hundreds of vehicle models. And they are heterogeneous with respect to household income, various taste on car attributes. On the one hand, consumers may share a common perspective regarding certain vehicle characteristics, but personal taste fluctuate around the average towards observed car attributes. For example, all else equal, consumers typically consider vehicle MPG to be a strictly positive attribute on the grounds of reduced fuel expenditure or out of environmental concern. However, individuals may have varied opinions about how much this particular characteristic can benefit them given their different driving needs. Another problem that could jeopardize the identification of observed attributes is that some of the unobserved attributes could be correlated to the observed ones. Therefore we need to deal with the endogeneity problem.

Consider a typical consumer i, who is facing a discrete choice of purchasing a vehicle model j, or purchasing no vehicle (say, $j = 0$). The utility consumer i gains by purchasing vehicle model j is

$$u_{ij} = x_j \beta_i + \alpha_i (p_j - T_j) + \xi_j + \epsilon_{ij} \tag{3.5}$$

where u_{ij} represents the utility of consumer i purchasing vehicle j. p_j is the retail price of model j, and T_j is the tax credit which is positive for EVs and zero for non-EVs. x_j is a vector of vehicle characteristics of model j, with each car attribute being valued heterogeneously among consumers by β_i. We separate the mean and individual deviation of β_i by:

$$\beta_i = \beta + \Sigma\eta_i \tag{3.6}$$

where β (a $k \times 1$ vector) represent consumer average taste on observed car attributes (e.g. brand, segment, fuel efficiency, horsepower).[4] Σ is $k \times k$ diagonal matrix with σ_k as the diagonal elements. σ_k represents the standard deviation of the mean deviation. η_i (a $k \times 1$ vector) represents the unobserved mean deviation term of the heterogeneous consumer taste, where each element η_{ik} follows a standard normal distribution. Therefore, for each car attribute x_{jk}, $\sigma_k \times \eta_{ik}$ is the consumer taste deviation from the average taste, which is unobservable to economist and we assume it follows i.i.d. normal distribution $N(0, \sigma_k^2)$.

The price consumer pays for model j is the retail price p_j subtracts the claimable tax credit T_j. The parameter α_i is expected to be negative, meaning consumers prefer lower price, ceteris paribus. A heterogeneous taste on price, α_i, accounts for demographics of consumer i. The most relevant demographic under this circumstance should be household income. Following Miravete *et al.* (2018) and Xing *et al.* (2021), we form α_i as:

$$\alpha_i = \alpha / y_i \tag{3.7}$$

where y_i is the household income for consumer i. The fraction $\frac{p_j - T_j}{y_i}$ inside the utility function reflects the ratio of net price to income of model j for household i. T_j is the tax credit for model j in present. Recall in the introduction part we have explained that T_j, currently \$7,500 for most EVs, accounts for 16 percent of retail price of EV on average.

ξ_j represents the unobserved vehicle characteristics, including the interior facilities (e.g. GPS, stereo, mini-refrigerator, leather seat). These characteristics are less likely to be independent across years. On contrary, ξ_j at period $t + 1$ may not vary much from period t, or will be evolve with a trend when redesigned. Therefore, following Grennan (2013), Sweeting

[4]↑Segment contains convertible, coupe, CUV, hatchback, pick-up trucks, sedan, SUV, van, and wagon.

(2013) and Miravete *et al.* (2018), we assume the unobserved car attributes ξ_j follows the AR(1) process in which $\xi_{j,t+1}$ is correlated with $\xi_{j,t}$ through coefficient ρ_ξ:

$$\xi_{j,t+1} = \rho_\xi \xi_{j,t} + e_{j,t+1} \tag{3.8}$$

where ρ_ξ represents how similar the next period's unobserved model attribute is similar to current period's. In the results session we show the estimation of ρ_ξ is close to 1, confirming a steady evolution pattern of the unobserved characteristics. $e_{j,t+1}$ is the shock of unobserved car attributes in the next period unobservable to economists.

ϵ_{ij} in the utility function 3.5 is the error term which is assumed to be *i.i.d* across individuals and follows the type one extreme value distribution across different models, for simplicity reasons to express a closed form solution of the probability of purchasing model j by individual i. In general, consumer taste for vehicle characteristic k varies around the mean value β_k with standard error σ_k. If we plug in the β_i function in equation (3.6) and price sensitivity in equation (3.7) to the utility function in equation (3.5), we have $u_{ij} = x_j(\beta + \Sigma\eta_i) + \alpha \cdot \frac{p_j - T_j}{y_i} + \xi_j + \epsilon_{ij}$. To simplify the expression, we name the mean utility of purchasing model j, the part homogeneous across households, δ_j. For the idiosyncratic utility, the part of utility that varies by household, we name it μ_{ij}:

$$\begin{aligned} \delta_j &= x_j\beta + \xi_j \\ \mu_{ij} &= \alpha \cdot \frac{p_j - T_j}{y_i} + x_j \Sigma \eta_i. \end{aligned} \tag{3.9}$$

Therefore utility function is $u_{ij} = \delta_j + \mu_{ij} + \epsilon_{ij}$. The probability that individual i purchases model j, can be solved based on the distribution of ϵ_{ij}. Simulate the set of private tastes $[\eta_{i1}, \eta_{i2}, ..., \eta_{iK}]$ and household income y_i by n_s times based on the distribution assumptions (details will be described in the data section), we can estimate the simulated market share of model j across n_s draws as:[5]

$$\hat{s}_j = \frac{1}{n_s} \sum_{i=1}^{n_s} \frac{e^{\delta_j + \mu_{ij}}}{1 + \sum_j e^{\delta_j + \mu_{ij}}}. \tag{3.10}$$

[5]↑This paper uses $n_s = 6,000$. For example, for household income, we randomly draw 6,000 households each year from our sample. Details will be described later.

Here we normalize the utility of the outside choice ($j = 0$, purchasing no car or purchasing a car from a secondary market) as zero and the market share of $j = 0$ is $\hat{s}_j = \frac{1}{n_s}\sum_{i=1}^{n_s}\frac{1}{1+\sum_j e^{\delta_j+\mu_{ij}}}$. S_0 in our data varies by year with an average market share as 89.69 percent.

Let θ_1 represents all the demand side of parameters to be estimated, and we will estimate them together with the supply coefficients introduced in the following section. The estimation procedure is explained in section 3.4.3.

3.4.2 Supply of automobiles

In this section we introduce the profit maximization procedure for manufacturers. For each period t, manufacturer f produces a set of vehicle models $\mathcal{F}_f$ with car attributes x_j for model $j \in \mathcal{F}_f$. The total potential consumers in period t is M (total number of households in the U.S.).[6] The U.S. automobile market has around 19 manufacturers providing roughly 226 - 245 heterogeneous products (vehicle models) each year in 2012 - 2019. Following Berry *et al.* (1995), Xing *et al.* (2021) etc., we assume an oligopoly Bertrand competition market structure of the U.S. automobile market, that is, manufacturers compete on prices of multi-heterogeneous models and reach a non-cooperative Bertrand-Nash price equilibrium in each time period:

$$\max_{p_j, j\in\mathcal{F}_f} \ \pi_f = \sum_{j\in\mathcal{F}_f}(p_j - mc_j - b\cdot\mathbb{I}_{fc}\cdot(CAFE_{fc}^{target} - CAFE_{fc}^{observed}))Ms_j(P, X, \theta_1) \tag{3.11}$$

where mc_j is the marginal cost of producing model j in a single period, and market share equilibrium $s_j(P, X, \theta_1)$ depends on car attributes (X) and optimal retail prices P of all available models on the market. b is the penalty per car per MPG below the CAFE target. Currently it is \$55. $\mathbb{I}_{fc}$ is an indicator which equals to 1 if the observed CAFE for the

[6]↑The market size M, total number of households in the U.S., varies by year. The first order condition of the profit maximizing strategy does not contain M, but it matters of calculating the market share of each model.

manufacturer f under vehicle type (the fleet) c falls below the corresponding CAFE standard. The first order condition with respect to the retail price for model j is:

$$s_j(P,X,\theta_1) + \sum_{r \in \mathcal{F}_f} (p_r - mc_r - b \cdot \mathbb{I}_{fc} \cdot (CAFE_{fc}^{target} - CAFE_{fc}^{observed})) \frac{\partial s_r(P,X,\theta_1)}{\partial p_j} = 0 \;\; \forall j \in J \tag{3.12}$$

The market share can be calculated using equation 3.10. With our observations on retail prices, car attributes and post-estimation parameters, we can recover the marginal cost mc, which is the only unknown in (3.12): $mc = P - CAFE_{penalty} - \Omega^{-1} s(P,X,\hat{\theta})$, where $CAFE_{penalty}$ is the CAFE penalty vector, Ω is a $J \times J$ matrix with element $\Omega_{jr} = -\frac{\partial s_r(P,X,\hat{\theta})}{\partial p_j}$ if model j and r are produced by the same firm, and $\Omega_{jr} = 0$ otherwise. We form the marginal cost function as a linear form:

$$ln(mc_j) = Z_j \gamma + \omega_j \tag{3.13}$$

where Z_j is the supply-side controls relevant to vehicle production, such as the whether is is an EV, horsepower, steel price, vehicle size, fuel efficiency etc. ω_j is the unobserved supply shocks. We estimate all supply parameter set θ_2 containing γ, and demand side parameters θ_1 using a GMM estimator with instrument variables introduced in the section 3.4.3. We aggregate parameter set from the demand and supply sides as θ.

3.4.3 Identification and estimation procedure

To identify the parameter associated with the observed car attributes, we use conventional instruments for the random coefficient model. For each car attribute x_{jk}, we construct four instrument statistics following Miravete *et al.* (2018) as:

$$\begin{aligned} H^1_{jk} &= \sum_{r \neq j, r \in \mathcal{F}_f} |x_{rk} - x_{jk}|^2 \\ H^2_{jk} &= \sum_{r \notin \mathcal{F}_f} |x_{rk} - x_{jk}|^2 \\ H^3_{jk} &= \sum_{r \neq j} |x_{rk} - x_{jk}| \times \mathbb{I}_{|x_{rk} - x_{jk}| < sd(x_k)} \\ H^4_{jk} &= \sum_{r \neq j, r \in \text{Fuel}_j} |x_{rk} - x_{jk}| \times \mathbb{I}_{|x_{rk} - x_{jk}| < sd(x_k)} \end{aligned} \tag{3.14}$$

where $|x_{rk} - x_{jk}|$ is the attribute difference between model j and model r. For example, the difference in horsepower between Toyota Camry and Chevrolet Malibu. Berry *et al.* (1995) uses the summation of other products' characteristics x_{rk} directly as the IV for own characteristics x_{jk}. The intuition of these BLP-style IVs is that the observed attributes (e.g., horsepower) between competitive models (e.g., Toyota Camry and Chevrolet Malibu) are highly correlated, but such observed attributes of competitors (e.g., horsepower of Toyota Camry) are less likely to be correlated with unobserved attributes for the own model (e.g., interior facilities of Chevrolet Malibu). The modification by Miravete *et al.* (2018) takes the same intuition with a replacement of x_{rk} with the difference $|x_{rk} - x_{jk}|^2$, which is smaller in magnitude when summing over the competitive models.

The first instrument H^1_{jk} takes only the other models within the same manufacturer (e.g. MPG of Toyota Corolla and Prius etc., as IV for MPG of Toyota Camry); The second instrument H^2_{jk} includes all other models outside manufacturer f but within the same model year (e.g. MPG of Honda Accord and Chevrolet Malibu etc., as IV for MPG of Toyota Camry); The third IV H^3_{jk} considers only "close" competitors whose attribute difference is below the standard error of attribute k (indicator $\mathbb{I}_{|x_{rk} - x_{jk}| < sd(x_k)} = 1$); while the fourth IV considers only close competitors within the sale fuel type (Fuel $\in$ {EV, non-EV}).

IVs for the binary variable "EV", the indicator of whether the model is an EV model, includes the total number of EV models within the same manufacturer and number of total available EV models produced by other manufacturers. We adopt this method following Bresnahan *et al.* (1997) and Miravete *et al.* (2018). IVs for the observed controls of the supply side are formed with the same methodology.

We estimate the the set of unknown parameters θ using a generalized method of moments (GMM) estimator. The demand side error $\hat{e}$ is derived from equation (3.8) and the supply side error $\hat{\omega}$ is constructed from equation (3.13). We can estimate θ using the GMM estimator:

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}}\ g(\theta)' HWH' g(\theta) \tag{3.15}$$

where $g(\theta)$ is the stacked demand side errors and supply side errors. H contains exogenous variables and IVs for endogenous attributes, which is orthogonal to the error term $g(\theta)$ by construction. The weighting matrix in GMM, $W = E[Z'g(\theta)g(\theta)'Z]^{-1}$, can be asymptotically estimated using available data by iteration.[7] We use the final estimates for counterfactual analysis.

3.5 Data

Our data is obtained from WardsAuto from model year 2012 to 2019. It is right after the EV models are generally available to the vehicle market, and right before the pandemic when the market has been under a recession. Figure 3.3 shows the market share of EV by month, which has been increased over the years and has reached roughly 1.5 percent in 2019. The sudden increase of EV market share at the second-half year of 2018 is due to the introduction of Tesla Model 3. Even though the market share of EV is still low, producing an EV model has been popular among manufacturers. Out of 20 manufacturers in our data set, 12 of them sell at least one EV model at year 2019 (see Figure A.2). Figure A.3 shows that the available EV series, a sub-category of models, has increased steadily especially for

[7]↑We can start with an initial guess $W = [H'H]^{-1}$ and update with the loop one estimates for the second loop estimation. See Berry *et al.* (1995).

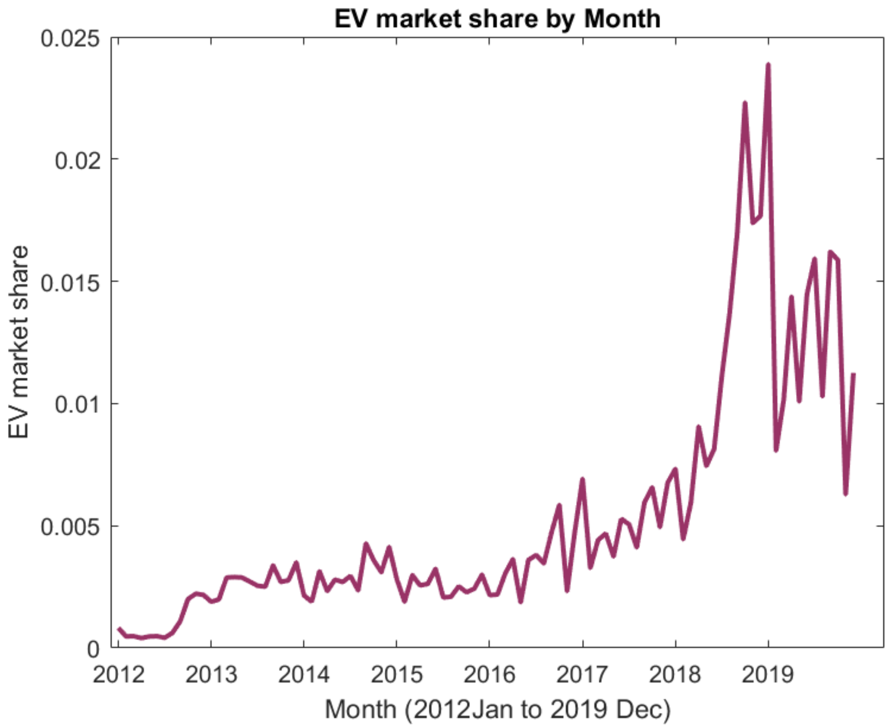


Figure 3.3. EV market share by month (Jan. 2012 to Dec. 2019)

light-truck EVs. The EV market has been competitive with Tesla Model 3 starting to lead the market since 2018 (see Figure A.4).

EVs are attractive to consumers for various reasons. For example, in CA, which accounts for a big share of the EV market, EVs are allowed to use the HOV lane which is a big attraction of owning an EV. Another advantage of purchasing an EV is for its fuel economy. The average fuel prices in 2012 is 3.695 \$/gallon and is 2.698 \$/gallon in 2019 (see Figure A.5).[8] Despite the fact that gas has become cheaper during this time period, EV still saves expenses compared to conventional-engine vehicles. The higher MPGe of an EV, the more energy efficient it is.[9] The sales-weighted average MPGe for EVs is on average five times of the average MPG for other vehicles (see Figure 3.4). Even though CAFE target has been increasing since 2011, we observe the average MPG for non-EVs are not responding actively.

[8]↑Source: https://www.usinflationcalculator.com/gasoline-prices-adjusted-for-inflation/. The values are nominal rates without inflation adjustment.

[9]↑MPGe is MPG gasoline equivalent. It is neither fuel price nor electricity price related. Instead, it measures the number of miles an EV can travel with 33.7 kilowatt-hours (kWh).

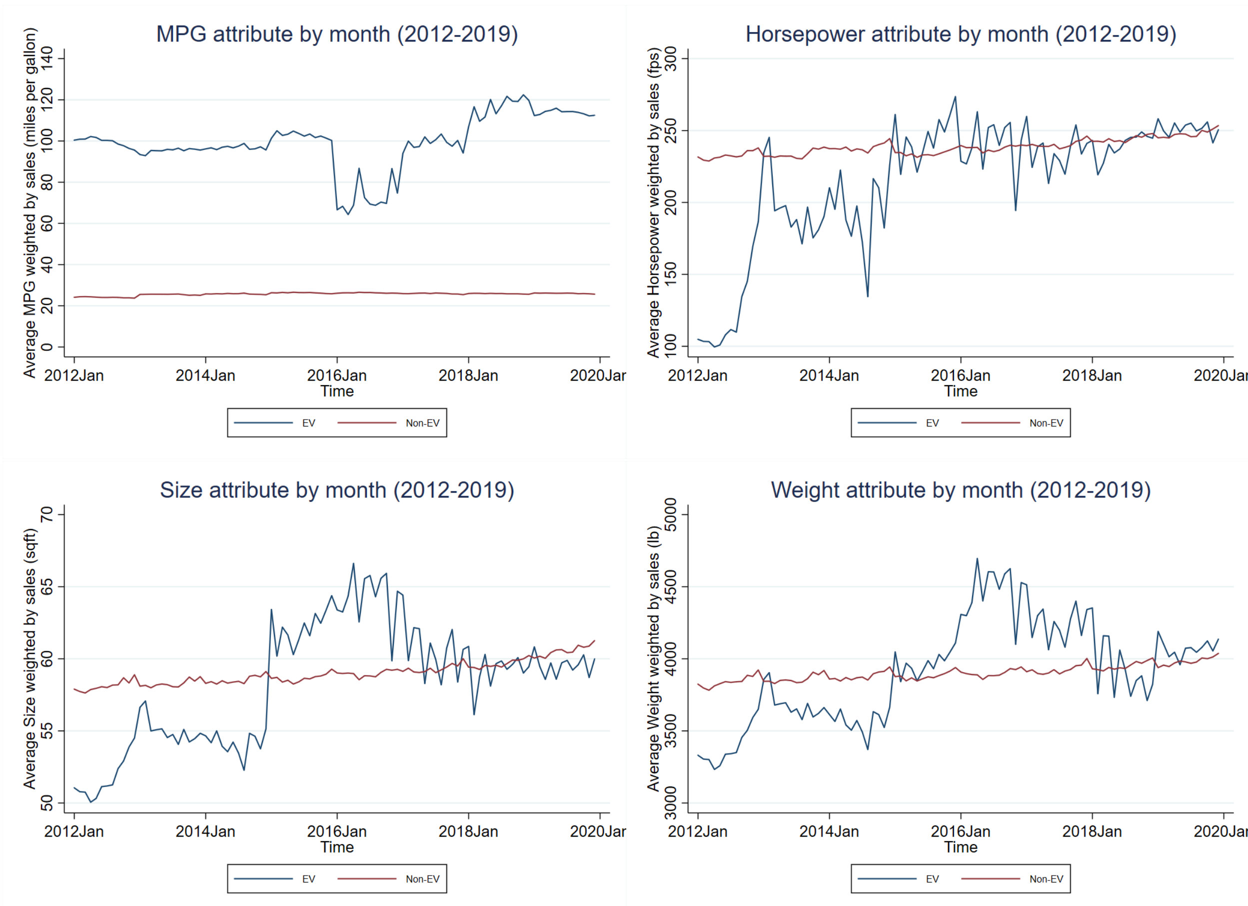


Figure 3.4. Sales weighted average attributes by month (Jan. 2012 - Dec. 2019)

The price of EV is generally higher than other type of vehicles. Figure 3.5 shows that the sales weighted average price of EV has been increased from 2012 to 2017, but has gradually fell. Even after the deduction of the tax credit, EV is still 40 percent more expensive than non-EV on average at the end of 2019.

Figure 3.4 and Table 3.1 show selected attributes statistics. During the early years of EV development, EV is designed with lower horsepower, smaller size and less weight compared to other types of vehicles. But theses attributes of EVs have caught up with others in recent years. PWR (power-to-weight-ratio) is a measurement of actual performance of the engine calculated as the horsepower per hundred pounds of weight. The price index for iron

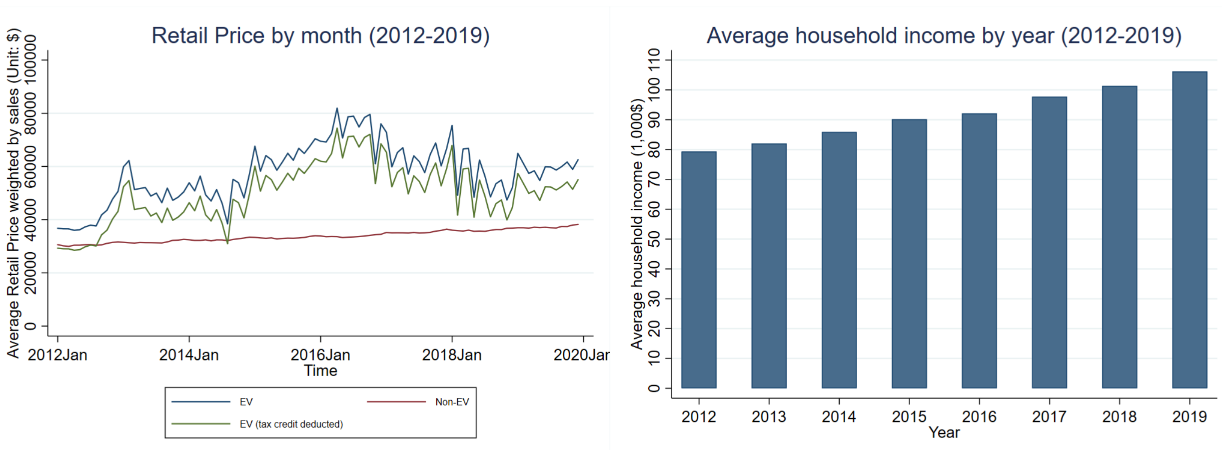


Figure 3.5. Sales weighted average retail price by month and weighted average household income (Jan. 2012 - Dec. 2019)

and steel (SPI) affects marginal cost. We multiply SPI with SIZE as a control of the cost function.[10]

Equation (3.10) requires random draws from the national income distribution. We obtained household income data from American Community Survey (ACS) of Integrated Public Use Microdata Series (IPUMS, USA) which contains 158,297 household income sample with household weight from 2012 to 2019 (roughly 20,000 households per year). 6,000 households are randomly selected based on household weight per year for the Monte Carlo simulations. The average household income has increased from 79,353 in 2012 to 106,181 dollars based on ACS (see Figure 3.5).

We also obtained the total number of households based on full IPUMS samples in each year and the 1 percent density, for outside product market share calculation purposes (see Figure A.6).[11] The outside options combine purchasing no vehicle this year and purchasing from the second-hand market. The total number of households has increased slowly, and the number of vehicle sales has increased by 20 percent (from 13.4 to 16.1 million) during 2012 to 2019. Overall, the market share for the outside options S_0 does not vary much across years (see Figure 3.6). The average S_0 is 89.7 percent, meaning roughly 10 percent of US households purchase a new vehicle each year.

Figure A.7 shows the CAFE target (in red line) and observed CAFE performance under two vehicle types (car and light truck) for four representative manufacturers (General Motors, Toyota, Honda, and Ford). Because of the increasing CAFE standard shown in Figure 3.1 and Figure 3.2, the manufacturer-specific CAFE target has been increasing from 2012 to 2019. Each manufacturer faces a distinct target each year based on the harmonic mean of sales weighted MPG it produced. There are three types of manufacturers. Honda is a representative firm of "rule followers". The observed CAFE for its light trucks meets the standard every year, and it basically meets the CAFE target for cars with only a few decimal points below the standard in recent years. Manufacturers including General Motors, Land Rover and Porsche are "rule breakers" whose CAFE performances miss the targets every

[10]↑SPI is not seasonality adjusted.

[11]↑Total number of household is calculated as full IPUMS samples in ACS each year times 100, as the ACS contains 1-in-100 national random sample of the population.

Table 3.1. Summary statistics of selected vehicle attributes

	Horsepower	PWR	SIZE	KPE	MPG	SPI	Fuel Price
2012 (all manufacturers)							
EV	157.17	4.33	82.40	27.28	100.82		
Non-EV	263.28	6.60	96.76	6.08	22.47		
All	261.88	6.57	96.57	6.36	23.51	240.70	3.69
2012 Nissan							
EV	107.00	3.17	84.70	26.98	99.70		
Non-EV	273.12	6.84	95.94	5.81	21.46		
All	265.57	6.67	95.43	6.77	25.02		
2012 Tesla Motors							
EV	300.00	7.33	99.77	24.06	88.90		
2012 Mitsubishi							
EV	64.50	2.49	62.73	30.81	113.85		
Non-EV	177.71	5.29	89.16	6.66	24.62		
All	158.84	4.82	84.75	10.69	39.49		
2019 (all manufacturers)							
EV	237.87	5.54	97.17	35.90	96.85		
Non-EV	273.05	6.82	97.63	9.32	25.15		
All	272.04	6.79	97.62	10.08	27.20	222.20	2.70
2019 Nissan							
EV	147.00	4.24	86.36	42.16	113.75		
Non-EV	275.19	6.87	98.00	8.94	24.11		
All	269.08	6.74	97.45	10.52	28.38		
2019 Tesla Motors							
EV	260.78	5.67	106.60	38.07	102.71		
2019 General Motors							
EV	200.00	5.61	79.15	44.44	119.90		
Non-EV	275.86	6.67	101.64	9.25	24.96		
All	273.81	6.64	101.03	10.20	27.52		
2019 Hyundai							
EV	191.00	4.71	93.48	22.16	59.78		
Non-EV	236.44	6.42	93.16	9.99	26.94		
All	231.90	6.25	93.19	11.20	30.23		
2019 Jaguar Land Rover							
EV	344.75	7.21	101.36	28.32	76.40		
Non-EV	307.67	7.67	101.76	8.82	23.79		
All	311.37	7.63	101.72	10.77	29.05		

All statistics are shown as the mean. Horsepower is in unit of foot-pounds per second (ft-lb/s, or fps). PWR is horsepower per 100 pounds of weight. SIZE is measured as the length times the width of a vehicle in unit of square feet. Note that SIZE is different from "footprint" which is the wheelbase times the average of front and rear track width. Footprint is smaller than SIZE. KPE is the fuel economy measured as the MPG (fuel efficiency) divided by fuel price. SPI is the iron and steel price index published by Bureau of Labor Statistics.

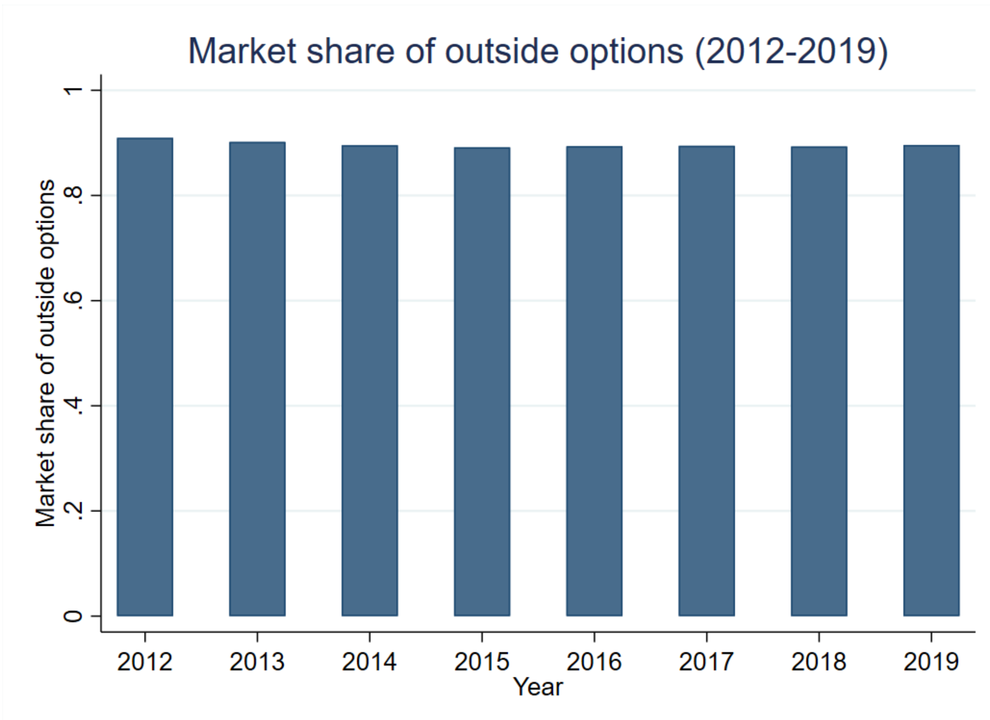


Figure 3.6. Market share of outside options S_0 (2012 - 2019)

$$S_0 = \frac{\text{Total number of household} - \text{Total vehicle sales}}{\text{Total number of household}}$$

year. Other manufacturers such as Toyota and Ford meet the standard in some years and miss the targets in other years or vehicle types.

Table 3.2 shows the number of manufacturers that fails to meet CAFE standards under each vehicle type in each year. More than half of the manufacturers face civil penalties under each vehicle type. With CAFE standard becoming stricter, the number of firms failing the CAFE standard under the vehicle type of cars has increased. As mentioned in the introduction section, the average penalty per vehicle accounts for only a very small proportion of the retail price. Therefore the statistics indicate the some manufacturers have tried less hard in recent years to meet the standards.

Table 3.2. Number of manufacturers which failed CAFE standard by year and vehicle type

	2012	2013	2014	2015	2016	2017	2018	2019
Firms producing Cars								
Total # of firms	20	20	19	19	19	19	19	19
# of firms failed CAFE	14	12	11	11	13	18	17	17
Average penalty ($/vehicle)	213	211	182	225	166	172	259	271
S.D. of penalty ($/vehicle)	102	110	120	101	145	166	170	229
Firms producing Light Trucks								
Total # of firms	19	19	18	18	19	19	19	19
# of firms failed CAFE	13	11	11	12	11	12	13	13
Average penalty ($/vehicle)	161	174	178	165	205	214	177	181
S.D. of penalty ($/vehicle)	54	43	31	26	29	47	60	71

# of firms failed CAFE is counted as the number of manufacturers whose CAFE performance is more than 0.5 miles per gallon below the CAFE standard (penalty level higher than $55 \times 0.5 = \$27.5$). Average penalty is calculated as the sales weight penalty per vehicle if the CAFE target is missed by more than 0.5 miles per gallon.

3.6 Results

For the demand side estimation, we include PWR, SIZE, KPE and EV indicator as the observed car attributes. PWR measures the relative engine power per pound of weight. KPE represents fuel economy which is the fuel efficiency measurement (MPG) per dollar of fuel price. We also add a year trend and an interaction term of EV and time trend to add more flexibility to the consumer taste evolution specifically to EV. For the supply side control choices, we adjust the observed characteristics to accommodate cost concerns in the production process. All the coefficients are reported as estimates with instrument variables described in equation (3.14).

3.6.1 Random coefficient estimates

Table 3.3 shows the estimation results of the Logit model and the preferred random coefficient (RC) model. Logit model assumes there is no heterogeneity in consumer tastes on car attributes and prices, and the unobserved car attributes are independent across time. We report the Logit estimates for comparison with RC estimates. The mean utility coefficient β shows that consumers dislike EV at the beginning of period, all else equal. The large negative coefficient of EV is as expected – If other observed attributes of an EV, especially fuel efficiency (one of EV's greatest advantages), are the same as a gasoline vehicle, EVs will be less attractive to consumers because of its shorter miles range, safety concerns, etc. But recall that the fuel economy (KPE) of an EV is usually four to six times of a non-EV, the utility gain from higher KPE would compensate the low baseline utility of EV. The interaction term of EV and trend indicates a positive consumer taste evolution towards purchasing an EV, but not significant.

All else equal (e.g., horsepower, size, and MPG), the marginal cost of producing an EV is slightly smaller than producing a non-EV. Developing an EV model could require large R&D expenditure as the sunk cost. But the marginal cost of producing an EV model is 1.27 percent less compared to a non-EV.[12] Vehicles with higher engine power per pound of weight, larger size, and higher fuel efficiency are more costly to produce, which is reasonable and the coefficients are significant. We do not find strong evidence that vehicles are less expensive to produce over time, nor that EVs are less expensive to produce over time.

The coefficients of the idiosyncratic utility are large in size with more significance compered to the mean utility estimates, which means consumer tastes towards observed attributes are largely heterogeneous. Imposing the homogeneous taste restriction would lead

[12]↑The dependent variable of marginal cost function is in a *log* form, as shown in equation (3.13).

Table 3.3. Logit model and random coefficients model estimates

	(1) Logit Model		(2) RC Model	
	Estimate	SE	Estimate	SE
Mean utility (β)				
CONSTANT	-8.5184***	(0.8987)	-12.4788*	(7.0655)
PWR	-1.7357***	(0.6016)	-1.8855	(6.3007)
SIZE	0.1831	(0.6999)	-1.2199	(4.2688)
KPE	-0.0094	(0.0274)	0.5602	(0.6052)
TREND	-0.0007	(0.0211)	-0.1450	(0.1048)
EV	-1.0908	(1.2518)	-17.5796	(11.7356)
EV $\times$ TREND	-0.1773	(0.1625)	1.0311	(1.2341)
Heterogeneous demographics (α)				
PRICE/INCOME	-0.8142**	(0.3252)	-4.1179***	(0.5623)
Idiosyncratic utility (σ)				
CONSTANT			7.4743**	(3.5267)
PWR			1.1293	(2.9910)
SIZE			6.6141***	(2.4819)
KPE			1.1966***	(0.5022)
EV			0.4002	(2.4056)
Coefficient of AR(1) process for unobserved car attributes ξ				
ρ_ξ			0.9899***	(0.0082)
Marginal cost (γ)				
log(PWR/SPI)	2.2131***	(0.5210)	1.9318***	(0.4038)
log(SIZE $\times$ SPI)	2.6164***	(0.6175)	3.4175***	(0.3556)
log(MPG)	1.6876***	(0.6318)	1.7476***	(0.4165)
TREND	-0.0192	(0.0118)	-0.0078	(0.0090)
EV	-0.4320	(1.0672)	-1.2766**	(0.6026)
EV $\times$ TREND	-0.0571	(0.0928)	0.0604	(0.0958)

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The total number of observation is 1,880, which contains 226 - 245 models each year from 2012 to 2019 (a model-year combination). Logit model and RC model use the same IV defined in (3.14). Random coefficient model is based on 6,000 simulated agents in each year. Both mean utility estimates and marginal cost contains 37 brand fixed effects and 7 segment fixed effects estimates which are not reported in the table. We replace heterogeneous income across individuals to the annual average income for estimating α in the Logit model. PWR in this table is horsepower per tenth pound of weight. SIZE is defined as the (inch/100)^2. KPE (fuel economy) is defined as one tenth of MPG per fuel price in dollars.

to largely biased estimates on EV and price sensitivity. Consumers are more price sensitive based on RC estimates compared to Logit. The unobserved vehicle attributes, ξ, evolves via the AR(1) process through coefficient ρ_ξ. We find ρ_ξ is significant and close to one, indicating that the unobserved car attributes in the current year are very similar to the previous year.

Figure 3.7 shows the average Lerner index of producing EV and non-EV across years. The Lerner index is calculated as the difference between the price received by manufacturers (retail price − CAFE penalty per vehicle) and marginal cost divided by the price received by manufacturers (or $\frac{P-MC}{P}$). EV is in general less profitable than other types of vehicles except 2017 and 2018. The Lerner index for non-EVs are relatively stable and is on average 0.5424.

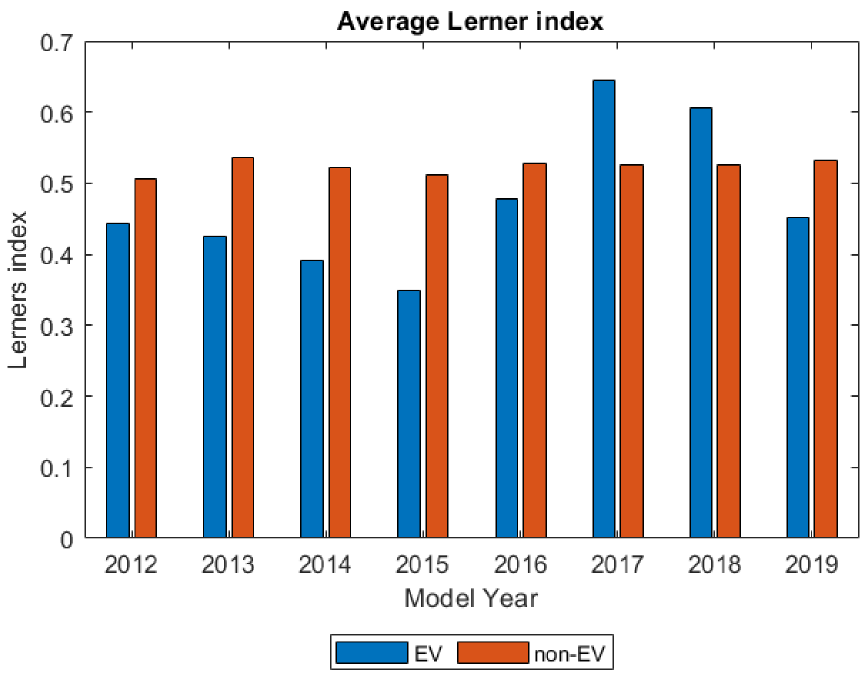


Figure 3.7. Average Lerner Index of EV and non-EV (2012 - 2019)

3.6.2 Counterfactual analysis: no tax credit

To answer the research question of how the generous tax credit has facilitated the diffusion of EV, we remove the tax credit for EV and estimate the new market equilibrium. Figure

3.8 shows the average price the consumer pays for an EV would be 24.97 percent higher if there is no tax credit for EV, and the amount ($11,571) is even higher than the tax credit ($7,500 for most EV models). We find that removing the tax credit of EV generates very mild impact on both market share and retail price of non-EVs. The average price of non-EVs will only decrease by $16.22.

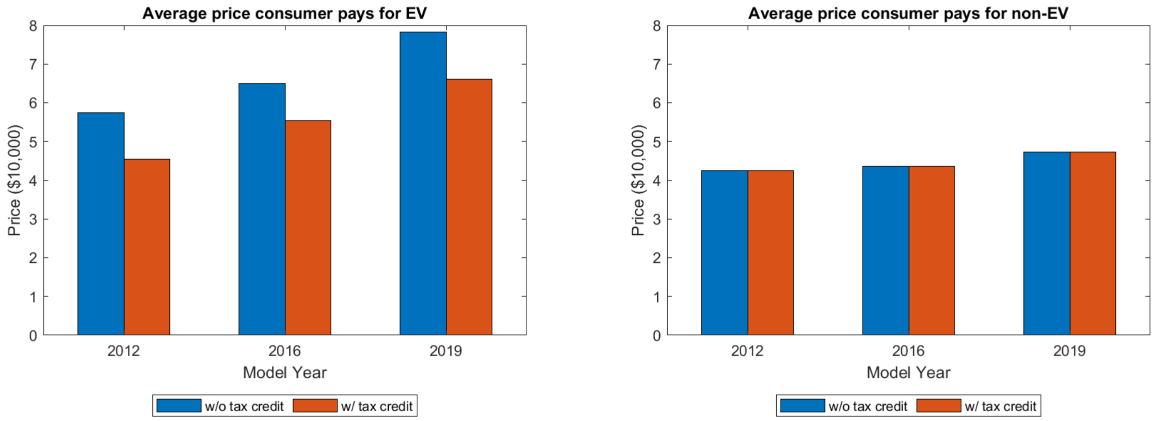


Figure 3.8. Average price consumers pay for EV and non-EV with and without tax credit (2012 - 2019)

Market share of EV will decrease by 35.82 percent if there is no tax credit (see Figure 3.9), which means 64.18 percent of consumer will still by EV without the tax credit. It is a similar estimate compared to Xing *et al.* (2021) who state that 70 percent of consumers would buy EVs regardless of the tax credit, and their data is up to 2014 – ours is up to 2019. The loyalty of EV customers would motivate manufacturers to mark up more if there is no tax credit to increase their profit in the EV sector. Market share of non-EV will increase mildly by 0.67 percent.

3.6.3 Counterfactual analysis: no CAFE penalty

The second research question is how the current CAFE system has accelerated the diffusion of EV. To answer this question, we change the CAFE penalty from $55 per vehicle per mpg below the standard to $0. The price impact on EV varies by year but is generally mild, with an average increase of the price of EV by 3.4 percent. This effect happens through

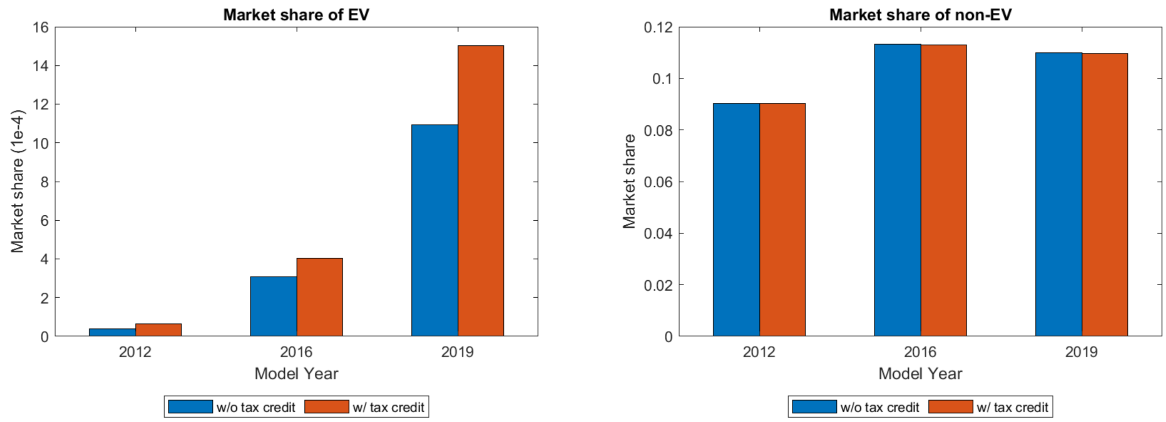


Figure 3.9. Market share of EV and non-EV with and without tax credit (2012 - 2019)

Note: The market share of EV and non-EV does not sum to one hundred percent as there are consumers who do not purchase any vehicle (the annual market share of the outside option is 89.7 percent from 2012 to 2019).

the channel that manufacturers have no pressure meeting CAFE standard by ensuring a relatively large market share of EV. Instead, the manufacturers will mark up the price of EV to enlarge their profit margin, while taking advantage of the loyalty of EV consumers.

On the contrary, removing the CAFE standard generates opposite impact on the price of non-EV compared to EV. On average, the price of other types of vehicles decreases by 3.26 percent (or $1,520). Recall that removing the tax credit of EV generates almost no impact on the non-EV prices. But taking off the CAFE penalty instantaneously enlarges the possible markup of all vehicles facing a CAFE penalty. The large competitive non-EV market will respond with an overall mark down to maintain a market share. On the other hand, imposing a CAFE penalty (on average $197 per vehicle if fails CAFE) leads to an average increase of non-EV mark-up by $1,520, which is far exceeds the penalty. It eventually harms the non-EV consumers' welfare in a large scale.

We fail to find evidence that the increasingly stricter CAFE standard favors the market share of EV nor other types of vehicles (see Figure 3.11). It indicates that both EV and non-EV consumers do not shift their choices just because the CAFE system increases the average price of non-EV by 3.26 percent and decreases the price of EV by 3.4 percent. In

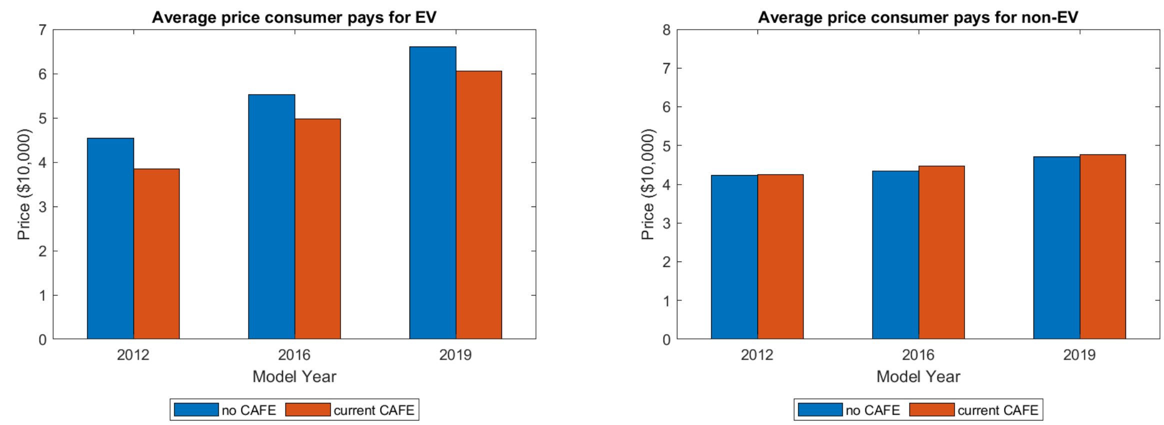


Figure 3.10. Average price consumers pay for EV and non-EV with and without CAFE system (2012 - 2019)

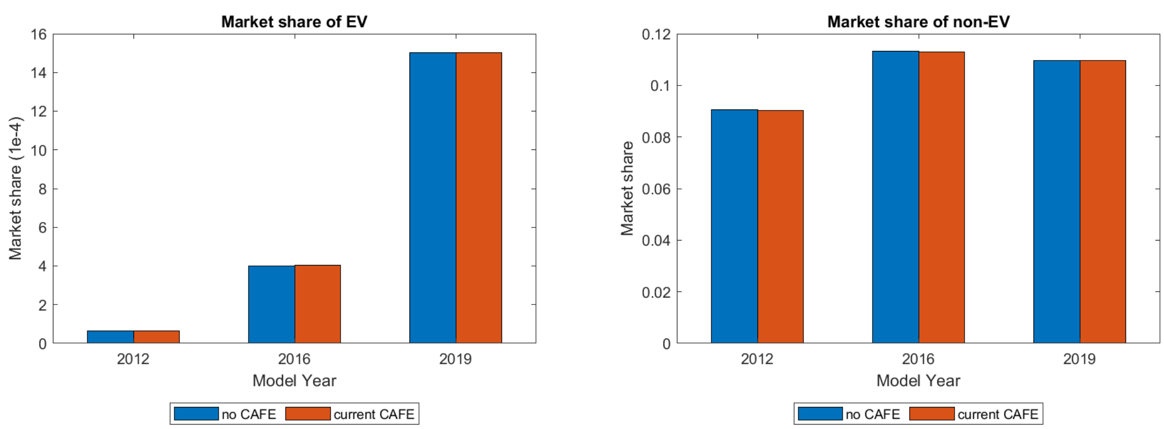


Figure 3.11. Market share of EV and non-EV with and without CAFE system (2012 - 2019)

fact, the average cross-price elasticity between EV and non-EV is far below the cross-price elasticity within each fuel type (see Figure A.8).

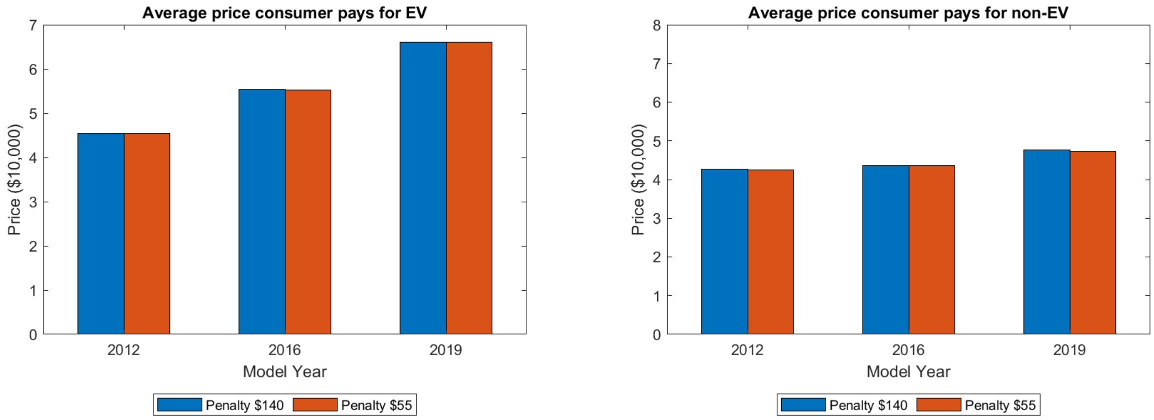


Figure 3.12. Average price consumers pay for EV and non-EV if CAFE penalty increases from \$55 to \$140 per vehicle per mpg below the standard (2012 - 2019)

3.6.4 Counterfactual analysis: increasing the CAFE penalty from \$55 to \$140 per vehicle per mpg below the standard

There has been a proposal of increasing the CAFE penalty level from \$55 to \$140 per vehicle per mpg below the standard, to catch up with the inflation rate.[13] We conducted the counterfactual analysis of replacing the current rate to the new proposed rate. Since the average penalty level is \$197 per vehicle per mpg below the standard, increasing the CAFE penalty unit would roughly increase the penalty by \$304 if the sales do not change.

We find that the price of EV will increase by 0.11 percent and the price of non-EV will increase by 0.39 percent if the proposed penalty level is implemented. More intuitively, the increased penalty would pass \$51.11 on EV consumers and \$172.92 on non-EV consumers on average. But the impact on the diffusion of EV is very mild. The market share of EV will only increase by 0.23 percent and the non-EV market share will decrease by 0.12 percent (see Figure 3.13). This result is as expected, considering the small proportion of the increased penalty with respect to the average retail price.

[13]↑E.g., https://www.federalregister.gov/documents/2021/01/14/2021-00278/civil-penalties.

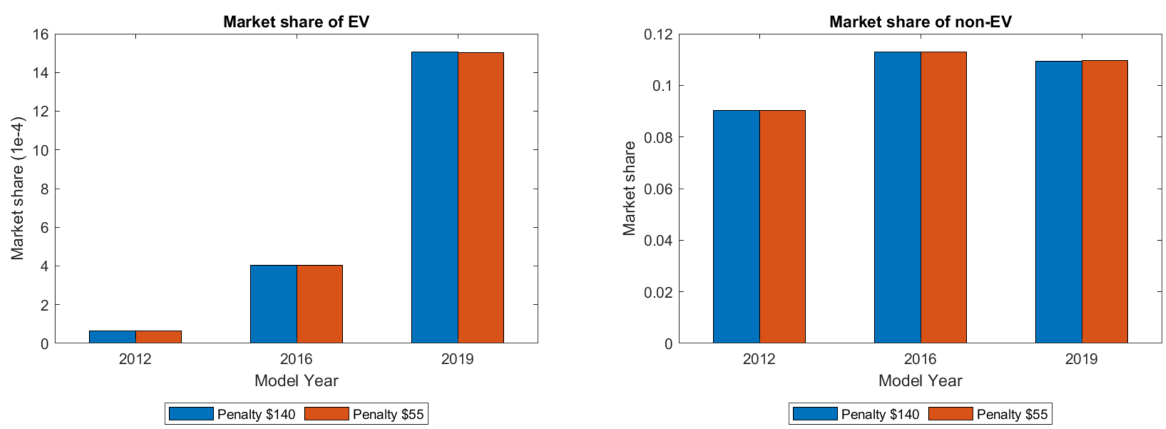


Figure 3.13. Market share of EV and non-EV if CAFE penalty increases from \$55 to \$140 per vehicle per mpg below the standard (2012 - 2019)

3.7 Conclusion

This paper uses the random coefficient model with post-estimation counterfactual analysis to answer two research questions: (1) How much the tax credit has facilitated the diffusion of EV; (2) How much the CAFE standard and penalty level have facilitated the diffusion of EV. We obtain the data from WardsAuto which contains rich vehicle attributes, retail price and sales data from 2012 to 2019. We find that the EV market share will decrease by 35.82 percent if there is no tax credit. The current CAFE system generates very mild impact on the market share of EV. CAFE marks down the price of EV on average by 3.4 percent but marks up the price of other types of vehicles by 3.26 percent, whose absolute value far exceeds the CAFE penalty itself and harms the non-EV consumers' welfare. We also find that increasing the penalty level from \$55 to \$140 per vehicle per mpg below the standard will only increase the EV market share by 0.23 percent and decrease the non-EV market share by 0.12 percent.

Our findings indicate that imposing a low CAFE penalty level relative to the retail price will not favour the market share of EV significantly. Mathematically, the combination of the current CAFE target measured in MPG and a penalty level around \$55 - \$140 per MPG below the target only imposes a few hundred dollars of penalty per vehicle in average, which is far less than the average/medium retail price of vehicles. Even thought the CAFE system generates mild impact on the market share of EV, the civil penalties received by the government can be used to continue subsidizing consumers who purchase EV. According to our findings, the current tax credit before the phasing-out generates a much larger impact on the market share of EV compared to the current CAFE system.

4. RESIDENTIAL SOLAR PANELS ADOPTION: PEER EFFECTS AND EQUILIBRIUM BEHAVIOR

4.1 Introduction

The installation of residential solar photovoltaic (PV) systems continues to increase in the US, with the installed capacity of 2019 almost twelve folds of 2010, and the average installation price dropped by about 70 percent in the last decade (SEIA).[1] In 2019, 2.6 percent of all electricity in the United States was solar, of which 19.5 percent is from residential solar PV (U.S. Energy Information Administration). From a broad public perspective, research related to solar energy helps further opportunities for continued environmental sustainability and green urban development, and from an academic perspective residential solar energy provides a unique opportunity for further study of behavioral interaction that generates these public benefits.

While solar energy may be of interest to both households and firms, our focus is exclusively on residential solar PV adoption. A household may choose to have solar panels installed on their property for different reasons, with one important reason being the associated monetary benefits.[2] However, such investment decision made by consumers could be attributed to non-monetary concerns; perhaps more interesting from a behavioral research perspective is the well-cited idea that the visibility of the solar system is also an important consideration for a household that may be considering whether or not to adopt solar panels. A visible solar system and/or a conversation between neighbors that a solar system has been installed could reduce the uncertainty of the technology among non-adopters, send a positive signal of green energy contribution, and generate a social incentive to non-adopters to behave pro-socially (Bollinger and Gillingham 2019, Mundaca and Samahita 2020). That is, it is widely believed that there are peer effects associated with household solar panel adoption

[1] ↑Source: https://www.seia.org/solar-industry-research-data.

[2] ↑The monetary benefits associated with household solar panel adoption may include tax credit, a reduction in electricity bill, and the value of energy sold back to the grid. Households across the United States have faced various financing/installation options given different incentives available in different states in different years. These different options have been well documented, and cost-benefit analyses have been conducted (e.g., Jung and Tyner 2014).

that is driven by conspicuous environmental consumption and related social norms (Lobel and Perakis 2011, Chen 2014, Rode and Weber 2016, Parkins *et al.* 2018).[3]

Basically, households adopt solar PV partly because their neighbors have made or are expected to make the same decision. In other words, peer effects in solar PV adoption can be interpreted as to what extent would a household decide to install solar PV because of the ongoing exposure of solar interests around the neighborhood. One the one hand, green technology exposure in the adjacent neighborhood serves as visible advertisement for availability of such technology and profitability in utility saving which stimulates neighbors' self-exploration in individual solar potential (Bala and Goyal 1998, Im *et al.* 2007). On the other hand, observing or learning neighbor's solar system generates invisible social incentives to show their environmental concerns, receive lower utility bills as their neighbors do, or simply a social pressure of "keeping up with the Joneses" (Im *et al.* 2007, Richter 2013, Rode and Weber 2016). A result of this behavior is a cluster of solar panel adoptions in particular neighborhoods.

In the solar panels adoption case, it is reasonable to believe that the existence of solar PV technology is publicly well-known because of the growing capacity of installed residential solar PV. Information of a new technology spreads through neighborhood exposure which exacerbates public awareness of this innovation; after gathering solar-related public information, potential customers are motivated to gather further information through local installers or online sources for household-specific payback period and quote information. Each potential household will receive a private signal about solar PV quality and worthiness of investment after this self-exploration. Even if public information could be homogeneous among non-adopters, private information varies by household (Board and Meyer-ter-Vehn 2018, Moretti 2011). The worthiness of a solar PV system depends on whether the household owns the house, remaining residence years (because the payback period of a solar PV system usually lasts about 6-8 years), family affordability, opportunity cost, enough exposure to sunlight, and self-fulfillment in following up the neighborhood trend. For non-adopters whose current evaluation in the worthiness of the solar system is below their reservation value, they are

[3]↑More generally, there is a growing literature that shows that peer effects (or conspicuous consumption behavior) is evident in a variety of environmental contexts (e.g., Delgado, Harriger, and Khanna 2015).

waiting for the right timing to adopt when their updated evaluation goes beyond their reservation threshold – with a possibility that the growing population with solar systems could trigger the adoption behavior.

In this paper, we use a structural (i.e., utility-based) model of household solar panel adoption that explicitly allows us to (i) identify and estimate a peer effects parameter that indicates whether and to what extent household solar panel adoption depends on the adoption decisions of others in the neighborhood, and (ii) use this parameter to understand broad equilibrium trends in solar panel adoption behavior. In particular, we use a recently developed continuous time optimal stopping model of de Paula (2009). This model is appropriate for studying household peer effects in solar panel adoption for several important reasons. First, this structural model is anchored to an economic utility framework, and as such, not only does the peer effects parameter have a proper economic interpretation, but the model provides equilibrium equations that allow us to understand the dynamic evolution of neighborhood solar panel adoption as it relates to household characteristics and peer influences. Second, being a continuous time optimal stopping model, the model reflects the reality that a household's solar panel adoption problem amounts to a one-time, irreversible decision.[4] Third, household decisions, within a neighborhood, are dynamic (not simultaneous). Each household has the opportunity to observe neighborhood adoption decisions over time, and then select the optimal adoption time (or to not adopt). Early-installed solar systems should have a longer impact comparing with newly installed ones. Fourth, the model is a formal network-based model, which allows us to develop explicit neighborhood structures on which the peer effects depends. This is fundamentally different to other recent attempts (described shortly) that have imposed the restriction that neighborhood influences are generically defined at a zip-code level. Finally, this model explicitly accounts for unobservable contextual and correlated effects that are known to lead to identification problems in econometric models of peer effects (e.g., Manski 1993); it is important to emphasize

[4]↑Technically, households with solar PV installed under Power Purchase Agreement (PPA) or a lease have the option to ask the developer to remove the system when the contract or lease ends – if they do not want to extend the contract nor purchase the system. But the peer effects takes place when the system is physically installed; besides, PPA contracts usually last twenty years and it is under early development in limited states. Therefore it is still reasonable to assume solar PV installation is a irreversible decision so as to identify the peer effects.

that the identification-related advantages of this model are not easily found in reduced-form alternative economic/econometric models.

As alluded to, others have investigated the possibility that household solar panel adoption is related to peer adoption decisions. Also alluded to are several important limitations of those papers that our paper, in part, is able to overcome – in addition to our equilibrium analysis that was not previously studied by others. Some papers (Bollinger and Gillingham 2012, Richter 2013, Balta-Ozkan *et al.* 2015, Baranzini *et al.* 2017) that investigate peer influences in household solar panel adoption make two strong assumptions. The first is that the relevant "neighborhood" is a zip-code. The second is that past adoption of solar panels within the "neighborhood" is exogenous, which is called an installed-base. These papers using reduced form models are insightful because they constitute preliminary investigation into the possibility that household solar panel adoption is dependent, in part, on peer adoption behavior. We note that Bollinger and Gillingham (2012) find insignificant peer effects parameters, while Graziano and Gillingham (2015) and Rode and Weber (2016) find significant influence of previous installers on current period installations using Connecticut and Germany data separately, and they both find diminishing neighbor effect over distance. At the same time, the results from these papers are linked to these two assumptions.

It is well-documented that peer effects are generated within geographical or social networks, and only under particularly strong assumptions about a network can one consistently estimate a peer effect from a group structure (such as a zip-code). Rode and Weber (2016) finds that solar panel peer effects fade and become less significant across space, such that neighbors who live nearby have higher (and significant) peer effects for adoption; thus by these results, aggregating neighborhoods to the zip-code level will moderate, or even render insignificant, the peer effect estimates as in Bollinger and Gillingham (2012). The assumption of an exogenous installed-base places strong restrictions on the manner in which information and decision-making is conducted within the neighborhood. Further, the non-structural models used in these papers do not lead to a set of equilibrium conditions that can be further analyzed to understand the dynamic evolution of solar panel adoption within a neighborhood.

The equilibrium analysis of our research is also related to models of diffusion (e.g., Jackson and Yarivy 2011). Well-known diffusion models include the classical and generalized Bass models in which households are either innovators or imitators, in which a significant imitation parameter indicates peer effects in (solar panel) adoption (e.g., the results in Guidolin and Mortarino 2010, Rao and Kishore 2010, Rode and Weber 2016). However, one major limitation of these models is that the model does not allow for an equilibrium of adopters and non-adopters. Rather, a positive imitation coefficient implies that the adoption rate will eventually converge to a hundred percent. This is unreasonable because we believe that households have different preferences for solar panels and face different degrees of social pressure for solar panel adoption, and more basically that some houses does not have market potential on account of not having the appropriate roof size/pitch or sun exposure. Due to various private information of solar PV, households will still have behavioral divergence even if public information has been diffused completely. Additionally, diffusion models treat the whole population as a peer group, which as noted is less ideal relative to an explicit network approach.

4.2 Literature Review

Current literature on analyzing peer effects in solar PV adoption are categorized into two types of reduced form models: diffusion model and the installed base method. Diffusion models, such as classical Bass model and generalized Bass model, assume there are two types of adopters – innovators and imitators. Innovators will adopt solar panels eventually at sometime regardless of what their peers behave, while imitators mimic the adopting action of existing adopters with a certain rate. Therefore a diffusion model contains an innovation coefficient and an imitation coefficient. A significant imitation coefficient indicates there are peer effects in the adopting process (Rode and Weber 2016, Guidolin and Mortarino 2010, Rao and Kishore 2010). The problem of applying diffusion model into solar PV adoption is that it is hard to identify an equilibrium. Theoretically, if there is a positive imitation coefficient, the adoption rate will converge to a hundred percent in the future, which means eventually every household will have solar panels on the roof. However, even for households with sufficient solar exposure and a short pay back period, some of them may still choose not to adopt due to financial reasons, or being naysayers to green technologies, etc. Therefore, it is hard to believe in reality that every household will adopt solar PV unless the government make it a mandatory regulation or devote enough financial support. There are diffusion model in network game setup that agents can shift between choices, which makes it possible to find an equilibrium (e.g., Jackson and Yarivy 2011). However, they are not appropriate for analyzing solar panels adoption as the installation of solar PV is basically irreversible. Besides, diffusion models treat a large population as a peer group, while peer effects of household behavior in solar PV adoption has been proved to be in a neighborhood level (Graziano and Gillingham 2015, Rode and Weber 2016).

In terms of analyzing regional peer effects, installed base method has been popular among researchers (Bollinger and Gillingham 2012, Richter 2013, Baranzini *et al.* 2017, Balta-Ozkan *et al.* 2015). For example, Bollinger and Gillingham (2012) analyzed county-level peer effects of solar panels adoption. Adoption fraction within one zip code during a specific period is influenced by the accumulated previous adoption within the same zip code area, which is also called the installed base. Installed base under the solar PV adoption context is the accumulated number or fraction of previously installed solar panel projects among the neighborhood. Researchers using the installed base method usually set up a time lag between the installed base and current adoption counts. For example, Bollinger and Gillingham (2012) sets a time lag of six months. And the installed-based users argue that because of the time lag they set up, the previous solar panel adoption only impact current adoption decision exogenously therefore simultaneity will not be an issue. However, considering the long period for one household to formalize the idea to real action,[5] it is reasonable to believe there exists endogenous peer effects during the decision period; that is, households who make the decision to adopt solar PV within six months affect each other's adoption decisions.[6] The popular method of installed base, which only consider the influence of previous adopters (e.g., six

[5]↑Averaged to 6 months by Bollinger and Gillingham (2012); 3 month according to Richter (2013).

[6]↑Previous research argue that previous adoptions happened before six months affect current period (within six months)'s adoption decisions exogenously, and we believe adoptions happen within an adjacent episode (does not need to be six month necessarily) affect each other's decision endogenously.

months apart) while ignoring the social interaction of contemporaneous adopters (e.g., with in six months), is incomplete.

Besides, aggregating adoption behavior in regional level causes bias in peer effects estimates. Rode and Weber (2016) finds that peer effects fade and become less significant for further neighborhood. Neighbors who live geographically nearby have higher peer effects while aggregating the adoption behavior in zip code level will moderate the estimation of peer effects, or even lead to insignificant results such as the estimates of Bollinger and Gillingham (2012). Using residential solar panel data and estimate household level peer effects within neighborhood or community will raise more interest to regional installers.

de Paula (2009) focuses on individual behavior of an irreversible action in a dynamic setting. Even his empirical study is not related to the adoption of renewable technology, the method is the most suitable one for analyzing solar PV adoption, to the author's knowledge. de Paula (2009) develops a dynamic model of optimal adopting time in a synchronization game among multiple decision makers. In a classical peer effects model, it is hard to separate endogenous peer effects and correlated effects (Manski 1993). de Paula (2009) manages to estimate the two parameters independently. The model starts with a latent utility differential function, with an optimal adopting time depending on the decisions of peers. Anytime there is one more adopter in the group, other members within this group tend to adopt earlier, with the possibility that an agent could follow other adopters at the same time.[7] Another advantage of de Paula's model is that the only information we need to derive all parameters (including peer effects and correlated effects) is the adopting time of each individual. Besides, with demographics collected for each individual, we are able to differentiate adopters and non-adopters therefore estimate a long-term adoption equilibrium.

A reduced form model of installed-base has limitations but could serve as a supporting analysis as a proof of the existence of peer effects in solar PV adoption, but the definition of peers need to be carefully addressed. While de Paula (2009)'s model should serve as the major method for estimating peer effects which allows the impact of both previous adopters as well as simultaneous or endogenous adopters. Besides, de Paula (2009) rules out those

[7]↑de Paula (2009) uses "quitters" instead of adopters in his paper but we accommodate the model setting under the solar PV adoption context.

households who are not intended to adopt solar PV anytime in the future, and can predict the long-run adoption pattern. Therefore, de Paula (2009)'s model is a better method to analyze solar PV adoption in three ways. First, it allows the endogenous interaction between neighbors. Second, it helps to predict future market equilibrium which may not be a full-population adoption. Third, the analysis is based on household level instead of aggregated regional level to it helps to evaluate a potential customer or target.

Overall, several fundamental limitations of current reduced form empirical methods motivate us to find a structural model in analyzing peer effects in solar PV adoption. If we could have access to residential solar panel data, an analysis of household level peer effects within neighborhood or community could raise more interest to regional installers and environmental agencies.

4.3 Model

We adopt the general theoretical framework developed by de Paula (2009) to analyze peer effects and equilibrium adoption behavior for household solar panel adoption. The basic principle underlying the model is that each household decides the optimal time to install solar panels (which includes not adopting). Define a state variable x_t to be the discounted accumulated reward a household collects if it adopts solar PV at time t, adjusted by a deduction of an opportunity cost C. Theoretically, a typical house with sufficient sunlight exposure will have a positive (monetary) net present value of investing in solar PV, considering future electricity savings. However, even if the household is aware that their house location has an average payback period of less than ten years, and/or the possibility of a purchasing method that would avoid a lump-sum payment, households may still choose not to adopt because they make decisions based on utility concern about the PV instead of monetary benefits only.[8] In general, households face a potential investment which is possibly costly but have substantial rewards once adopts. Reward could contain electricity savings spread into the future, potential property value increase, self-fulfillment through environmental contributions, etc. We set the net utility, reward minuses cost, depreciate

[8]↑Other purchasing methods include leasing, loan, or PPA, though there is limited access to these instruments in many states.

exponentially with a rate of γ. The same amount of net utility of installing solar PV at time t, $x_t - C$, is worth less to a consumer if obtained later. Intuitively, suppose the net utility of installing solar PV is fixed and positive, a consumer would always want to install right away to enjoy the benefits of having the solar PV. Therefore we assume the net utility gain depreciate exponentially. Thus, the household faces the problem

$$\max_t \; E_x[e^{-\gamma t}(x_t - C)] \tag{4.1}$$

in which a representative household is trying to find the optimal time t to make the investment of solar PV, with the reward x_t and an opportunity cost C.

4.3.1 Reward function

Reward function x_t captures the future discounted electricity savings, satisfaction from generating renewable energy or contributing to the environment, and potentially a utility loss if deviating from peers' behavior. The baseline reward of installing solar PV, x_t, is expected to grow over time as electricity price keeps an increasing trend, and green energy preference being strengthened. However, because of the uncertainty of future conditions, the reward function x_t is expected to evolve stochastically with some unexpected random factors. More importantly, the baseline and random evolution of x_t may not be independent across households. On the one hand, as more neighbors install solar PV on the roof, a household has stronger nudge sourced from peer pressure. Therefore neighbors' active adoptions could affect a household's reward negatively and lowers down the reservation price. On the other hand, neighborhood's simultaneous adopting behavior may be affected by unobserved correlated factors such as a neighborhood sales campaign. Those unobserved events may lead to simultaneous adopting behavior among the neighborhood. Therefore we need to separate peer effects with correlated effects when we set up the reward function.

Following Dixit and Pindyck (1994) and de Paula (2009), we model the state variable x_t through a geometric Brownian motion. That is, we model the incremental reward dx_t via a drift parameter, α, and a volatility parameter, σ, such that household reward evolves over time through

$$dx_t = \alpha x_t dt + \sigma x_t dW_t \tag{4.2}$$

where dW_t follows a Wiener process $N(0, \Delta t)$ which is random in each period, unobserved to economists and correlated between neighbors.[9] For example, a common negative shock on the perception of solar PV among the neighborhood, neighborhood sales campaign, etc. The associated parameter to the random shock, σ, measures how volatile the utility shock is. The larger the σ, the stronger role the correlated shocks plays in a change in utility. α captures the baseline observed utility. Empirically, α is constructed as a function $\alpha(\omega_i)$ including controls ω_i as: (1) household level electricity usage, green energy preference (e.g., whether the household owns electric vehicle, registration in energy saving programs); (2) neighborhood level controls (in a census block) including age, income, race, education, etc.; (3) peers' behavior measured as the accumulated adoptions of solar PV in current period among the neighborhood, which will be introduced in the next section.

To be more specific, the dynamic household reward evolves over time with a drift function α, and fluctuates with unobserved shocks captured by a random noise W_t (with the flexibility that W_t is correlated through neighbors). It is important to recognize that although the geometric brownian motion is not frequently used to model empirical economic features, in this case it is a natural, while still flexible, modeling structure. In the following subsection, we introduce how peer effects and correlated effects are built in the reward function with details.

4.3.2 Separating peer effects with correlated effects

As motivated, we believe that households face social incentives (pressure) related to solar panel adoption. This social incentive is made via adjustment to the drift parameter α given the number of other households within the network that have adopted solar panels. To capture the social incentive, we assume that the drift parameter α decreases by a fixed

[9]↑Therefore σdW_t follows distribution $N(0, \sigma^2 \Delta t)$.

number $\frac{1}{I_i - 1}\Delta\alpha$ if there is an additional adoption within the neighborhood. Here, I_i is the peer group size for household i, which is time-invariant and includes i. Depending on the how network structure is formed, I_i could refer to the number of households in a zip-code (e.g., Bollinger and Gillingham 2012), or the number of households located within a radius fixing household i as the center of the circle (Rode and Weber 2016, Graziano and Gillingham 2015). In this paper, we adopt the zip-code level for preliminary analysis and explore a more flexible definition of neighborhood using the model in de Paula (2009). Therefore, $\frac{1}{I_i - 1}$ measures the importance of a single neighbor who adopts solar PV. A neighbor in a larger neighborhood (larger I_i) plays a smaller role in affecting household i's utility.

Further define the maximal possible deduction on the drift as $\Delta\alpha$, in the event that all peer group members have adopted solar panels (except for household i). In this case, the accumulated neighborhood adoptions generate a full scale of peer effects $\frac{I_i - 1}{I_i - 1}\Delta\alpha = \Delta\alpha$ on the only non-adopter in the neighborhood. The reason we use deduction instead of addition regarding the peer effects influence is that the expected adoption time is positively correlated to the value of the drift, meaning household with a smaller drift actually adopts earlier. Therefore, peer effect $\Delta\alpha$ works as a deduction in the drift α and motivates a household to adopt earlier.[10]

To formalize the model of latent household utility for household i, let τ_j be the adopting time of individual j from the peer group of i. Sort the adopting time of I_i households from

[10]↑In the case of homophily, $\Delta\alpha$ leads to a substantial degree of pressure on the household to adopt solar panels. On the other hand, $\Delta\alpha$ could be negative in the case of heterophily, in which case household utility x_t^i grows faster as the household becomes increasingly distinct as others adopt.

low to high as τ_1 to τ_N. The stochastic process of incremental reward for household i, dx_t^i, follows

$$dx_t^i = \begin{cases} \alpha x_t^i dt + \sigma x_t^i dW_t^i, & \text{if } t \leq \tau_1 \\ (\alpha - \frac{1}{I_i - 1}\Delta\alpha) x_t^i dt + \sigma x_t^i dW_t^i, & \text{if } \tau_1 < t \leq \tau_2 \\ \dots \\ (\alpha - \frac{k}{I_i - 1}\Delta\alpha) x_t^i dt + \sigma x_t^i dW_t^i, & \text{if } \tau_k < t \leq \tau_{k+1} \\ \dots \\ (\alpha - \Delta\alpha) x_t^i dt + \sigma x_t^i dW_t^i, & \text{if } \tau_{I_i - 1} < t \leq \tau_N. \end{cases} \tag{4.3}$$

This model structure shows that peer effects (assuming homophily: $\Delta\alpha > 0$, which is a testable assumption) hinder the utility increase – the lower the drift $\alpha - \frac{k}{N-1}\Delta\alpha$, the slower x_t^i will grow. As the fraction of neighborhood solar panel installation $\frac{k}{N-1}$ increases, the reward function x_t^i grows slower.

As a final note about the volatility part in the reward function. As stated, W_t^i follows a Wiener process; we further allow for a covariance between W_t^i and W_t^j given by $\langle W^i, W^j \rangle_t = \rho t$. ρ reflects correlated effects – the fact that peer group members tend to behave similarly because they share similar unobserved characteristics (Manski 1993) or under a common shock. A correlated path of W_t reflects a correlation across peers so that they are more likely to share similar background and experience. It is well-understood that peer effect models, in general, need to account for correlated effects to be identified.

4.3.3 Solution of optimal adopting time and identification of peer effects through simultaneous adopting behavior

The optimal time τ_i to maximize the expected utility in equation (4.1) is solved when the reward function x_t reaches a threshold z (will be introduced shortly) after an evolution period of τ_i. With the increment of the reward function dx_t evolves by equation (4.3), x_t

can be solved by the Ito's Lemma, which yields the log version of reward (Dixit and Pindyck 1994):

$$\log x_t^i = \log x_0^i + \left(\alpha - \frac{\sigma^2}{2}\right) t - \Delta\alpha \sum_{j:j\neq i} (t-\tau_j) \frac{\mathbb{I}_{t>\tau_j}}{I_i - 1} + \sigma W_t^i \tag{4.4}$$

where $\mathbb{I}_{t>\tau_j}$ is an indicator which equals to one if household i adopts solar panels later than j. The optimal adopting time for each household depends on the value of a threshold $z(\alpha - \frac{k}{N-1}\Delta\alpha, \sigma, C, \gamma)$, where the baseline threshold $z(\alpha, \sigma, C, \gamma)$ is given by

$$z(\alpha, \sigma, C, \gamma) = \frac{\beta(\alpha, \sigma, \gamma)}{\beta(\alpha, \sigma, \gamma) - 1} C \tag{4.5}$$

where

$$\beta(\alpha, \sigma, \gamma) = 1/2 - \alpha/\sigma^2 + \sqrt{[\alpha/\sigma^2 - 1/2]^2 + 2\gamma/\sigma^2} \tag{4.6}$$

This threshold means that in a situation in which k neighbors out of a peer group size of I_i have adopted solar panels at time t, household i will choose to adopt solar panels at time t if x_t^i hits the threshold value $z(\alpha - \frac{k}{I_i-1}\Delta\alpha, \sigma, C, \gamma)$.

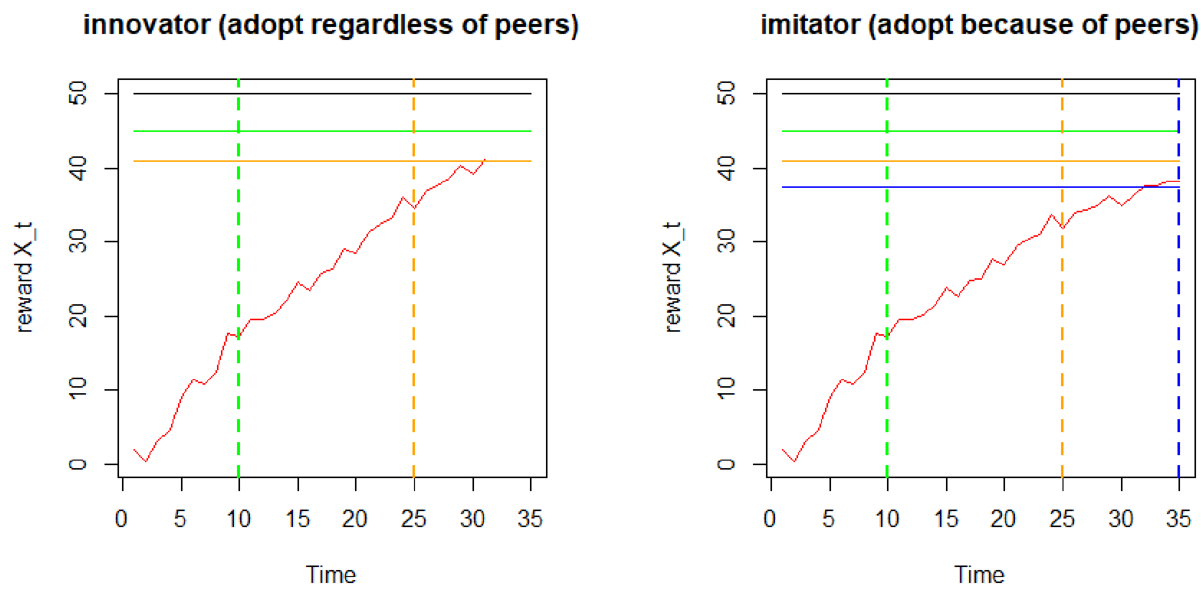
To provide some intuition for the solution to this model, even though early adopters around household i make the utility of household i increases slower, the threshold itself drops even more which actually fastens the adopting behavior of household i. In other words, previous adopters around household i increases the speed at which the reward, x_t^i hits the adoption threshold of household i. There are two possible cases for household i to adopt solar panels: (1) Household i initiates the adoption by itself (as called "innovator" in the diffusion literature); (2) Household i follows another initiative adopter in current period and adopt simultaneously with this adopter (as called "imitator" in the diffusion literature).

More formally, let z_k^i represent the threshold value of household i when there has been k adopters in the neighborhood. When household i's own reward x_τ^i reaches the adoption threshold z_k^i at time τ, it is an innovator. As shown in Figure 4.1a, let the upper black bar be the reservation value to adopt solar PV at time 0. There are two peer adoptions at time 10 and 25, which lowers the threshold to the green bar and orange bar separately. This household will not adopt solar PV at time 25 as the reward x_τ^i (the red line) has not reach the threshold (orange bar). But as x_τ^i evolves over time it hits the threshold at time 31 and this is the adopting time for i.

Figure 4.1b illustrates the imitator case. The increasing trend of the reward function x_t becomes slower as two peers adopt solar panels at time 10 and 25. The third adoption among the peers at time 35 drags the threshold from $\overline{z}(\alpha - \frac{2}{N-1}\Delta\alpha, \sigma, C, \gamma)$ (orange bar) to $\underline{z}(\alpha - \frac{3}{N-1}\Delta\alpha, \sigma, C, \gamma)$ (lowest blue bar) below x_t, which triggers household i to adopt simultaneously with the initiative adopter (in blue) at time 35. Therefore, a positive $\Delta\alpha$ indicates the evidence of concurrent adoption behavior, or endogenous peer effects.

The peer effect, $\Delta\alpha$, is identified through a smooth evolution of the reward function but a discontinuous evolution of the reservation value (e.g. the threshold z) caused by peers' behavior, which leads to simultaneous adoptions. Ideally, if there is no peer effects ($\Delta\alpha = 0$), adoptions occur randomly by each household whenever x_t hits a time-invariant threshold z. Theoretically, the probability that two adoptions happen exactly at the same time, which is measured continuously, is zero. Simultaneous adoption is only possible with peer effects being strictly positive. Note that the correlated effects parameter ρ does not affect the threshold z. Even if $\rho = 1$, or households share the exact same shock, adoption time among neighbors will be closer to each other but not as a clustering at the exact same time because of the heterogeneous drift $\alpha(\omega_i)$. Therefore the observed simultaneous adoption pattern helps to identify peer effects.

Empirically, the time of adopting solar PV is discretized in days instead of being measured continuously, but we use a non-parametric test developed in de Paula (2009) for evidence of peer effects shown in the results section.



(a) Initiative adoption (b) Follower adoption

4.3.4 Equilibrium of solar panels adoption

One of the advantages of this model is that we can define the equilibrium of solar panel adoption within each neighborhood. Mathematically, we can define the solar panel adoption equilibrium as:

$$\tau_i^* = \sum_{k=1}^{I_i} \left(\prod_{j=1}^{k-1} \mathbb{I}_{x^i_{\tau_j} < z^i_j} \right) \mathbb{I}_{x^i_{\tau_k} \geq z^i_k} \tau_k \tag{4.7}$$

where τ_i^* is a vector of adoption times among all households. Household i and k will adopt simultaneously if the latent utility of household i has not reached the threshold z^i_{k-1} but is above or equal to z^i_k. This equilibrium is economically important. Previous empirical papers investigating peer effects and solar panel adoption – such as Bollinger and Gillingham (2012) – use the installed base model to identify peer effects; however, such a static model cannot be used to predict future adoption equilibrium. de Paula (2009) allows for an equilibrium prediction with the flexibility that some households may never adopt solar panels (with optimal adoption time $t = \infty$). These never-adopters are proved to have a higher drift α than the discount rate γ. As described shortly (in the empirical section), we will make α a function of covariates $\alpha(\omega_i) = \omega_i \alpha$ where ω_i are (observable) household characteristics and α contains the coefficients. With α being estimated, we can distinguish the households who will never adopt solar panel by checking whether they have $\alpha(\omega_i)$ higher than the discount rate γ.

4.3.5 Empirical estimation strategy

An empirical model amounts to gathering household level data on solar panel adoption, household characteristics, and geographical location, in order to estimate the parameters $(\alpha, \Delta\alpha, \rho, \sigma)$. Empirically, we can observe the realized adoption equilibrium $(\tau_1, \tau_2, ..., \tau_N)$ in an area before some time T, which is the end of the observed data. Though future adoptions are not observable, we can nevertheless predict dynamic changes to the neighborhood equilibrium post-estimation. Our data obtained from PG&E contains exact household addresses; indeed, the data contains household controls of utility usage and registration in energy saving programs not only for solar panel adopters, but also for non-adopters as well. We choose area in California with densely distributed solar panel installations to conduct our analysis since we need enough current adopters to estimate the parameters. The average adoption rate in the data is 20 percent.

To operationalize an empirical model, we first need to define the network structure of the neighborhood. Graziano and Gillingham (2015) define the baseline households as all households living within 0.5 miles radius of a pre-picked center, and define neighbors of the baseline households as households live within 0.5 to 2 miles radius of the same pre-picked center; Rode and Weber (2016) also define neighbors (peer groups) as households located in various distance bands outside an inner circle of households. Since their dependent variable is the number of newly installed PV systems within a radius, they need to pick a center of a circle which is arbitrary. Besides, their estimation of parameters is relative to the chosen center of this circle. Our work is instead household focused – we define households inside a community as a peer group.Community boundary is chosen based on the location pattern of houses, and communities are not adjacent to each other, which gives more validation that households across communities make adoption decisions independently.

Second, is specification of the parameter vector that needs to be estimated and discussion of the identification problem. The full list of unknown parameters that needs to be estimated is $\psi = (\alpha, \Delta\alpha, \sigma, \rho, \gamma, C)$, in which $\alpha = \alpha(\omega_i)$ is a function of observed household and neighborhood controls (in a census block level). Theoretically, as long as ω_i contains one continuous random covariate, and a sufficiently large number of observations compared to the number of parameters, the full set of variables ψ are identified (see Theorem 3 in de Paula 2009). However, we follow de Paula (2009) and normalize C and γ to a fixed level across all households and focus on the estimation of peer effects.

Third, is estimation of the parameters. Given data on the adoption time across neighborhoods $(\tau_1, \tau_2, ..., \tau_N)$ as well as housing characteristics of each household with solar PV, we can estimate the parameter set ψ. Under the modeling structure described earlier, the optimal stopping time τ for each household (the time that x_i touches threshold z) follows an inverse Gaussian distribution (de Paula 2009). In a simplified case that there is no peer effects ($\Delta\alpha = 0$) and no correlated effects ($\rho = 0$), the probability density distribution of random variable τ can be expressed as:

$$f(\tau; \mu, \lambda) = \left[\frac{\lambda}{2\pi\tau^3}\right]^{1/2} \exp\left\{\frac{-\lambda(x-\mu)^2}{2\mu^2\tau}\right\}. \tag{4.8}$$

If the initial condition x_0 is zero, the drift μ and volatility σ are identified as:

$$\frac{z}{\alpha} = \mu \tag{4.9}$$

$$\frac{z^2}{\sigma^2} = \lambda \tag{4.10}$$

where z is the threshold defined in (4.5) which is a function of α, σ, C and γ. Again this is a simplified condition with no peer effects and no correlation between households' lifetime utility. Under this simplification, the optimal stopping time to adopt solar panels for household i is not influenced by other households – $(\tau_1, \tau_2, ..., \tau_N)$ are independent inverse Gaussian random variables in which parameters μ and λ can be estimated using ML estimator – mean and harmonic mean of adoption time. Then we can recover α and σ via (4.9) and (4.10).[11] However, this is not consistent with the network structure we put into the solar panels adoption game, as there will be endogenous interaction in the adoption outcome between neighbors ($\Delta\alpha \neq 0$), and correlated unobservables within the peer group ($\rho \neq 0$). Under flexibility of peer effects and correlated effects, $(\tau_1, \tau_2, ..., \tau_N)$ are not independent variables – the adoption time τ_i affects the adoption time of other households within the peer group. Instead we have $(\tau_1, \tau_2, ..., \tau_N)$ being correlated inverse Gaussian random variables in which the first adoption, or the minimum adoption time across the peer group follows a cumulated distribution function as $G(t) = P(\tau_1^* \& \tau_2^* \& ... \& \tau_N^* \leq t)$, which is a function of α, ρ and σ after parameter replacement.[12] However, with thousands of observations it is almost impossible to derive $G(t)$, so that the MLE method of estimating ψ is not applicable, and so we turn to the simulated minimum distance estimator following de Paula (2009) to estimate ψ.

If we normalize the discount rate γ, the net cost C, and the initial condition x_0, ψ can be estimated by minimizing the distance:

$$\min_{\psi} \left\| N^{-1} \sum_{n=1}^{N} m(\tau_n) - N^{-1} \sum_{n=1}^{N} m(\tau_n(\psi)) \right\| \tag{4.11}$$

where N is the number of peer groups. In this paper, it refers to the number of "neighborhoods". As alluded to, we choose N communities not adjacent to each other and we assume the adoption behavior within a community depends on the peers' behavior but it is independent across communities. τ_n is the observed adoption time before time T and $\tau_n(\psi)$ is the simulated adoption time before time T based on the values of ψ. A vector of moments $m : \mathbb{R}_+ \to \mathbb{R}^k$ includes the mean, harmonic mean of adoption time, the average number of adopters in each discrete time period, and percentage of adoptions before the first, second and third quarter of T. The principle is to let the simulated adoption pattern across time to match the realized adoption trend as much as possible. Mean and harmonic mean are the ML estimator for the coefficients of inverse Gaussian distribution in absence of peer effects

[11] ↑Note that the two unknowns, (α and σ), in equations (4.9) and (4.10) are identified if we normalize C and γ. Otherwise the parameters α, σ, C, γ are not identified as there are too many unknowns.
[12] ↑Parameter replacement in the correlated case is not as straightforward as equations (4.9) and (4.10). In fact it is complicated even for a 2-agent game (de Paula 2009).

and correlated effects as shown in equation (4.8). These two moments are used to estimate α and σ. The other moments are related to the estimation of $\Delta\alpha$ and ρ. Higher $\Delta\alpha$ leads to higher frequency of simultaneous adoption, and higher ρ affects the overall speed of adoptions within a peer group. After we have estimated the parameter tuple $\psi^* = (\alpha, \Delta\alpha, \sigma, \rho)$, we can predict future equilibrium as well as the time to reach the equilibrium using simulation techniques.

4.4 Data

We obtain residential solar PV adoption data from both a public database and one utility company in California – Pacific Gas and Electric Company (PG&E). According to SEIA 2019, the accumulated installed solar capacity in California is as high as 25,016 megawatt (MW), which is 4.6 times of the the second highest state (North Carolina) and 6.6 times of the third highest state (Arizona). This paper focuses on the residential adoption in California. California Distributed Generation Statistics (CaliforniaDGStats) publishes the information of interconnected solar PV systems from three major utility companies in California (PG&E, SCE, and SDG&E) from 1982 to present.[13] As alluded to, once a residential system has been connected to the utility grid, it brings extra earning if the generated solar energy exceeds the usage. Therefore the utility companies keep track of all the net metering applications, including the key data of our interests – the date solar PV is installed.

By July 31st 2019, there has been 885,217 residential reported solar PV projects in California. The adoption rate, defined here as the count of PV projects divided by the number of households, is roughly 7.7%. CaliforniaDGStats shows that the most densely distributed county regarding the adoption rate of residential solar PV in California is the San Diego county (see Figure A.3). CaliforniaDGStats contains the installation information of 142,992 existing solar PV in the San Diego county. Figure 4.2 shows the accumulated adoption rate of residential solar PV in California and San Diego county. Solar PV installation starts accumulating rapidly since early 2000s. By July 31st 2019, roughly 12.6% households have solar PV at San Diego county.

[13]↑The data is publicly available at https://www.californiadgstats.ca.gov/downloads/

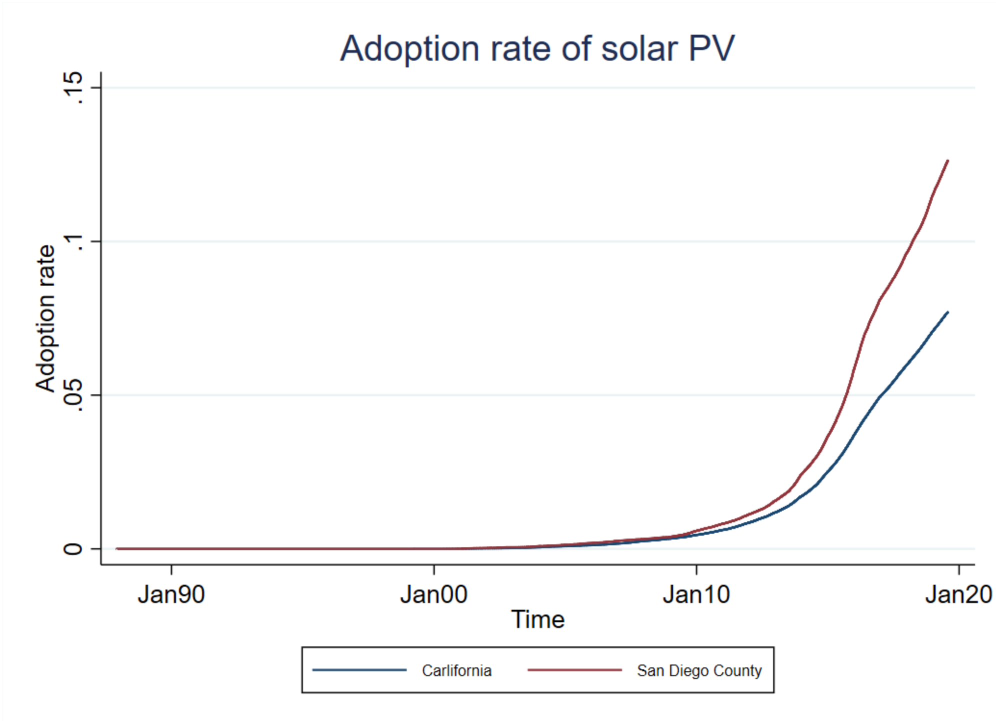


Figure 4.2. Accumulated adoption rate for California and San Diego County (1987 - 2019)

Note: By July 31st 2019, there has been 885,217 residential installed solar PV in California and 142,992 of them are located in the San Diego county. The figure shows the adoption rate defined as the ratio of the counted number of solar PV project to the total number of households.

One advantage of the public data set is that it contains relevant information such as the total system cost and whether the household owns at least one electric vehicle charging at the service address. We include these demographics as controls for the preliminary analysis for evidence of peer effects described in the results section. Another advantage, as mentioned above, is that it contains the adoption time by day. In fact, CaliforniaDGStats records three dates related to the solar PV projects – the date household files the application to connect their solar PV to the grid, the date the interconnection is completed, and the date it finally gets approved by the grid and starts counting the net metering. We believe the date household files the application is close to the date that the physical installation of the solar PV is completed, and is used for the measurement of optimal timing to adopt solar PV chosen by the household.

However, CaliforniaDGStats does not contain the address of each solar PV projects. The lowest level geographic information is zip-code. Table 4.1 shows the sample of adoption rate by zip-code at San Diego county. Note that zip-code has been used widely as the definition of a peer group such as Bollinger and Gillingham (2012). We can see that the adoption rate varies by zip-code from 1 percent to 48 percent across the San Diego county. We believe some of the variation is due to heterogeneous zip-code level demographics, but some of the clustering is because of peer effects spillovers. We show evidence of peer effects using a nonparametric test proposed by de Paula (2009) in the results section. Another characteristic of the public data set is that it only contains solar PV-related information of adopters but does not include non-adopters. Therefore, this data set is only used to analyze the adoption behavior among adopters. To analyze the dynamic adopting behavior among adjacent households, we obtained a confidential data set from PG&E.

Table 4.1. Residential solar PV adoption rate by zip-code of San Diego county

zipcode	Number of PV	Number of single family houses	Adoption rate
92061	234	489	47.85%
92065	3978	10306	38.60%
91935	1070	2812	38.05%
92036	189	509	37.13%
92082	2081	5673	36.68%
91901	1794	5309	33.79%
92064	4438	14334	30.96%
⋮	⋮	⋮	⋮
92102	643	10111	6.36%
91932	432	7065	6.11%
91950	639	12659	5.05%
92108	139	2894	4.80%
92113	507	10739	4.72%
92058	507	12177	4.16%
92101	33	2767	1.19%

Data source of installed solar PV count: https://www.californiadgstats.ca.gov/downloads/. Data source of number of single family houses by zip code:
https://california.hometownlocator.com/zip-codes/countyzips,scfips,06073,c,san%20diego.cfm. We exclude multi-family houses and only include single family houses for potential customer counts. There are 96 counties in total.

The data we obtained from PG&E contains only a sample of the whole service territory for confidential reasons. Therefore we choose the area which has a densely distributed solar PV – San Jose. To be clear, the sample we obtained is a "sample" relative to the service territory of PG&E (mostly north California), but the data we obtained which covers 18 zip-codes in San Jose includes a full sample of households under each zip-code. It contains the standard household address, monthly utility usage, and registration in energy saving programs for both houses with net metering connected to the grid, and the ones without. Figure A.9 shows a sample community of house location pattern and adoption information. The grey dots represents non-adopters and the red ones represent there are interconnected solar PV under the household address.

To apply the methodology proposed by de Paula (2009), we need N realization of solar PV adoption, which means N communities whose adoption behavior is believed to be independent across each other. Recall that the zip-code definition of peer group usually include adjacent zip-codes which makes the independence assumption less persuasive. But our data set gives more flexibility to choose independent communities because it contains the physical address of each household. Empirically, we pick 20 communities with an average peer group size of 101 and average adoption rate of 19.77%. The choice of communities is random but we accommodate the shape of the surrounding house location patterns. And we scatter the location choices such that communities are not adjacent to each other. We focus only on the suburb area of San Jose instead of downtown where multi family houses outnumbers the single family houses and are less likely to have solar PV. Figure 4.3 shows the location and adoption information of the 20 communities.

We merge zip-code level demographics data with the public data set, as zip-code is the lowest level location information. And we merge census block group level demographics with the PG&E data, as block group is the smallest classification available at US Census Bureau.[14] Table 4.2 shows the summary statistics of the public data. For 78,972 observations, the average time to adopt solar PV is the third quarter of 2016 (6,468 days since Jan. 1st

[14]↑We first obtain the census tract and block group information under each address from Geocoder (source: https://geocoding.geo.census.gov/geocoder, vintage: ACS2019 Current), and downloaded the demographics for each block group from US Census Bureau using the 2019 American Community Survey tables.

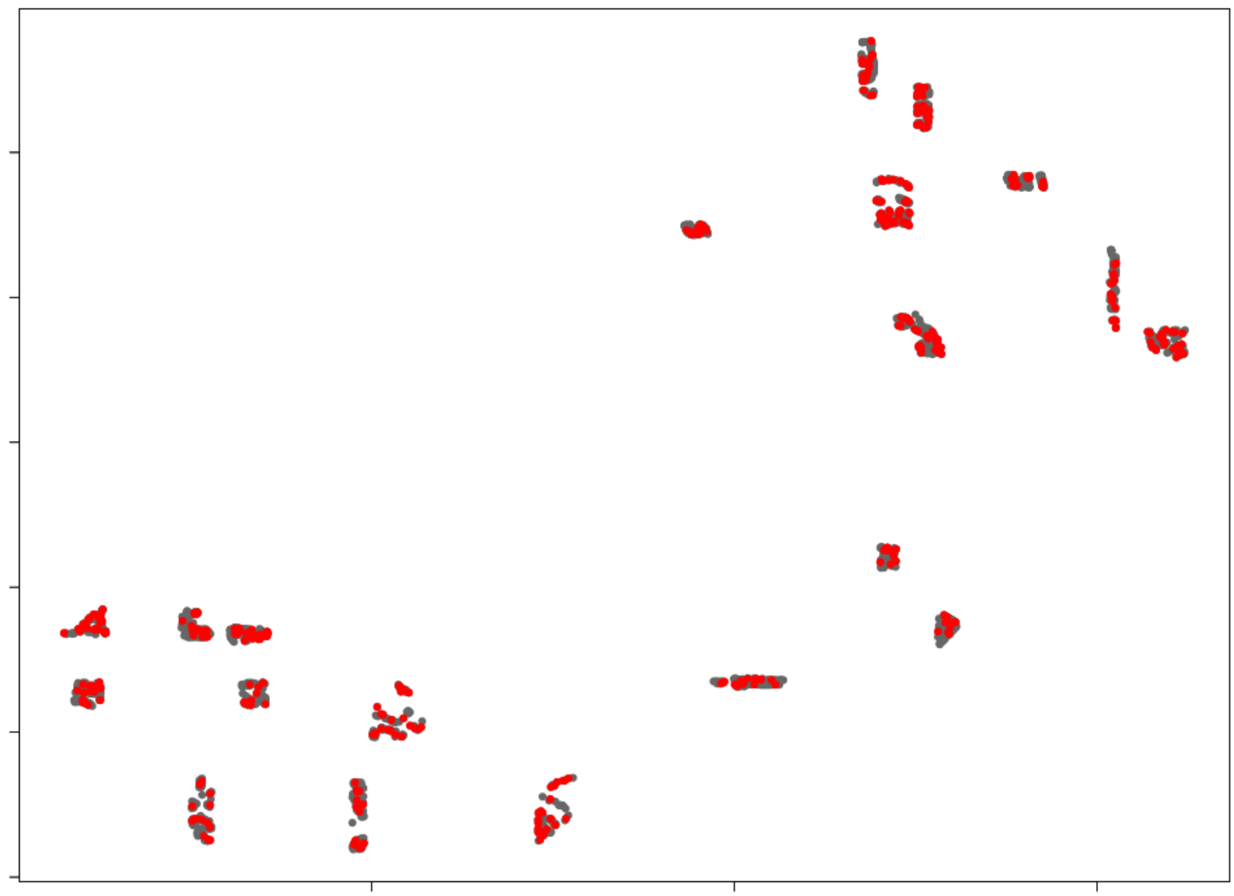


Figure 4.3. 20 communities in suburb San Jose
Note: Red circle represents residential solar PV installed by 2019 and grey circle represents no residential solar PV installed under the house address. The visualization is relatively blurry compared to Figure A.9 as this one zooms out multiple times.

1999), and the average cost is $18,597. 76.5% of the population in the San Diego county is White, Asian accounts for 7.8% in average, and 32.6% is Hispanic or Latino. 23% of the population is under 18 years old, and 15.7% is above 65 years old.

Table 4.2. Summary statistics of public data (CaliforniaDGStats)

Variable	Mean	Std. Dev.	Min	Max
Days	6468	616	5171	7516
Num of single family houses	12579	4513	31	20534
At least one electric vehicle charging	.00698	.08324	0	1
Total system cost ($1,000)	18.597	14.297	4.753	64.718
Sex ratio (males per 100 females)	98.733	5.838	80.7	201.9
% Under 18 years	.230	.031	.071	.336
% 65 years and over	.157	.044	.065	.502
% White	.765	.094	.355	.924
% Black or African American	.034	.030	0	.152
% American Indian and Alaska Native	.009	.025	0	.355
% Asian	.078	.059	0	.294
% Hispanic or Latino	.326	.160	.01	.721

Total number of observations: 78,972. Days: Number of days before adopting solar PV counted from Jan. 1st 1999. Days, electric vehicle and total system cost are in household level obtained from CaliforniaDGStats, and the rest of demographics are in zip-code level obtained from US Census Bureau.

To control the neighborhood characteristics (the "contextual effects" as in Manski 1993) in the optimal stopping time model proposed by de Paula (2009), we merge census block group demographics with the data obtained from PG&E. Table 4.3 shows the summary statistics of final merged PG&E data with demographics. There are 400 households with solar PV installed by 2019 out of 2,020 observations in the 20 communities visualized in Figure 4.3.The average adoption time is mid-year 2014 (3,497 days since Jan 1st 2005). The total usage of electricity and bill are defined as the monthly average usage and bill before adopting solar PV (if applicable). These statistics drop significantly or even become negative after solar PV is installed. The race composition in San Jose is different than San Diego as only 45.7% of population is white. 65.3% of the population has college degree. PG&E offers two utility discount programs for low income families - California Alternate Rates for Energy Program (CARE) and Family Electric Rate Assistance Program (FERA). To apply for CARE or FERA, a household need to meet some low income guideline by household size, and FERA specifically requires three or more people in a household. Enrollment in these two programs indicates relatively low household income per capita. Figure 4.4 shows the diffusion path of solar PV for the final 20 selected communities.

Table 4.3. Summary statistics of PG&E data

Variable	Obs	Mean	Std. Dev.	Min	Max
Days	400	3497	1064	335	5230
Total usage (kwh/1,000)	2,020	.744	.375	.053	4.830
Total billing ($)	2,020	155	113	9	1324
CARE	2,020	.047	.211	0	1
FERA	2,020	.003	.054	0	1
% White	2,020	.457	.198	.054	.854
% College degree or above	2,020	.653	.116	.312	.867
Either CARE or FERA	2,020	.050	.217	0	1
Number of households by community	20	101	5.400	87	109
Number of adoptions by community	20	20	7.334	9	39
Adoption rate by community	20	0.198	0.071	0.085	0.402

Total number of observations: 2,020. Number of solar PV installed: 400. Adoption rate is 19.8 in the 20 communities. Days: Number of days before adopting solar PV counted from Jan. 1st 2005. Days, total usage (kwh/1,000), total bill, CARE and FERA are in household level obtained from PG&E, and the other demographics are in census block group level obtained from US Census Bureau.

4.5 Results

In this section, we first show two preliminary evidence of peer effects using the public data which contains only adopters with zip-code as the most precise description of household location. The first method uses an econometrics model which is motivated by equation (4.4). The second model uses a nonparametric test proposed by de Paula (2009) to test peer effects with discretized time. Then we show the estimation results of the model described in this paper and discuss the implication of our findings.

4.5.1 Preliminary results: econometric model

If there is no peer effect, meaning the solar PV adoption decision of each household is an independent process regardless of peers' behavior, peer group size of each adopter should be

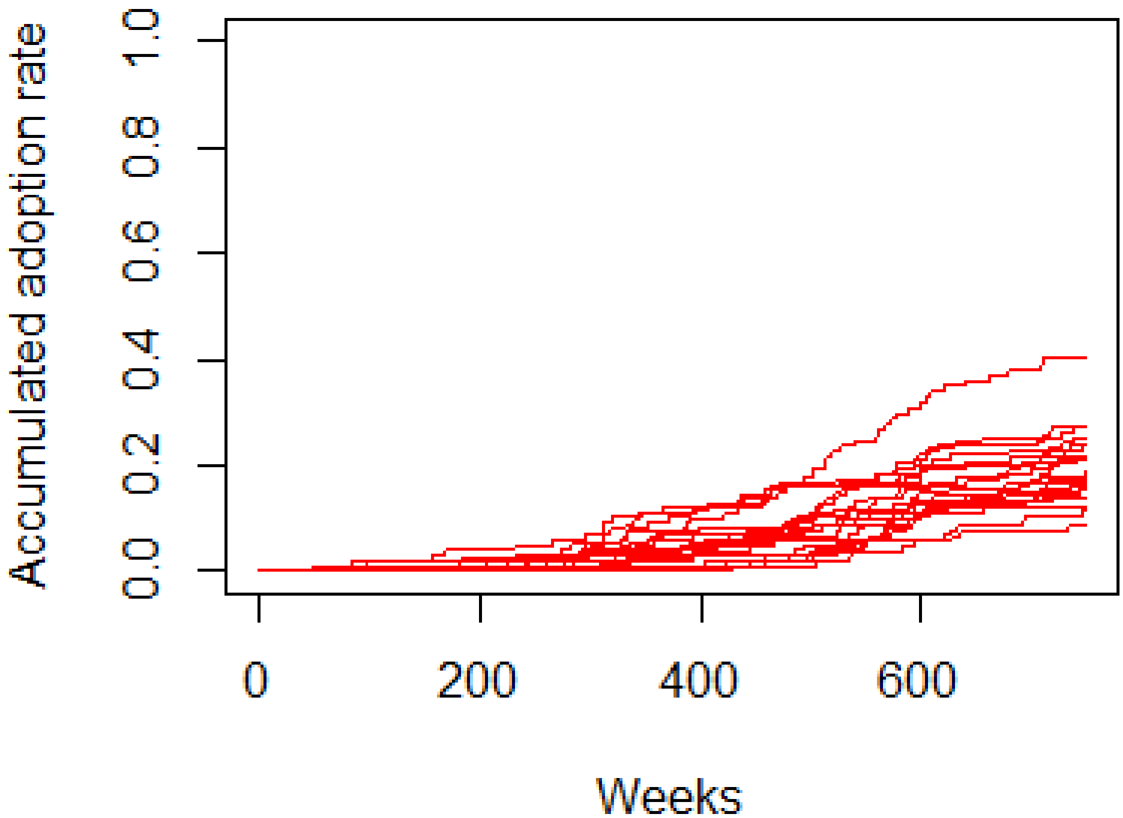


Figure 4.4. Diffusion paths for 20 selected communities in suburb San Jose
Note: Weeks is the number of weeks since Jan 1st 2005.

an irrelevant factor for the adoption time. As described in the model section, peer effects is measured as a proportion of peers who have installed solar PV prior to current non-adopters. This is not a specific feature in the model of de Paula (2009), but also in the installed based method (e.g., Bollinger and Gillingham 2012) and the diffusion models. The larger the peer group size, the smaller influence a single adoption within the peer group generates for household i. Both equation (4.3) and equation (4.4) illustrates the impact channel through I_i, the peer group size of household i. Ceteris paribus, the larger the I_i, the longer household

i will wait to adopt solar PV, as the previous accumulated adoptions generate smaller weight of impact on lowering the reservation value of household i.

Table 4.4 shows the regression results of number of days waited to adopt solar PV on the log form of number of single family houses under each zip-code. We adopt the same peer group definition of a zip-code level as Bollinger and Gillingham (2012) for this preliminary analysis. We find that one percent increase regarding the peer group size postpones the adoption date for each household by 28 - 36 days. This statement is only possible with peer effects present. The result is robust after we add demographics including age and race. And we also find significant peer effects evidence if the data is collapsed in zip-code level as shown in Table A.5.

Besides the evidence of peer effects, we find a interesting substitution pattern between green energy investments. If a household owns an electric vehicle, the date of installing solar PV will be postponed by 156 - 170 days. Both EV and solar PV are considered as large investments in the residential sector to contribute to the environment. And we find consumers will postpone their support in one product if they already own another one.[15] We find that the greater the percentage of young people under eighteen withn a zip-code, more quickly the PV is adopted. We think one possible explanation is that higher proportion of young people indicates a demographic of more children within each household. Therefore a household would be more likely to install solar PV to save electricity spending due to a larger family size. If a household lives in a zip-code which everyone is white, the adoption date will be postponed by 322 days compared to the case that everyone is non-white.[16] And this postpone effect is larger for a complete change in the race proportion of Black or African American, by more than 3 years (1,188 days).

[15]↑If owns an EV, a household may also want the PV so as to use solar to charge the vehicle and generate additional savings. We believe the substitution pattern we find in our research is a net effect accounting for the benefits of having PV sooner to charge the EV and the large investment cost of installing PV.

[16]↑Note that this control is the proportion of white households within each zip-code instead of an individual race being white.

Table 4.4. Household level regressions

Dependent variable: Number of days since Jan. 1st 1999 before adopting solar PV

	(1) w/o demographics	(2) w/ demographics
log(num of single family houses)	35.721***	28.256***
	(2.894)	(3.920)
Total system cost ($1,000)	21.498***	21.648***
	(0.140)	(0.139)
At least one electric vehicle charging	156.041***	169.710***
	(22.889)	(22.974)
Sex ratio (males per 100 females)		-0.501
		(0.391)
% Under 18 years		-504.342***
		(112.424)
% 65 years and over		-78.757
		(91.698)
% White		321.889***
		(87.508)
% Black or African American		1188.420***
		(143.449)
% American Indian and Alaska Native		375.711***
		(136.295)
% Asian		352.799***
		(94.237)
% Hispanic or Latino		273.977***
		(16.560)
Constant	5734.496***	5571.609***
	(27.173)	(110.874)
Observations	78,974	78,972
R^2	0.250	0.256

We exclude the observations with the lowest 1% and highest 1% total system cost.

4.5.2 Preliminary results: nonparametric test

If adoption time is measured continuously, the simultaneous adoption behavior itself will be sufficient evidence of peer effects as explained in the model section. However, our data of solar PV adoption is measured in days. de Paula (2009) proposed a nonparametric test for peer effects under a discretized time scenario. If there is no peer effects, households adopt solar PV independently. The distribution of adoptions in each thinly discretized episode is less likely be clustered in a high frequency. Suppose we double the length of the episode, the number of adoptions in each twice-length episode should be roughly doubled. However, with peer effects present, doubling the episode length will not double the number of simultaneous adoptions, because of the clustering in the original thinly discretized episode.

Mathematically, let Δ represents the length of each episode. And $x_{n,\Delta}$ represent the proportion of simultaneous adoption among community $n \in N$. The expected value of $x_{n,\Delta}$ should be the probability of simultaneous adoption denoted as $E(x_{n,\Delta}) = p(\Delta)$. If there is no peer effects, $x_{n,\Delta=2\text{ days}}$ should be roughly twice of $x_{n,\Delta=1\text{ day}}$. The nonparametric test de Paula (2009) proposes states that:

$$\sqrt{N}\frac{1}{\sigma}\left[\frac{\bar{x}_{\Delta_2}}{\bar{x}_{\Delta_1}} - \frac{\Delta_2}{\Delta_1} - \xi\left(\frac{\bar{x}_{\Delta_3}}{\bar{x}_{\Delta_1}} - \frac{\Delta_3}{\Delta_1}\right)\right] \to N(0,1) \tag{4.12}$$

where

$$\sigma^2 = \begin{bmatrix} \frac{\xi p(\Delta_3)-p(\Delta_2)}{p(\Delta_1)^2} & \frac{1}{p(\Delta_1)} & -\frac{\xi}{p(\Delta_1)} \end{bmatrix} var \begin{bmatrix} x_{n,\Delta_1} \\ x_{n,\Delta_2} \\ x_{n,\Delta_3} \end{bmatrix} \begin{bmatrix} \frac{\xi p(\Delta_3)-p(\Delta_2)}{p(\Delta_1)^2} \\ \frac{1}{p(\Delta_1)} \\ -\frac{\xi}{p(\Delta_1)} \end{bmatrix} \tag{4.13}$$

and

$$\xi = \frac{\Delta_2(\Delta_2-\Delta_1)}{\Delta_3(\Delta_3-\Delta_1)} \tag{4.14}$$

Δ_1, Δ_2 and Δ_3 are three discretized time scenarios. In the public data set, the shorted episode is one day. And we can recount the number simultaneous adoptions if the time is discretized in every Δ_2 days (x_{n,Δ_2}) and every Δ_3 days (x_{n,Δ_3}). $\bar{x}_\Delta = \frac{1}{N}\sum_n x_{n,\Delta}$ is the estimated probability of simultaneous adoption under discretized episode Δ. Table A.6

shows the frequency of simultaneous adoptions under six scenarios of Δ. We can see that as the length of discretized time scenario increases, the number of adopters in each episode shifts further to higher clustering cases. The nonparametric test is whether the number of simultaneous adoption cases increases by the same multiplier as the length of the episode increases.

The null hypothesis of the nonparametric test is there is no peer effects. Table 4.5 shows the test result under six combination of Δ_2 and Δ_3, while keeping Δ_1 as the observed length of time episode – 1 day. When the length of episode doubles, or $\frac{\Delta_2}{\Delta_1} = 2$, the estimated probability of simultaneous adoptions is less than doubled; When the length of episode is tripled, the estimated probability of simultaneous adoptions is far less than tripled. All six combination cases strongly reject the null that there is no peer effects in this process.

Table 4.5. Nonparametric test of simultaneous adoptions

$$\sqrt{N}\frac{1}{\sigma}\left[\frac{\bar{x}_{\Delta_2}}{\bar{x}_{\Delta_1}} - \frac{\Delta_2}{\Delta_1} - \xi\left(\frac{\bar{x}_{\Delta_3}}{\bar{x}_{\Delta_1}} - \frac{\Delta_3}{\Delta_1}\right)\right] \to N(0,1)$$

H_0 : There is no peer effects.

$\frac{\Delta_2}{\Delta_1}$	$\frac{\Delta_3}{\Delta_1}$	$\bar{x}_{\Delta_1}$	$\bar{x}_{\Delta_2}$	$\bar{x}_{\Delta_3}$	t-statistic
2	3	0.0010210	0.0014452	0.0018162	-9.996
2	5	0.0010210	0.0014452	0.0024427	-9.916
2	10	0.0010210	0.0014452	0.0043316	-13.367
3	4	0.0010210	0.0018162	0.0021253	-17.878
3	5	0.0010210	0.0018162	0.0024427	-16.471
3	10	0.0010210	0.0018162	0.0043316	-21.149

Number of observations: 91,042. Data source: CaliforniaDGStats. Data coverage: San Diego county. Adoption time range: Jan 20th 1999 - July 31st 2019 (7,497 days). $\Delta_1 = 1$ day. Number of zip-code (N): 56.

4.5.3 Results: dynamic optimal stopping time model

Tabel 4.6 shows the estimates of proposed optimal stopping time model. We find significant peer effects and correlated effects. The interpretation of coefficients α should be in an opposite direction compared to Logit or Probit model, as a lower drift leads to sooner adoption. We find that households with higher monthly utility usage will adopt earlier. If a household is registered for utility discount programs, indicating low income per capita, the expected adoption time will be postponed. Different than the findings using San Diego public data, we do not find significant evidence that living with a higher race proportion of the white will postpone the adoption date. But living with highly educated peers tends to accelerate the solar PV adoption. Figure 4.5 shows the observed and simulated adoption path based on 1000 simulations using the coefficients estimated.

Table 4.6. Estimation results of the optimal stopping time model

	Coefficients	S.E.
Drift (α)		
Constant	0.0532	(0.1562)
Total usage (kwh/1,000)	-0.0073	(0.0001)
Either CARE or FERA	0.0057	(0.0002)
% White	0.0040	(0.0119)
% College degree or above	-0.0059	(0.0000)
Volatility (σ)	0.1310	(0.0000)
Correlated effects (ρ)	0.0937	(0.0023)
Peer effects ($\Delta\alpha$)	0.0036	(0.0003)
Starting point (x_0)	3.5408	(0.0390)

Number of observations: 2,020. Data source: PG&E based on 20 selected communities.

One advantage of the model is that it can predict a future adoption equilibrium by focusing on the percentage of household whose predicted adoption time approaches infinity. Mathematically, these household will have a drift higher than the discount rate γ (set as 0.05 in this paper). Our data contains 2,020 households, and 400 of them have adopted solar PV by 2019. Based on our prediction, 136 households will never adopt solar PV ($\alpha(\omega_i) > \gamma$) if there is no peer effects. But this number will be reduced to 123 if we take account of peer effects ($\Delta\alpha = 0.0036$) and recount those whose drift post deduction of peer effects is still higher than γ. This statistic is based on the current adoption behavior that 19.8% of peers have adopted solar PV. When the adoption rate reaches 50% among the peer group, the number of households whose predicted adoption time approaches infinity will drop to 71. In other words, 13 out of 136 non-adopters has considered adopting solar PV because of peer effects by 2019 when the adoption rate is 19.8%. In the future, when 50% of households have

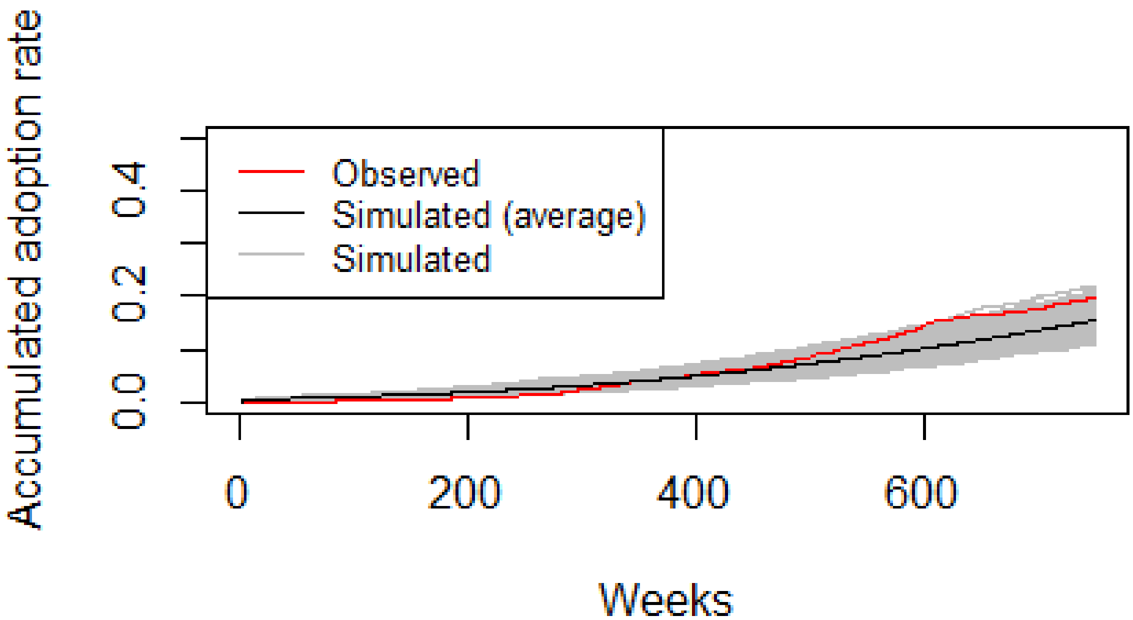


Figure 4.5. Observed adoption path and simulated paths
Note: Grey lines are based on 1,000 simulations with the estimates. Weeks are counted since Jan 1st, 2005.

solar PV in the selected area, there will be 52 more households consider purchasing solar PV because of peer effects from 2019 to the time 50% adoption rate is reached.

Figure 4.6 shows the effect of peer effects in triggering solar PV adoption. The area below the density function of drift $\alpha(\omega_i)$ and to the right of the threshold ($\gamma = 0.05$) is the percentage of naysayers to solar PV. The current prediction based on the blue density function shows there are 123 households out of 2,020 who will never adopt solar PV. But this statistic will reduce when there are more peers who have adopted solar PV. In fact, we not only can predict the percentage of naysayers, but we know who they are. It would be useful to know the characteristics of naysayers because that could help the local government to formulate effective policies to enhance the adoption of solar PV.

To be fair, "considering" purchasing solar PV only indicates the predicted adoption time for a household is finite, but it could be decades. Compared to predicting a long-term equilibrium, a more interesting question is what the equilibrium will be in the next decade based on current demographics information. Figure 4.7 shows the simulated adoption trend. In average, the adoption rate after ten years (2029) is estimated as 39.65% among the 20 communities, with a 95% confidence interval of 33.59% to 46.21%.

4.6 Conclusion

This paper applies a utility-based structural optimal stopping time model developed by de Paula (2009) to analyze solar PV adoption. This method specifically allows for an estimation of peer effects, which has been discussed broadly in previous literature. One advantage of this structural model compared to previous reduced-form models is that it allows us to predict future adoption equilibrium. In a marketing perspective, this model can be used to predict the future adoption time for each household based on observed household characteristic and the demographics of the community. Another advantage of this model is that it separates peer effects with unobserved correlated effects, which has been the major obstacle in the peer effects literature.

We use both an econometric model and nonparametric test to support the evidence of peer effects, using public solar PV data obtained from CaliforniaDGStats. And we apply

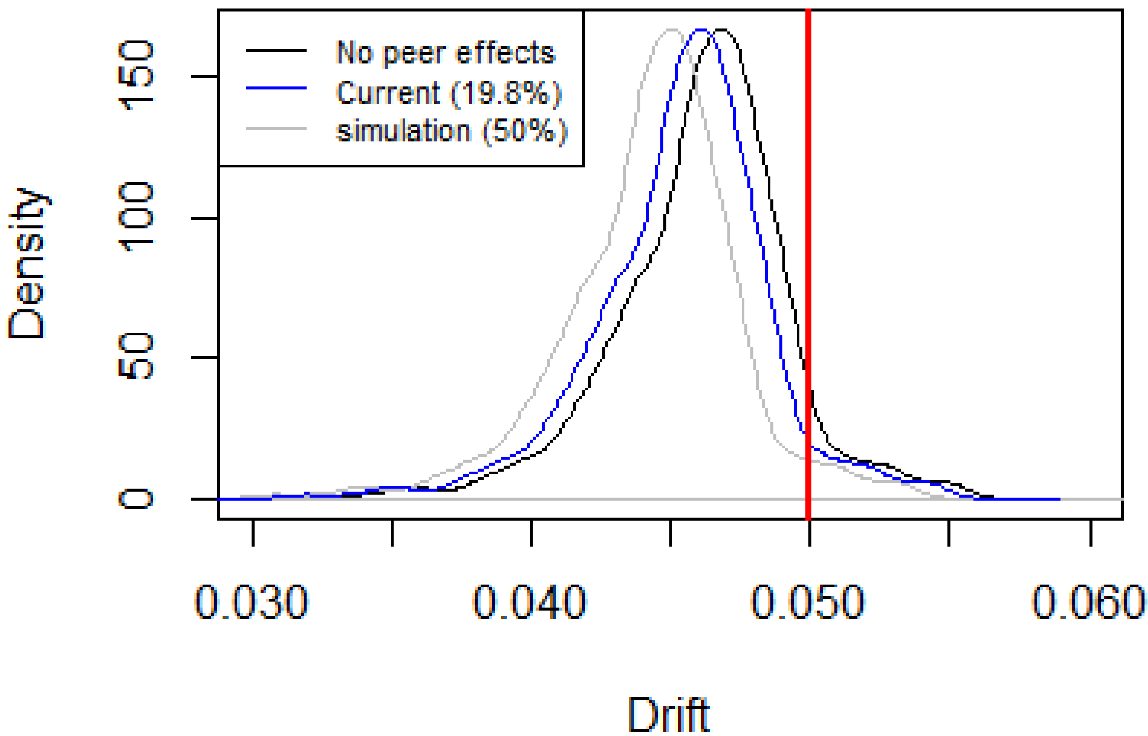


Figure 4.6. Observed adoption trend and simulated trend

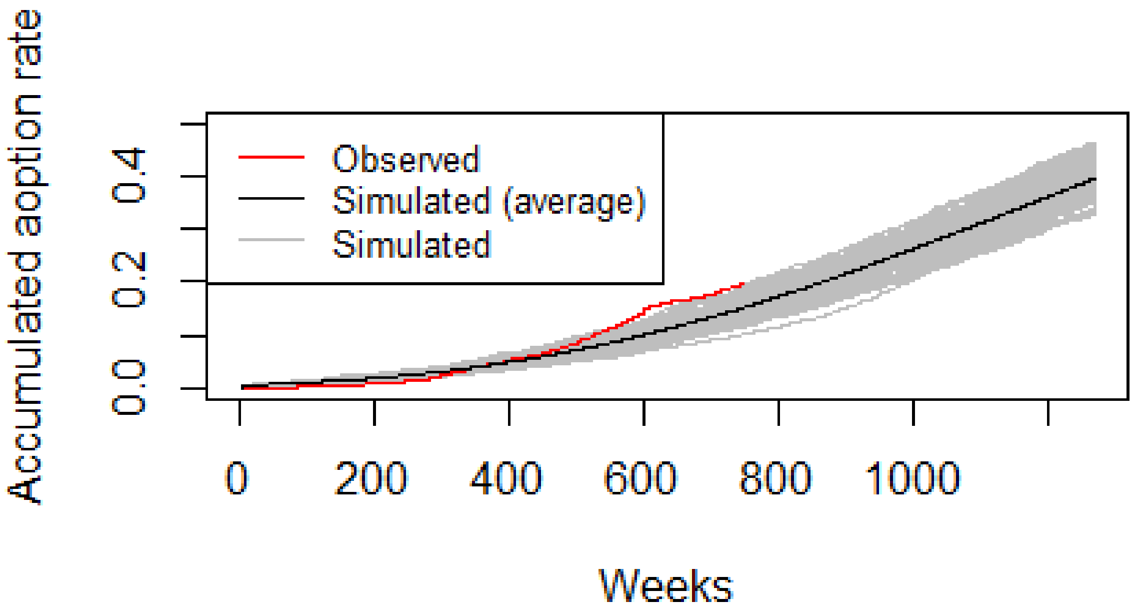


Figure 4.7. Observed adoption trend and simulated future adoption trend
Note: Grey lines are based on 100 simulations with the estimates. Weeks are counted since Jan 1st, 2005.

the optimal stopping time model with a confidential data set obtained from PG&E. We find significant peer effects and correlated effects in a case study which contains 20 non-adjacent communities in the suburb of San Jose. And we predicted the adoption rate in this area will increase from 19.77% in 2019 to 39.65% in 2029.

Peer effects in solar PV adoption indicates that early adopters generate influences on future potential adopters. If there is tax rebates available for early adopters which motivate more households to adopt solar PV, peer effects sourced from these early adopters could generate a larger impact for future adopters and shorten their waiting time. Currently all new houses in California are required to have solar PV. This policy, which theoretically increases the proportion of households with solar PV around a neighborhood when there are new house constructions, would impose a stronger peer effects for the remaining non-adopters.

REFERENCES

[1] C. F. Manski, "Identification of endogenous social effects: The reflection problem," *Review of Economic Studies*, vol. 60, pp. 531–542, 1993.

[2] A. de Paula, "Inference in a synchronization game with social iteractions," *Journal of Econometrics*, vol. 148, pp. 56–71, 2009.

[3] B. Bollinger and K. Gillingham, "Peer effects in the diffusion of solar photovoltaic panels," *Marketing Science*, vol. 31, no. 6, pp. 900–912, 2012.

[4] L. F. Lee *et al.*, "Binary choice model with social network under heterogeneous rational expectations," *The Review of Economics and Statistics*, vol. 96, no. 3, pp. 402–417, 2014.

[5] W. A. Brock and S. N. Durlauf, "Discrete choice with social interactions," *Review of Economic Studies*, vol. 68, pp. 235–260, 2001.

[6] L. Lee, "Identification and estimation of econometric models with group interactions, contextual factors and fixed effects," *Journal of Econometrics*, vol. 140, pp. 333–374, 2007.

[7] S. Berry *et al.*, "Automobile prices in market equilibrium," *Econometrica*, vol. 63, no. 4, pp. 841–890, 1995.

[8] E. J. Miravete *et al.*, "Fuel taxation, emissions policy, and competitive advantage in the diffusion of european diesel automobiles," *RAND Journal of Economics*, vol. 49, no. 3, pp. 504–540, 2018.

[9] J. Rode and A. Weber, "Does localized imitation drive technology adoption? A case study on rooftop PV system in Germany," *Journal of Environmental Economics and Management*, vol. 78, pp. 38–48, 2016.

[10] D. C. Ling, "Do the Chinese "keep up with the Jones"?: Implications of peer effects, growing economic disparities and relative deprivation on health outcomes among older adults in China," *China Economic Review*, vol. 20, pp. 65–81, 2009.

[11] N. Qian, "Missing woman and the price of tea in China: The effect of sex-specific earning on sex imbalance," *The Quarterly Journal of Economics*, vol. 123, no. 3, pp. 1251–1285, 2008.

[12] S. Wei and X. Zhang, "The competitive saving motive: Evidence from rising sex ratios and savings rates in China," *Journal of Political Economy*, vol. 119, no. 3, pp. 511–564, 2011.

[13] J. Angrist, "How do sex ratios affect marriage and labor markets? Evidence from America's second generation," *The Quarterly Journal of Economics*, vol. 117, no. 3, pp. 997–1038, 2002.

[14] K. Hardee *et al.*, "Family planning and women's lives in rural China," *International Family Planning Perspectives*, vol. 30, no. 2, pp. 68–76, 2003.

[15] C. L. W. Chan *et al.*, "Gender selection in China: Its meanings and implications," *Journal of Assisted Reproduction and Genetics*, vol. 19, no. 9, pp. 426–430, 2002.

[16] S. Greenhalgh and J. Bongaarts, "Fertility policy in China: Future options," *Science*, vol. 235, no. 4793, pp. 1167–1172, 1987.

[17] Y. Shi and J. J. Kennedy, "Delayed registration and identifying the "missing girls" in China," *The China Quarterly*, vol. 228, pp. 1018–1038, 2016.

[18] Y. Zeng and T. Hesketh, "The effects of China's universal two-child policy," *The Lancet*, vol. 388, no. 10054, pp. 1930–1938, 2016.

[19] D. Goodkind, "The astonishing population averted by China's birth restrictions: Estimates, nightmares, and reprogrammed ambitions," *Demography*, vol. 54, pp. 1375–1400, 2017.

[20] S. Bhalotra and T. Cochrane, "Where have all the young girls gone? Identification of sex selection in India," 2010, Discussion paper series // Forschungsinstitut zur Zukunft der Arbeit, No. 5381, Institute for the Study of Labor (IZA), Bonn.

[21] Y. O. F. MPH *et al.*, "The gender ratio imbalance and its relationship to risk of hiv/aids among African American women at historically black colleges and universities," *AIDS Care*, vol. 18, no. 4, pp. 323–331, 2006.

[22] M. Guo, "Parental status and late-life well-being in rural China: The benefits of having multiple children," *Aging and Mental Health*, vol. 18, no. 1, pp. 19–29, 2014.

[23] L. Meng, "Rebellion and revenge: The meaning of suicide of women in rural China," *International Journal of Social Welfare*, vol. 11, pp. 300–309, 2002.

[24] Y. Chen *et al.*, "Prenatal sex selection and missing girls in China: Evidence from the diffusion of diagnostic ultrasound," *Journal of Human Resources*, vol. 48, no. 1, pp. 36–70, 2013.

[25] D. Almond *et al.*, "Land reform and sex selection in China," *Journal of Political Economy*, vol. 127, no. 2, pp. 560–585, 2019.

[26] O. Bedford and K.-K. Hwang, "Guilt and shame in Chinese culture: A cross-cultural framework from the perspective of morality and identity," *Journal for the Theory of Social Behaviour*, vol. 33, no. 2, pp. 127–144, 2003.

[27] D. Goodkind, "Child underreporting, fertility, and sex ratio imbalance in China," *Demography*, vol. 48, no. 1, pp. 291–316, 2011.

[28] Q. J. Ding and T. Hesketh, "Family size, fertility preferences, and sex ratio in China in the era of the one child family policy: Results from national family planning and reproductive health," *British Medical Journal*, vol. 333, no. 7564, pp. 371–373, 2006.

[29] S. M. George, "Millions of missing girls: From fetal sexing to high technology sex selection in India," *Prenatal Diagnosis*, vol. 26, pp. 604–609, 2006.

[30] W. X. Zhu *et al.*, "China's excess males, sex selective abortion, and one child policy: Analysis of data from 2005 national intercensus survey," *British Medical Journal*, vol. 338:b, no. 1211, 2009.

[31] M. D. Gupta, "Selective discrimination against female children in rural Punjab, India," *Population and Development Review*, vol. 13, no. 1, pp. 77–100, 1987.

[32] P. Griffiths *et al.*, "Understanding the sex ratio in India: A simulation approach*," *Demography*, vol. 37, no. 4, pp. 477–488, 2000.

[33] S. Dubuc and D. Coleman, "An increase in the sex ratio of births to India-born mothers in England and Wales: Evidence for sex-selective abortion," *Population and Development Review*, vol. 33, no. 2, pp. 383–400, 2007.

[34] C. B. Park and N.-H. Cho, "Consequences of son preference in a low-fertility society: Imbalance of the sex ratio at birth in Korea," *Population and Development Review*, vol. 21, no. 1, pp. 59–84, 2009.

[35] J. Zhang, "Socioeconomic determinants of fertility in China: A microeconometric analysis," *Journal of Population Economics*, vol. 3, no. 2, pp. 105–23, 1990.

[36] A. Ebenstein, "The "missing girls" of China and the unintended consequences of the one child policy," *Journal of Human Resources*, vol. 45, no. 1, pp. 87–115, 2010.

[37] J. Abrevaya, "Are there missing girls in the United States? Evidence from birth data," *American Economic Journal: Applied Economics*, vol. 1, no. 2, pp. 1–34, 2009.

[38] A. Ebenstein, "Estimating a dynamic model of sex selection in China," *Demography*, vol. 48, no. 2, p. 783, 2011.

[39] J. Zhang and B. G. Spencer, "Who signs China's one-child certificate, and why?" *Journal of Population Economics*, vol. 5, no. 3, pp. 203–215, 1992.

[40] M. McElroy and D. T. Yang, "Carrots and sticks: Fertility effects of China's population policies," *American Economic Review*, vol. 90, no. 2, pp. 389–92, 2000.

[41] L. Li and X. Wu, "Gender of children, bargaining power, and intrahousehold resource allocation in China," *The Journal of Human Resources*, vol. 46, no. 2, pp. 295–316, 2011.

[42] A. Banerjee *et al.*, "The diffusion of microfinance," *Science*, vol. 341, no. 6144, 2013.

[43] L. Bursztyn *et al.*, "Understanding mechanisms underlying peer effects: Evidence from a field experiment on financial decisions," *Econometrica*, vol. 82, no. 4, pp. 1273–1301, 2014.

[44] D. J. Zimmerman, "Peer effects in academic outcomes: Evidence from a natural experiment," *The Review of Economics and Statistics*, vol. 85, no. 1, pp. 9–23, 2003.

[45] Y. Bramoullé *et al.*, "Identification of peer effects through social networks," *Journal of Econometrics*, vol. 150, pp. 41–55, 2009.

[46] S. E. Carrell *et al.*, "Does your cohort matter? Measuring peer effects in college achievement," *Journal of Labor Economics*, vol. 27, no. 3, pp. 439–464, 2009.

[47] M. R. Rosenzweig and J. Zhang, "Do population control policies induce more human capital investment? twins, birth weight and China's "one-child" policy," *Review of Economic Studies*, vol. 76, pp. 1149–1174, 2009.

[48] W. Huang *et al.*, "One-child policy and the rise of man-made twins," *Review of Economics and Statistics*, vol. 98, no. 3, pp. 467–476, 2016.

[49] W. A. Brock and S. N. Durlauf, "Interactions-based models," in *Handbook of Econometrics*, New York: North Holland, 2001, ch. 54, pp. 3463–568.

[50] Y. Li, "Hebei province: Rural single child born after 2016 will no longer be qualified for bonus points in the college entrance examination (in Chinese)," *Xinhua Net*, 2020. [Online]. Available:
.

[51] L. Li and X. Wu, "Gender of children, bargaining power, and intrahousehold resource allocation in China," *The Journal of Human Resources*, vol. 33, pp. 41–52, 2012.

[52] L. Zheng, "Sibling sex composition, intrahousehold resource allocation, and educational attainment in China," *The Journal of Chinese Sociology*, vol. 2, no. 2, 2015.

[53] P. K. Goldberg, "Effects of the corporateaverage fuel efficiency standards in the u.s.," *Journal of Industrial Economics*, vol. 46, pp. 1–33, 1998.

[54] A. Chandra *et al.*, "Green drivers or free riders: An analysis of tax rebates for hybrid vehicles," *Journal of Environmental Economics and Management*, vol. 60, pp. 78–93, 2010.

[55] J. Xing *et al.*, "What does an electric vehicle replace?" *Journal of Environmental Economics and Management*, vol. 107, 2021.

[56] J. DeShazo *et al.*, "Designing policy incentives for cleaner technologies: Lessons from california's plug-in electric vehicle rebate program," *Journal of Environmental Economics and Management*, vol. 84, pp. 18–43, 2017.

[57] C.-S. N. Shiau *et al.*, "A structural analysis of vehicle design responses to corporate average fuel economy policy," *Transportation Research Part A*, vol. 43, pp. 814–828, 2009.

[58] K. Ito and J. M. Sallee, "The economics of attribute-based regulation: Theory and evidence from fuel-economy standards," *The Review of Economics and Statistics*, vol. 100, pp. 319–336, 2018.

[59] M. R. Jacobsen, "Evaluating u.s. fuel economy standards in a model with producer and household heterogeneity," *American Economic Journal: Economic Policy*, vol. 5, pp. 1–26, 2013.

[60] B. M.Al-Alawi and T. H. Bradley, "Review of hybrid, plug-in hybrid,and electric vehicle market modeling studies," *Renewable and Sustainable Energy Reviews*, vol. 21, pp. 190–203, 2013.

[61] B. Sen *et al.*, "Will corporate average fuel economy (cafe) standard help? modeling cafe's impact on market share of electric vehicles," *Energy Policy*, vol. 109, pp. 279–287, 2017.

[62] A. Petrin, "Quantifying the benefits of new products: The case of the minivan," *Journal of Political Economy*, vol. 110, no. 4, pp. 705–729, 2002.

[63] B. A. Blonigen *et al.*, "Keeping it fresh: Strategic product redesigns and welfare," *International Journal of Industrial Organization*, vol. 53, pp. 170–214, 2017.

[64] A. Nevo, "Measuring market power in the ready-to-eat cereal industry," *Econometrica*, vol. 69, no. 2, pp. 307–342, 2001.

[65] R. S. Lee, "Vertical integration and exclusivity in platform and two-sided markets," *American Economic Review*, vol. 103, no. 7, pp. 2960–3000, 2013.

[66] P. Bayer *et al.*, "A unified framework for measuring preferences for schools and neighborhoods," *Journal of Political Economy*, vol. 115, no. 4, pp. 588–638, 2007.

[67] P. Bajari *et al.*, "Estimating dynamic models of imperfect competition," *Econometrica*, vol. 75, no. 5, pp. 1331–1370, 2007.

[68] M. Grennan, "Price discrimination and bargaining: Empirical evidence from medical devices," *American Economic Review*, vol. 103, no. 1, pp. 145–177, 2013.

[69] A. Sweeting, "Dynamic product positioning in differentiated product markets: The effect of fees for musical performance rights on the commercial radio industry," *Econometrica*, vol. 81, no. 5, pp. 1763–1803, 2013.

[70] T. F. Bresnahan *et al.*, "Market segmentation and the sources of rents from innovation: Personal computers in the late 1980s," *RAND Journal of Economics*, vol. 28, pp. 17–44, 1997.

[71] J. Jung and W. E. Tyner, "Economic and policy analysis for solar PV systems in Indiana," *Energy Policy*, vol. 74, pp. 123–133, 2014.

[72] B. Bollinger and K. Gillingham, "Learning-by-doing in solar photovoltaic installations," *Unpublished manuscript*, 2019.

[73] L. Mundaca and M. Samahita, "What drives home solar pv uptake? subsidies, peer effects and visibility in sweden," *Energy Research & Social Science*, vol. 60, 2020.

[74] R. Lobel and G. Perakis, "Consumer choice model for forecasting demand and designing incentives for solar technology," *Working paper*, 2011, University of Pennsylvania, Philadelphia.

[75] K. K. Chen, "Assessing the effects of customer innovativeness, environmental value and ecological lifestyles on residential solar power systems install intention," *Energy Policy*, vol. 67, pp. 951–961, 2014.

[76] J. R. Parkins *et al.*, "Predicting intention to adopt solar technology in Canada: The role of knowledge, public engagement, and visibility," *Energy Policy*, vol. 114, pp. 114–122, 2018.

[77] M. S. Delgado, J. L. Harriger, and N. Khanna, “The value of environmental status signaling,” *Ecological Economics*, vol. 111, pp. 1–11, 2015.

[78] V. Bala and S. Goyal, “Learning from neighbours,” *Review of Economic Studies*, vol. 65, no. 3, pp. 595–621, 1998.

[79] S. Im *et al.*, “Does innate consumer innovativeness relate to new product/service adoption behavior? The intervening role of social learning via vicarious innovativeness,” *Journal of the Academy of Marketing Science*, vol. 35, pp. 63–75, 2007.

[80] L.-L. Richter, “Social effects in the diffusion of solar photovoltaic technology in the UK,” 2013, Cambridge Working Paper in Economics 1357.

[81] S. Board and M. Meyer-ter-Vehn, “Learning dynamics in social networks,” *working paper*, 2018.

[82] E. Moretti, “Social learning and peer effects in consumption: Evidence from movie sales,” *Review of Economic Studies*, vol. 78, pp. 356–393, 2011.

[83] N. Balta-Ozkan *et al.*, “Regional distribution of photovoltaic deployment in the UK and its determinants: A spatial econometric approach,” *Energy Economics*, vol. 51, pp. 417–429, 2015.

[84] A. Baranzini *et al.*, “What drives social contagion in the adoption of solar phptovoltaic technology?,” 2017, Grantham Research Institute of Climate Change and Environment, Centre for Climate Change Economics and Policy Working Paper No. 308.

[85] M. Graziano and K. Gillingham, “Spatial patterns of solar photovoltaic system adoption: The influence of neighbors and the built environment,” *Journal of Economic Geography*, vol. 15, pp. 815–839, 2015.

[86] M. O. Jackson and L. Yarivy, “Chapter 14 - Diffusion, Strategic Interaction, and Social Structure,” *Handbook of Social Economics*, vol. 1, pp. 645–678, 2011.

[87] M. Guidolin and C. Mortarino, “Cross-country diffusion of photovoltaic systems: Modelling choices and forecasts for national adoption patterns,” *Technological Forecasting and Social Change*, vol. 77, pp. 279–296, 2010.

[88] K. U. Rao and V. Kishore, “A review of technology diffusion mdels with social reference to rnewable energy technologies,” *Renewable and Sustainable Energy Reviews*, vol. 14, pp. 1070–1078, 2010.

[89] A. K. Dixit and R. S. Pindyck, *Investment Under Uncertainty*. Princeton, New Jersey: Princeton University Press, 1994.

A. APPENDICES

A.1 Chapter 1 Appendices

A.1.1 Density graphs of age gaps between two children

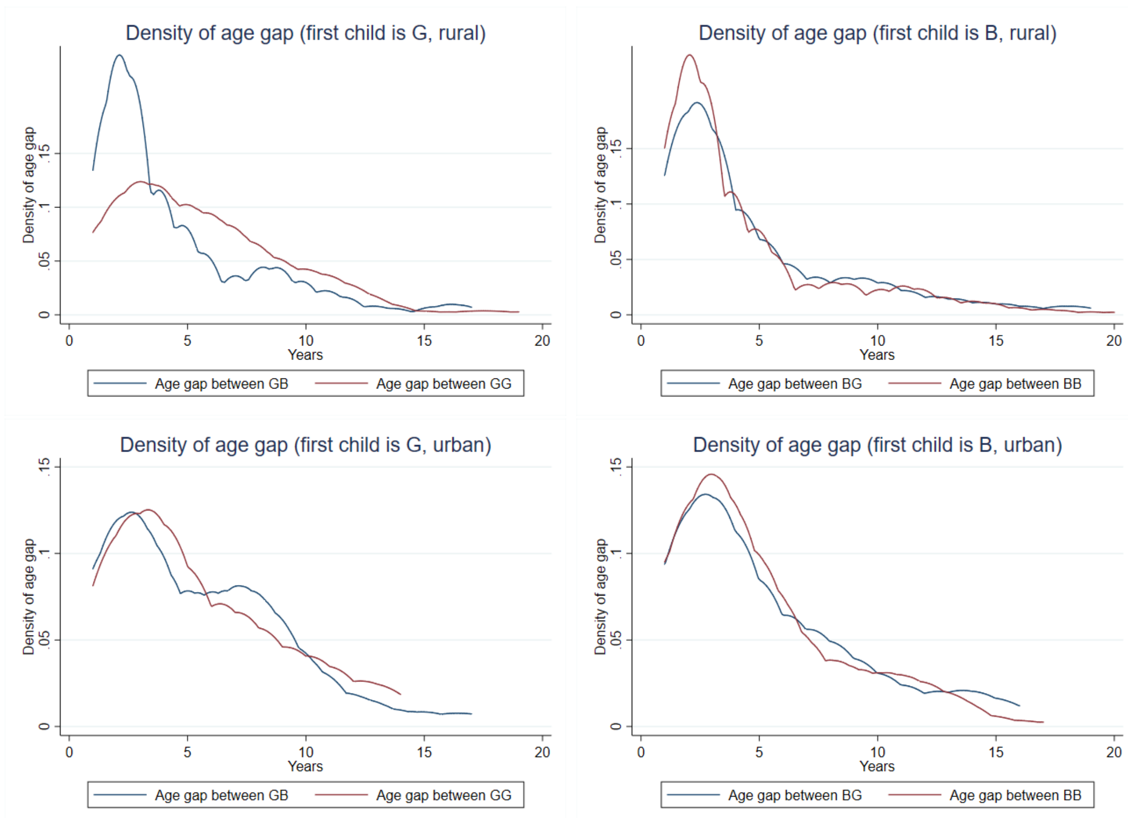


Figure A.1. Density of age gaps between two children (if applicable) in sample I by sex composition and area type

Source. China Family Panel Studies (year 2016). The average age gaps between two children by sex composition and area type are shown in Figure 2.6.

A.1.2 Correlation coefficients tables

Table A.1. Correlation coefficients across own and contextual variables in Sample I

	EDUP	INCOMEP	1 GIRLP	AGE MOP	INLAWP
MO EDU	0.346	0.159	0.127	0.009	-0.052
FA EDU	0.247	0.111	0.072	0.009	-0.076
INCOME	0.145	0.362	0.062	-0.02	0.066
FARMING	-0.3	-0.32	-0.084	0	0.01
RURAL	-0.249	-0.233	-0.061	0.014	0.03
1 GIRL	0.086	0.053	0.064	0.016	0.026
AG HUKOU	-0.331	-0.248	-0.062	-0.045	0.006
1.5 POLICY	-0.09	-0.099	-0.041	-0.046	-0.13
AGE MO	0.118	0.056	-0.009	0.051	-0.019
FA INLAW	-0.045	0.03	-0.004	-0.012	0.087
MO INLAW	-0.031	0.044	0.02	0.017	0.052

Horizontal variables are contextual characteristics. Vertical variables are own characteristics. MO EDU is mother's education years, FA EDU is father's education years, INCOME is annual family income in unit of 50,000 *yuan*, FARMING is whether engaged in agricultural production, RURAL is rural indicator, 1 GIRL is first child is a girl, AG HUKOU is either of parent has agricultural *hukou*, 1.5 POLICY is qualified for 1.5 child policy, AGE MO is mother's age at first birth, FA INLAW is living with father-in-law of the mother, MO INLAW is living with mother-in-law of the mother; EDUP is education years of peers, INCOMEP is annual income of peers in unit of 50,000 *yuan*, 1 GIRLP is % of peers with firstborn daughters, AGE MOP is mother's age at first birth among all peers, INLAWP is % of peers living with either in-law of the mother.

Table A.2. Correlation coefficients of own characteristics variables in Sample I

	MO EDU	FA EDU	INCOME	FARMING	RURAL	1 GIRL	AG HUKOU	1.5 POLICY	AGE MO	FA INLAW	MO INLAW
MO EDU	1	0.445	0.254	-0.382	-0.374	0.039	-0.458	-0.142	0.178	0.009	0.004
FA EDU	0.445	1	0.209	-0.312	-0.265	0.051	-0.388	-0.096	0.127	0.013	0.014
INCOME	0.254	0.209	1	-0.278	-0.234	-0.021	-0.218	-0.128	-0.011	0.037	0.065
FARMING	-0.382	-0.312	-0.278	1	0.51	-0.039	0.569	0.195	-0.166	0.051	0.019
RURAL	-0.374	-0.265	-0.234	0.51	1	-0.041	0.482	0.17	-0.126	0.028	-0.003
1 GIRL	0.039	0.051	-0.021	-0.039	-0.041	1	-0.045	0.593	0.043	-0.009	0
AG HUKOU	-0.458	-0.388	-0.218	0.569	0.482	-0.045	1	0.302	-0.167	0.016	-0.024
1.5 POLICY	-0.142	-0.096	-0.128	0.195	0.17	0.593	0.302	1	-0.048	-0.016	-0.027
AGE MO	0.178	0.127	-0.011	-0.166	-0.126	0.043	-0.167	-0.048	1	0.059	0.067
FA INLAW	0.009	0.013	0.037	0.051	0.028	-0.009	0.016	-0.016	0.059	1	0.425
MO INLAW	0.004	0.014	0.065	0.019	-0.003	0	-0.024	-0.027	0.067	0.425	1

Both horizontal variables and vertical variables are own characteristics. MO EDU is mother's education years, FA EDU is father's education years, INCOME is annual family income in unit of 50,000 *yuan*, FARMING is whether engaged in agricultural production, RURAL is rural indicator, 1 GIRL is first child is a girl, AG HUKOU is either of parent has agricultural *hukou*, 1.5 POLICY is qualified for 1.5 child policy, AGE MO is mother's age at first birth, FA INLAW is living with father-in-law of the mother, MO INLAW is living with mother-in-law of the mother.

A.1.3 No living with parent-in-law of the mother

We find peer effects estimates are robust after we drop the controls related to living with a parent-in-law of the mother, which includes living with the mother-in-law of the mother, living with the father-in-law of the mother within individual controls, and the percentage of peers living with either of the parent-in-law of the mother within the contextual controls (see Table A.3). We think living with a parent-in-law generates intrahousehold pressure on family planning, such as having more children and having a son. However, we find these controls are insignificant after we control for other individual and contextual demographics. Table A.3 shows that dropping these three statistically insignificant controls still leads to robust estimates of peer effects for both research questions.

Table A.3. Drop controls of living with parent-in-law of the mother

	2nd child	Son
	(1)	(2)
Peer effects	0.402***	-0.072
	(0.138)	(0.289)
Individual controls		
Mother's education years	-0.031***	-0.017**
	(0.009)	(0.007)
Father's education years	0.020**	0.012*
	(0.008)	(0.007)
Annual family income in unit of 50,000 *yuan*	0.065**	0.081***
	(0.028)	(0.023)
Whether engaged in ag production	0.122	0.065
	(0.079)	(0.069)
Rural indicator	0.383***	0.110*
	(0.072)	(0.065)
First child is a girl	0.339***	
	(0.084)	
Either of parent has ag *hukou*	0.368***	0.281***
	(0.090)	(0.084)
Qualified for 1.5 child policy	0.604***	
	(0.124)	
Mother's age at first birth	-0.078***	-0.027***
	(0.009)	(0.007)
Contextual controls		
Education years of peers	-0.084***	-0.120***
	(0.028)	(0.037)
Annual income of peers in unit of 50,000 *yuan*	-0.005	-0.036
	(0.070)	(0.068)
% of peers with firstborn daughter	-0.326*	
	(0.195)	
Mother's age at first birth among all peers	0.056***	0.055***
	(0.011)	(0.017)
Constant	0.547*	0.452
	(0.302)	(0.298)
Province FE	Y	Y
Number of obs.	1,901	2,811
log-likelihood	-833	-1,264

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Contextual controls are leave-i-out mean of peers' characteristics for each individual.

A.2 Chapter 2 Appendices

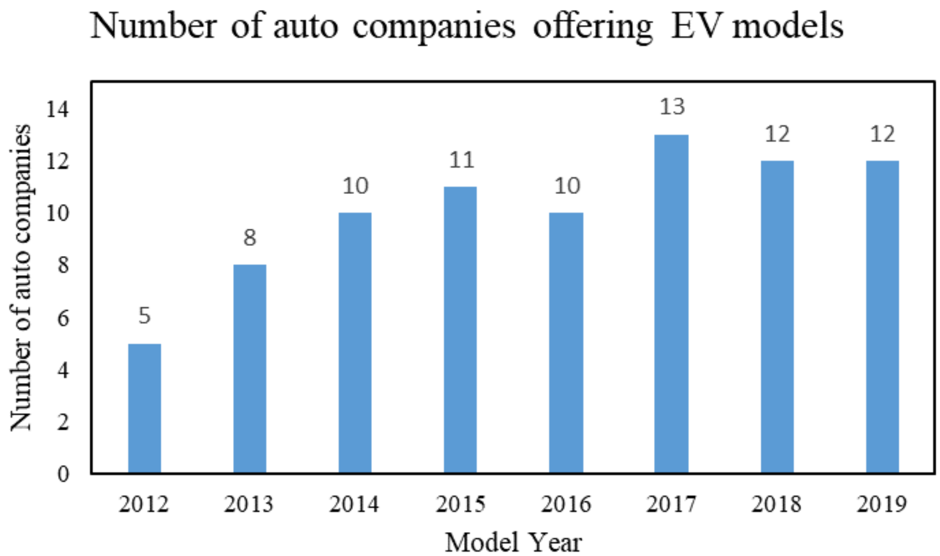


Figure A.2. Number of auto companies offering EV models by model year (2012 - 2019)

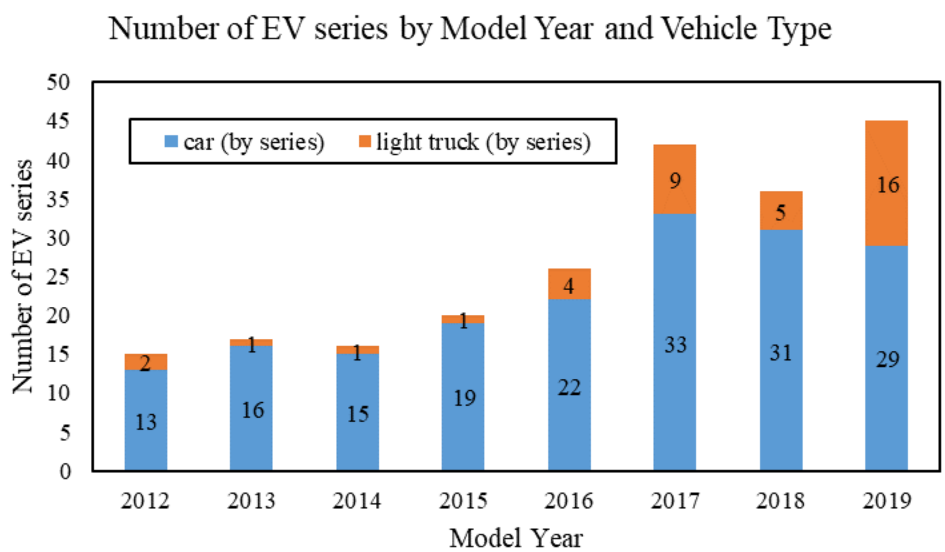


Figure A.3. Number of EV series by model year and vehicle type (2012 - 2019)

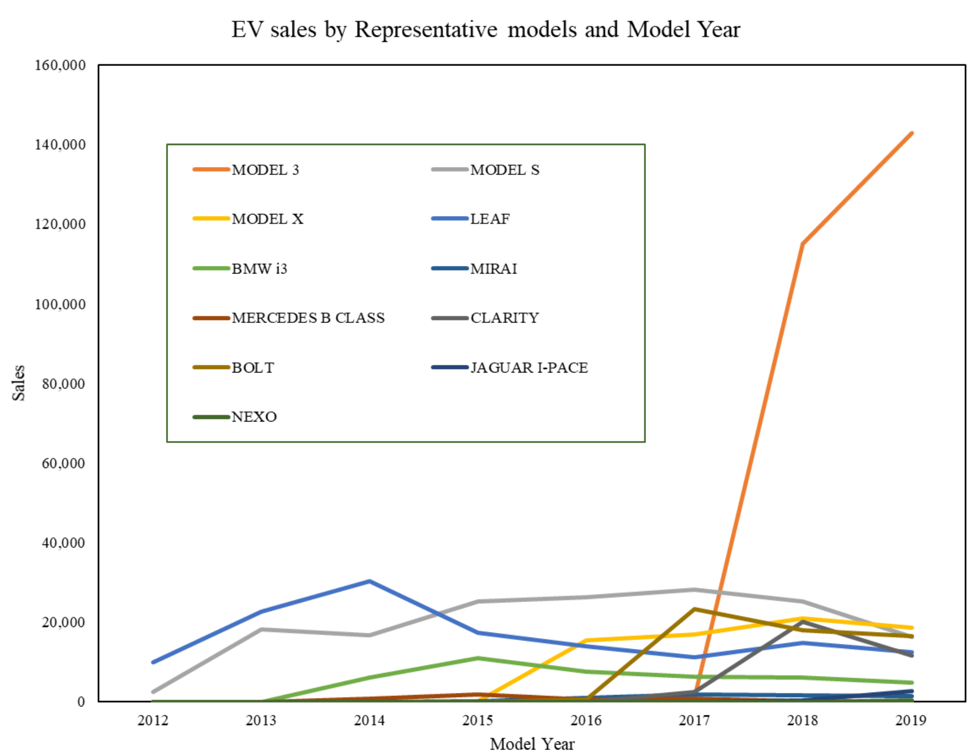


Figure A.4. EV sales by representative models and model year (2012 - 2019)

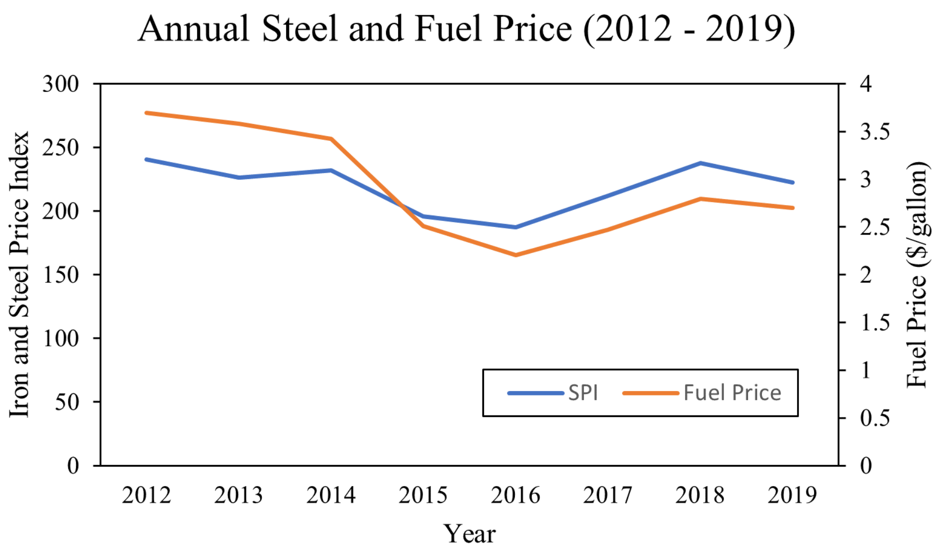
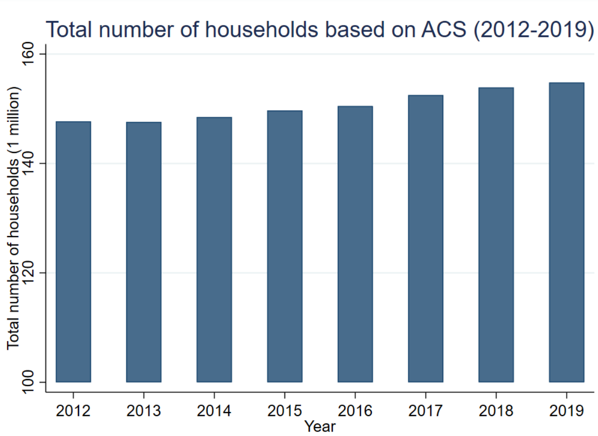


Figure A.5. Steel and fuel price (no seasonality/inflation adjusted 2012 - 2019)



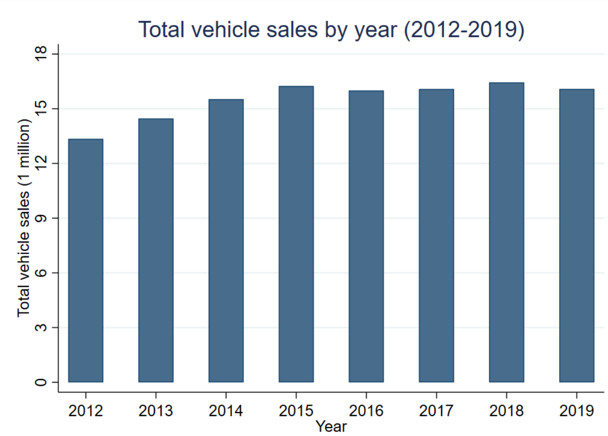


Figure A.6. Total number of households in US based on ACS sample representation and total sales of vehicles (2012 - 2019)
Source of number of households. 1 % American Community Survey (2012 - 2019)

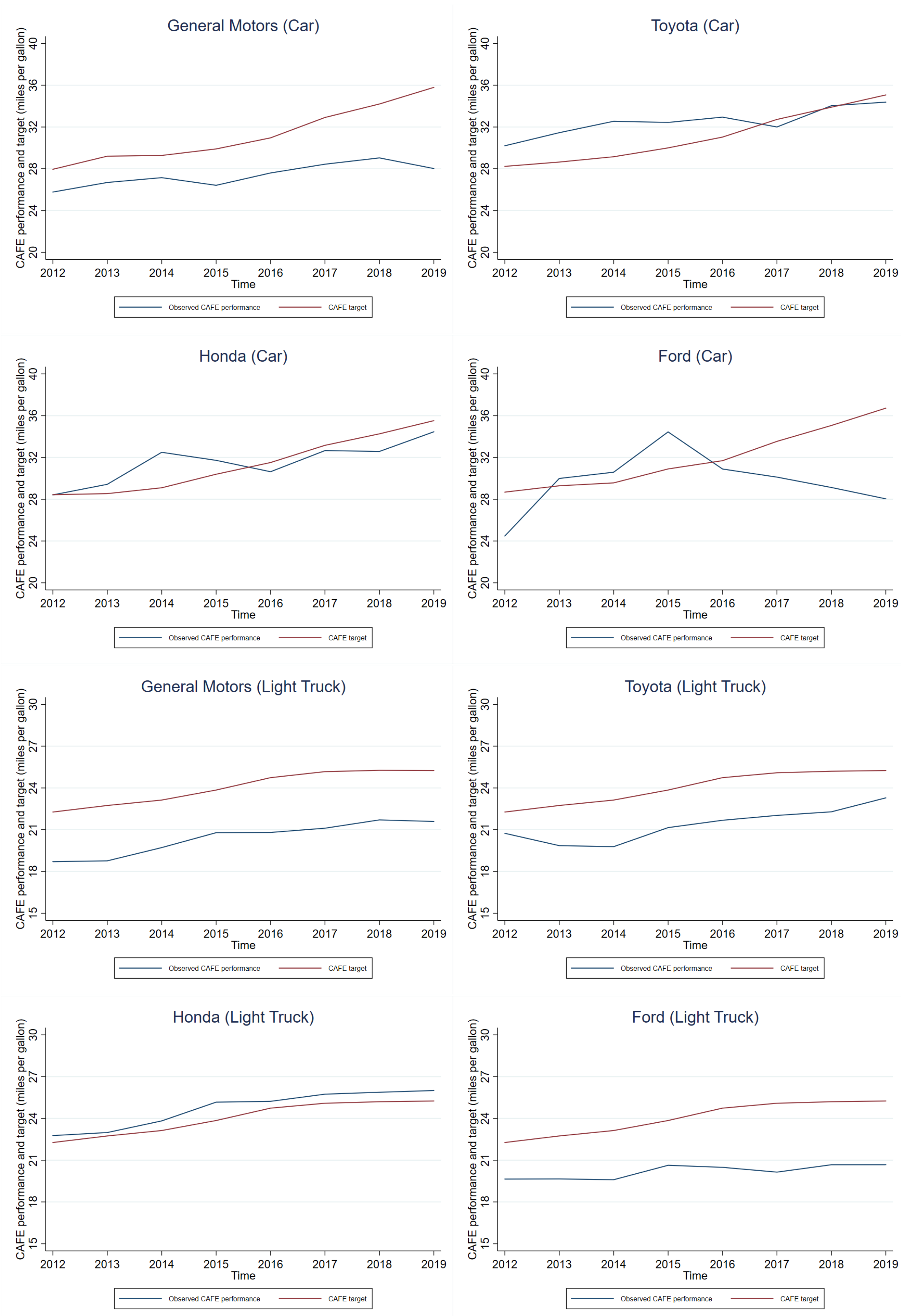


Figure A.7. Observed CAFE performance and CAFE target for representative manufacturers (2012 - 2019)

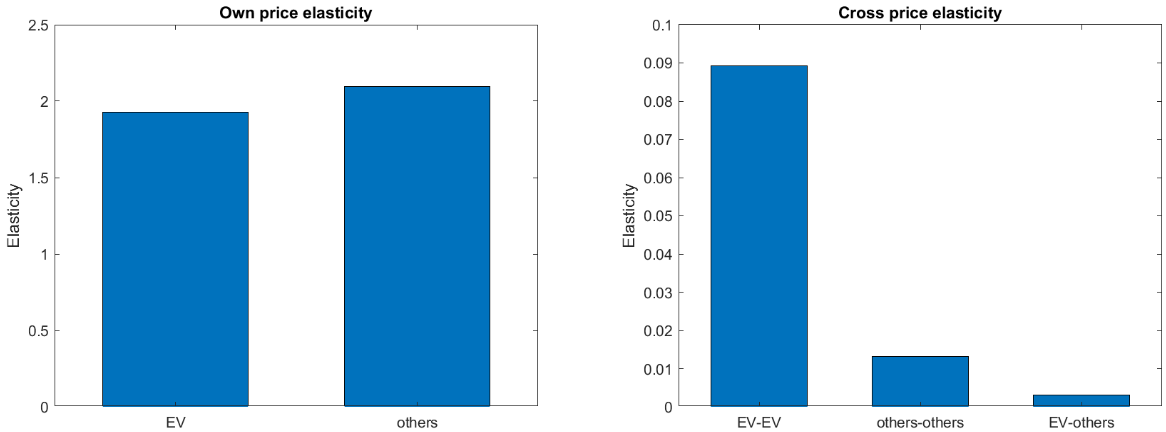


Figure A.8. Average own-price and cross-price elasticity

Table A.4. Logit model without instruments estimates

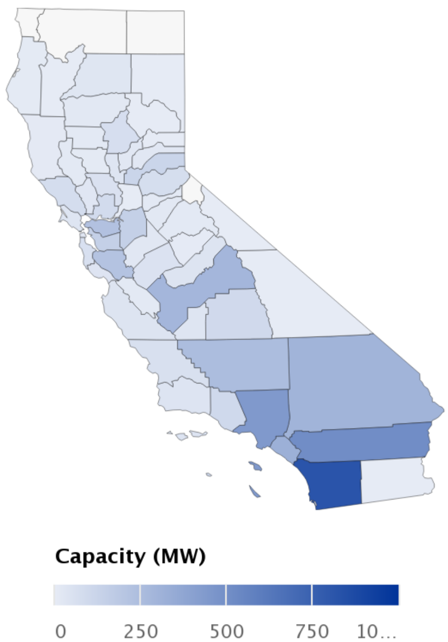
	(1) Monthly data	(2) Yealy data
HPW	11.717***	10.572***
	(1.094)	(3.550)
SIZE	3.882***	3.953***
	(0.094)	(0.313)
MPG	3.995***	3.914***
	(0.274)	(0.906)
Trend	-0.002***	-0.022
	(0.000)	(0.014)
EV	-4.234***	-4.006***
	(0.309)	(1.001)
EV $\times$ Trend	0.009***	0.055
	(0.003)	(0.115)
Price/Income	-1.267***	-1.184***
	(0.110)	(0.343)
Constant	-16.156***	-15.960***
	(0.235)	(0.766)
Observations	22408	1880
R^2	0.355	0.376

We have monthly sales data but the car attributes data are by year. If we merge monthly sales data with annual car attributes data , we are able to obtain a larger data size (22,408). This table shows a preliminary comparison of using the monthly data versus aggregated yearly data in a Logit model. The results do not vary a lot from each other. However, computing the RC estimates using a 12 times larger data set raises the computation burden significantly. Therefore this paper uses aggregated yearly data.

A.3 Chapter 3 Appendices

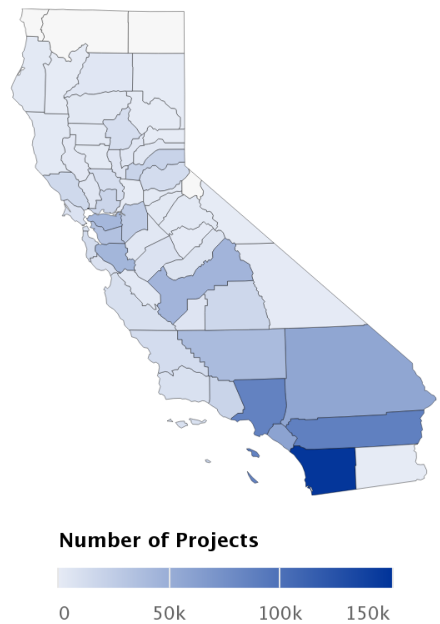
Installled Capacity By County

(Residential Sector)



Installed Projects By County

(Residential Sector)



Data source: https://www.californiadgstats.ca.gov/charts/

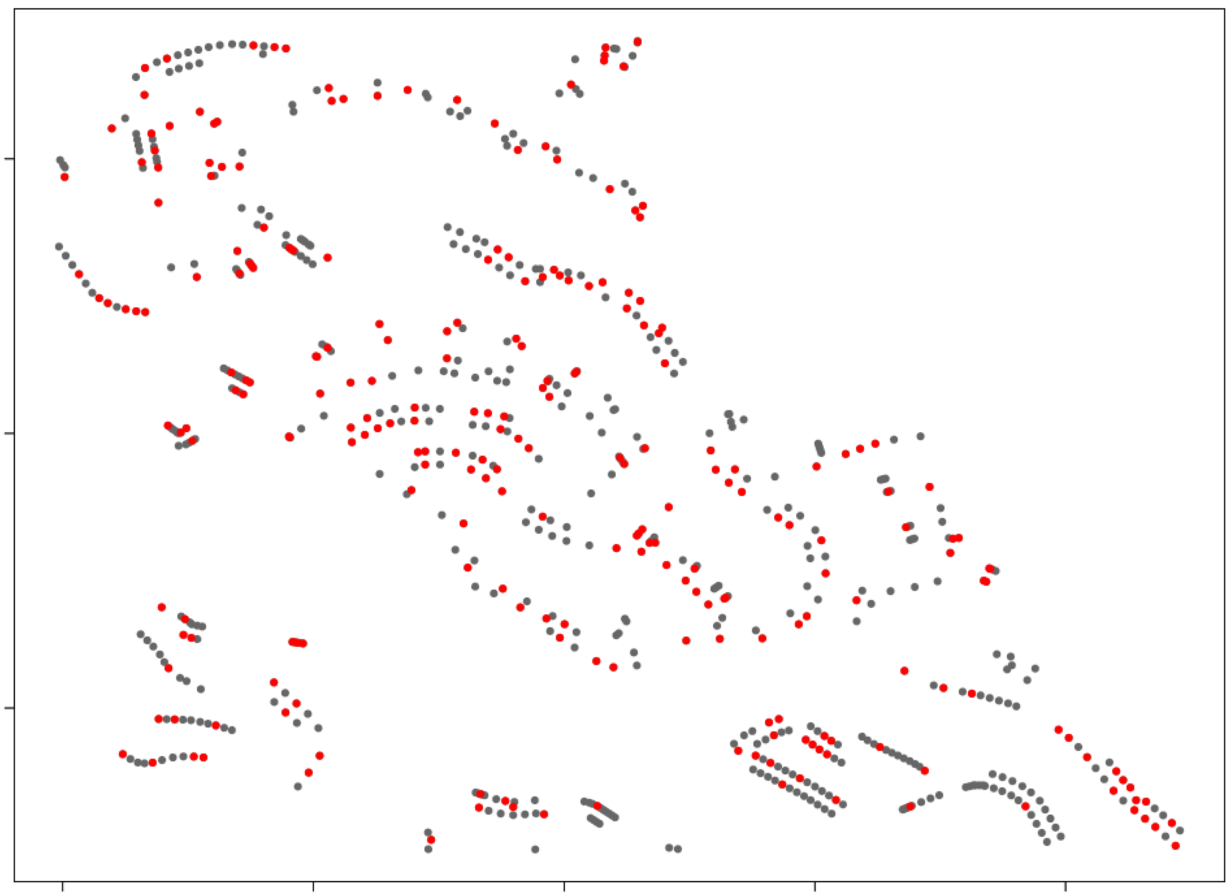


Figure A.9. A sample community in California
Note: Red circle represents residential solar PV installed by 2019 and grey circle represents no residential solar PV installed by 2019.

Table A.5. Zipcode level regressions

Dependent variable: Average number of days before adopting solar PV within a zip-code counted since Jan. 1st 1999

	(1) w/o demographics	(2) w/ demographics
log(num of single family houses)	54.046***	53.752**
	(19.627)	(23.809)
Total system cost ($1,000)	28.217	72.441***
	(29.505)	(13.031)
% At least one electric vehicle charging	-7585.904**	-2423.956
	(3361.585)	(2523.778)
Sex ratio (males per 100 females)		1.919
		(1.361)
% Under 18 years		234.904
		(691.246)
% 65 years and over		-160.524
		(596.336)
% White		775.508
		(599.748)
% Black or African American		2377.477***
		(876.908)
% American Indian and Alaska Native		1032.163
		(748.377)
% Asian		1230.274*
		(656.252)
% Hispanic or Latino		403.639**
		(151.952)
Constant	5292.597***	3410.402***
	(576.191)	(580.971)
Observations	62	61
R^2	0.282	0.734

We exclude the observations with the lowest 1% and highest 1% total system cost.

Table A.6. Frequency of simultaneous adoptions in various episode scenarios

Num of adopters in one episode	$\Delta = 1$	$\Delta = 2$	$\Delta = 3$	$\Delta = 4$	$\Delta = 5$	$\Delta = 10$
1	25,675	17,369	13,801	11,191	9,216	4,939
2	10,287	8,002	6,498	5,487	4,510	2,374
3	4,996	4,499	3,873	3,472	3,029	1,542
4	2,545	2,741	2,615	2,393	2,161	1,141
5	1,279	1,807	1,754	1,748	1,623	923
6	770	1,148	1,235	1,268	1,242	764
7	413	717	829	904	971	699
8	219	401	584	631	761	637
9	140	278	392	505	563	537
10	77	194	277	374	397	456
11	40	125	184	264	327	419
12	20	66	152	189	228	361
13	15	34	85	125	167	273
14	14	34	76	96	137	273
15	5	18	45	63	90	246
16	8	14	28	49	73	196
17	4	9	19	36	51	147
18	4	3	13	21	35	129
19	3	9	15	14	22	100
20	2	3	9	11	26	105

Highly clustered cases (number of adopters more than 20 in one episode) is omitted in the table. The numbers are shown as the frequency. For example, there are 10,287 paired households adopting at the same day if time is discretized by day ($\Delta = 1$ day).

VITA

Jixuan (Edie) Yao was born in Zibo, China. She holds an BS degree in Actuarial Science from Shanghai University of Finance and Economics in 2014, by which she has passed 6 professional actuarial exams from Society of Actuaries (SOA). After her undergraduate study in Shanghai, she joined Cornell University and obtained a MS degree of Applied Economics and Management in 2016. Her PhD study in Agricultural Economics at Purdue started at Fall 2016, and she has been the instructor of Math Camp for new PhD students and a math/stats course for MS students since Fall 2018. She also received a MS degree in Economics at Purdue. Her research interests contain two parallel fields: family/labor economics, which she concentrates in gender inequality; and environmental economics with a focus on the diffusion of renewable energy.